



HARVARD
MEDICAL SCHOOL



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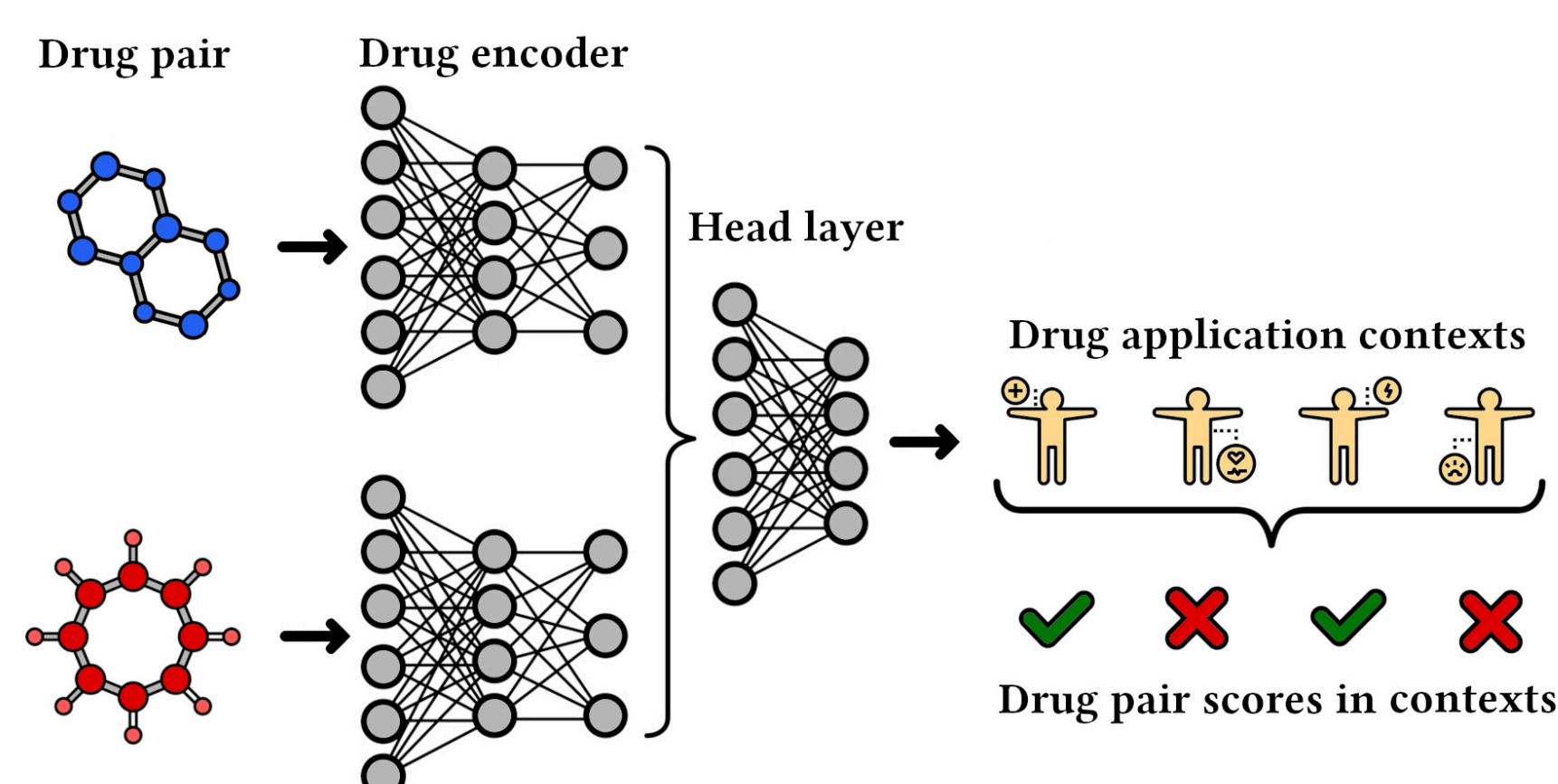
ChemicalX: A Deep Learning Library for Drug Pair Scoring

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The Pair Scoring Task



The Training Algorithm

Data: \mathcal{X}_D - Drug feature set.
 \mathcal{X}_C - Context feature set.
 \mathcal{B} - Labeled drug pair - context batch.

Result: \mathcal{L} - The cost for the batch.

$\mathcal{L} \leftarrow 0$

for $(d, d', c, y^{d,d',c}) \in \mathcal{B}$ **do**
 $\mathbf{h}^d \leftarrow f_D(\mathbf{x}^d, \mathcal{G}^d, \mathbf{X}_N^d, \mathbf{X}_E^d)$
 $\mathbf{h}^{d'} \leftarrow f_D(\mathbf{x}^{d'}, \mathcal{G}^{d'}, \mathbf{X}_N^{d'}, \mathbf{X}_E^{d'})$
 $\mathbf{h}^c \leftarrow f_C(\mathbf{x}^c)$
 $\hat{y}^{d,d',c} \leftarrow f_H(\mathbf{h}^d, \mathbf{h}^{d'}, \mathbf{h}^c)$
 $\mathcal{L} \leftarrow \mathcal{L} + \ell(y^{d,d',c}, \hat{y}^{d,d',c})$

end

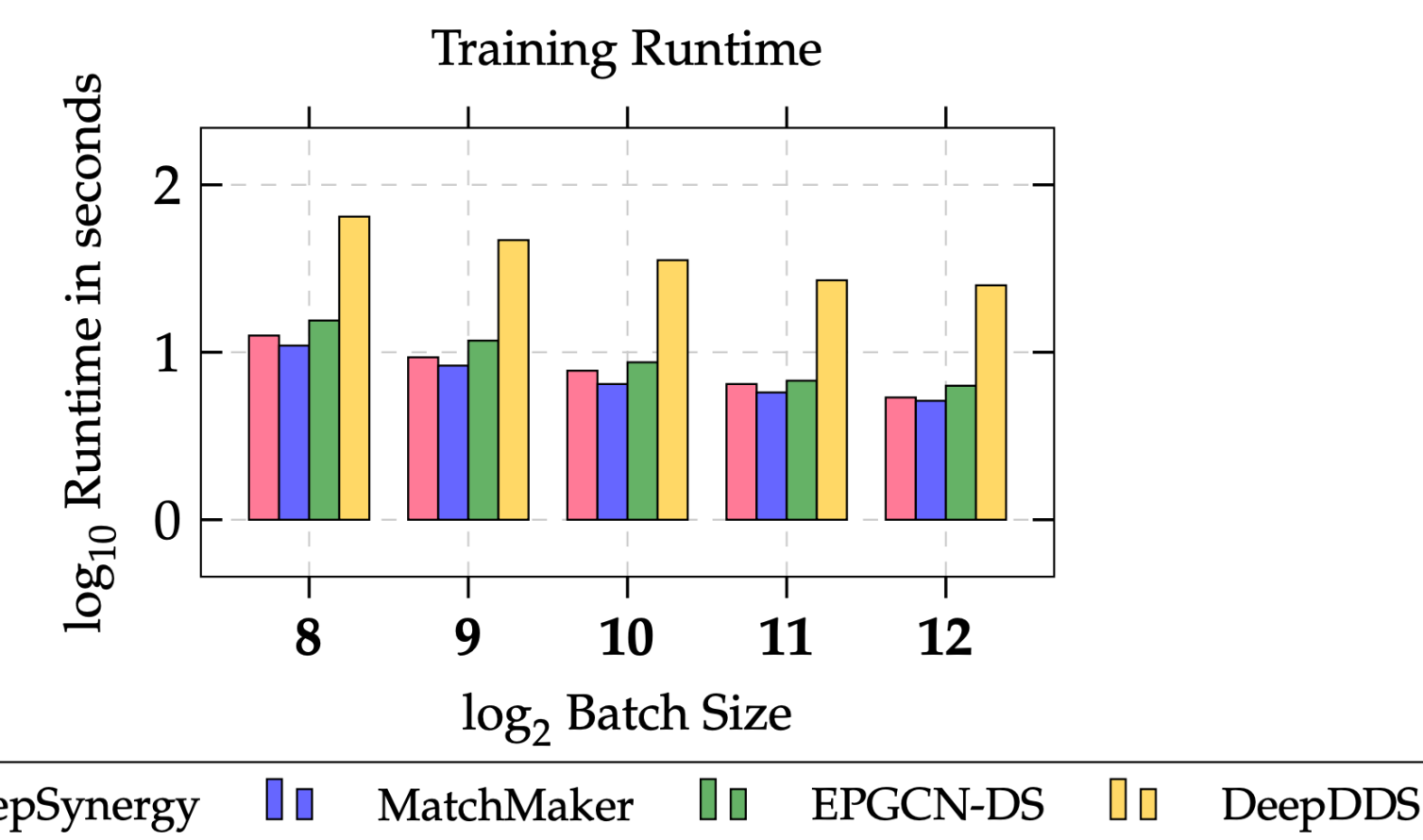
The Library Design

```
1 from chemicalx.data import DrugCombDB, BatchGenerator
2
3 loader = DrugCombDB()
4
5 context_set = loader.get_context_features()
6 drug_set = loader.get_drug_features()
7 triples = loader.get_labeled_triples()
8
9 generator = BatchGenerator(batch_size=1024,
10                             context_features=True,
11                             drug_features=True,
12                             drug_molecules=False,
13                             context_feature_set=context_set,
14                             drug_feature_set=drug_set,
15                             labeled_triples=triples)
```

```
1 import torch
2 from chemicalx.models import DeepSynergy
3
4 model = DeepSynergy(context_channels=112,
5                     drug_channels=256)
6
7 optimizer = torch.optim.Adam(model.parameters())
8 model.train()
9 loss = torch.nn.BCELoss()
10
11 for epoch in range(200):
12     for batch in generator:
13         optimizer.zero_grad()
14         prediction = model(batch.context_features,
15                             batch.drug_features_left,
16                             batch.drug_features_right)
17         loss_value = loss(prediction, batch.labels)
18         loss_value.backward()
19         optimizer.step()
```

Experimental Validation

		AUROC	AUPR	F ₁
DeepDDI	■	.929 ± .001	.907 ± .001	.848 ± .009
DeepSynergy	■	.940 ± .001	.919 ± .001	.887 ± .001
MR-GNN		.937 ± .002	.917 ± .001	.875 ± .002
SSI-DDI		.823 ± .002	.800 ± .003	.756 ± .001
EPGCN-DS		.855 ± .003	.834 ± .002	.785 ± .004
DeepDrug	■	.923 ± .004	.904 ± .002	.857 ± .002
GCN-BMP		.709 ± .003	.694 ± .002	.592 ± .003
DeepDDS		.915 ± .002	.898 ± .002	.839 ± .003
MatchMaker	■	.912 ± .002	.892 ± .001	.849 ± .001



References

Rozemberczki et al., *A Unified View of Relational Deep Learning for Drug Pair Scoring*. IJCAI, 2022.
Rozemberczki et al., *MOOMIN: Deep Molecular Omics Network for Anti-Cancer Drug Combination Therapy*. CIKM, 2022.

