

Figure 1: Comparison of classical and functional translation of a Gaussian signal. Top Row (Classical Translation): The Gaussian signal moves uniformly across the grid without changing shape. Bottom Row (Functional Translation): The Gaussian signal distorts as low-frequency components move at different speeds than high-frequency components, demonstrating relaxed symmetry.

	Penn94	Pokec	Genius	Twitch-Gamers	Wiki
GCN	82.47 ± 0.3	75.45 ± 0.2	87.42 ± 0.4	62.18 ± 0.3	OOM
LINK	80.79 ± 0.5	80.54 ± 0.0	73.56 ± 0.1	64.85 ± 0.2	57.11 ± 0.3
LINKX	84.71 ± 0.5	82.04 ± 0.1	90.77 ± 0.3	$\textbf{66.06} \pm 0.2$	59.80 ± 0.4
GPRGNN	83.54 ± 0.3	80.74 ± 0.2	90.15 ± 0.3	62.59 ± 0.4	58.73 ± 0.3
ChebNet	82.59 ± 0.3	72.71 ± 0.7	89.36 ± 0.3	62.31 ± 0.4	OOM
ChebNetII	84.86 ± 0.3	82.33 ± 0.3	90.85 ± 0.3	65.03 ± 0.3	60.95 ± 0.4
BernNet	83.26 ± 0.3	81.67 ± 0.2	90.47 ± 0.3	64.27 ± 0.3	59.02 ± 0.3
OptBasisGNN	84.85 ± 0.4	82.83 ± 0.0	90.83 ± 0.1	65.17 ± 0.2	61.85 ± 0.0
att-Node-level NLSFs	84.93 ± 0.2	82.51 ± 0.3	90.92 ± 0.2	65.76 ± 0.3	62.03 ± 0.2
att-Node-level rem-NLSFs	$\textbf{85.19} \pm 0.3$	$\textbf{82.96} \pm 0.1$	$\textbf{91.24} \pm 0.1$	65.97 ± 0.2	$\textbf{62.44} \pm 0.3$

Table 1: Experimental results on large heterophilic graphs. The results for BernNet, ChebNet, ChebNetII, and GPRGNN are taken from He et al. (2022), while the results for OptBasisGNN are taken from Guo et al. (2023). All other competing results are taken from Lim et al. (2021).

	Cora	Citeseer	Pubmed	Chameleon	Squirrel	Actor
GCN	81.92 ± 0.9	70.73 ± 1.1	80.14 ± 0.6	43.64 ± 1.9	33.26 ± 0.8	27.63 ± 1.7
GAT	83.64 ± 0.7	71.32 ± 1.3	79.45 ± 0.7	42.19 ± 1.3	28.21 ± 0.9	29.46 ± 0.9
SAGE	74.01 ± 2.1	66.40 ± 1.2	79.91 ± 0.9	41.92 ± 0.7	27.64 ± 2.1	30.85 ± 1.8
ChebNet	79.72 ± 1.1	70.48 ± 1.0	76.47 ± 1.5	44.95 ± 1.2	33.82 ± 0.8	27.42 ± 2.3
ChebNetII	83.95 ± 0.8	71.76 ± 1.2	81.38 ± 1.3	46.37 ± 3.1	34.40 ± 1.1	33.48 ± 1.2
CayleyNet	81.76 ± 1.9	68.32 ± 2.3	77.48 ± 2.1	38.29 ± 3.2	26.53 ± 3.3	30.62 ± 2.8
APPNP	83.19 ± 0.8	71.93 ± 0.8	$\textbf{82.69} \pm 1.4$	37.43 ± 1.9	25.68 ± 1.3	$\textbf{35.98} \pm 1.3$
GPRGNN	82.82 ± 1.3	70.28 ± 1.4	81.31 ± 2.6	39.27 ± 2.3	26.09 ± 1.3	31.47 ± 1.6
ARMA	81.64 ± 1.2	69.91 ± 1.6	79.24 ± 0.5	39.40 ± 1.8	27.42 ± 0.7	30.42 ± 2.6
JacobiConv	84.12 ± 0.7	72.59 ± 1.4	82.05 ± 1.9	49.66 ± 1.9	33.65 ± 0.8	34.61 ± 0.7
BernNet	82.96 ± 1.1	71.25 ± 1.0	81.07 ± 1.6	42.65 ± 3.4	31.68 ± 1.5	33.92 ± 0.8
Specformer	82.27 ± 0.7	73.45 ± 1.4	81.62 ± 1.0	49.79 ± 1.2	38.24 ± 0.9	34.12 ± 0.6
OptBasisGNN	81.97 ± 1.2	70.46 ± 1.6	80.38 ± 0.9	47.12 ± 2.4	37.66 ± 1.1	34.84 ± 1.3
att-Node-level NLSFs	84.75 ± 0.7	73.62 ± 1.1	81.93 ± 1.0	49.68 ± 1.6	38.25 ± 0.7	34.72 ± 0.9
att-Node-level rem-NLSFs	$\textbf{85.37} \pm 1.8$	$\textbf{75.41} \pm 0.8$	82.22 ± 1.2	$\textbf{50.58} \pm 1.3$	$\textbf{38.39} \pm 0.9$	35.13 ± 1.0

Table 2: Semi-supervised node classification accuracy.

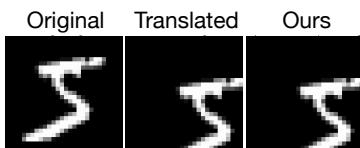


Figure 2: Approximate a standard translation by functional translation on a perturbed graph.

	MNIST	Perturbed MNIST
Ours	99.19	99.16

Table 3: Classification accuracy on the MNIST and perturbed MNIST using NLSFs.