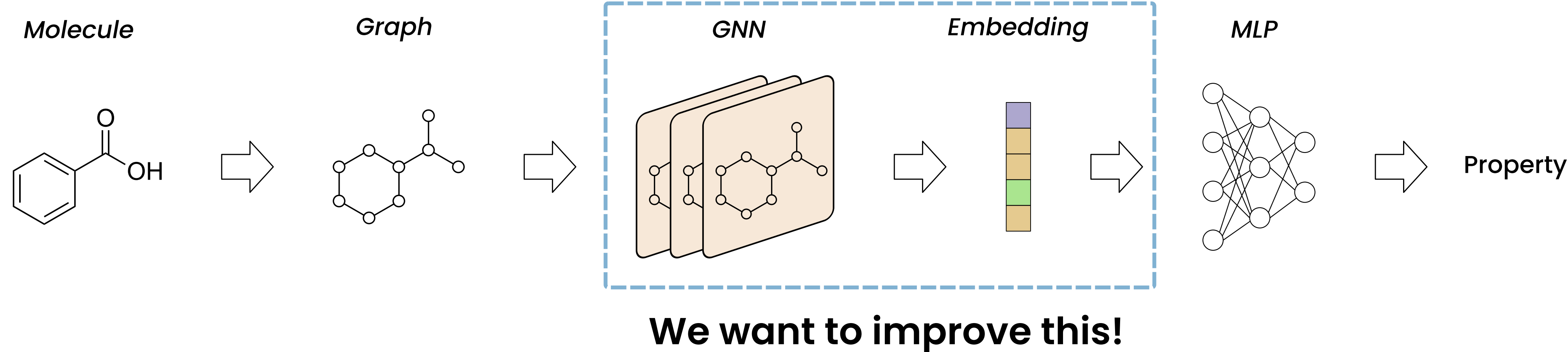


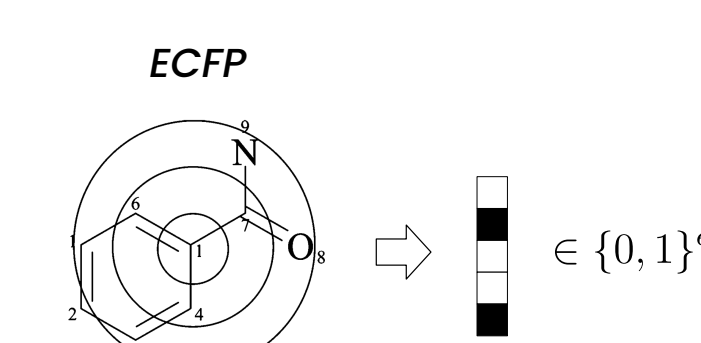


The Problem



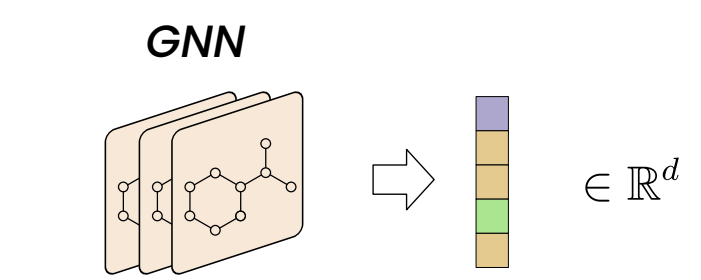
ECFP

- ▶ Generate good embeddings
- ▶ Are not trainable



GNN

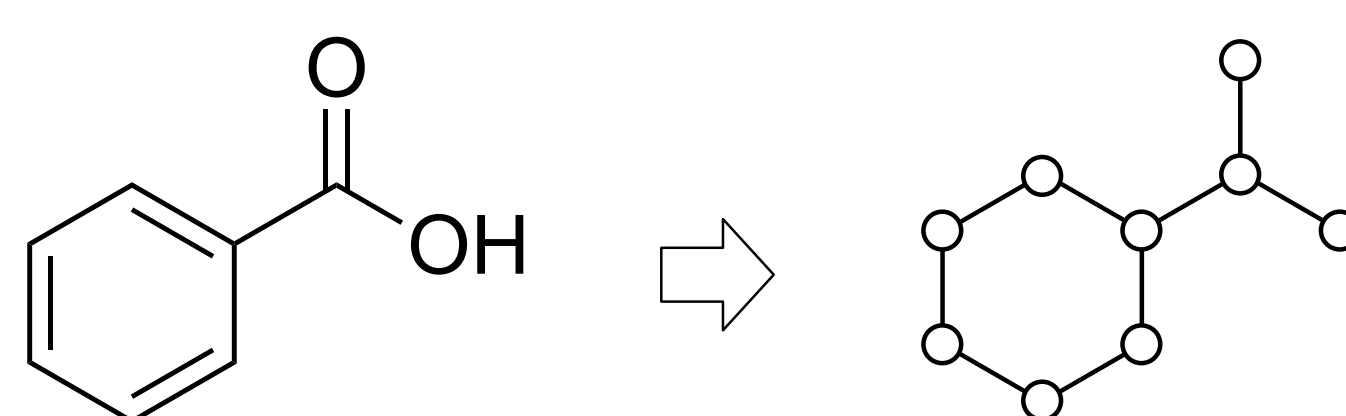
- ▶ Generate worse default embeddings than ECFPs
- ▶ Are end-to-end trainable



0. Motivation

- ▶ Improve **Molecular Property Predictions**
- ▶ Create better **embeddings** of molecules using **Graph Neural Networks (GNNs)**
- ▶ Make use of large amounts of **unlabeled data**

1. Molecules as Graphs



- ▶ Abstract **Molecules as Graphs**
- ▶ Enrich with **Node & Edge Features**

Node Features

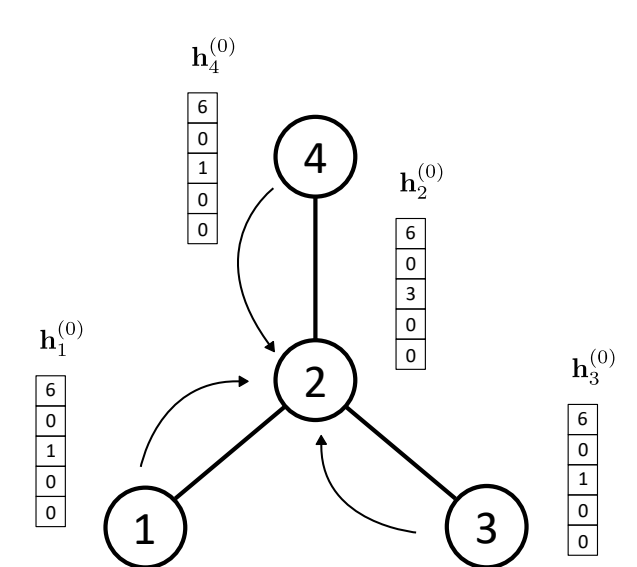
atomic_num,
chirality,
degree,
formal charge
num_hs
num_radical_e
hybridization,
is_aromatic,
is_in_ring

Edge Features

bond_type,
stereoinfo,
is_conjugated

The Approach

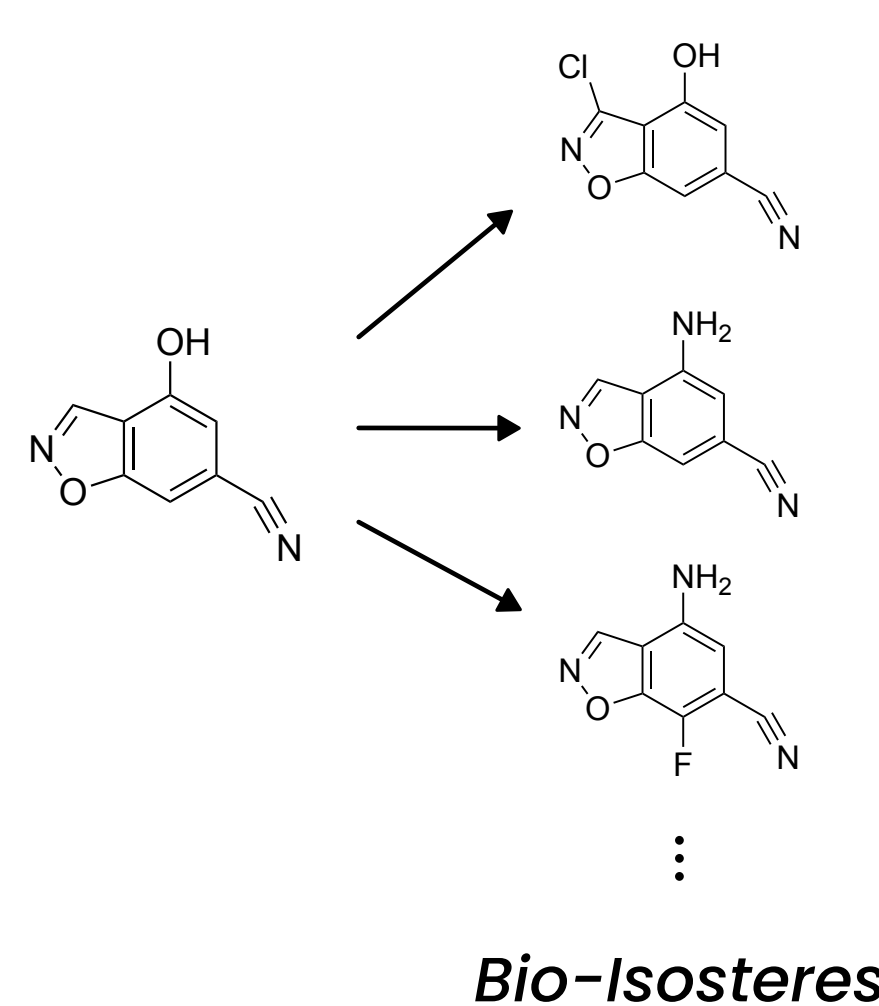
2. Graph Neural Networks(GNN)



Message Passing Framework

- ▶ $\mathbf{m}_u^{(i)} = \text{Aggregate}^{(i)}(\{\{\mathbf{h}_v^{(i)} \mid v \in \mathcal{N}(u)\}\})$
- ▶ $\mathbf{h}_u^{(i+1)} = \text{Combine}^{(i)}(\mathbf{h}_u^{(i)}, \mathbf{m}_u^{(i)})$

3. Data Augmentation



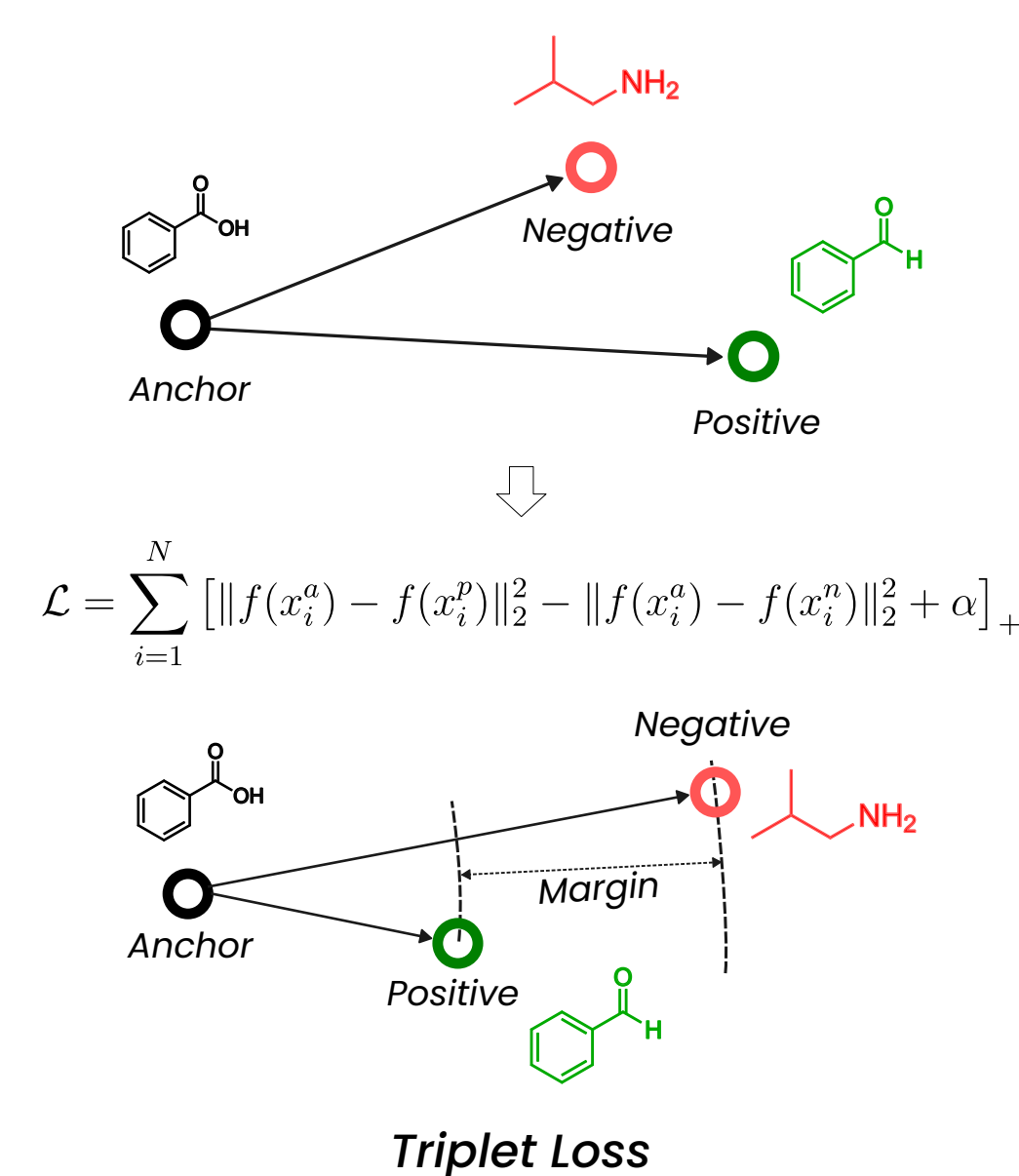
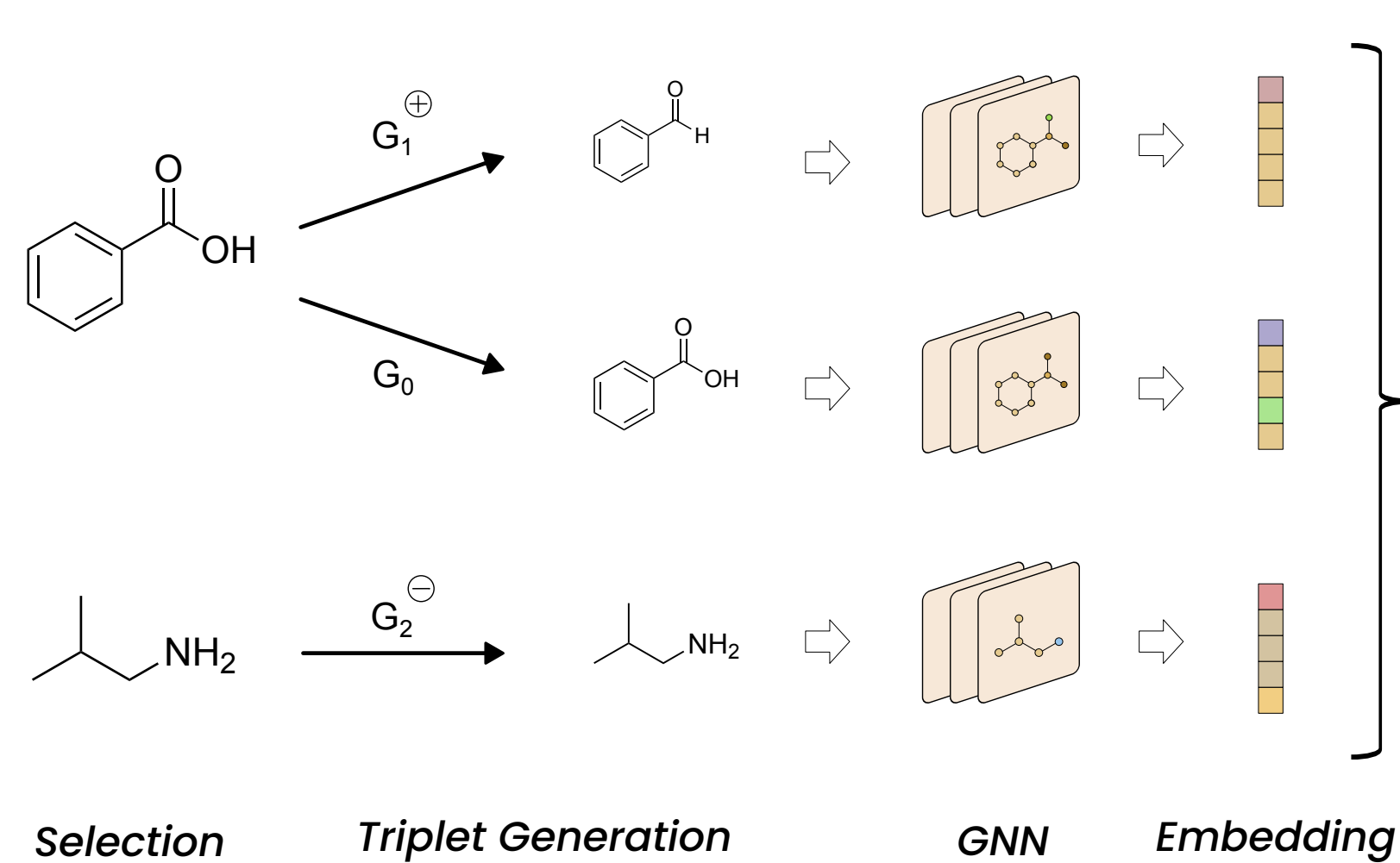
10M Molecules	
label	smiles
0	N#Cc1cc(O)c2oncc2c1
1	Cc1nccc(C=CC(C)Cl)n1
2	O=PCOCC(COCP=O)OCP=O
3	COc1ccc(Br)cc1SC
4	CSC1C(=O)N=NC=C1Cl
5	COCCNc1nccc2occc12
6	O=C1CCCCC(OC(=O)C1
7	Fc1cccc(Oc2ccccc2)c1
8	CCOc1c(Cc)cccc1OC
9	CCOCCCO[Si]c1cccc1
...	...

Augmentations

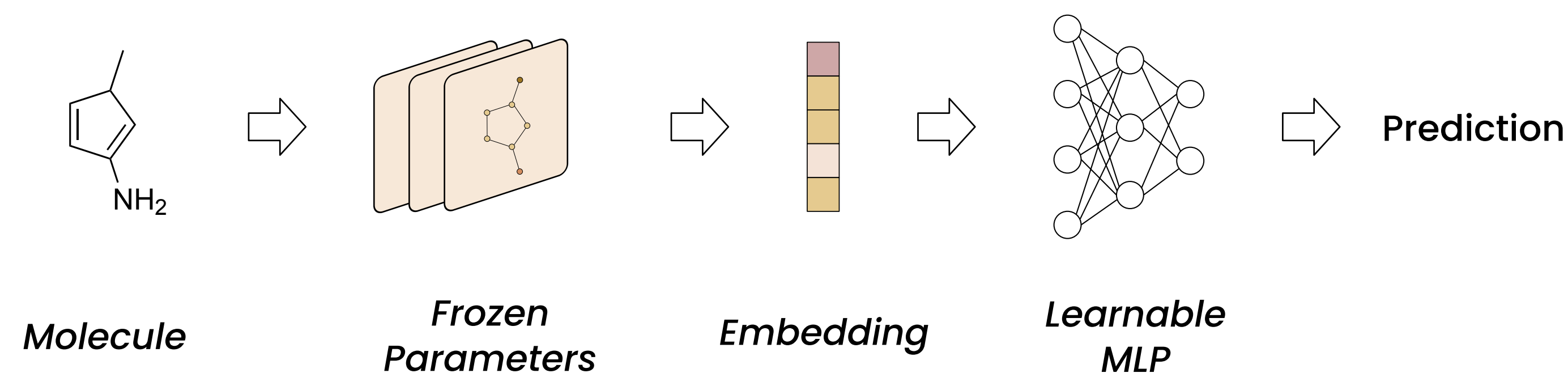
120M Molecules	
label	smiles
0	N#Cc1cc(O)c2oncc2c1
0	N#Cc1cc(O)c2onc(Cl)c2c1
0	N#Cc1cc(N)c2oncc2c1
0	N#Cc1cc(O)c2oncc2c1F
1	Cc1nccc(C=CC(C)Cl)n1
1	Cc1nccc(C=CC(Cl)CF)n1
1	Cc1nccc(C=PC(C)Cl)n1
2	O=PCOCC(COCP=O)OCP=O
2	O=PCOCC(OC(=O)C(F)OCP=O
2	O=PCOCC(OC(=O)C(Cl)OCP=O
...	...

- ▶ Input: **10M Molecules**
- ▶ **130 Augmentation Rules**
- ▶ Out: **120M Molecules**

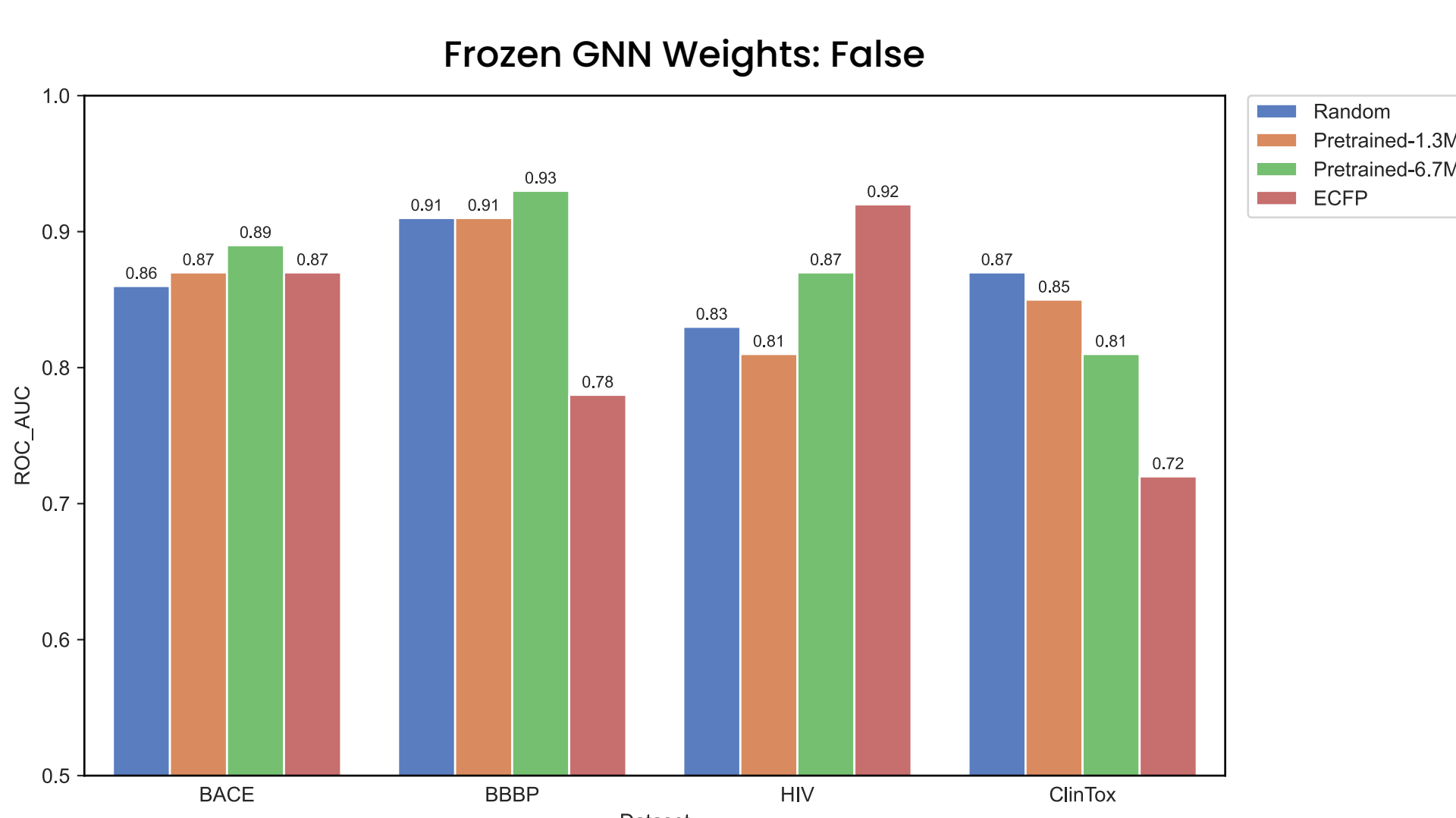
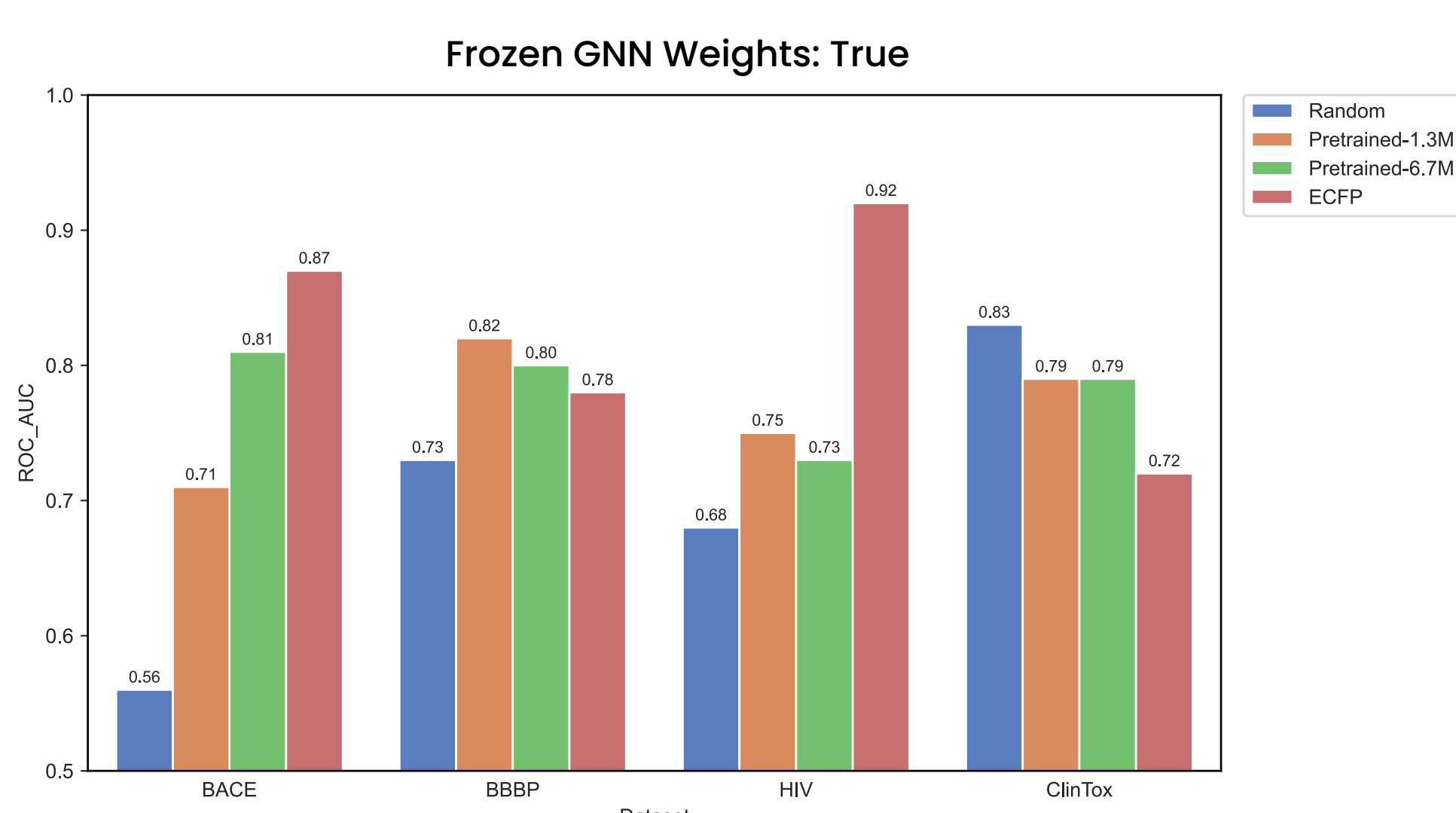
4. Self-Supervised Pre-Training



5. Fine-Tuning



The Results



6. Conclusion

- ▶ Pre-Training **improves embeddings** vs. randomly initialized GNNs
- ▶ ECFPs still have **comparatively good embeddings**
- ▶ Further investigation of embeddings is required