





Finding Structure-Property Relationships for Molecular Property Predictions with Globally Explainable AI

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Motivation
Powerful AI models have become a useful tool for arious predictive and generative tasks.
For example, <i>Graph Neural Networks (GNNs)</i> can be effectively used or various molecular property prediction tasks in chemistry and material

- By understanding the internal behavior of high-performing models we can learn about the *structure-property relationships* of the underlying tasks.
- Novel insights into the underlying rule behind certain molecular properties can ultimately help us with *drug discovery* and *material design*.
- We can gain understanding of a model's inner workings through various *Explainable AI (xAI)* methods.



Extract Scientific Insights from High-Performing AI Models

a. Explainable MEGAN Model

- Train *Multi-Explanation Graph Attention Network (MEGAN)* for molecular property prediction.
- Model creates *Local Explanation Masks* directly alongside main target prediction.

Negative Contribution Positive Contribution

b. Clustering Latent Explanations

- Contrastive learning objective: latent space similarity ⇒ structural similarity of subgraph motifs.
- Latent space clusters ⇒ elements with similar local explanation.
- *HDBSCAN* clustering to find dense clusters of elements in latent space.

c. Analyzing Concept Clusters

- Each explanation embedding is associated with an average contribution towards the final prediction outcome.
- ⇒ Associating Structure (cluster motif) with Property (average contribution).
- Genetic Algorithm finds a small yet representative Prototype Graph for each cluster.

d. LLM-based Causal Hypothesis

- Convert representative prototype graph for each cluster into string *SMILES* representation.
- Prompt language model (e.g. GPT-4) with prototype SMILES and average contribution.
- ⇒ Language model creates a hypothesis about a possible causal reason behind the observed structure-property relationship.

Global Concept Explanations for Graph Neural Networks...

AqSolDB - LogS Water Solbuility Prediction

Long Alkene Chain

Non-Mutagenic	Mutagenic
max nodes = 3 max nodes = 4 max nodes = 24	max nodes = 3 max nodes = 4 max nodes = 24

Mutag - Mutagenicity Classification

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Molecules containing the "C-O" substructure have a tendency to be soluble in water. The polar nature of the carbon-oxygen bond and the ability to form hydrogen bonds with water molecules are hypothesized to be the driving forces behind the high influence on water solubility.



 \checkmark) consistent with hypotheses previously published by Kazius *et al.* [4].

...Rediscover Known Structure Property Relationships From Chemistry Literature

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