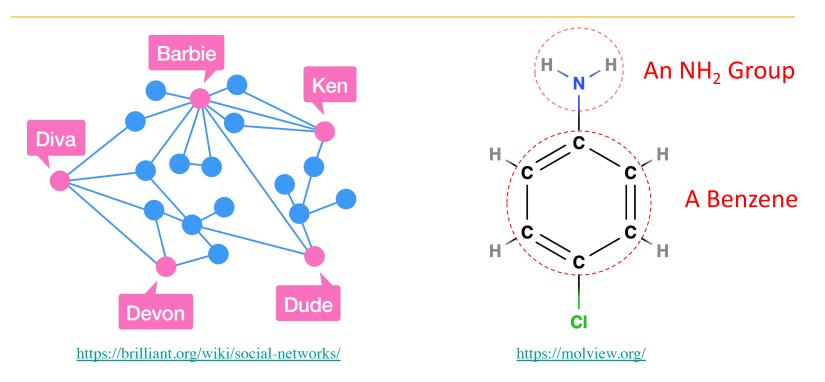
## IOWA STATE UNIVERSITY

**Department of Computer Science** 

### Molecular Representation Learning via Heterogeneous Motif Graph Neural Networks

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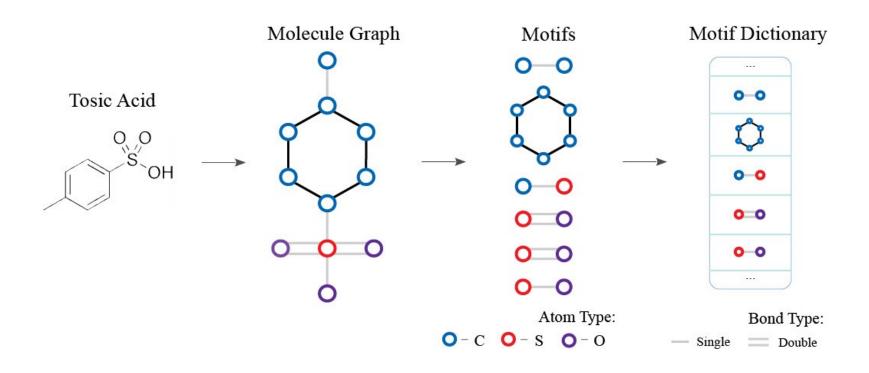
#### **MOLECULAR GRAPH VS OTHER GRAPH**



- 1. Common sub-graphs (motifs) in molecular graphs have special meanings
- 2. Most existing GNNs fail to consider motif patterns sharing among molecular graphs

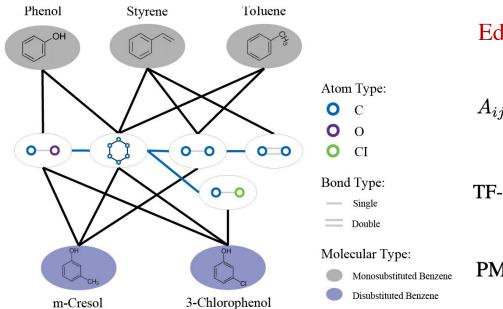
Motifs deserve more attention when designing GNNs for molecular representation learning.

#### **MOTIF VOCABULARY**



We build a motif vocabulary/dictionary by searching all molecular graphs and extract important subgraphs.

#### **HETEROGENEOUS MOTIF GRAPH**



#### Edge weight:

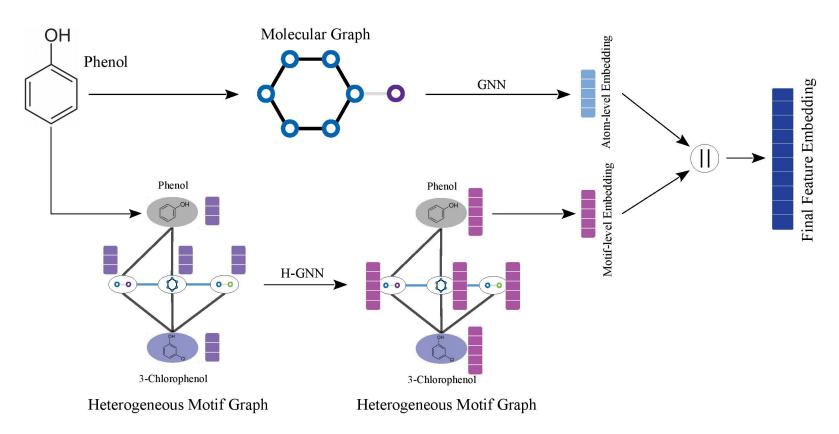
 $A_{ij} = \begin{cases} \mathsf{PMI}_{ij}, & \text{if } i, j \text{ are motifs} \\ \mathsf{TF}\text{-}\mathsf{IDF}_{ij}, & \text{if } i \text{ or } j \text{ is a motif} \\ 0, & \mathsf{Otherwise} \end{cases}$ 

$$\text{TF-IDF}_{ij} = C(i)_j \left( \log \frac{1+M}{1+N(i)} + 1 \right)$$

 $ext{PMI}_{ij} = \log rac{p(i,j)}{p(i)p(j)}$ 

Based on the motif vocabulary, we build a heterogeneous graph that contains motif nodes and molecular nodes.

#### **HETEROGENEOUS MOTIF GRAPH NEURAL NETWORKS**



We construct a heterogeneous motif graph to learn both atom-level and motif-level representation simultaneously.

#### **EXPERIMENTAL RESULTS**

METHODS	РТС	MUTAG	NCI1	PROTEINS	MUTAGENICITY
PatchySAN	$\textbf{60.0} \pm \textbf{4.8}$	$\textbf{92.6} \pm \textbf{4.2}$	$\textbf{78.6} \pm 1.9$	$\textbf{75.9} \pm 2.8$	-
GCN	$\textbf{64.2} \pm \textbf{4.3}$	$\textbf{85.6} \pm 5.8$	$\textbf{80.2}\pm2.0$	$\textbf{76.0} \pm 3.2$	$\textbf{79.8} \pm 1.6$
GraphSAGE	$\textbf{63.9}\pm7.7$	$\textbf{85.1}\pm7.6$	<b>77.7</b> ± 1.5	$\textbf{75.9}\pm3.2$	$\textbf{78.8} \pm 1.2$
DGCNN	$\textbf{58.6} \pm 2.5$	$\textbf{85.8} \pm 1.7$	$\textbf{74.4}\pm0.5$	$\textbf{75.5}\pm0.9$	-
GIN	$\textbf{64.6} \pm 7.0$	$\textbf{89.4} \pm 5.6$	<b>82.7</b> ± 1.7	$\textbf{76.2} \pm 2.8$	-
PPGN	$\textbf{66.2} \pm 6.5$	$\textbf{90.6} \pm 8.7$	$\textbf{83.2}\pm1.1$	$\textbf{77.2} \pm 4.7$	-
CapsGNN	-	$\textbf{86.7}\pm6.9$	$\textbf{78.4} \pm 1.6$	$\textbf{76.3}\pm3.6$	-
WEGL	$\textbf{64.6} \pm 7.4$	$\textbf{88.3} \pm 5.1$	$\textbf{76.8} \pm 1.7$	$\textbf{76.1}\pm3.3$	-
GraphNorm	$\textbf{64.9}\pm7.5$	$\textbf{91.6}\pm6.5$	$\textbf{81.4}\pm2.4$	$\textbf{77.4} \pm 4.9$	-
GSN	$\textbf{68.2}\pm7.2$	$\textbf{90.6} \pm 7.5$	$\textbf{83.5}\pm2.3$	$\textbf{76.6} \pm 5.0$	-
OURS	$\textbf{78.8} \pm \textbf{6.5}$	$\textbf{96.3} \pm \textbf{2.6}$	83.6 ± 1.5	$\textbf{79.9} \pm \textbf{3.1}$	$\textbf{83.0} \pm 1.1$

# Thank you for listening!

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