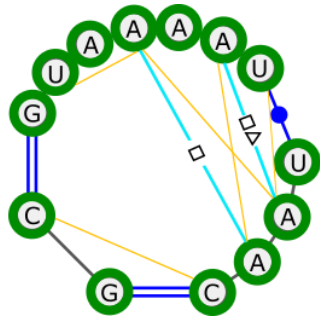
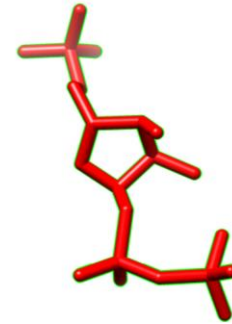


Relational Graph Convolutional Networks for RNA structure analysis and binding predictions



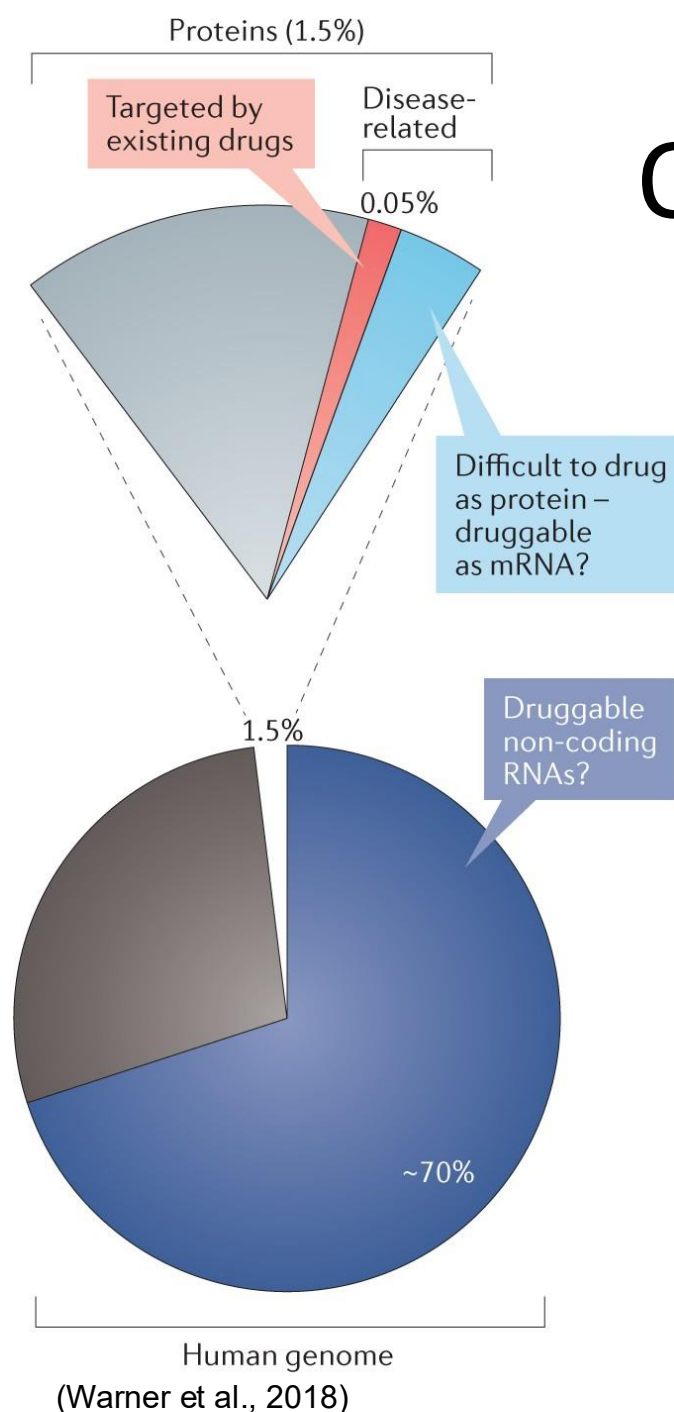
Jérôme Waldispühl
School of Computer Science
McGill University

✉ jerome.waldispuhl@mcgill.ca



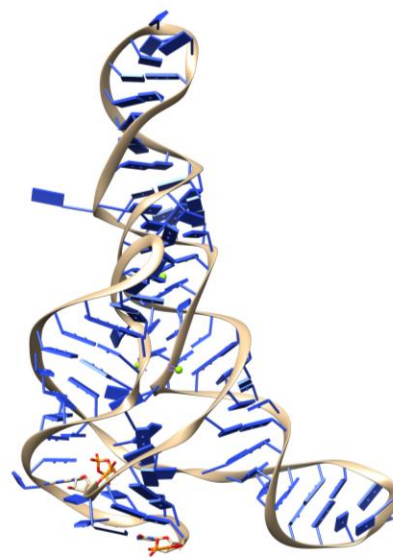
<http://csb.cs.mcgill.ca>



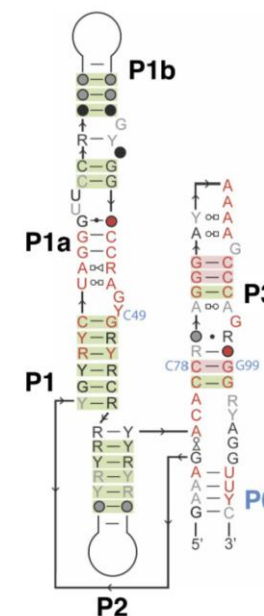
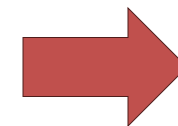


Objectives & Motivations

Challenge: How to screen the full data set?



PRPP riboswitch (Perselis & Serganov, 2018).



- 3D data is rare and 3D structures hard to predict
- Geometric DL is sensitive

- Lightweight
- Fast & robust algorithms
- Easier to acquire
- Retain structural signal

Relational Graph Convolutional Network (RGCN)

$$h_i^{(l+1)} = \phi \left(W_0^{(l)} h_i^{(l)} + \sum_{r \in \mathcal{R}} \sum_{j \in \mathcal{N}_r(i)} \frac{1}{|\mathcal{N}_r(i)|} W_r^{(l)} h_j^{(l)} \right)$$

$h_i^{(l+1)}$: representation of node i at layer l

$\mathcal{R}$: relations (edge types)

$\mathcal{N}_r(i)$: neighbors of node i



Semi-supervised learning and docking data augmentation
for small molecule binding affinity prediction

RNAmigos

(Oliver *et al.*, 2020)

(Carjaval-Patiño *et al.*, 2025)



Carlos G. Oliver
Vanderbilt University



Vincent Mallet
Les Mines



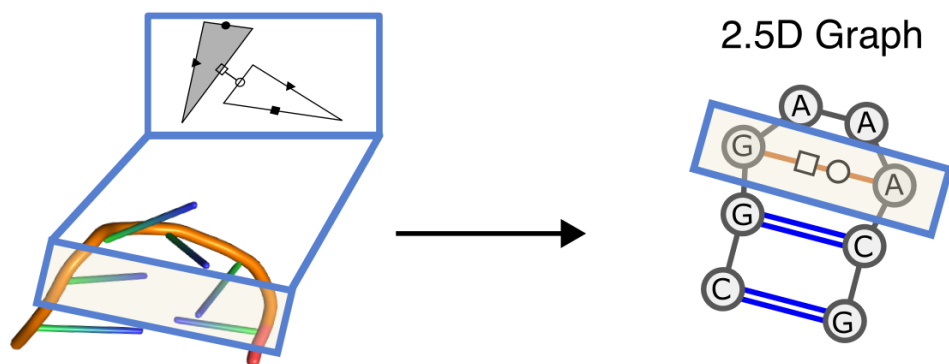
Juan Carjaval
Univ. Nac. de Colombia



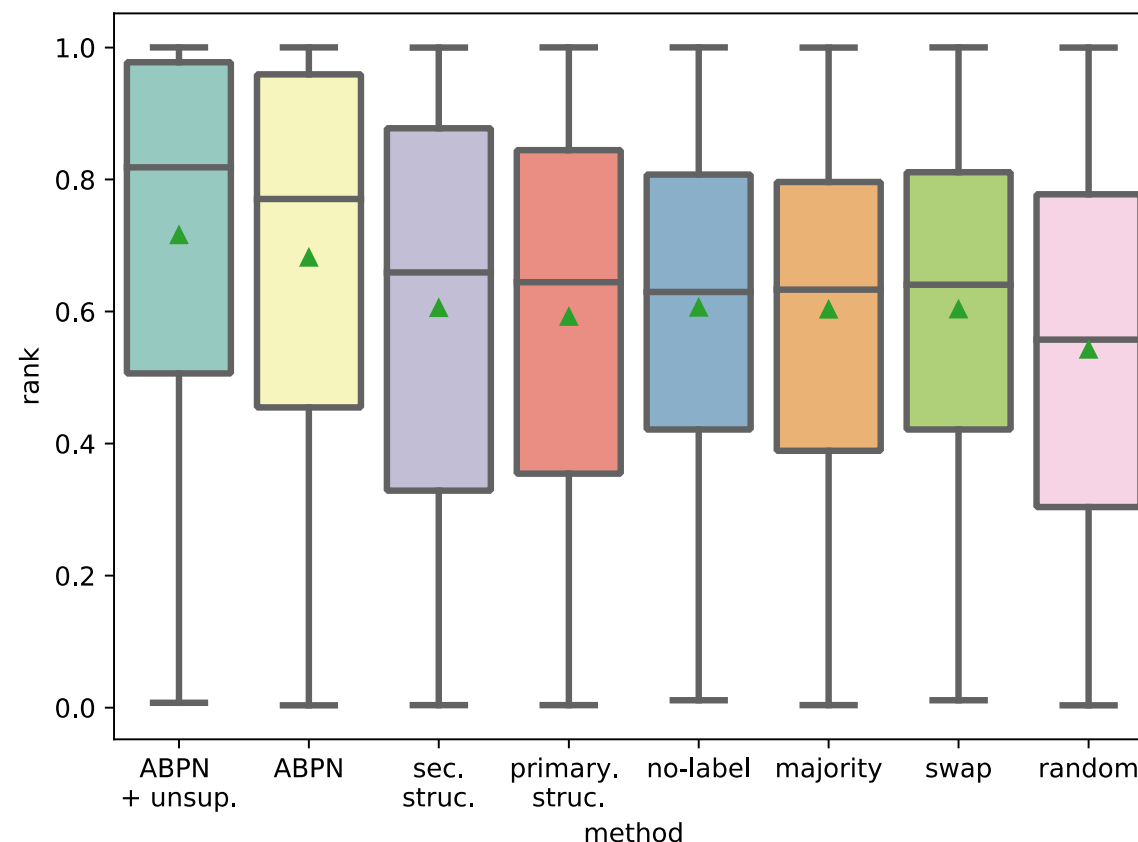
David Becerra
McGill University

RNAmigos1: Proof of concept

Encode binding pockets as graphs labelled with Leontis-Westhof base pair classification.



Given a motif **RNAmigos1** outputs the **fingerprint** of a ligand.



(Oliver *et al.*, 2020)

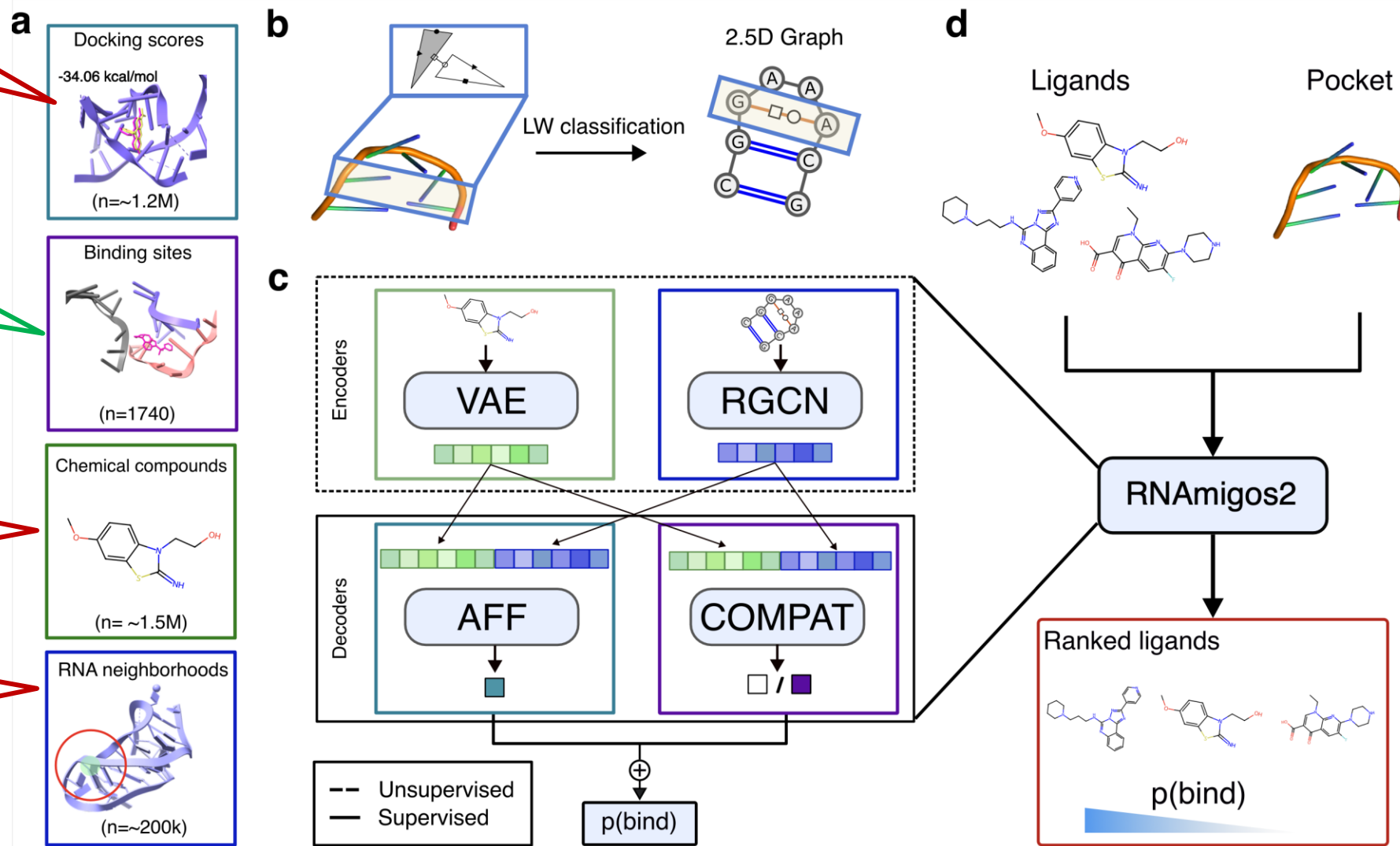
RNAmigos2 overview

large-scale
docking
experiment

Original PDB
dataset

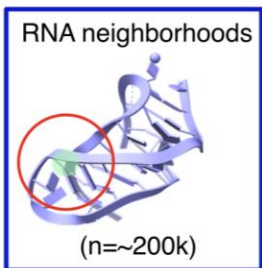
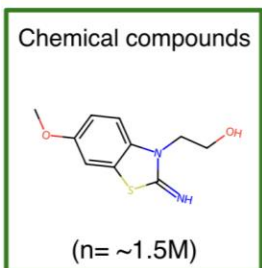
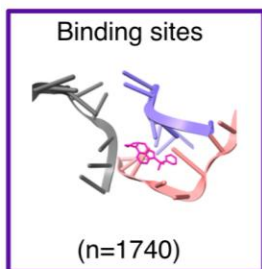
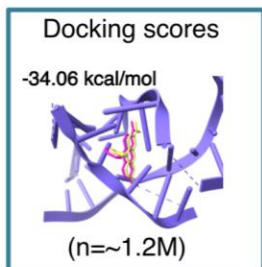
Unlabeled
drug-like
compounds

Unlabeled
RNA target
sites



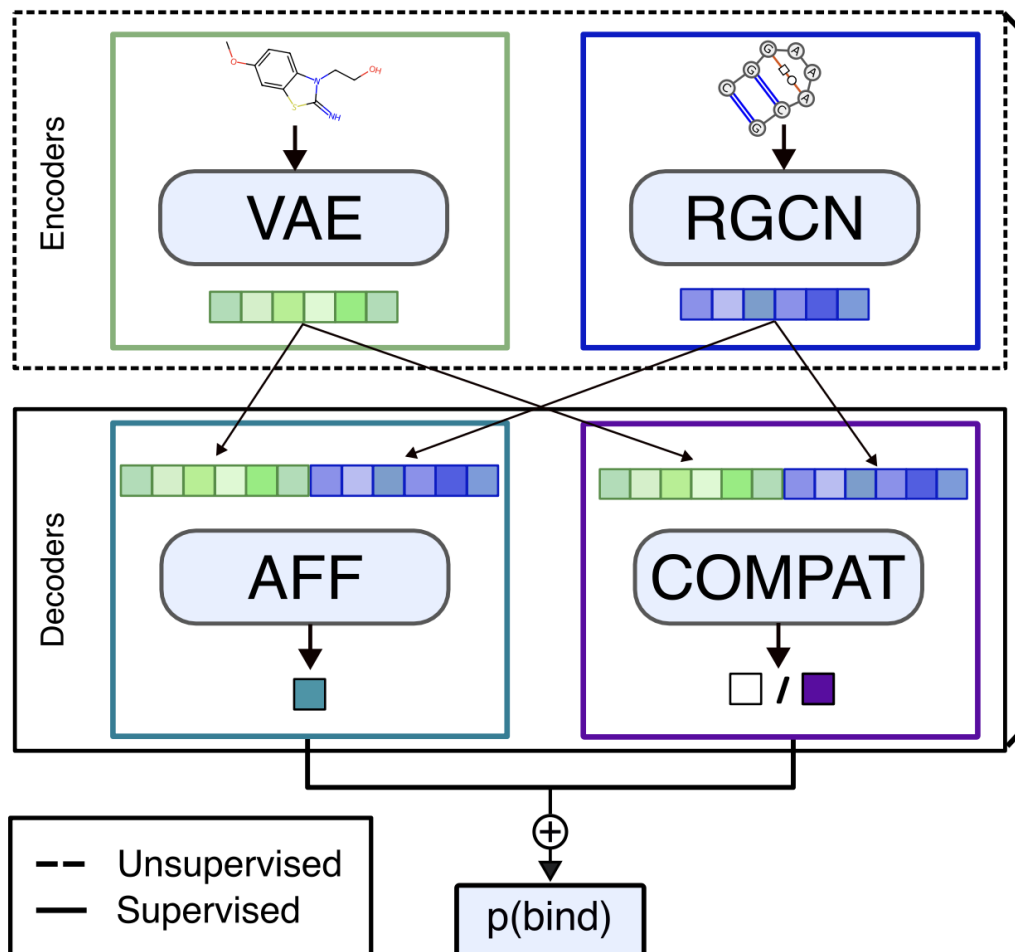
(Carjaval-Patiño *et al.*, 2025)

Data source



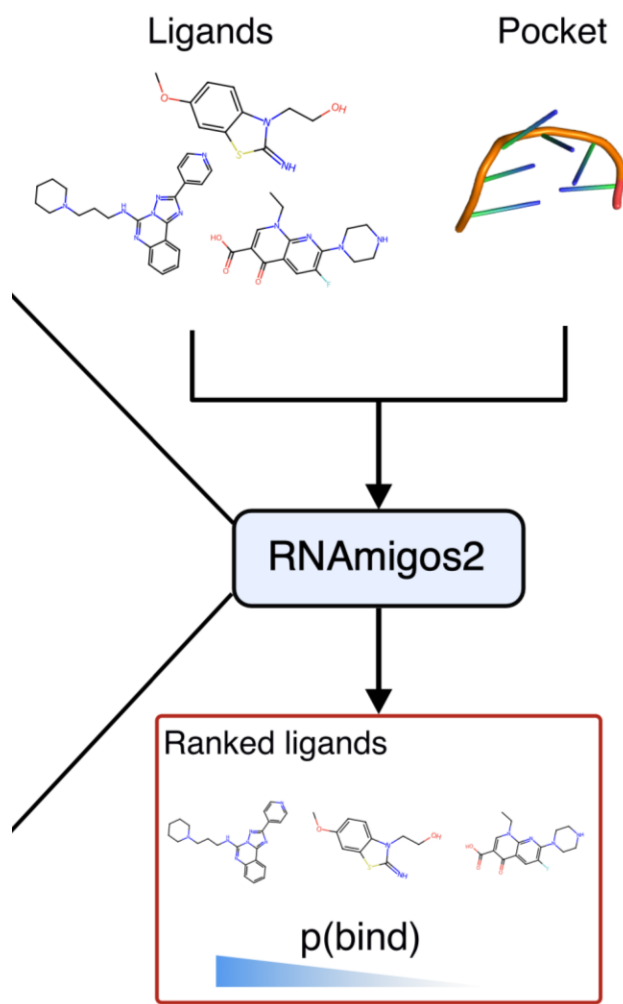
- **Docking scores** : ~1.2M RNA-pocket / ligand pairs scored by rDock.
 - **Binding sites** : 1,740 native RNA–small-molecule complexes from the PDB.
 - **Chemical compounds** : ~1.5M unlabeled drug-like molecules for VAE pre-training.
 - **RNA neighborhoods** : ~200k binding-site-like subgraphs from the PDB for RGCCN pre-training.
- (Carjaval-Patiño *et al.*, 2025)

Encoder & Decoder



- **Encoders** (unsupervised): a VAE on small molecules and an RGCN on pocket 2.5D graphs.
- **Decoders** (supervised, joint): AFF predicts the rDock docking score; COMPAT predicts native vs. decoy.
- All four heads share the same encoders.

Scoring

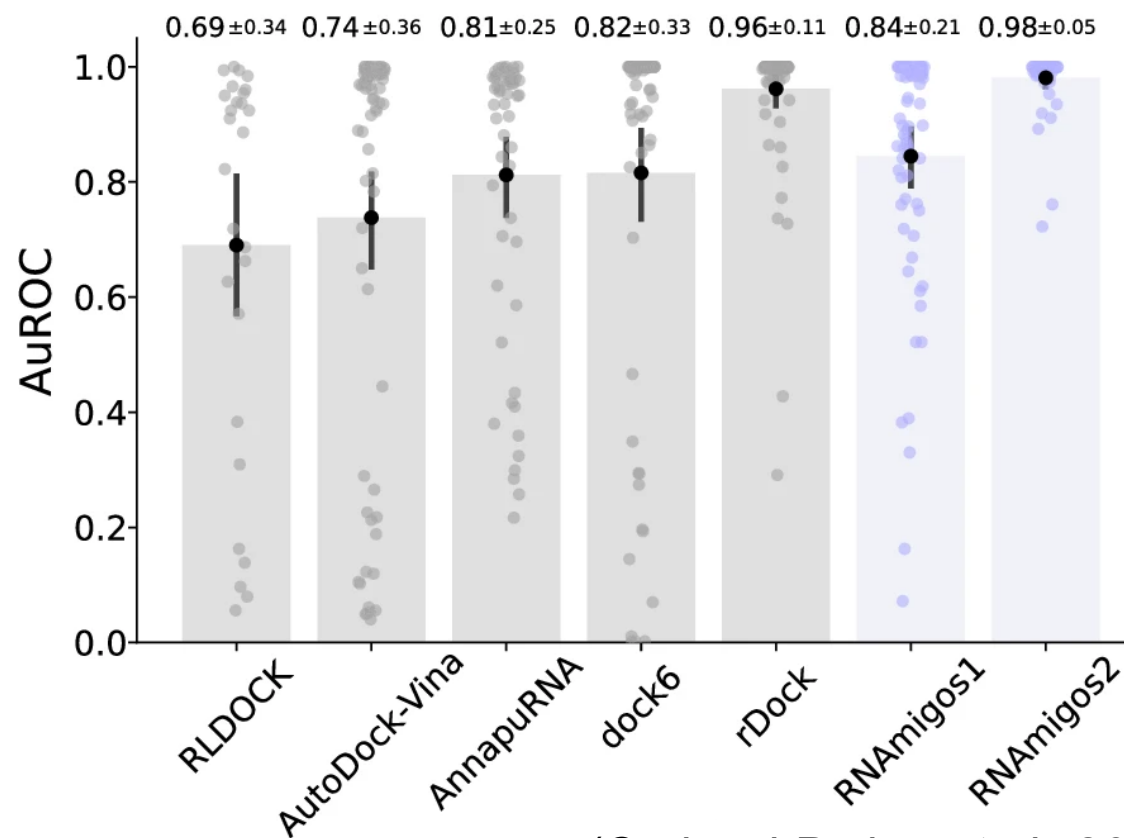
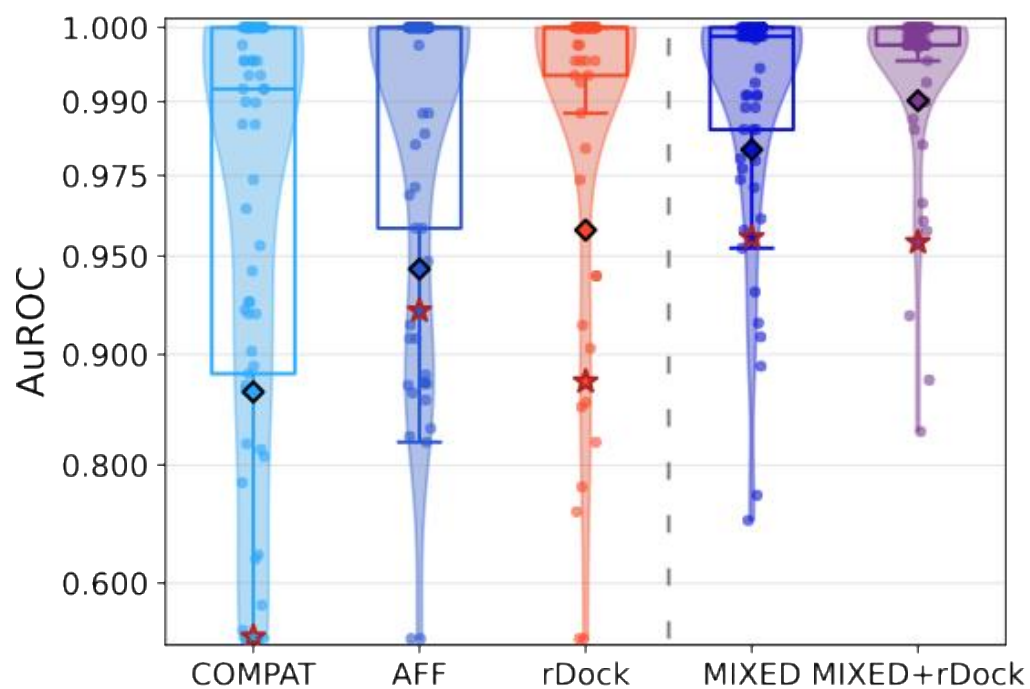


Input: a target pocket + a library of compounds:

1. Encode pocket once with the trained RGCN.
2. Encode every compound with the VAE.
3. For each (pocket, compound), get scores from both the AFF and COMPAT heads.
4. Ensemble $\rightarrow$ final $p(\text{bind})$.

Virtual Screening (VS) Performance

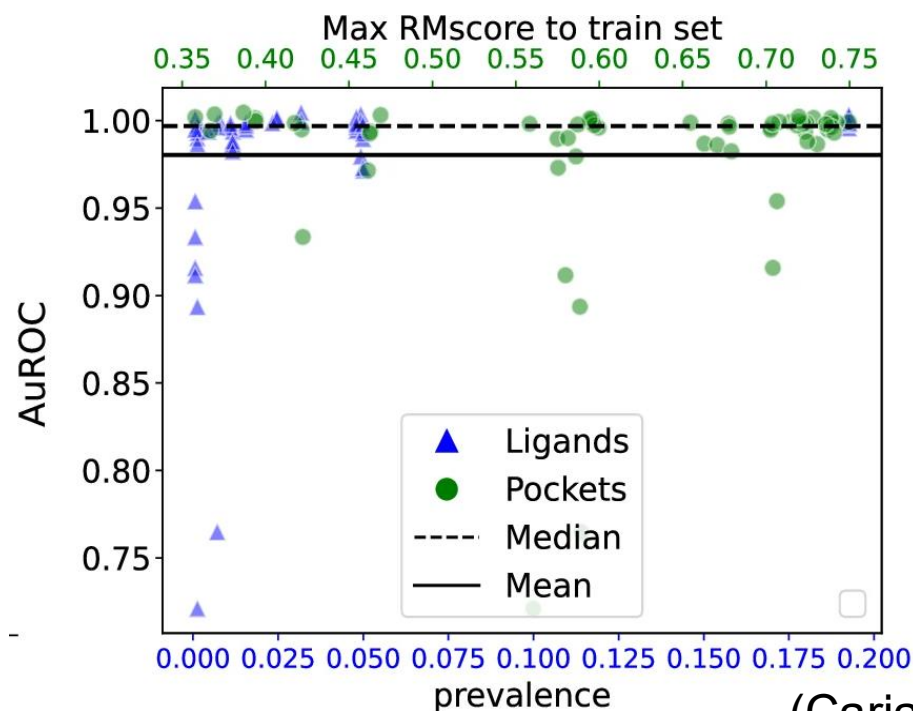
- Candidate ligands: PDB (native) + filtered ChEMBL (decoy) compounds.
- For each PDB binding sites, score all compounds and sort them.



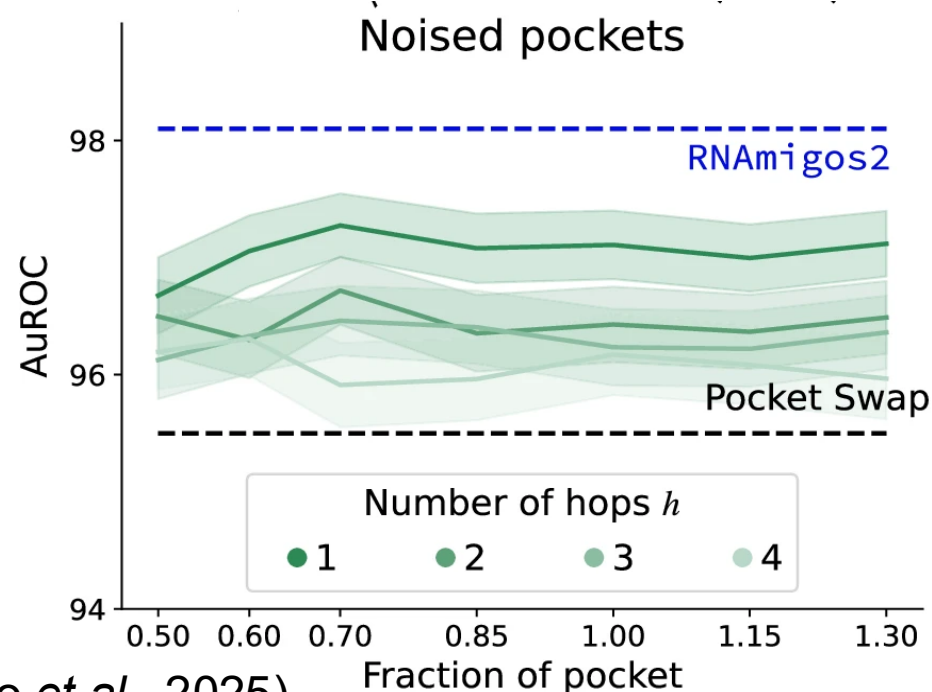
(Carjaval-Patiño *et al.*, 2025)

(some) Challenges of validation

- Leakage from pre-training
- Repeat experiments with multiple random seeds
- Class imbalance (e.g., PDB ligand don't display drug-like features)
- Generalization to unseen (distant) instances
- Validate the model leverage ligand **AND** structure features



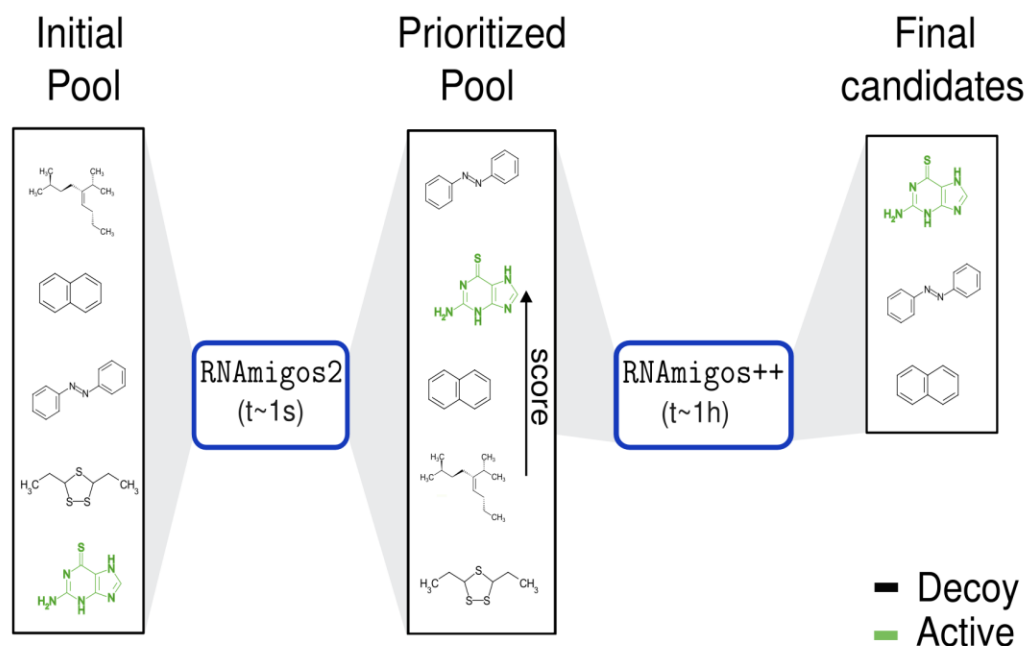
(Carjaval-Patiño *et al.*, 2025)



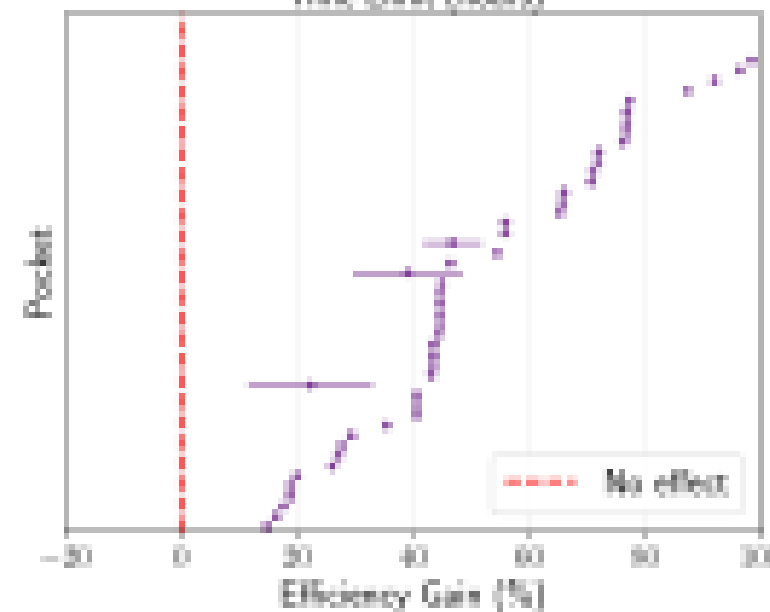
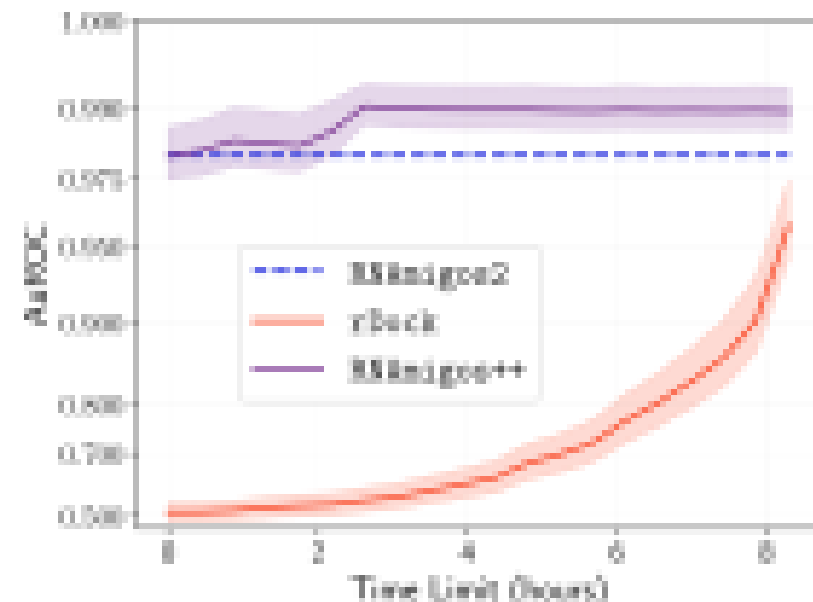
A hybrid docking strategy

Objective: Even if you do not fully trust RNAmigos, you can use it to accelerate classical docking

1. RNAmigos2 ranks candidates
2. Docking tool (rDock) scores the best candidates

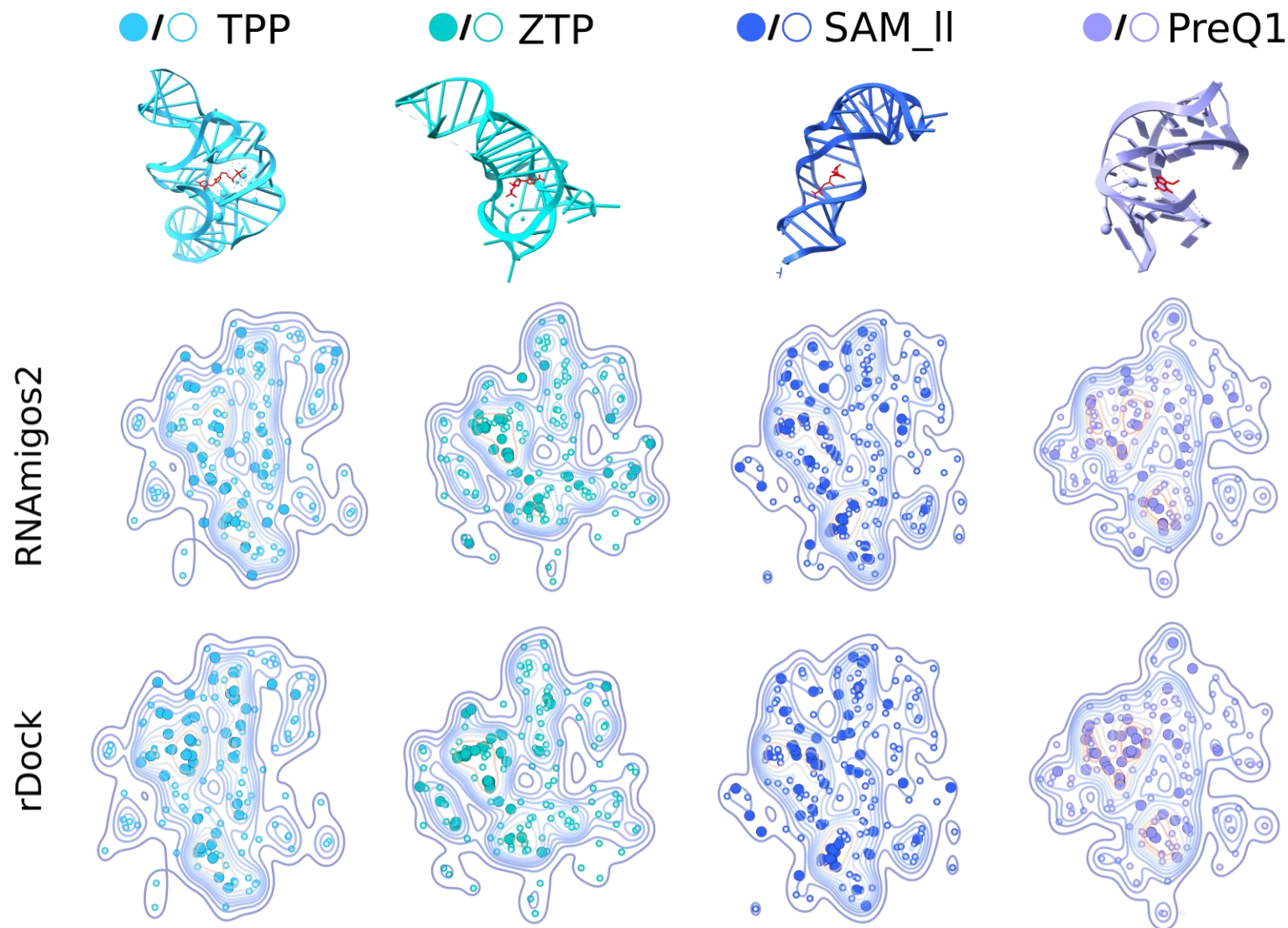


Performance:



(Blind) Test on ROBIN large-scale in-vitro assay

- 24,572 small molecules
- 36 Nucleic acid targets
- Mixed model (combined with rDock)
- Similar accuracy at fraction of running time



Try it yourself!

README MIT license

Using the tool with Collab

The easiest way to use the tool is to use Google Colab.

 [Open in Colab](#)

You will need to provide a cif file, a binding site in the form of a list of binding pocket nodes and a list of ligand smiles.

Using the tool locally

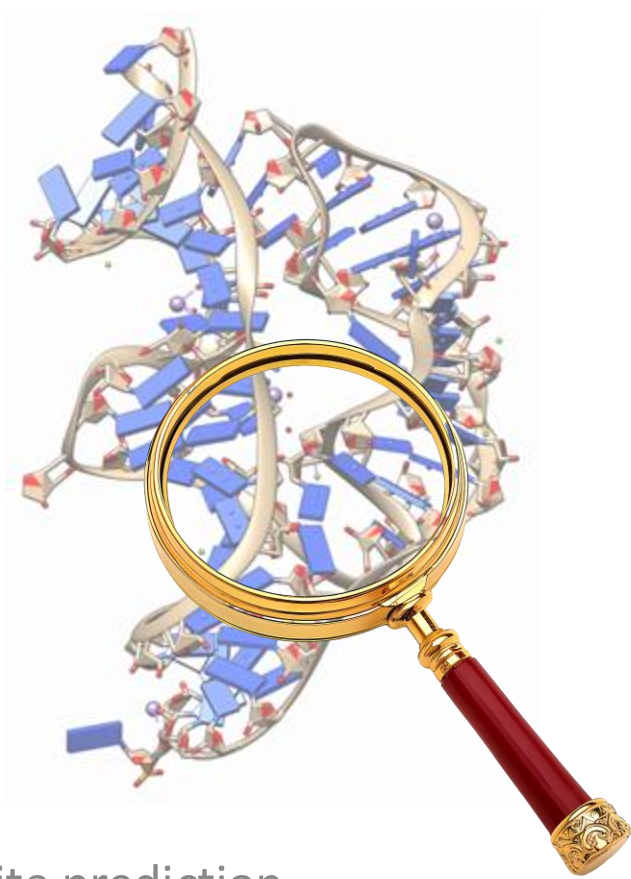
A local use of the tool is also possible by following the next steps. NOTE: This has been tested on Linux Ubuntu 24 and Mac OS 13 and 14. No special hardware requirement, inference code runs on common desktops and laptops.

First, create a conda environment:

```
git clone https://github.com/cgoliver/rnamigos2.git
cd rnamigos2/
conda create -n rnamigos2
conda activate rnamigos2
pip install numpy==1.26
pip install torch==2.2.2+cpu torchaudio==2.2.2 torchdata==0.7.1 torchvision==0.17.2 --index-ur
pip install dgl -f https://data.dgl.ai/wheels/torch-2.2/repo.html
pip install -r requirements.txt
```

To run RNAmigos2.0 on your own target and ligands, use the `rnamigos/inference.py` script.

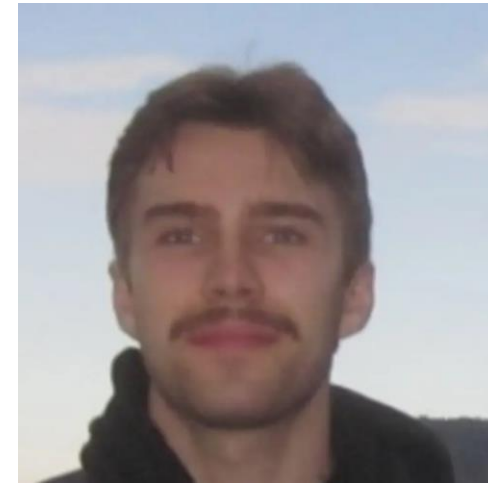
<https://github.com/cgoliver/rnamigos2>
carlos.oliver@vanderbilt.edu



Binding site prediction

Ribo-LENS

(Nitchi *et al.*, submitted)

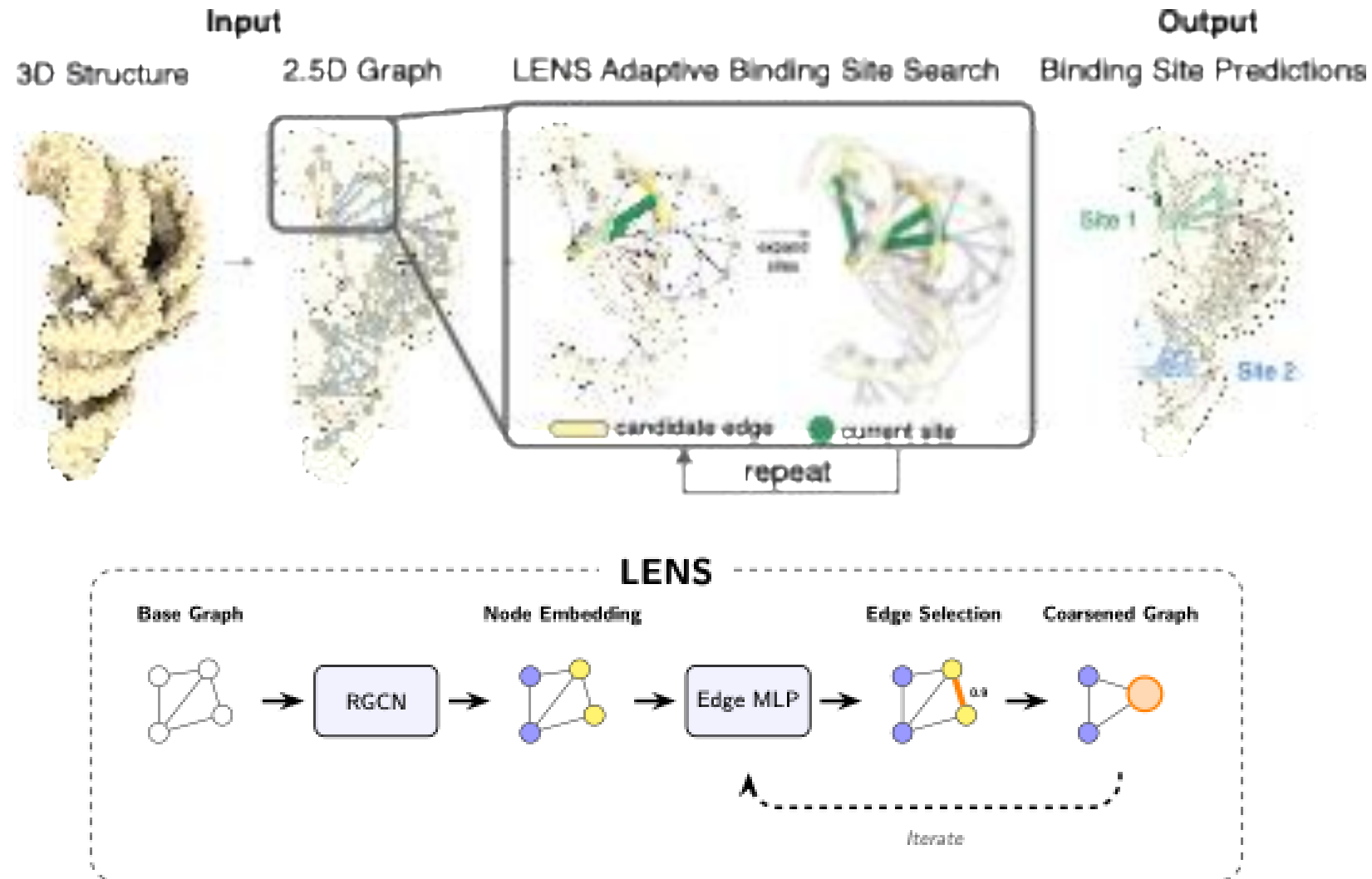


David Nitchi
McGill University



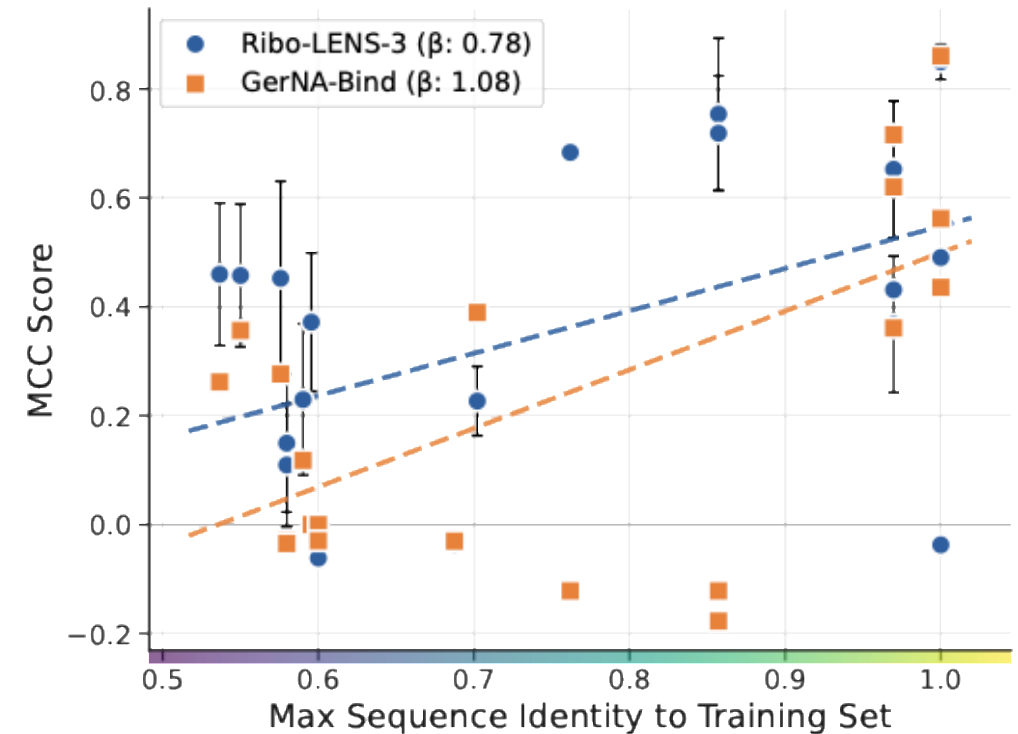
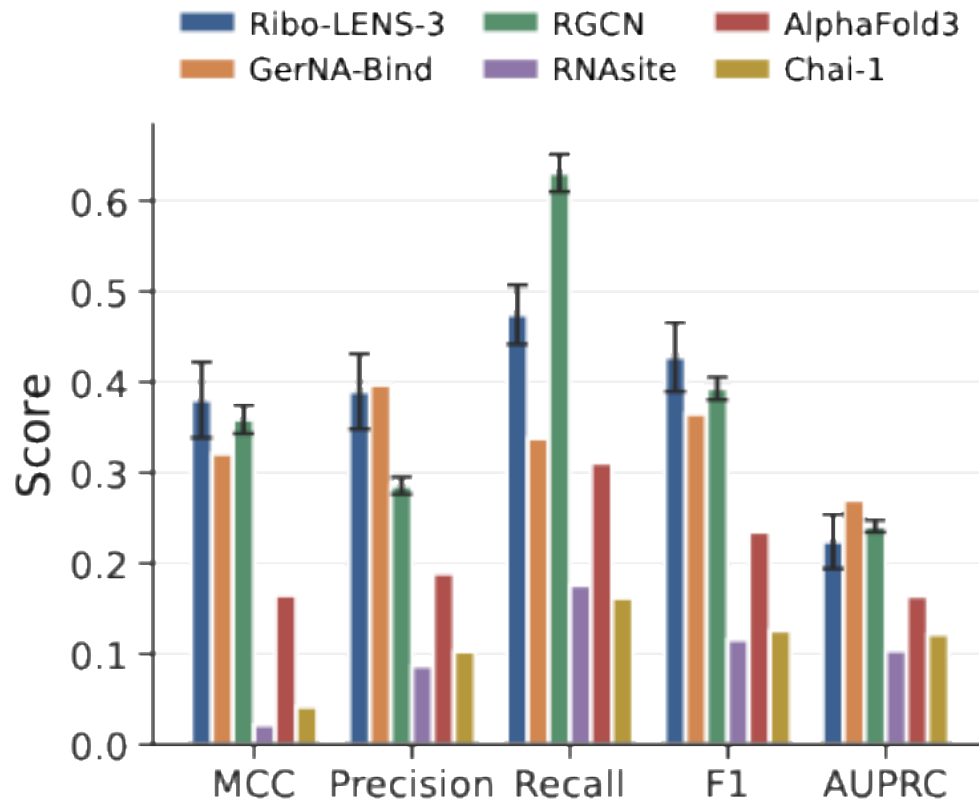
Carlos G. Oliver
Vanderbilt University

Ribo-LENS framework



(Nitchi *et al.*, 2026)

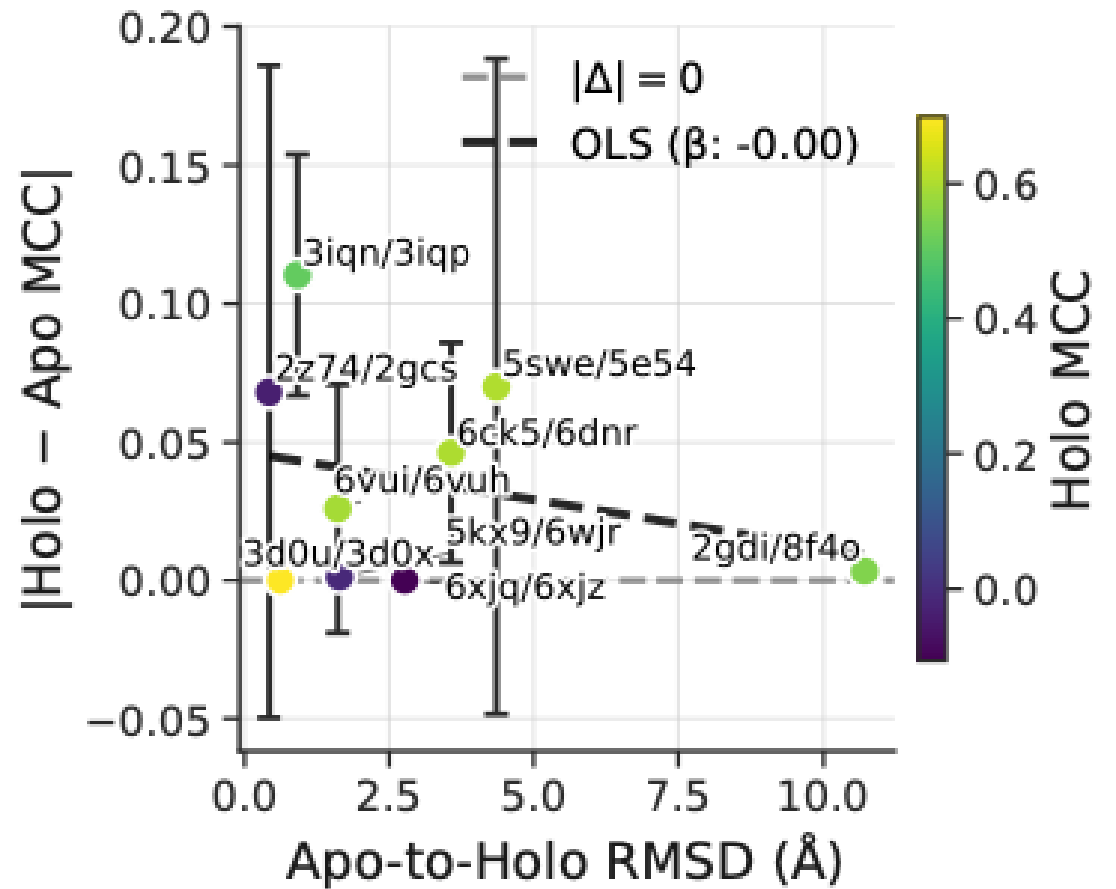
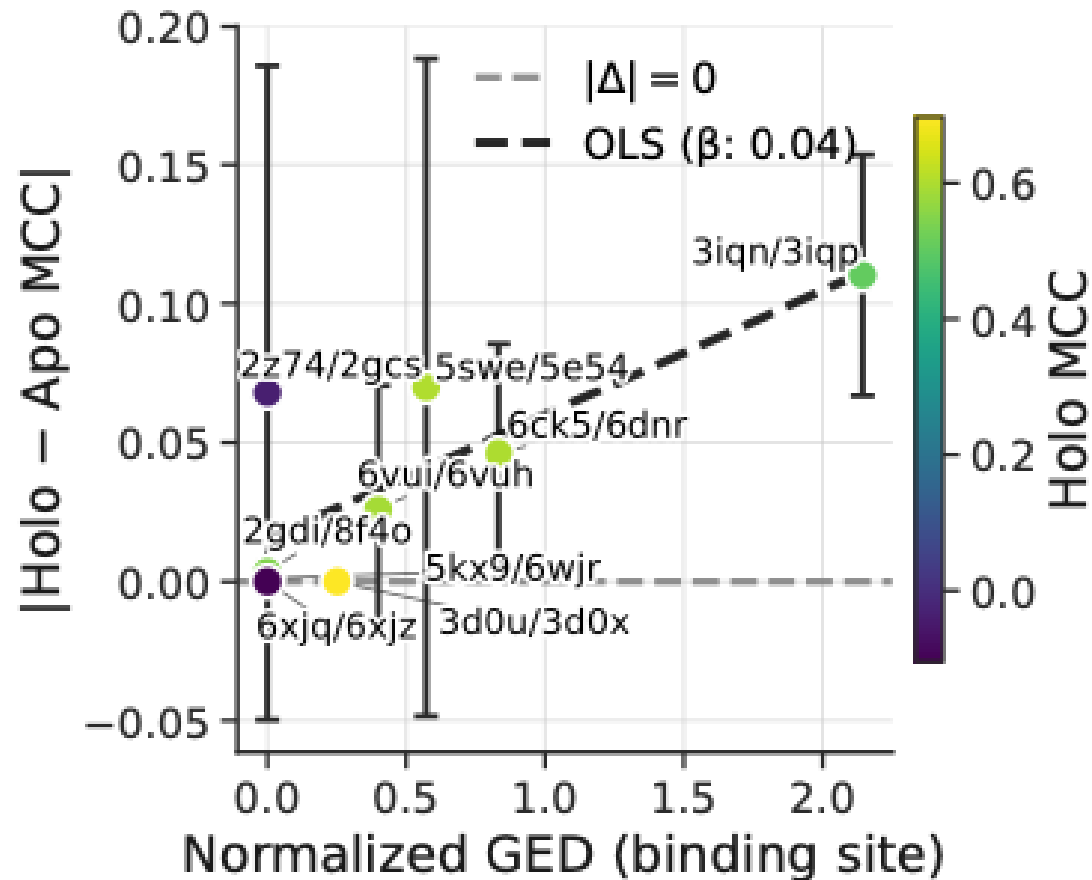
Benchmark on GerNA-Bind test set



- GerNA-Bind test set (Xia *et al.*, 2025) from HARIBOSS (Panei *et al.*, 2022).
- Split: training set (structures <2020) & test sets (structures >2020).
- Positive: nucleotides < 4Å

(Nitchi *et al.*, 2026)

APO/HOLO conformational robustness



- Benchmark from fPocketR (Veenbass et al., 2025)
- GED: Graph Edit Distance
- RMSD: Backbone

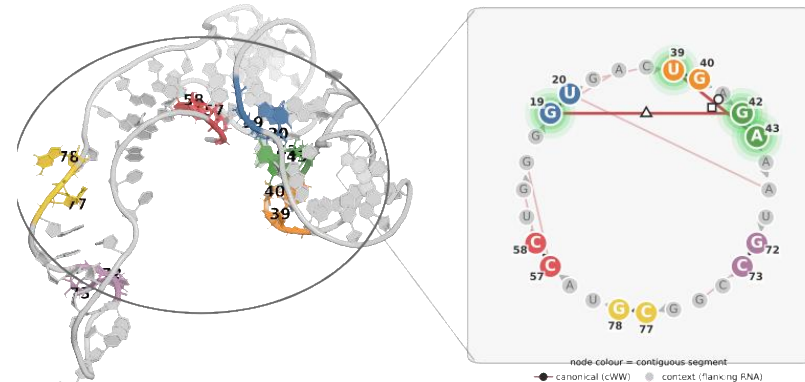
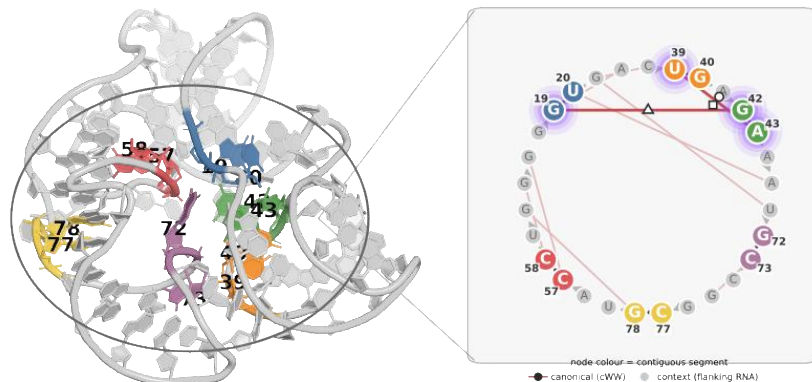
(Nitchi *et al.*, 2026)

APO/HOLO case study

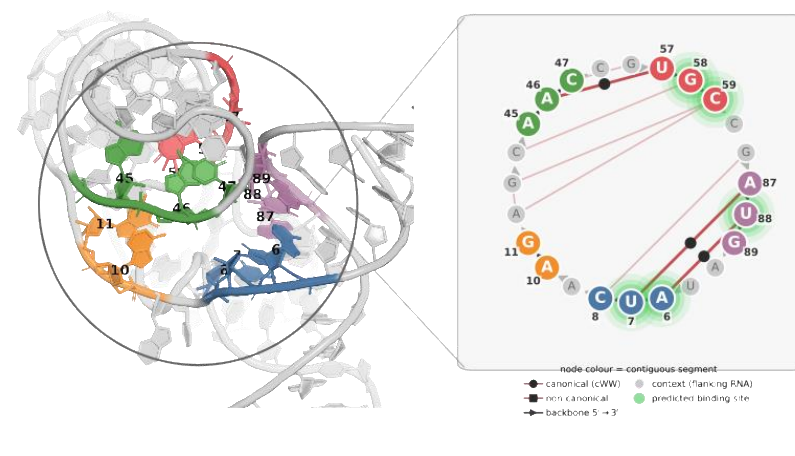
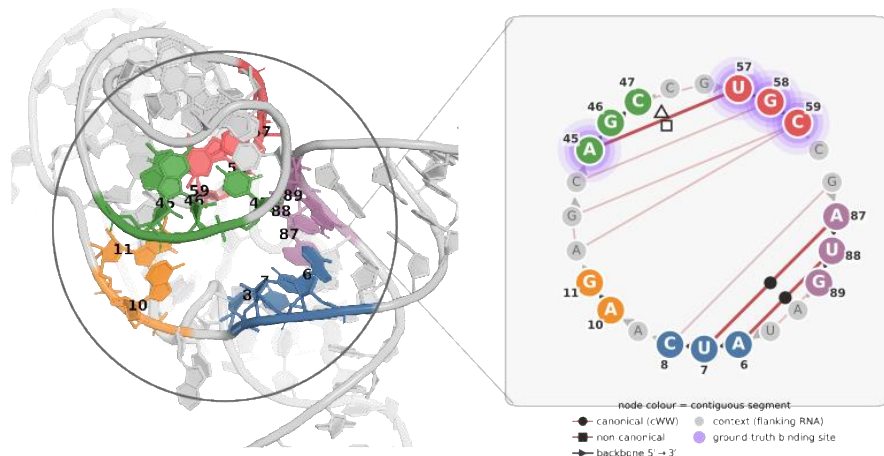
HOLO

APO

Conserved 2.5D
Distant 3D



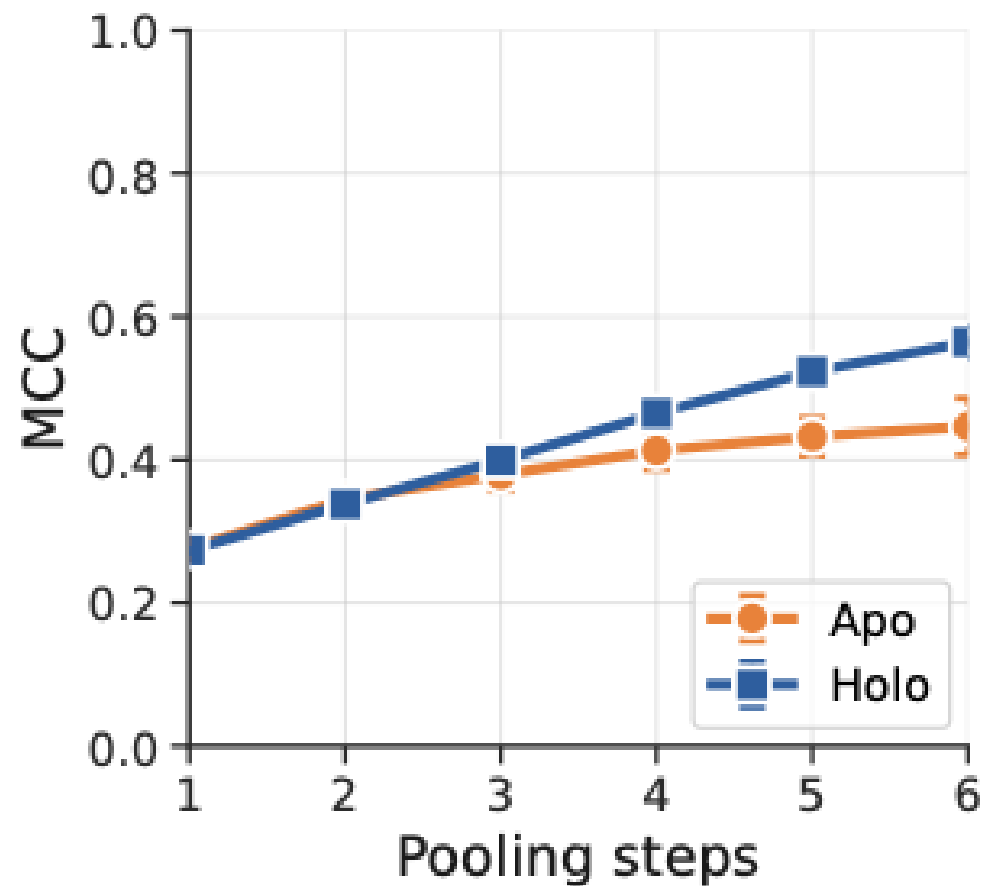
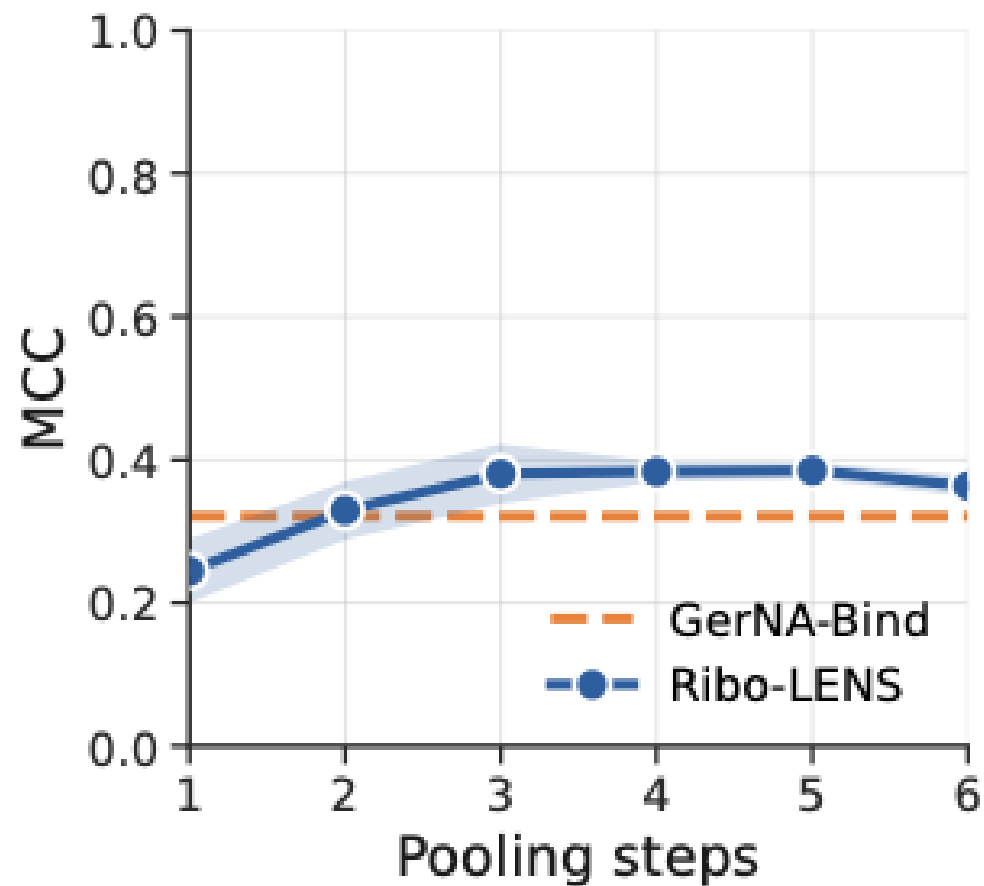
Distant 2.5D
Conserved 3D



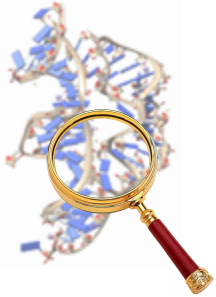
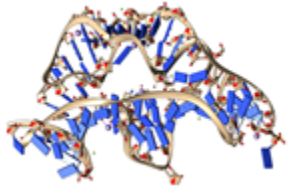
(Nitchi *et al.*, 2026)

Purple glow: True site; Green glow: Ribo-LENS prediction

What is the impact of pooling?



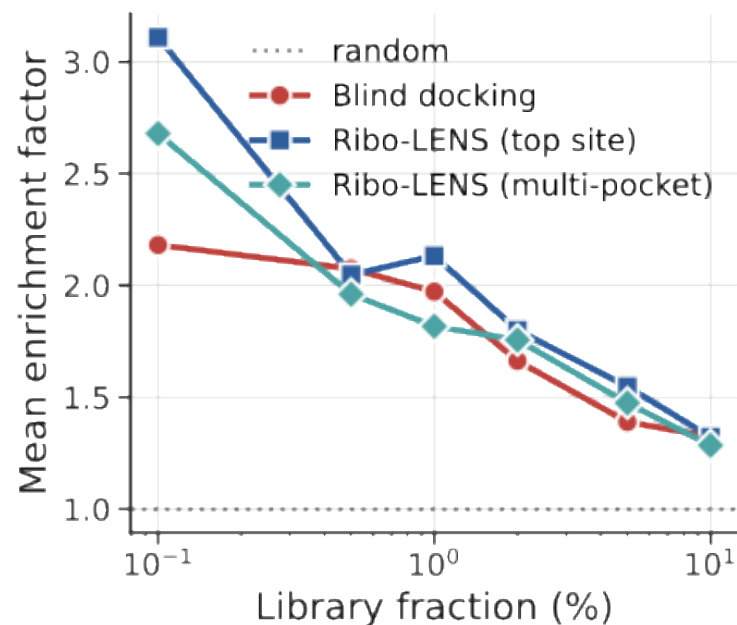
Simulation of sequence-based virtual-screening



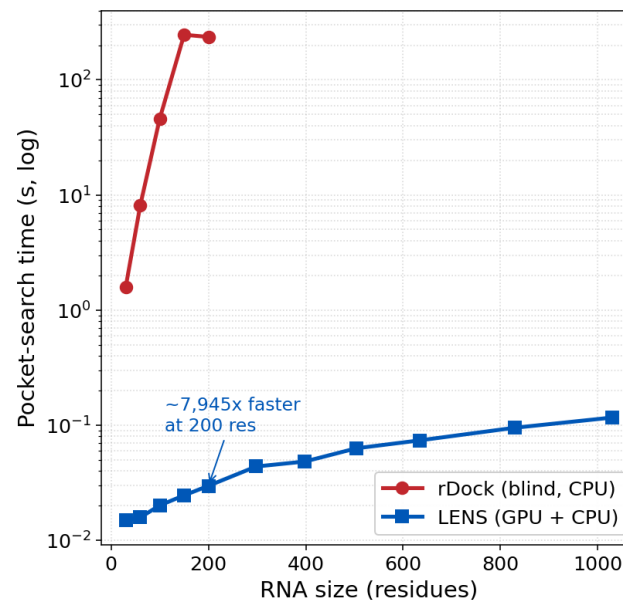
- ~25,000 small molecules binding against target 27 RNAs
- Retain only RNAs for which we can predict a structure (14)
- Predict 3D structure (RhoFold+)
- Extract 2.5D graph (for Ribo-LENS)
- Predict binding site from 2.5D with Ribo-LENS
- 3 pooling steps, no threshold
- Dock small molecule library on candidate sites with rDock
- Additional blind docking with rDock for a baseline
- Compute enrichment score

Ribo-LENS vs Blind Docking

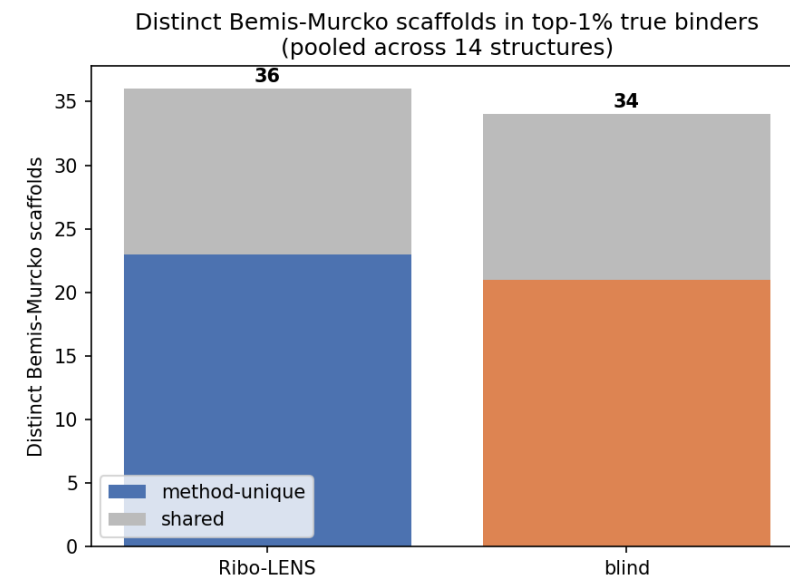
Accuracy



Time



Diversity



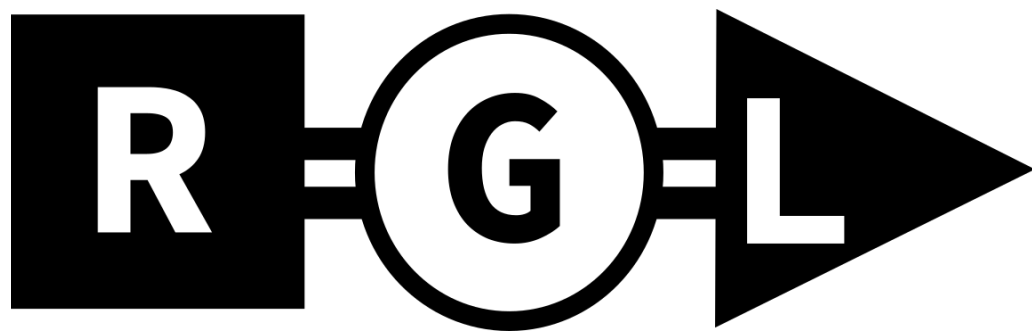
Enrichment factor:

$$EF_{x\%} = \frac{a_x/n_x}{A/N}$$

a_x : #compounds in top $x\%$ of ranking

n_x : #experimentally confirmed active among them

(Nitchi *et al.*, 2026)



Carlos G. Oliver
Vanderbilt University



Vincent Mallet
Les Mines

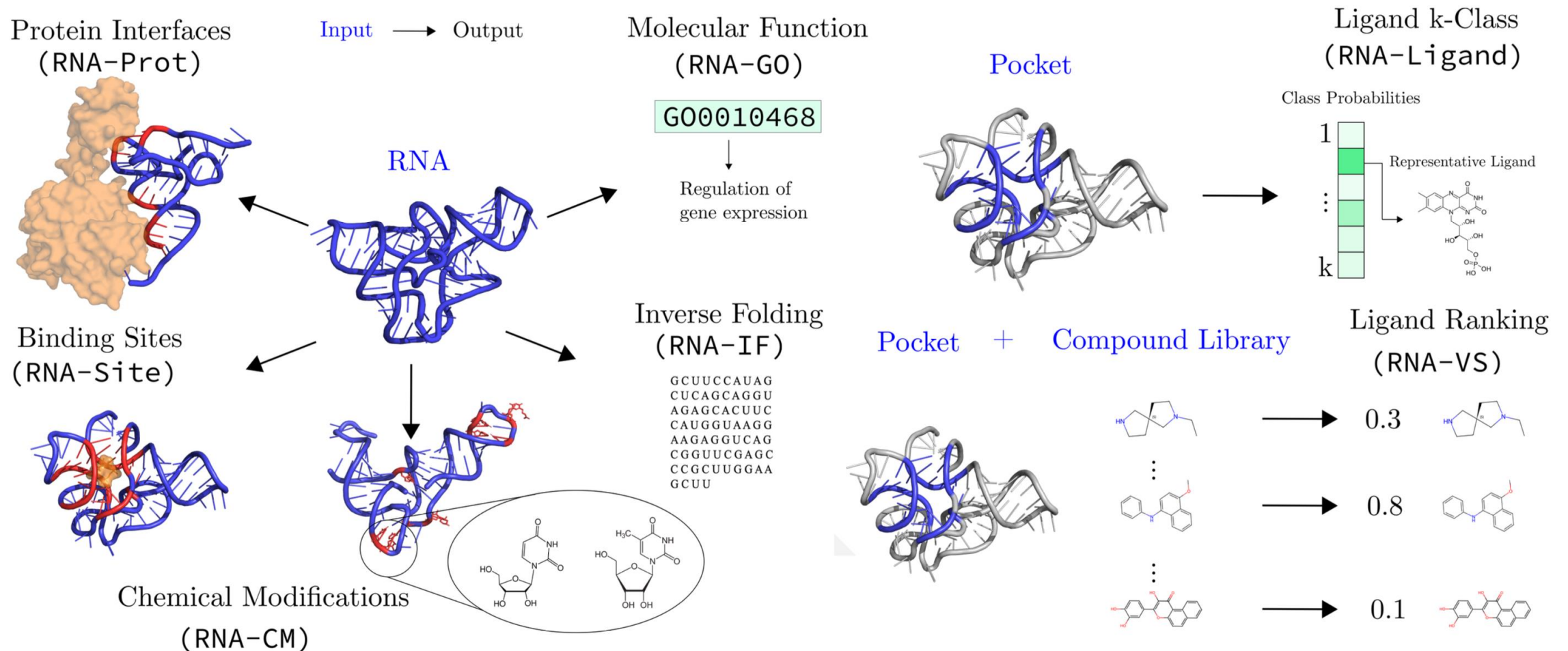
Prediction on small molecules binding RNA

RNAglib

(Mallet *et al.*, 2022)

(Oliver *et al.*, 2025)

rnaglib: A framework for RNA ML applications



(Mallet *et al.*, 2022; Wyss *et al.*, 2026)

Shoutout

Reasoning in RNA-targeting drug design

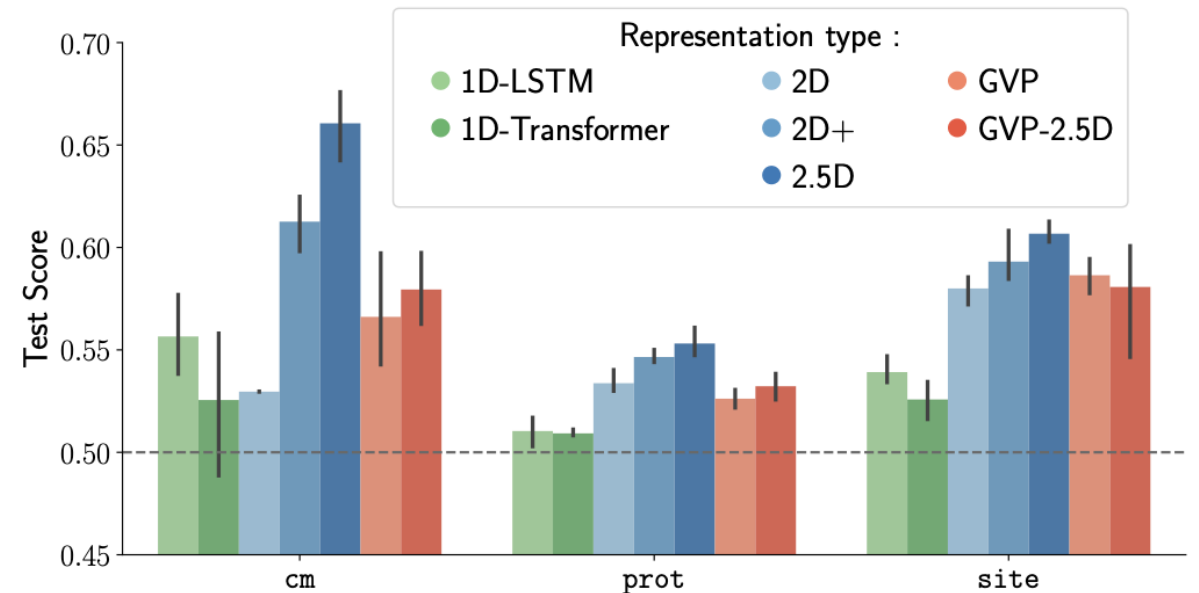
Review and benchmarks of ML methods

	Metric		Without swapping	Target swapping	Performance gap
Boltz 2	AuROC	global	0.535	0.533 ± 0.004	-0.4%
		target	0.530	0.529 ± 0.002	-0.2%
RNAmigos 2	AuROC	target	0.899	0.791 ± 0.007	-12.0%
RSAPred	AuROC	global	0.600	0.670 ± 0.057	+11.7%
		target	0.581	0.449 ± 0.047	-22.7%
DeepRSMA	PCC	global	0.784	0.424 ± 0.064	-46.2%
		target	0.430	0.351 ± 0.021	-22.5%
GerNA-Bind	AuROC	global	0.783	0.514 ± 0.005	-34.4%
		target	0.765	0.529 ± 0.005	-30.9%
RNAsmol (Mol perturbation)	AuROC	global	0.974	0.975 ± 0.000	+0.1%
		target	0.972	0.973 ± 0.002	+0.1%
RNAsmol (Net perturbation)	AuROC	global	0.717	0.546 ± 0.009	-23.8%
		target	0.651	0.569 ± 0.008	-12.6%

(Karroucha *et al.*, 2026)

Comprehensive benchmarking for RNA structure-function modeling

Exploring structure representations with rnaglib



(Wyss *et al.*, 2026)

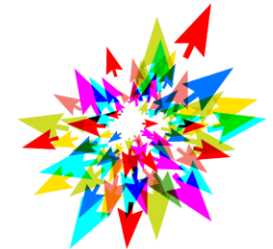
Acknowledgments



- Jacques Boitreaud, Chai discovery
- David Becerra, McGill
- Juan Carjaval-Patiño, U. Nacional de Colombia
- Arnaud Chol, McGill
- Will Hamilton, MILA
- David Hiraki, McGill
- Vincent Mallet, Les Mines
- Nicolas Moitessier, McGill
- David Nitchi, McGill
- Carlos G. Oliver, Vanderbilt University
- Yann Ponty, CNRS/X
- Étienne Reboul, IBPC
- Vladimir Reinharz, UQàM
- Roman Sarrazin-Gendron, UQàM
- Antoine Soulé, MILA
- Antoine Taly, IBPC
- Éric Westhof, Université de Strasbourg
- Javona Whitebear, McGill
- Hua-Ting Yao, Univ. Vienna



compute | calcul
canada | canada



References

Nitchi, D., Waldispühl, J., Oliver, C. Adaptive 2.5D base-pairing subgraph search detects RNA small-molecule binding sites. *bioRxiv* 2026.07.07.737024 (2026).

<https://doi.org/10.64898/2026.07.07.737024>

Carvajal-Patiño, J.G., Mallet, V., Becerra, D. *et al.* RNAmigos2: accelerated structure-based RNA virtual screening with deep graph learning. *Nat Commun* **16**, 2799 (2025).

<https://doi.org/10.1038/s41467-025-57852-0>

Mallet, V., Oliver, C., Broadbent, J. *et al.* RNAglib: a python package for RNA 2.5 D graphs, *Bioinformatics*, 38:5, 1458–1459 (2022). <https://doi.org/10.1093/bioinformatics/btab844>

Oliver, C., Mallet, V., Sarrazin Gendron, R. *et al.* Augmented base pairing networks encode RNA-small molecule binding preferences, *Nucleic Acids Research*, 48:14, 690–7699 (2020).

<https://doi.org/10.1093/nar/gkaa583>