Patterns, Volume 3

Supplemental information

Quantitative evaluation of explainable graph

neural networks for molecular property prediction

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Figure S1. The average Attribution-Accuracy values. (A) four GNN models and (B) six XAI methods. (C-F) Detailed Attribution Accuracies for combinations of all XAI methods and GNN models for each dataset.



Figure S2. Visualization of Benzene dataset. The embeddings learned by CMPNN+IG over the Benzene dataset shown by t-SNE, together with representatively 3 benzene and 3 non-benzene molecules.



Figure S3. Results of XAI-assisted FPs experiments with Random Forest. (A) The ROC curves of Morgan-FP, Morgan-FP + MACCS-FP, and Morgan-FP + XAI-FP with Random Forest on the OGB-HIV, OGB-BACE and OGB-BBBP dataset. (B) The predicted results of Morgan-FP + XAI-FPs, Morgan-FP + MACCS-FP and Morgan-FP with Random Forest model for the IGC50 dataset. (C) The predicted results of Morgan-FP + XAI-FPs, Morgan-FP + MACCS-FP and Morgan-FP with Random Forest model for the LD50 dataset.

FreeSolv	Lipophilicity	ESOL	ClinTox	BBBP
R^2	R^2	R^2	AUROC	AUROC
0.640 ^a	0.577ª	0.778^{a}	0.640 ^a	0.955ª
<u>0.935^b</u>	<u>0.776^b</u>	-	0.935 ^b	0.763 ^b
0.923 ^a	0.697 ^a	0.939 ^a	0.923ª	0.960 ^a
0.678°	0.740 ^c	0.925°	0.688°	0.953°
0.922	0.688	0.929	0.933	<u>0.962</u>
0.919	0.685	0.924	0.889	0.959
0.941	0.798	0.919	<u>0.938</u>	0.961
0.933	0.823	<u>0.932</u>	0.941	0.963
	FreeSolv R ² 0.640 ^a 0.935 ^b 0.923 ^a 0.678 ^c 0.922 0.919 0.933	FreeSolvLipophilicity R^2 R^2 0.640^a 0.577^a 0.935^b 0.776^b 0.923^a 0.697^a 0.678^c 0.740^c 0.922 0.688 0.919 0.685 0.933 0.823	FreeSolvLipophilicityESOL R^2 R^2 R^2 0.640^a 0.577^a 0.778^a 0.935^b 0.776^b - 0.923^a 0.697^a 0.939^a 0.678^c 0.740^c 0.925^c 0.922 0.688 0.929 0.919 0.685 0.924 0.941 0.798 0.919 0.933 0.823 0.932	FreeSolvLipophilicityESOLClinTox R^2 R^2 R^2 AUROC 0.640^a 0.577^a 0.778^a 0.640^a 0.935^b 0.776^b - 0.935^b 0.923^a 0.697^a 0.939^a 0.923^a 0.678^c 0.740^c 0.925^c 0.688^c 0.922 0.688 0.929 0.933 0.919 0.685 0.924 0.889 0.933 0.823 0.932 0.941

Table S1. Predictive Performance comparison of baseline methods (from previous literature) with our GNN models on FreeSolv, Lipophilicity, ESOL, ClinTox, BBBP benchmarks.

^aThe prediction results are derived from Wu et al^[1].

^bThe prediction results are derived from Chen et al^[2].

^cThe prediction results are derived from Chen et al^[3].

Tab	le S2.	Predictive	Perfor	rmance	compa	rison o	f baseline	e methods	(from	previous	literature) with
our	GNN I	models on	LD50,	IGC50,	LC50,	LC50D	M, LogP	datasets.				

Datasets	LD50	IGC50	LC50	LC50DM	LogP
Methods	R^2	R^2	R^2	R^2	R^2
ECFP4	0.586ª	0.647 ^a	0.573 ^a	0.452 ^a	0.857ª
MACCS	0.643 ^a	0.643 ^a	0.608 ^a	0.434 ^a	0.867 ^a
HybridModel	0.629ª	0.810 ^a	0.678 ^a	0.616 ^a	0.893ª
AGBT-FP	0.671ª	0.842 ^a	<u>0.783^a</u>	0.830 ^a	0.905 ^a
GraphSAGE	0.654	0.778	0.731	0.724	0.904
GAT	0.662	0.809	0.742	0.798	0.899
GraphNET	0.683	0.834	0.793	0.810	<u>0.923</u>
CMPNN	<u>0.679</u>	<u>0.841</u>	0.776	<u>0.813</u>	0.939

^aThe prediction results are derived from Chen et al^[2].

Table S3. Explainability Performance comparison of baseline methods (RF and XGBoost) with GNN models (explained by IG).

Datasets	3MR	Benzene	Hepatotoxicity	Mutagenicity
Methods		Attri	bution-ACC	
RF + Feature Importances	0.516	0.621	0.523	0.607
XGBoost + SHAP Values	0.678	0.740	0.701	0.688
GraphSAGE + IG	<u>0.948</u>	<u>0.866</u>	0.894	0.831
GAT + IG	0.897	0.789	0.853	0.848
GraphNET + IG	0.939	0.856	0.935	0.884
CMPNN + IG	0.963	0.907	0.929	0.885

Ground-truth	CMPNN+IG	GraphNET+IG	GraphSAGE+IG	GAT+IG
×of	*08	×of	×~~	*-06
HOLE	HOLE	HOLO	HOLD	HOLO
2-3	2-3	2~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~	~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~	2~~£
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CMPNN+Random	CMPNN+CAM	CMPNN+SmoothGrad	CMPNN+GradCAM	CMPNN+GradInput
CMPNN+Random	CMPNN+CAM	CMPNN+SmoothGrad	CMPNN+GradCAM	CMPNN+GradInput
CMPNN+Random	CMPNN+CAM	CMPNN+SmoothGrad	CMPNN+GradCAM	CMPNN+GradInput
CMPNN+Random	CMPNN+CAM	CMPNN+SmoothGrad	CMPNN+GradCAM	CMPNN+GradInput

**Table S4.** The predicted substructures by representative combinations of GNN models and XAI methods.

	Prediction Performance		Explanation Performance		
	Accuracy	Precision	Attribution-ACC	Attribution-Precision	
Random	-	-	0.568	0.123	
XAI	0.92	<u>0.800</u>	<u>0.839</u>	<u>0.431</u>	
MC1	<u>0.68</u>	0.842	0.820	0.352	
MC2	0.60	0.596	0.852	0.471	
MC3	0.62	0.667	0.801	0.232	
MC4	0.50	0.559	0.804	0.180	
MC5	0.58	0.595	0.794	0.294	
MC6	0.54	0.594	0.759	0.197	
MC7	0.62	0.656	0.804	0.220	

Table S5. The Performance comparison of XAI method and medicinal chemists.

#### Table S6. Statistics of XAI-Benchmarks.

Benchmark	Task	Dataset Name	Compounds	Substructure
Synthetic	Classification	3MR	3152	Three-membered ring
Benchmarks	Classification	Benzene	12000	Benzene ring
	Classification	Mutagenicity	6506	Mutagenicity alerts
Experimental Benchmarks	Classification	Hepatotoxicity	587	Hepatotoxic alerts
	Classification	CYP450	9122	Substructure differences

Features	Description	Size
Atom		
Atom type	Type of atom (ex.C,N,O), by atomic number.	100
# Bonds	Number of bonds the atom is involved in.	6
Formal charge	Integer electronic charge assigned to atom.	5
Chirality	Unspecified, tetrahedral CW/CCW, or other.	4
# Hs	Number of bonded Hydrogen atom.	5
Hybridization	sp, sp ² , sp ³ , sp ³ d, or sp ³ d ²	5
Aromaticity	Whether this atom is part of an aromatic system.	1
Atomic mass	Mass of the atom, divided by 100.	1
Bond		
Bond type	Single, double, triple, or aromatic.	4
Conjugated	Whether the bond is conjugated.	1
In ring	Whether the bond is part of a ring.	1
Stereo	None, any, E/Z or cis/trans.	6

 Table S7. Atom features and Bond features.

Model	Hyperparameters	Range
	Batch size	{32, 64}
	Learning rate	{0.0001, 0.001, 0.01}
CraphSACE	Embedding size	{32, 64, 128}
GraphisAGE	Num of layer	{3, 5}
	Aggregation type	{Add, Mean, Max}
	Num of epoch	{50, 100, 300}
	Batch size	{50, 64}
	Learning rate	{0.0001, 0.001, 0.01}
	L2 regularization	{0.0, 0.1}
GAT	Embedding size	{128, 256}
GAT	Num of layer	{2, 4}
	Attention head	{4, 8}
	Dropout	{0.0, 0.1}
	Num of epoch	{50, 100, 300}
	Batch size	{32, 64}
	Learning rate	{0.001, 0.01}
	L2 regularization	{0.0, 0.1}
	Node embedding size	{64, 256}
GraphNET	Edge embedding size	{32, 64}
	Num of layer	{2, 4}
	Num of Set2Set layer	{2, 3}
	Aggregation type	{Add, Mean, Max}
	Num of epoch	{30, 100, 300}
	Batch size	{50, 64}
	Learning rate	{0.0001, 0.001}
	L2 regularization	{0.0, 0.1}
	Embedding size	{256, 300}
	Dropout	{0.0, 0.1}
	Num of layer	{2, 4}
	Undirected	{False, True}
	Num of FFN layer	{2, 5}
	Embedding size of FFN layer	{256, 512}
	Num of epoch	{30, 50}

 Table S8.
 Hyperparameter ranges for four types of GNN models.

Task	Dataset	Compounds	Train	Test
	OGB-BBBP	1835	1631	204
Classification	OGB-BACE	1362	1210	152
	OGB-HIV	37014	32901	4113
Degraceien	IGC50	1792	1434	358
Regression	LD50	7413	5931	1482

**Table S9.** The summary of public benchmark for XAI-assisted Fingerprints Experiments.

**Table S10.** Experiment results of XAI-assisted Fingerprints on Hepatotoxicity and AmesMutagenicity datasets.

	Hepatotoxicity		Ames Mu	tagenicity
Metric	ACC	%increase	AUROC	%increase
Morgan-FP	0.517	-	0.871	-
Morgan-FP + MACCS-FP	0.526	1.74%	0.893	2.52%
Morgan-FP + XAI-FP	0.548	5.99%	0.904	3.79%

**Table S11.** Hyperparameter ranges for Random Forest in XAI-assisted Experiments.

Model	Hyperparameters	Range
	n_estimators	{100, 200, 500, 800, 1000}
	max_depth	{5, 6, 7, 8}
Dondom Foroat	min_samples_split	{2, 3, 4}
Random Forest	min_samples_leaf	{1, 3, 5}
	min_weight_fraction_leaf	{0.0, 0.1, 0.2}
	max_leaf_nodes	{None, 1, 5}

### **Supplemental References**

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