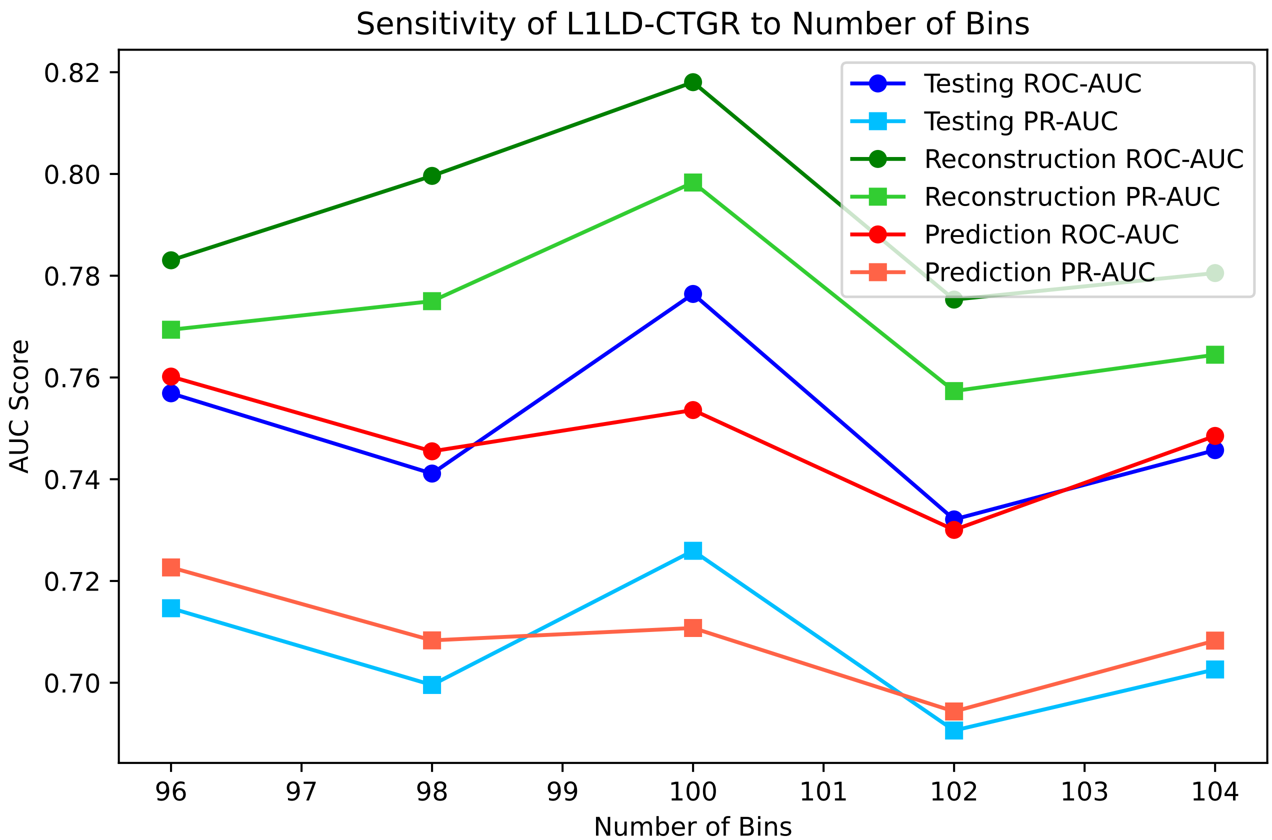

Figure 1: Sensitivity of ℓ_1LD-CTGR to the number of bins on the USLegis data set. We change the number of bins in the interval $[96, 104]$ and fix other hyperparameters. ℓ_1LD-CTGR shows robust AUC scores to this change.

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 CanParl and USLegis 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.

		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**	0.632 ±0.013
	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**	0.604 ±0.016
Contacts	ROC	0.674 ±0.011	0.508 ±0.021	0.555 ±0.011	**0.862 ±0.006**	0.854 ±0.007	0.539 ±0.012	0.589 ±0.013	0.681 ±0.014
	PR	0.657 ±0.016	0.570 ±0.019	0.563 ±0.013	0.567 ±0.009	**0.876 ±0.016**	0.840 ±0.013	0.634 ±0.019	0.674 ±0.013
HyperText	ROC	0.589 ±0.006	0.486 ±0.014	0.619 ±0.011	0.560 ±0.004	0.702 ±0.010	**0.862 ±0.006**	0.607 ±0.006	0.699 ±0.011
	PR	0.569 ±0.008	0.542 ±0.013	0.624 ±0.007	0.572 ±0.004	0.727 ±0.007	**0.863 ±0.003**	0.580 ±0.009	0.690 ±0.010
Infectious	ROC	0.781 ±0.003	0.501 ±0.009	0.851 ±0.011	0.613 ±0.005	0.911 ±0.001	**0.940 ±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	0.912 ±0.004	**0.934 ±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	0.563 ±0.007
	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
USLegis	ROC	0.493 ±0.003	0.478 ±0.011	0.490 ±0.017	0.525 ±0.012	0.491 ±0.005	0.511 ±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	0.524 ±0.008	0.588 ±0.018	**0.712 ±0.012**
CanParl	ROC	**0.701 ±0.004**	0.479 ±0.009	0.583 ±0.011	0.508 ±0.009	0.595 ±0.004	0.572 ±0.009	0.593 ±0.013	0.665 ±0.004
	PR	0.649 ±0.004	0.542 ±0.009	0.643 ±0.015	0.527 ±0.014	0.574 ±0.005	0.558 ±0.005	0.614 ±0.008	**0.652 ±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 CanParl and USLegis 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.

		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	**0.721 ±0.011**
	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	**0.702 ±0.012**
Contacts	ROC	0.517 ±0.021	0.489 ±0.029	0.461 ±0.025	0.557 ±0.009	0.910 ±0.001	**0.912 ±0.002**	0.670 ±0.016	0.720 ±0.019
	PR	0.526 ±0.019	0.553 ±0.031	0.509 ±0.023	0.579 ±0.017	**0.902 ±0.003**	0.897 ±0.001	0.714 ±0.025	0.756 ±0.028
HyperText	ROC	0.570 ±0.011	0.498 ±0.015	0.613 ±0.014	0.554 ±0.015	0.641 ±0.016	0.718 ±0.001	0.619 ±0.011	**0.721 ±0.010**
	PR	0.595 ±0.013	0.554 ±0.017	0.651 ±0.008	0.571 ±0.008	0.645 ±0.001	0.702 ±0.001	0.591 ±0.024	**0.712 ±0.011**
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**
USLegis	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**
CanParl	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 CanParl and USLegis 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.

		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	**0.910 ±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	**0.918 ±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	**0.891 ±0.013**	0.876 ±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	**0.901 ±0.003**	0.892 ±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	0.693 ±0.005	**0.885 ±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	0.705 ±0.008	**0.870 ±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**
USLegis	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**
CanParl	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.

Dataset	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	$2.74E-1 \pm 1.41E-2$	$2.77E-1 \pm 1.37E-2$
USLegis	$1.86E-2 \pm 9.39E-4$	$1.76E-2 \pm 9.10E-4$
CanParl	$2.49E-2 \pm 1.20E-3$	$2.44E-2 \pm 1.31E-3$
Synthetic-α (More Outliers)	$1.93E-4 \pm 8.97E-6$	$1.94E-4 \pm 9.44E-6$