# Analysis of Atom-level pretraining with QM data for Graph Neural Networks Molecular property models

### Abstract

Despite the rapid and significant advancements in deep learning for Quantitative Structure-Activity Relationship (QSAR) models, the challenge of learning robust molecular representations that effectively generalize in real-world scenarios to novel compounds remains an elusive and unresolved task. This study examines how atom-level pretraining with quantum mechanics (QM) data can mitigate violations of assumptions regarding the distributional similarity between training and test data and therefore improve performance and generalization in downstream tasks. In the public dataset Therapeutics Data Commons (TDC), we show how pretraining on atom-level QM improves performance overall and makes the activation of the features distribution shifts. To the best of our knowledge, this is the first time that hidden state molecular representations are analyzed to compare the effects of molecule-level and atom-level pretraining on QM data.

### **A** Supplementary Materials

A.1 Distribution of activations of features for scratch, HOMO-LUMO pretrained and Atom-level pretrained networks in TDC Lipophilicity Dataset















Figure 4: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained— across test split of caco2 wang dataset.



Figure 5: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained—across test split of dili dataset.

## Distribution of Activations for 20 Features for caco2\_wang



Distribution of Activations for 20 Features for bioavailability\_ma

Figure 6: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained— across test split of bioavailability ma dataset.



Figure 7: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained—across test split of pgp broccatelli dataset.



Distribution of Activations for 20 Features for ames

Figure 8: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained— across test split of ames dataset.



Figure 9: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained—across test split of half life obach dataset.



Figure 10: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained— across test split of herg dataset.



Figure 11: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained— across test split of ppbr az dataset.

### Distribution of Activations for 20 Features for cyp2c9\_substrate\_carbonmangels



Figure 12: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained— across test split of cyp2c9 substrate carbonmangels dataset.



Figure 13: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained—across test split of cyp2c9 veith dataset.

#### Dim 1 Dim 2 Dim 3 Dim 4 Dim 5 Dim 6 Dim 7 Dim 8 Dim 9 Dim 10 Scratch 5000 1000 trained Atom-level Pretrained 500 Dim 13 Dim 12 Dim 14 Dim 15 Dim 16 Dim 17 Dim 18 Dim 19 Dim 11 Dim 20 Scratch Scratch HL Atom-level Pretrained 100 -2.5 0.0 2.5 -2.5 0.0 2.5 2.5 0.0 2.5 -2.5 0.0 2.5 -2.5 0.0 2.5 -2.5 0.0 2.5 -10 -2.5 0.0 2.5

Figure 14: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained— across test split of clearance microsome az dataset.



Figure 15: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained— across test split of solubility aqsoldb dataset.

#### Distribution of Activations for 20 Features for clearance\_hepatocyte\_az



Figure 16: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained— across test split of clearance hepatocyte az dataset.



Figure 17: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained—across test split of hia hou dataset.



### Distribution of Activations for 20 Features for bbb\_martins

Figure 18: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained—across test split of bbb martins dataset.



Figure 19: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained—across test split of lipophilicity astrazeneca dataset.



Figure 20: Distribution of first 20 features from the first layer of the Graphormer network for three

different training approaches --scratch, HOMO-LUMO pretrained and atom-level pretrained-across test split of cyp3a4 veith dataset.



Figure 21: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches ---scratch, HOMO-LUMO pretrained and atom-level pretrained--across test split of ld50 zhu dataset.

## Distribution of Activations for 20 Features for cyp3a4\_veith

### Distribution of Activations for 20 Features for cyp3a4\_substrate\_carbonmangels



Figure 22: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained— across test split of cyp3a4 substrate carbonmangels dataset.



Figure 23: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained—across test split of cyp2d6 veith dataset.

#### Dim 1 Dim 2 Dim Dim 4 Dim 5 Dim 6 Dim 7 Dim 8 Dim 9 Dim 10 Scratch Pretrained Atom-level Pretrained 250 Dim 12 Dim 13 Dim 14 Dim 15 Dim 16 Dim 17 Dim 18 Dim 19 Dim 11 Dim 20 Scratch 50 hL Atom-level Pretrained -2.5 0.0 2.5 -2.5 0.0 2.5 2.5 0.0 2.5 0.0 2.5 2.5 -2.5 0.0 2.5 -2.5 0.0 2.5 -2.5 0.0 2.5 -2.5 0.0 -25

Figure 24: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained— across test split of cyp2d6 substrate carbonmangels dataset.



Figure 25: Distribution of first 20 features from the first layer of the Graphormer network for three different training approaches —scratch, HOMO-LUMO pretrained and atom-level pretrained— across test split of vdss lombardo dataset.

### Distribution of Activations for 20 Features for cyp2d6\_substrate\_carbonmangels