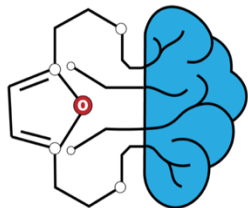
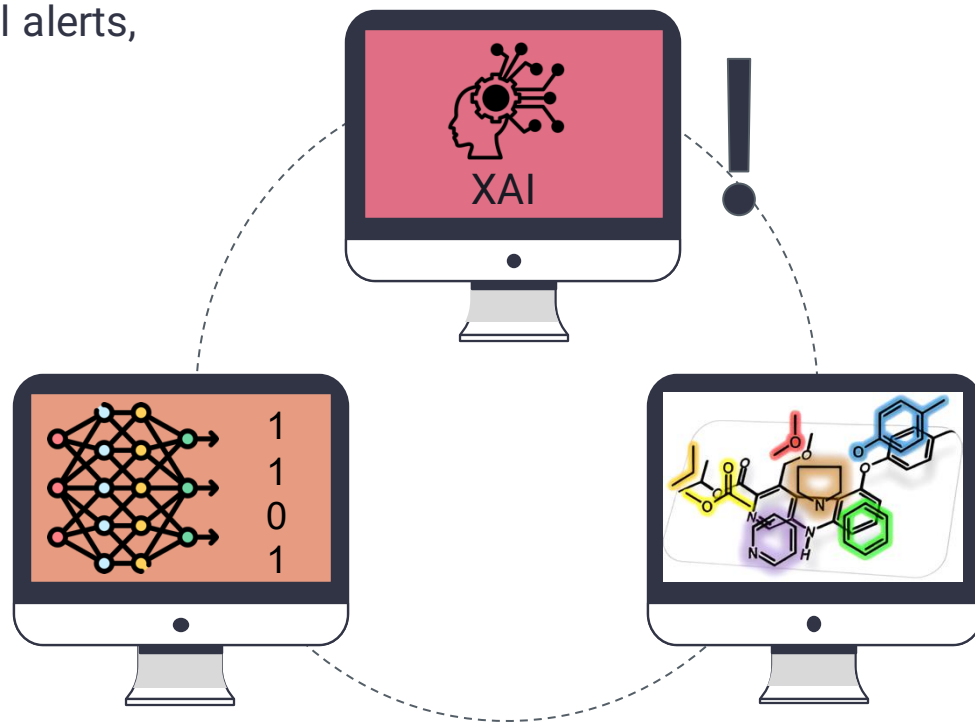


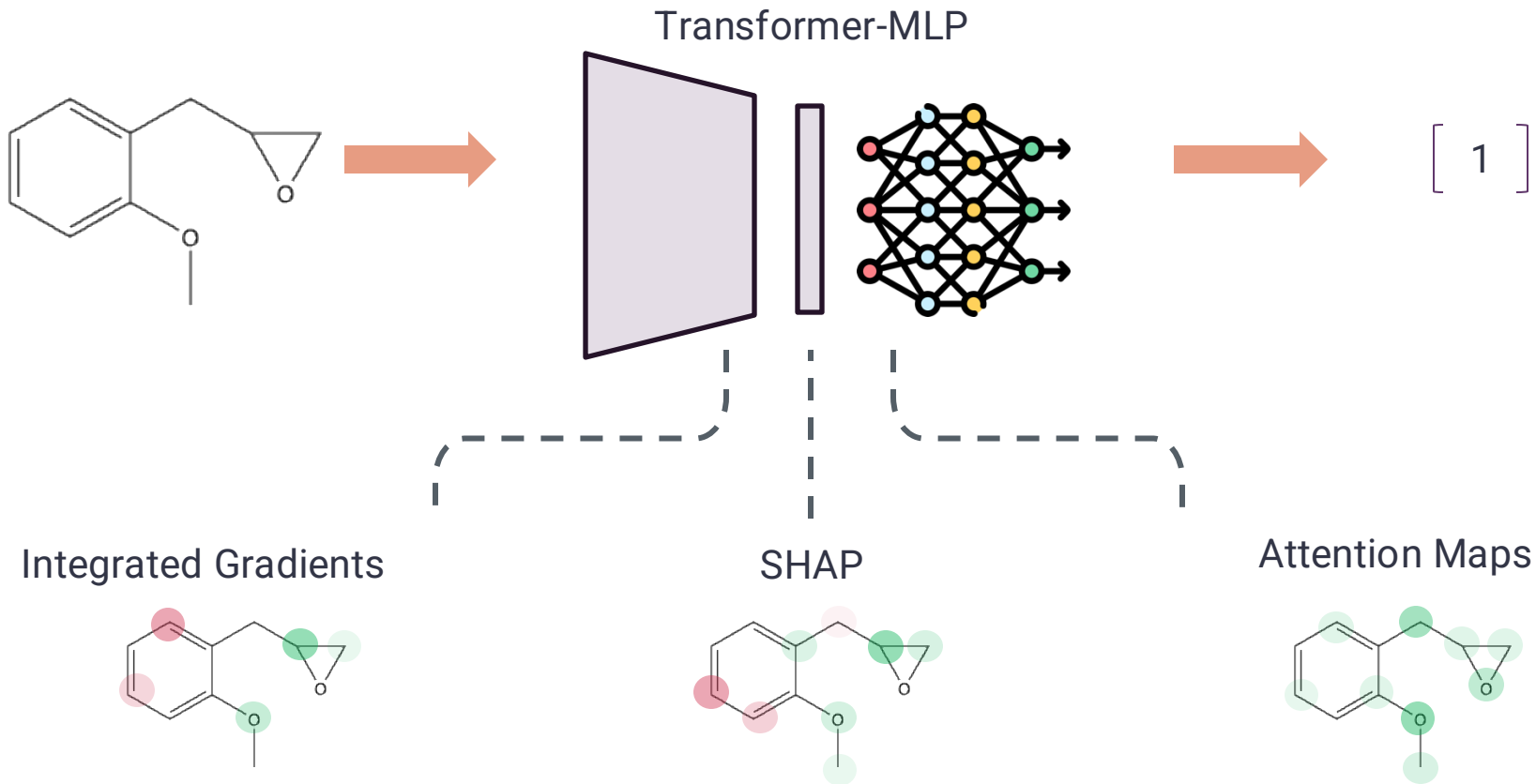
Explainable AI for functional groups

DC2: Khasanova Dina

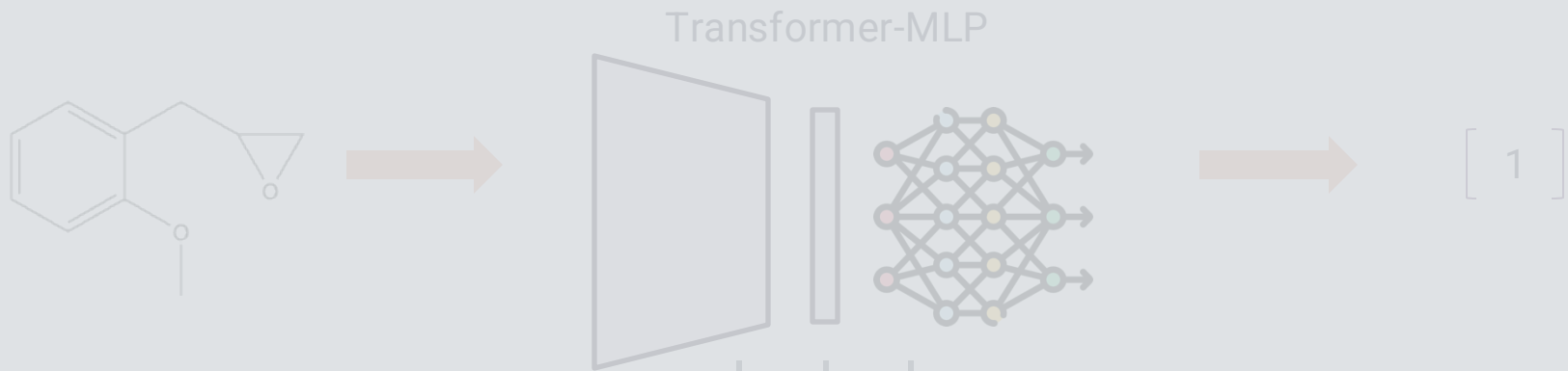


The reliability of XAI is important for eventually converting learned rules into structural alerts, CSRML, or SMARTS.





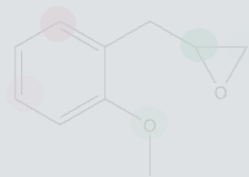
Hartog, P.B.R., Krüger, F., Genheden, S. et al. Using test-time augmentation to investigate explainable AI: inconsistencies between method, model and human intuition. J Cheminform 16, 39 (2024). <https://doi.org/10.1186/s13321-024-00824-1>



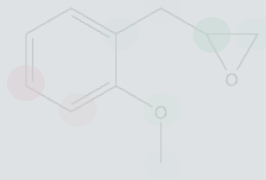
Are XAI methods inconsistent?



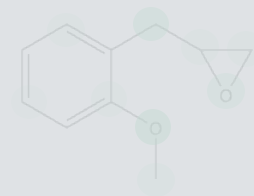
Integrated Gradients



SHAP



Attention Maps



Hartog, P.B.R., Krüger, F., Genheden, S. et al. Using test-time augmentation to investigate explainable AI: inconsistencies between method, model and human intuition. J Cheminform 16, 39 (2024). <https://doi.org/10.1186/s13321-024-00824-1>

Table 7 AUROC, accuracy, F1, MCC precision and recall scores of MLP models transfer learned on Ames data

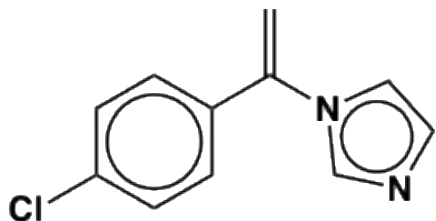
	Training	AUROC↑	Accuracy↑	F1↑	MCC↑	Precision↑	Recall↑
No training	Untrained	0.652	0.516	0.143	0.063	0.081	0.619
	Native	0.676	0.634	0.624	0.269	0.607	0.642
Variations	Random split	0.856	0.788	0.788	0.576	0.789	0.787
	Train set	0.873	0.792	0.792	0.584	0.792	0.792
	CNN	0.709	0.650	0.657	0.300	0.671	0.644
Encoder only	Enumerated	0.810	0.739	0.739	0.478	0.738	0.739
	C2C	0.734	0.666	0.666	0.332	0.665	0.666
	R2C	0.738	0.670	0.670	0.339	0.670	0.670
	E2C	0.731	0.665	0.665	0.331	0.665	0.665
	MC2C	0.754	0.682	0.682	0.364	0.683	0.682
Encoder-decoder	MR2C	0.694	0.653	0.652	0.305	0.651	0.653
	ME2C	0.804	0.719	0.719	0.438	0.719	0.719
	C2C	0.716	0.662	0.662	0.324	0.663	0.662
	R2C	0.698	0.634	0.634	0.269	0.634	0.634
	E2C	0.748	0.677	0.678	0.354	0.679	0.676
	MC2C	0.751	0.682	0.682	0.365	0.681	0.683
	MR2C	0.698	0.647	0.647	0.294	0.647	0.647
	ME2C	0.772	0.696	0.697	0.393	0.699	0.695

When the model's accuracy is low, each XAI method attempts to identify which features contributed to the incorrect predictions, leading to different features being highlighted and resulting in high cosine distances.

Objective of the Project:

- To build a high-accuracy model for deterministic labels like **functional groups**, which are well-defined and universally agreed upon, to assess how accurate or inaccurate existing explainability methods are.

non-canonical SMILES



c1(C(=C)n2ccnc2)ccc(cc1)Cl
c1cn(C(c2ccc(Cl)cc2)=C)cn1
c1(C(=C)n2ccnc2)ccc(cc1)Cl
c1ncn(C(c2ccc(cc2)Cl)=C)c1
C=C(n1ccnc1)c1ccc(Cl)cc1
c1(Cl)ccc(C(n2ccnc2)=C)cc1
c1(ccc(cc1)C(n1cncc1)=C)Cl
c1(Cl)ccc(C(n2ccnc2)=C)cc1
Clc1ccc(cc1)C(=C)n1ccnc1
c1(C(n2cncc2)=C)ccc(Cl)cc1
C=C(c1ccc(Cl)cc1)n1ccnc1

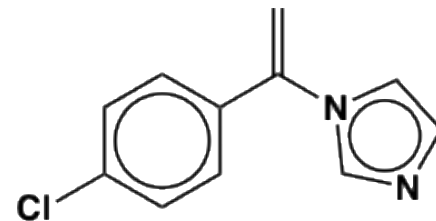
Encoder



Decoder

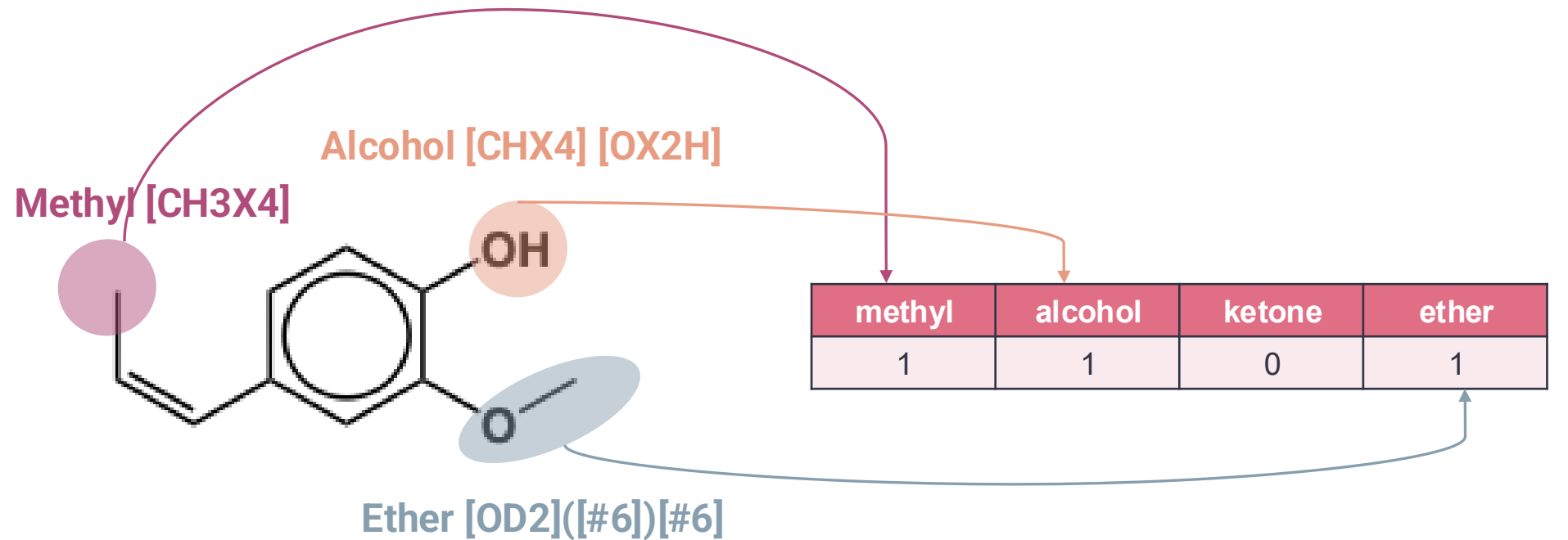
canonical SMILES

C=C(c1ccc(Cl)cc1)n1ccnc1

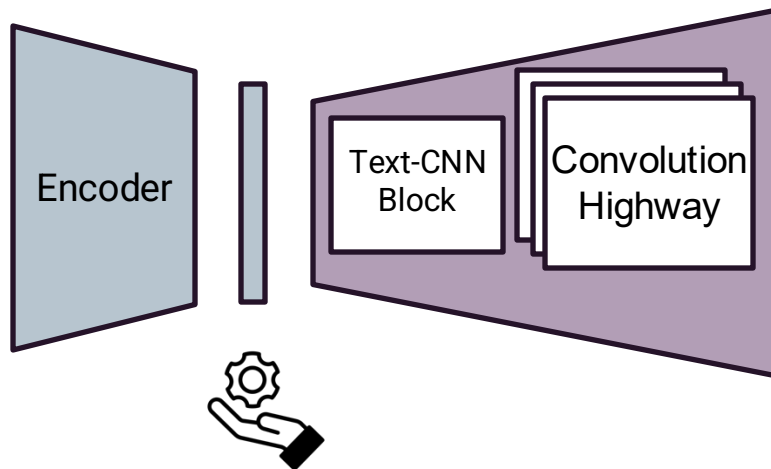
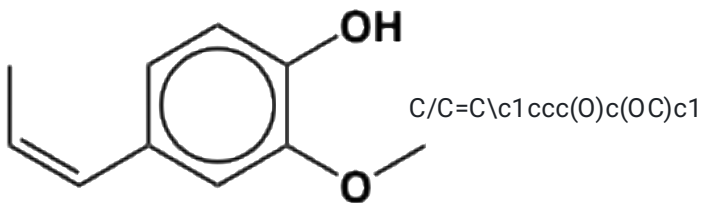


ChEMBL dataset
(≈2M molecules)

Models



Methods



Functional Groups

Alcohol	...	Methyl
1	...	0
...	...	...
1	...	1



TOX21 dataset
($\approx 9K$ molecules)

Models

XAI methods:

Gradient-based

Integrated Gradients ✓

SHAP GradientExplainer ✓

Backpropagation-Based

SHAP DeepExplainer

DeepLIFT ✓

Perturbation-based

SHAP KernelExplainer

LIME

Occlusion ✓

Attention-based

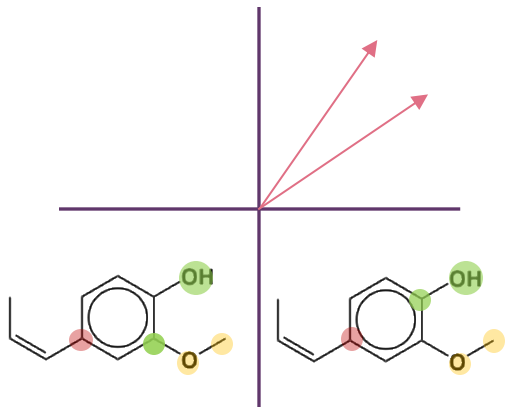
Grad-CAM ✓

Attention Maps

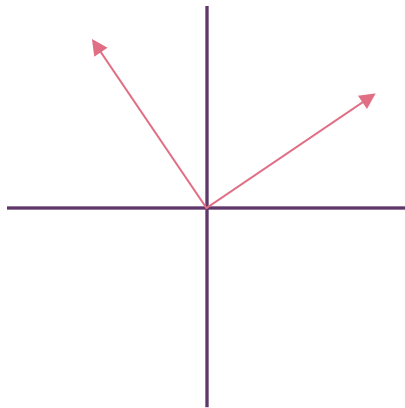
XAI

Cosine similarity

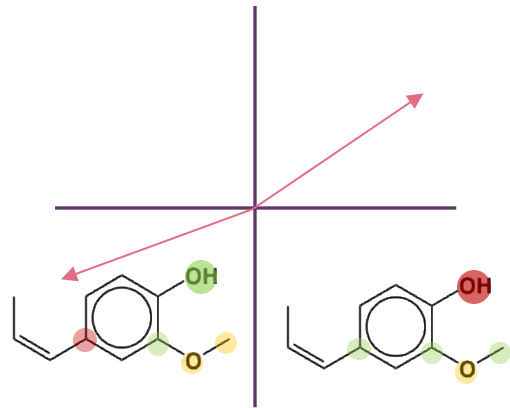
Similar



Unrelated



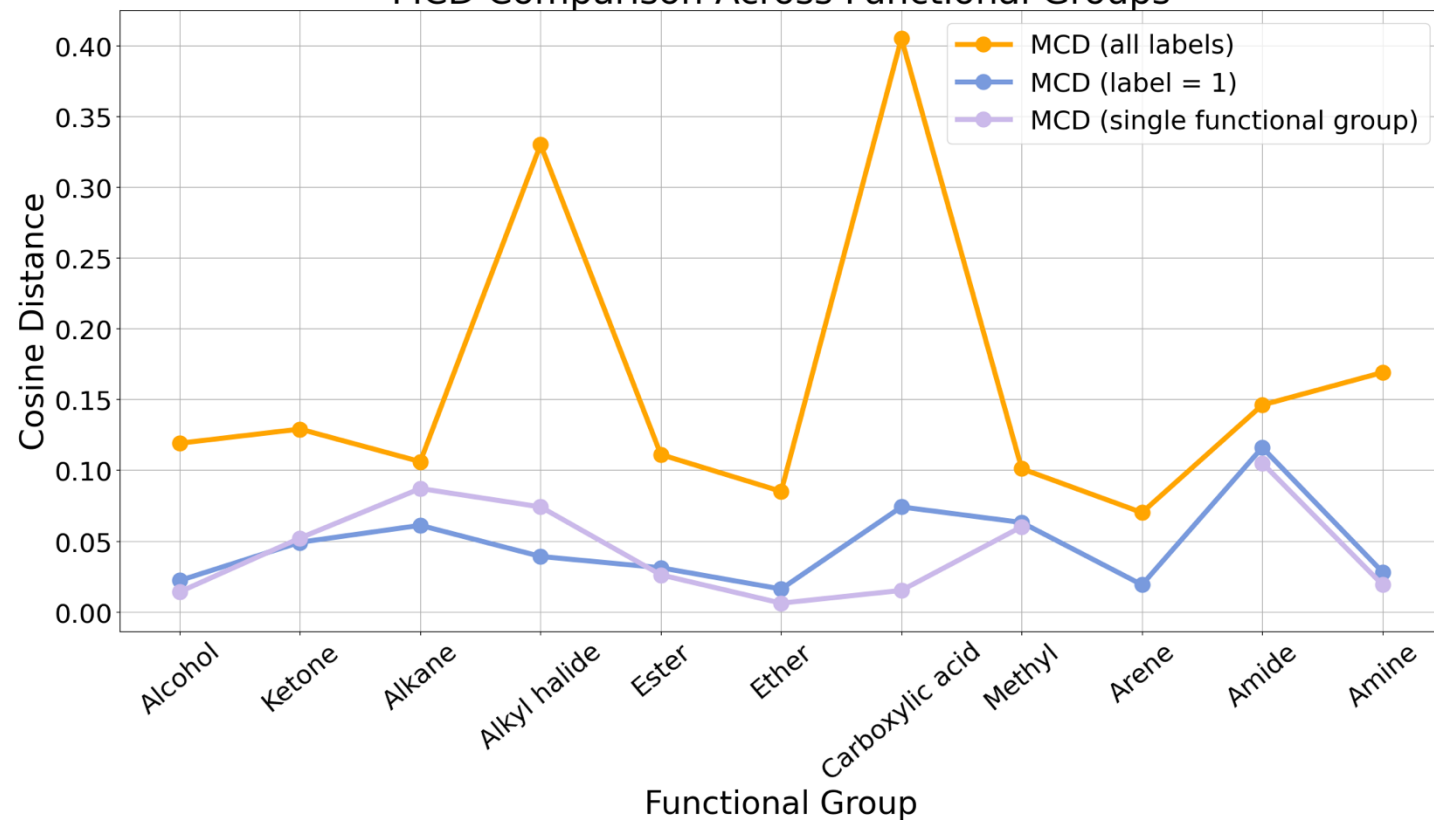
Opposite



$$A \cdot B = \|A\| \|B\| \cos \theta$$

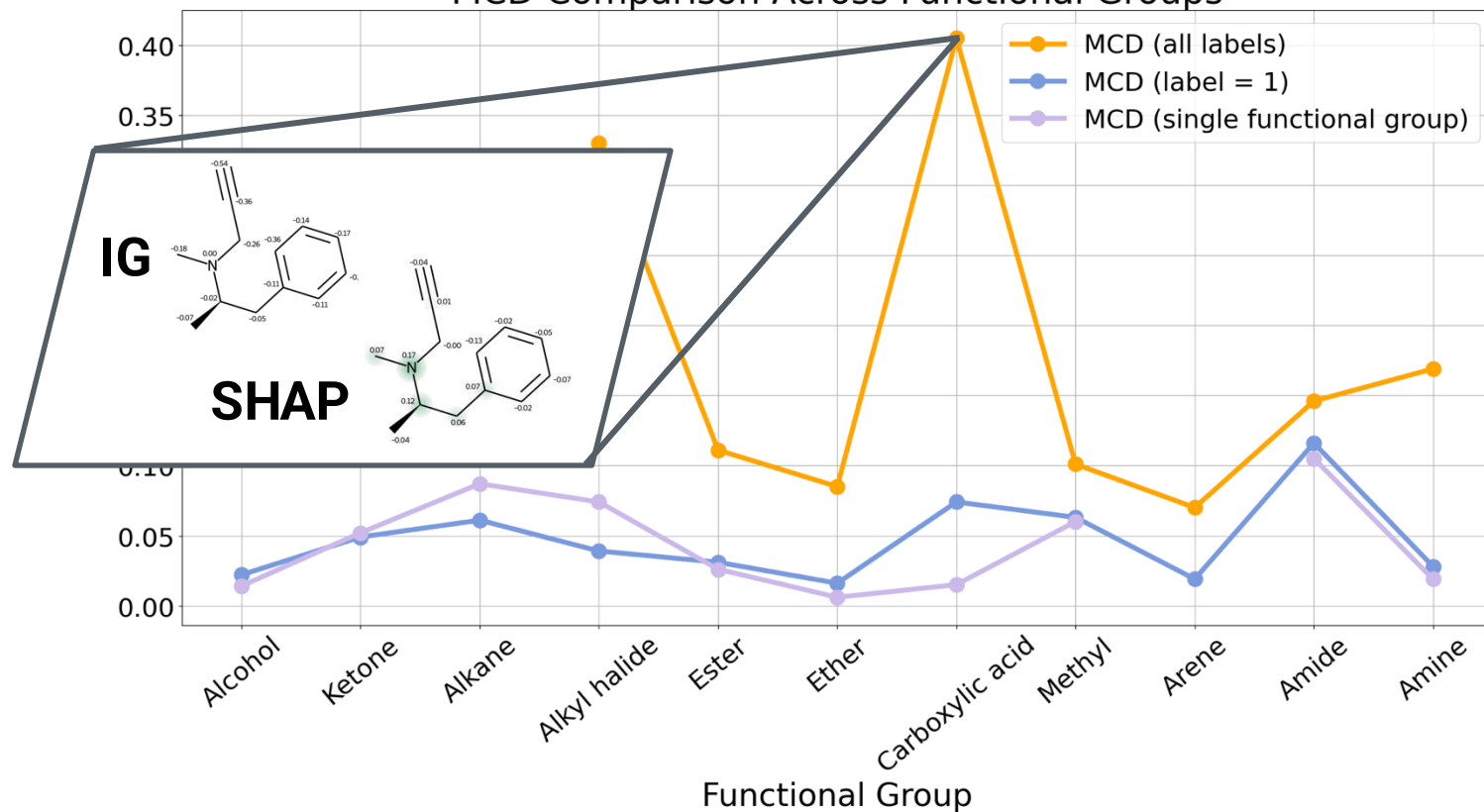
$$\text{Cosine Distance} = 1 - \text{Cosine Similarity}$$

MCD Comparison Across Functional Groups



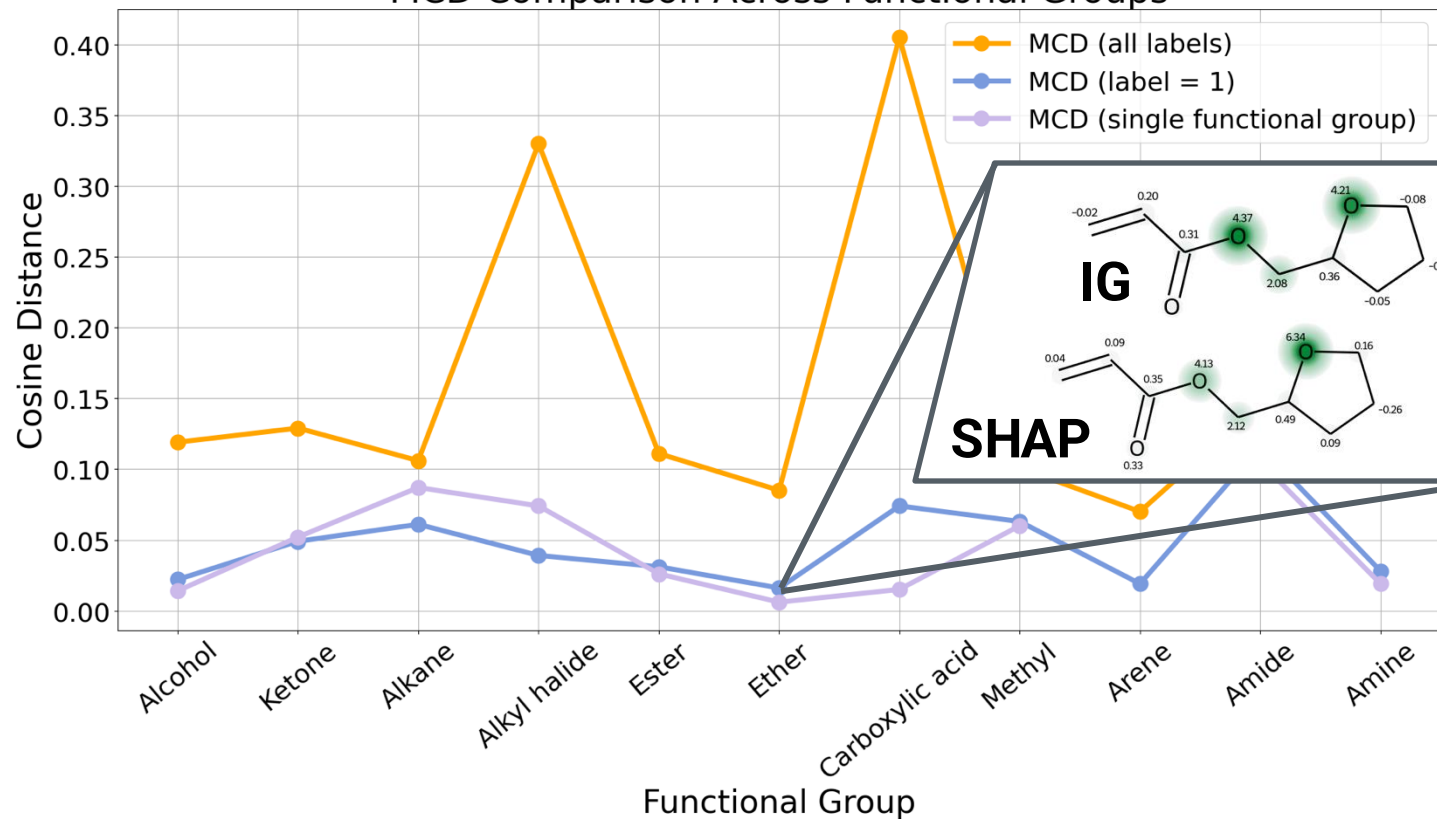
Results

MCD Comparison Across Functional Groups



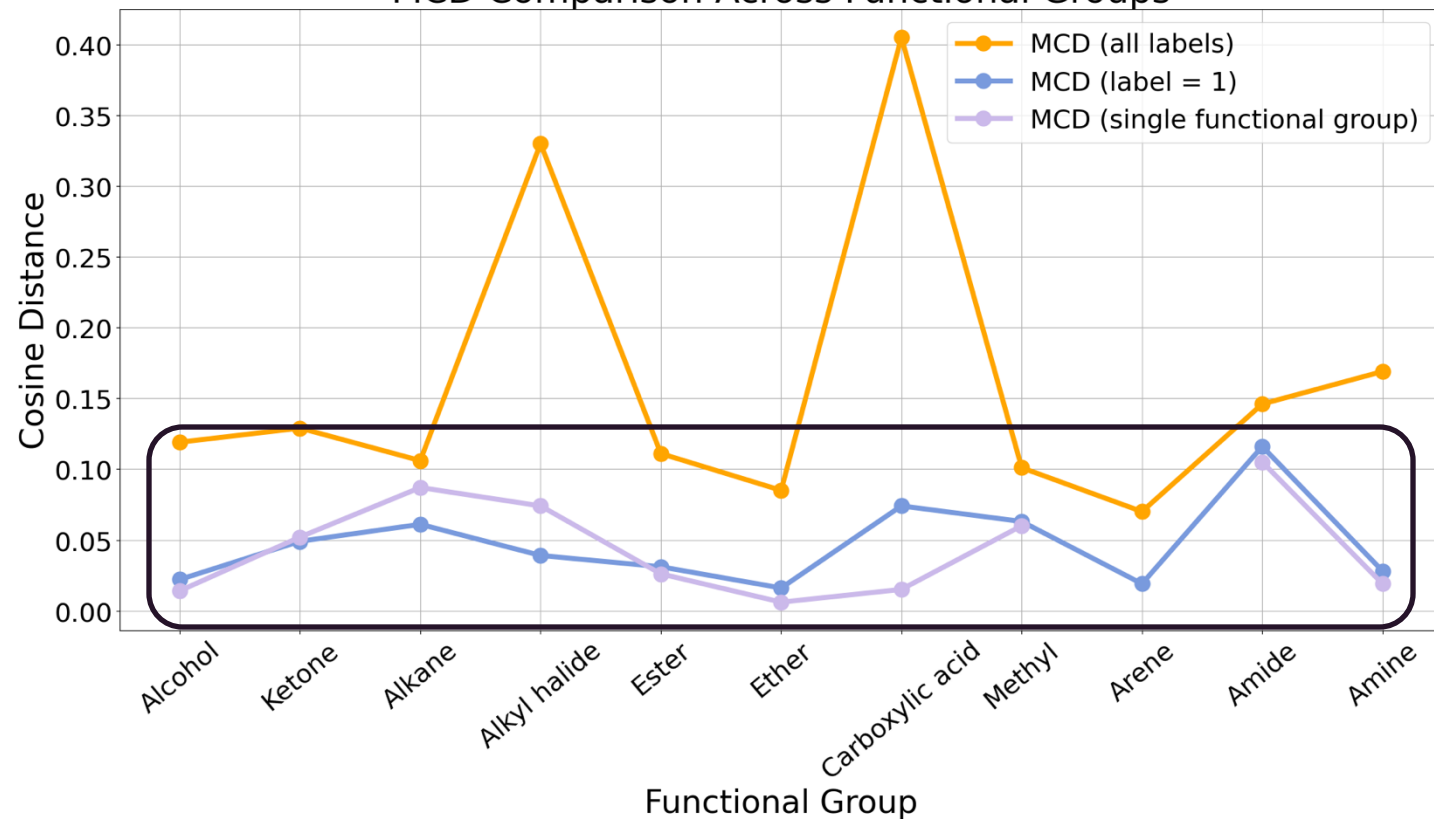
Results

MCD Comparison Across Functional Groups

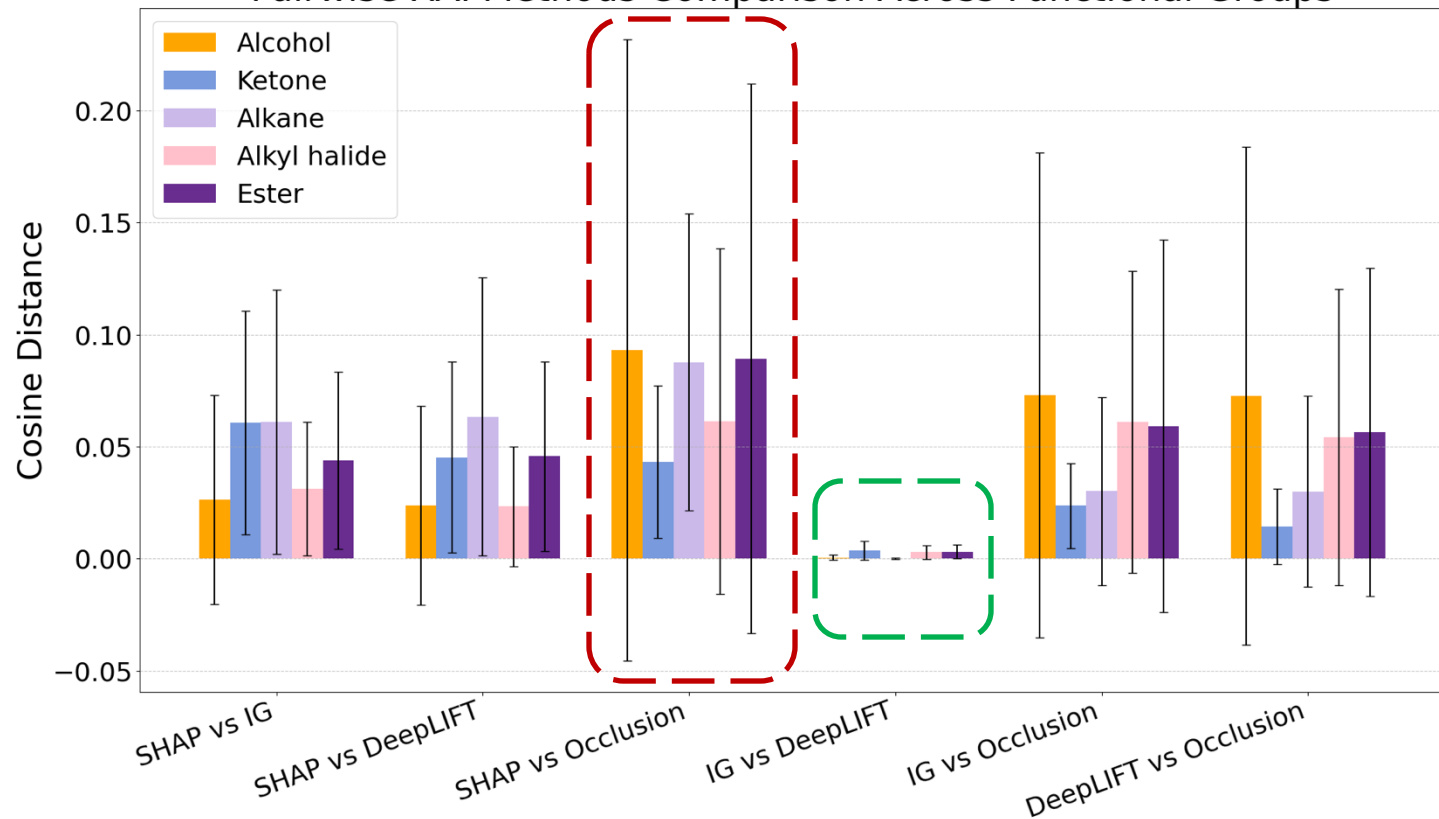


Results

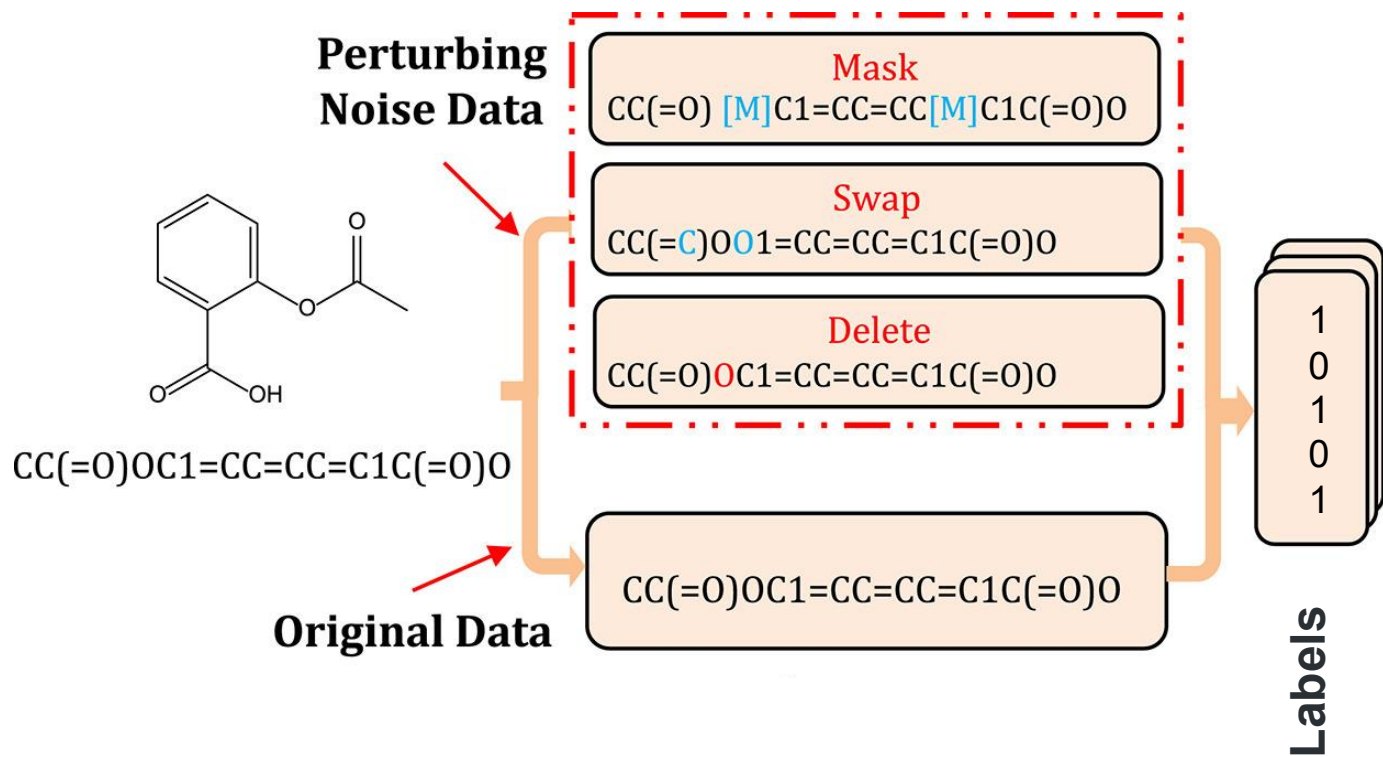
MCD Comparison Across Functional Groups



Pairwise XAI Methods Comparison Across Functional Groups

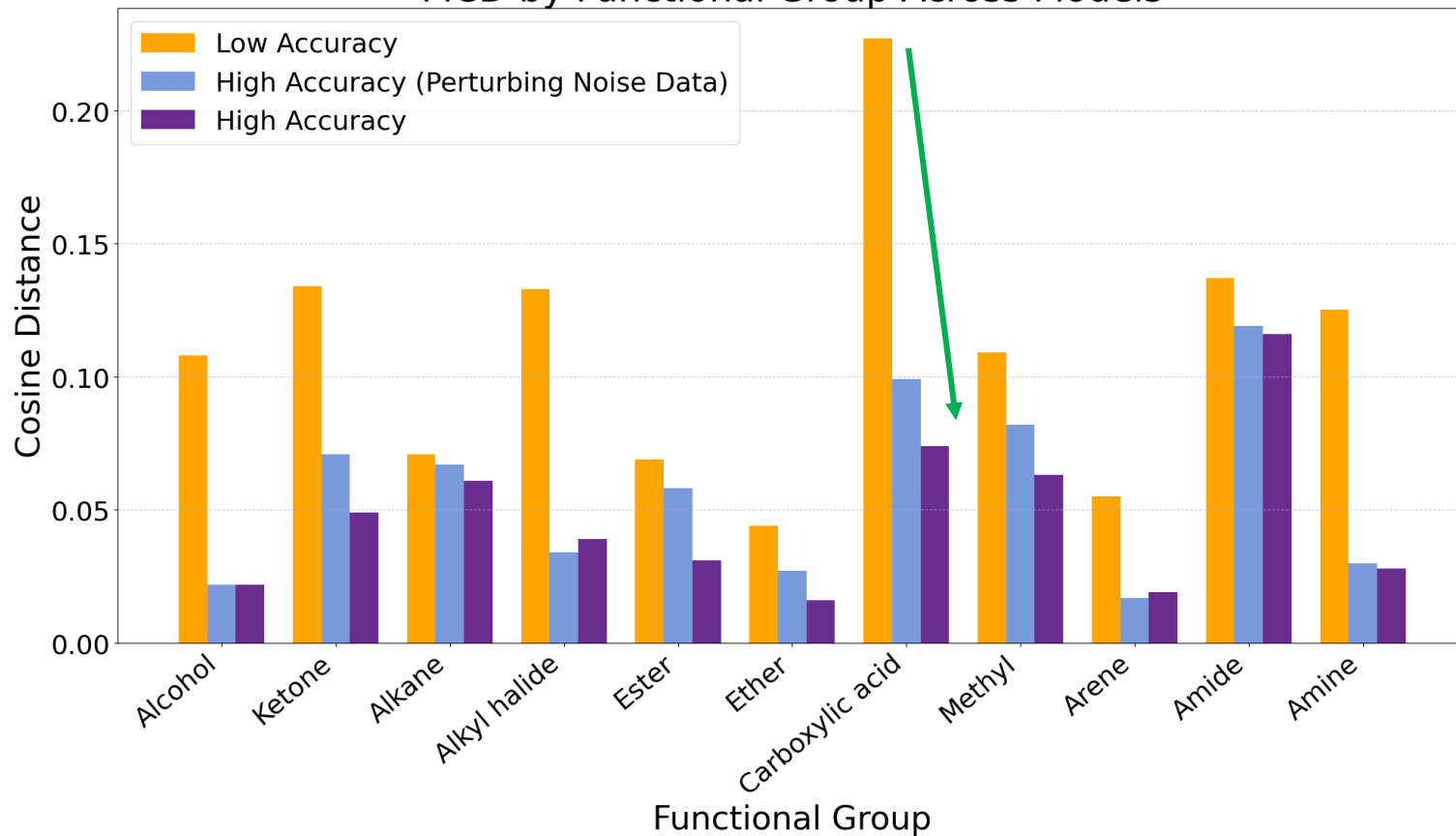


Results



Results

MCD by Functional Group Across Models



Results

**Thank you
for your attention!**