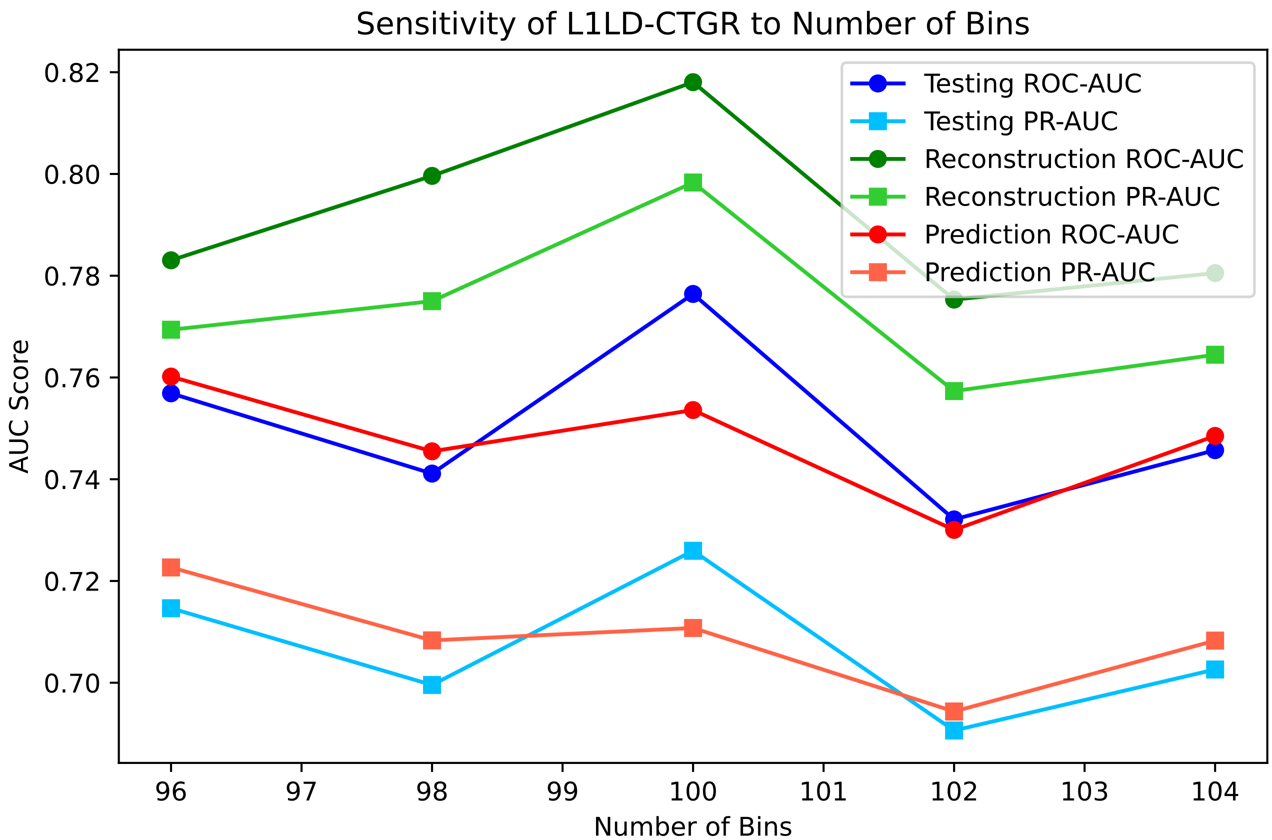

Figure 1: Sensitivity of ℓ_1LD-CTGR to the number of bins on the US Legis. data set. We change the number of bins in the interval $[96, 104]$ and fix other hyperparameters. ℓ_1LD-CTGR shows robust AUC scores to this change.

Table 1: Performance of different methods for network reconstruction (in-sample) across diverse data sets. TCL and GraphMixer are two new compared methods from (Yu et al., 2023), while Can. Parl. and US Legis. are two new data sets from (Poursafaei et al., 2022). We also double the initial relative distance parameter in Synthetic-α to generate more outliers for experiments, shown as "Synthetic-α (More Outliers)". In this setting, ℓ_1LD-CTGR significantly outperforms GRASSP.

Data Set		Node2Vec	CTDNE	HTNE	PIVEM	TCL	GraphMixer	GRASSP	ℓ_1LD-CTGR
Synthetic-α	ROC	0.627 ±0.004	0.518 ±0.006	0.573 ±0.009	0.554 ±0.002	0.550 ±0.021	0.431 ±0.084	**0.724 ±0.004**	0.687 ±0.006
	PR	0.629 ±0.006	0.568 ±0.011	0.545 ±0.008	0.567 ±0.003	0.567 ±0.020	0.503 ±0.034	**0.756 ±0.005**	0.643 ±0.008
Synthetic-β	ROC	0.541 ±0.006	0.493 ±0.008	0.535 ±0.008	0.531 ±0.006	0.528 ±0.061	0.448 ±0.006	**0.843 ±0.015**	0.610 ±0.021
	PR	0.545 ±0.004	0.557 ±0.006	0.591 ±0.006	0.536 ±0.006	0.621 ±0.054	0.573 ±0.016	**0.756 ±0.011**	0.554 ±0.017
Contacts	ROC	0.674 ±0.011	0.508 ±0.021	0.555 ±0.011	0.539 ±0.012	0.594 ±0.007	0.539 ±0.012	0.589 ±0.013	**0.676 ±0.016**
	PR	0.657 ±0.016	0.570 ±0.019	0.563 ±0.013	0.567 ±0.009	0.616 ±0.016	0.614 ±0.013	0.634 ±0.019	**0.676 ±0.021**
HyperText	ROC	0.589 ±0.006	0.486 ±0.014	0.619 ±0.011	0.560 ±0.004	0.602 ±0.010	0.662 ±0.006	0.607 ±0.006	**0.694 ±0.011**
	PR	0.569 ±0.008	0.542 ±0.013	0.624 ±0.007	0.572 ±0.004	0.627 ±0.007	0.663 ±0.003	0.580 ±0.009	**0.691 ±0.014**
Infectious	ROC	0.781 ±0.003	0.501 ±0.009	0.851 ±0.011	0.613 ±0.005	0.811 ±0.001	0.804 ±0.001	0.738 ±0.018	**0.861 ±0.021**
	PR	0.742 ±0.008	0.566 ±0.011	0.819 ±0.009	0.630 ±0.007	0.812 ±0.004	0.801 ±0.001	0.708 ±0.016	**0.832 ±0.019**
Facebook	ROC	0.506 ±0.002	0.473 ±0.005	0.445 ±0.003	0.482 ±0.002	0.510 ±0.002	0.5 ±0.009	0.5 ±0.000	**0.612 ±0.004**
	PR	0.515 ±0.004	0.489 ±0.005	0.481 ±0.003	**0.625 ±0.003**	0.520 ±0.001	0.53 ±0.006	0.5 ±0.000	0.588 ±0.004
NeurIPS	ROC	0.433 ±0.004	0.489 ±0.011	0.431 ±0.011	0.510 ±0.009	**0.635 ±0.001**	0.634 ±0.001	0.548 ±0.018	0.528 ±0.009
	PR	0.476 ±0.004	0.541 ±0.015	0.448 ±0.008	0.525 ±0.008	**0.580 ±0.004**	0.578 ±0.006	0.506 ±0.025	0.501 ±0.008
US Legis.	ROC	0.493 ±0.003	0.478 ±0.011	0.490 ±0.017	0.525 ±0.012	0.750 ±0.005	0.766 ±0.014	0.662 ±0.012	**0.767 ±0.014**
	PR	0.510 ±0.004	0.524 ±0.013	0.576 ±0.020	0.561 ±0.012	0.515 ±0.004	0.700 ±0.008	0.588 ±0.018	**0.712 ±0.012**
Can. Parl.	ROC	0.701 ±0.004	0.479 ±0.009	0.583 ±0.011	0.508 ±0.009	0.687 ±0.004	0.761 ±0.009	0.593 ±0.013	**0.826 ±0.004**
	PR	0.649 ±0.004	0.542 ±0.009	0.643 ±0.015	0.527 ±0.014	0.634 ±0.005	0.743 ±0.005	0.614 ±0.008	**0.793 ±0.003**
Synthetic-α (More Outliers)	ROC	0.524 ±0.013	0.550 ±0.016	0.535 ±0.021	0.567 ±0.018	0.281 ±0.042	0.300 ±0.038	0.577 ±0.028	**0.793 ±0.038**
	PR	0.538 ±0.023	0.555 ±0.027	0.602 ±0.019	0.642 ±0.016	0.400 ±0.009	0.412 ±0.027	0.509 ±0.029	**0.708 ±0.039**

Table 2: Performance of different methods for network completion (out-of-sample) across diverse data sets. TCL and GraphMixer are two new compared methods from (Yu et al., 2023), while Can. Parl. and US Legis. are two new data sets from (Poursafaei et al., 2022). We also double the initial relative distance parameter in Synthetic-α to generate more outliers for experiments, shown as "Synthetic-α (More Outliers)". In this setting, ℓ_1LD-CTGR significantly outperforms GRASSP.

Data Set		Node2Vec	CTDNE	HTNE	PIVEM	TCL	GraphMixer	GRASSP	ℓ_1LD-CTGR
Synthetic-α	ROC	0.696 ±0.003	0.536 ±0.006	0.339 ±0.013	0.522 ±0.002	0.541 ±0.029	0.540 ±0.033	0.630 ±0.011	**0.750 ±0.008**
	PR	0.681 ±0.008	0.557 ±0.007	0.485 ±0.011	0.534 ±0.003	0.528 ±0.008	0.550 ±0.020	0.687 ±0.011	**0.695 ±0.009**
Synthetic-β	ROC	0.656 ±0.007	0.507 ±0.009	0.377 ±0.009	0.542 ±0.007	0.550 ±0.011	0.564 ±0.043	0.612 ±0.018	**0.661 ±0.013**
	PR	**0.694 ±0.007**	0.569 ±0.011	0.578 ±0.004	0.566 ±0.009	0.556 ±0.010	0.563 ±0.043	0.540 ±0.024	0.641 ±0.018
Contacts	ROC	0.517 ±0.021	0.489 ±0.029	0.461 ±0.025	0.557 ±0.009	0.610 ±0.001	0.621 ±0.002	0.670 ±0.016	**0.680 ±0.017**
	PR	0.526 ±0.019	0.553 ±0.031	0.509 ±0.023	0.579 ±0.017	0.602 ±0.003	0.687 ±0.001	0.714 ±0.025	**0.724 ±0.028**
HyperText	ROC	0.570 ±0.011	0.498 ±0.015	0.613 ±0.014	0.554 ±0.015	0.641 ±0.016	0.658 ±0.001	0.619 ±0.011	**0.671 ±0.012**
	PR	0.595 ±0.013	0.554 ±0.017	0.651 ±0.008	0.571 ±0.008	0.645 ±0.001	0.652 ±0.001	0.591 ±0.024	**0.672 ±0.015**
Infectious	ROC	0.681 ±0.004	0.534 ±0.009	0.651 ±0.018	0.578 ±0.003	0.728 ±0.000	0.724 ±0.001	0.728 ±0.029	**0.756 ±0.017**
	PR	0.632 ±0.011	0.585 ±0.008	0.611 ±0.016	0.592 ±0.004	0.731 ±0.001	0.723 ±0.003	0.711 ±0.028	**0.779 ±0.017**
Facebook	ROC	0.529 ±0.002	0.340 ±0.005	0.463 ±0.003	0.482 ±0.002	0.533 ±0.002	0.571 ±0.004	0.5 ±0.000	**0.572 ±0.004**
	PR	0.572 ±0.004	0.501 ±0.005	0.511 ±0.003	0.608 ±0.003	0.549 ±0.001	0.620 ±0.002	0.5 ±0.000	**0.687 ±0.004**
NeurIPS	ROC	0.355 ±0.002	0.455 ±0.018	0.222 ±0.026	0.469 ±0.014	0.503 ±0.000	0.467 ±0.001	0.360 ±0.031	**0.533 ±0.022**
	PR	0.355 ±0.002	0.435 ±0.022	0.289 ±0.028	0.468 ±0.027	0.504 ±0.000	0.536 ±0.002	0.468 ±0.026	**0.559 ±0.019**
US Legis.	ROC	0.393 ±0.003	0.490 ±0.009	0.492 ±0.014	0.510 ±0.010	0.749 ±0.006	0.770 ±0.015	0.656 ±0.013	**0.776 ±0.013**
	PR	0.486 ±0.004	0.534 ±0.014	0.542 ±0.016	0.529 ±0.011	0.684 ±0.005	0.707 ±0.013	0.587 ±0.015	**0.725 ±0.012**
Can. Parl.	ROC	0.675 ±0.003	0.509 ±0.010	0.473 ±0.011	0.529 ±0.012	0.734 ±0.008	0.801 ±0.014	0.678 ±0.009	**0.810 ±0.009**
	PR	0.616 ±0.004	0.568 ±0.013	0.538 ±0.016	0.545 ±0.010	0.692 ±0.002	0.739 ±0.012	0.709 ±0.008	**0.761 ±0.010**
Synthetic-α (More Outliers)	ROC	0.459 ±0.009	0.489 ±0.021	0.542 ±0.019	0.578 ±0.030	0.602 ±0.020	0.619 ±0.016	0.559 ±0.024	**0.817 ±0.030**
	PR	0.471 ±0.013	0.493 ±0.019	0.574 ±0.020	0.562 ±0.027	0.590 ±0.016	0.586 ±0.011	0.527 ±0.021	**0.813 ±0.031**

Table 3: Performance of different methods for network prediction (across-sample) across diverse data sets. TCL and GraphMixer are two new compared methods from (Yu et al., 2023), while Can. Parl. and US Legis. are two new data sets from (Poursafaei et al., 2022). We also double the initial relative distance parameter in Synthetic-α to generate more outliers for experiments, shown as "Synthetic-α (More Outliers)". In this setting, ℓ_1LD-CTGR significantly outperforms GRASSP.

Data Set		Node2Vec	CTDNE	HTNE	PIVEM	TCL	GraphMixer	GRASSP	ℓ_1LD-CTGR
Synthetic-α	ROC	0.748 ±0.005	0.517 ±0.007	0.606 ±0.009	0.602 ±0.006	0.588 ±0.059	0.493 ±0.108	0.901 ±0.013	**0.912 ±0.018**
	PR	0.673 ±0.011	0.562 ±0.015	0.641 ±0.013	0.614 ±0.005	0.579 ±0.078	0.531 ±0.049	**0.913 ±0.011**	0.881 ±0.011
Synthetic-β	ROC	0.514 ±0.003	0.491 ±0.012	0.593 ±0.006	0.588 ±0.006	0.456 ±0.008	0.363 ±0.056	0.861 ±0.014	**0.864 ±0.014**
	PR	0.578 ±0.007	0.555 ±0.018	0.639 ±0.005	0.598 ±0.006	0.503 ±0.009	0.465 ±0.035	0.829 ±0.014	**0.831 ±0.016**
Contacts	ROC	0.738 ±0.009	0.509 ±0.016	0.604 ±0.003	0.493 ±0.011	0.681 ±0.013	0.676 ±0.004	0.763 ±0.016	**0.767 ±0.018**
	PR	0.687 ±0.015	0.565 ±0.017	0.601 ±0.004	0.497 ±0.010	0.691 ±0.003	0.692 ±0.001	0.714 ±0.020	**0.721 ±0.018**
HyperText	ROC	0.552 ±0.003	0.491 ±0.011	0.501 ±0.019	0.516 ±0.006	0.513 ±0.005	0.525 ±0.001	**0.607 ±0.007**	0.568 ±0.005
	PR	0.518 ±0.011	0.552 ±0.005	0.502 ±0.018	0.516 ±0.004	0.525 ±0.008	0.537 ±0.004	0.569 ±0.009	**0.576 ±0.009**
Infectious	ROC	0.869 ±0.002	0.508 ±0.006	0.730 ±0.017	0.517 ±0.008	0.867 ±0.003	0.859 ±0.003	0.898 ±0.015	**0.901 ±0.016**
	PR	0.875 ±0.007	0.555 ±0.014	0.771 ±0.013	0.602 ±0.009	0.866 ±0.007	0.852 ±0.005	0.861 ±0.017	**0.888 ±0.016**
Facebook	ROC	0.489 ±0.002	0.503 ±0.005	0.468 ±0.003	0.483 ±0.002	0.493 ±0.001	0.472 ±0.004	0.491 ±0.006	**0.528 ±0.004**
	PR	0.513 ±0.006	0.517 ±0.005	0.462 ±0.009	0.491 ±0.003	0.512 ±0.001	0.517 ±0.002	0.498 ±0.006	**0.535 ±0.003**
NeurIPS	ROC	0.445 ±0.004	0.504 ±0.009	0.510 ±0.018	0.507 ±0.014	0.5 ±0.000	0.5 ±0.000	0.761 ±0.010	**0.778 ±0.011**
	PR	0.470 ±0.004	0.569 ±0.011	0.517 ±0.022	0.505 ±0.012	0.5 ±0.000	0.5 ±0.000	0.675 ±0.019	**0.723 ±0.013**
US Legis.	ROC	0.475 ±0.003	0.466 ±0.011	0.490 ±0.017	0.463 ±0.012	0.482 ±0.011	0.469 ±0.015	0.565 ±0.012	**0.754 ±0.014**
	PR	0.496 ±0.004	0.513 ±0.013	0.593 ±0.020	0.481 ±0.012	0.505 ±0.008	0.505 ±0.013	0.537 ±0.018	**0.711 ±0.012**
Can. Parl.	ROC	0.654 ±0.005	0.504 ±0.012	0.512 ±0.016	0.504 ±0.010	0.569 ±0.008	0.582 ±0.014	0.678 ±0.010	**0.715 ±0.010**
	PR	0.597 ±0.004	0.565 ±0.009	0.527 ±0.011	0.496 ±0.005	0.548 ±0.005	0.557 ±0.009	0.609 ±0.008	**0.651 ±0.008**
Synthetic-α (More Outliers)	ROC	0.486 ±0.003	0.511 ±0.019	0.575 ±0.016	0.588 ±0.014	0.420 ±0.015	0.446 ±0.066	0.875 ±0.020	**0.922 ±0.018**
	PR	0.491 ±0.012	0.495 ±0.019	0.614 ±0.020	0.502 ±0.017	0.454 ±0.011	0.510 ±0.014	0.819 ±0.019	**0.890 ±0.019**

Table 4: Average running time (in seconds) per epoch of GRASSP and ℓ_1LD-CTGR on different data sets (mean $\pm$ STD). Results are conducted on a device with an Intel(R) Xeon(R) Gold 6330 CPU, 1 TB RAM, and eight NVIDIA A100 GPUs. ℓ_1LD-CTGR shows the same order of computational time as that of GRASSP.

Data Set	GRASSP	ℓ_1LD-CTGR
Synthetic-α	$1.85E-4 \pm 8.89E-6$	$1.79E-4 \pm 8.77E-6$
Synthetic-β	$1.64E-4 \pm 7.15E-6$	$1.66E-4 \pm 7.81E-6$
Contacts	$3.21E-3 \pm 1.60E-4$	$3.09E-3 \pm 1.45E-4$
HyperText	$6.18E-3 \pm 2.98E-4$	$6.22E-3 \pm 2.90E-4$
Infectious	$6.15E-3 \pm 3.00E-4$	$6.15E-3 \pm 2.79E-4$
Facebook	$4.49 \pm 2.18E-1$	$4.55 \pm 2.33E-1$
NeurIPS	$2.74E-1 \pm 1.41E-2$	$2.77E-1 \pm 1.37E-2$
US Legis.	$1.86E-2 \pm 9.39E-4$	$1.76E-2 \pm 9.10E-4$
Can. Parl.	$2.49E-2 \pm 1.20E-3$	$2.44E-2 \pm 1.31E-3$
Synthetic-α (More Outliers)	$1.93E-4 \pm 8.97E-6$	$1.94E-4 \pm 9.44E-6$