



## RESEARCH TRACK



# GROOT: Effective Design of Biological Sequences with Limited Experimental Data

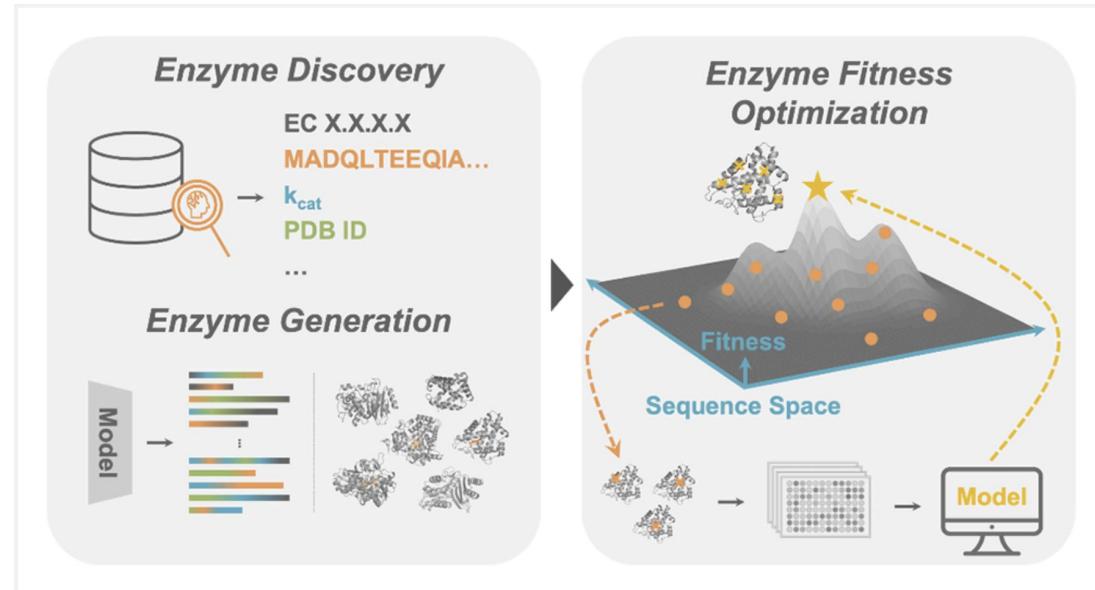
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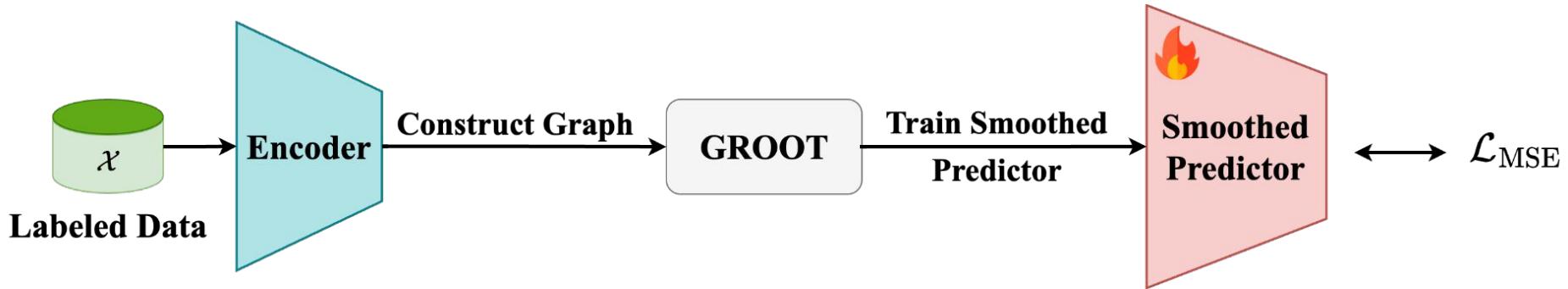


# Motivation

- **Rapid design via ML:** Modern protein optimization models can propose thousands of variants in silico, dramatically accelerating the design cycle.
- **Limited data scenarios:** Existing methods neglect the scenario of extremely limited labeled data and fail to utilize the abundant unlabeled data.
- **Label bottleneck:** Training such models **requires ground-truth fitness labels**, yet each measurement demands cloning, expression, purification, and functional assays—costly in time, money, and lab resources.
- **Need for sample-efficient methods:** To unlock ML-guided experimental design, we must develop algorithms that **learn from few labels**, reducing wet-lab burden without sacrificing performance.

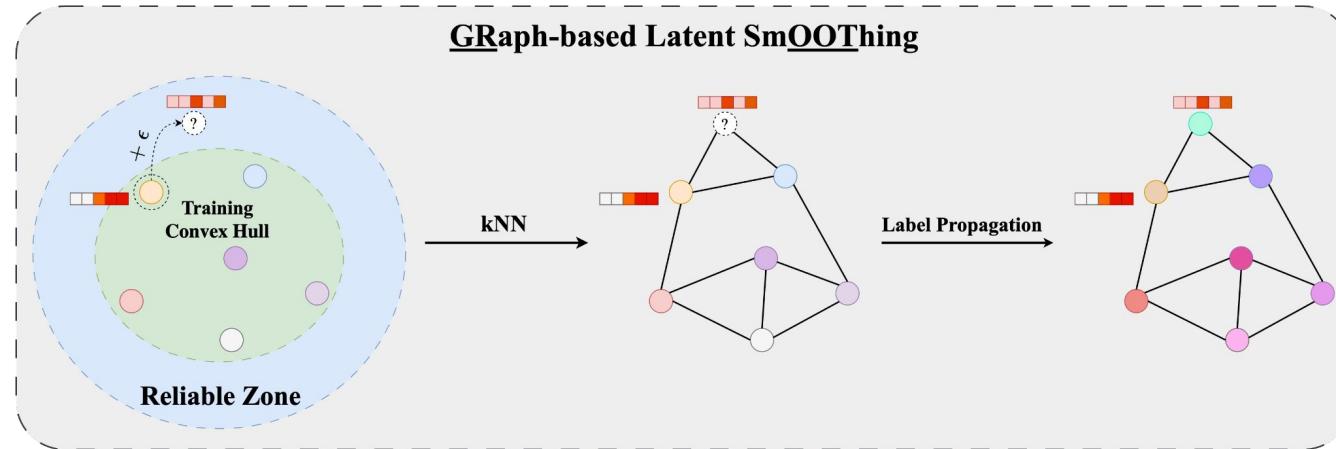


# Method: Overview

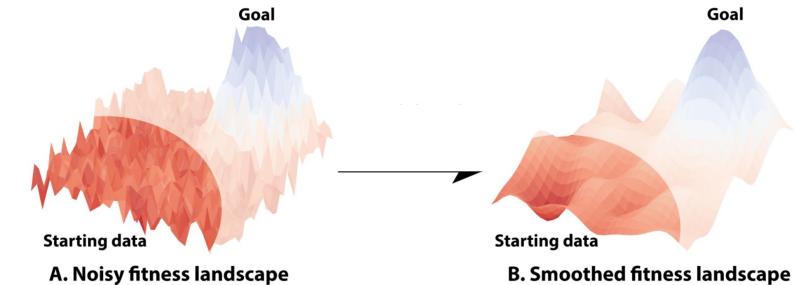


1. Train a VAE with labeled  $\mathbb{X}$  and unlabeled data.
2. **Encode labeled sequences**  $\rightarrow$  latent vectors.
3. **GROOT** synthesizes new samples  $\mathbb{S}$  with pseudo experimental labels.
4. **Train a predictor** on these samples  $(\mathbb{X} \cap \mathbb{S})$  with MSE loss.

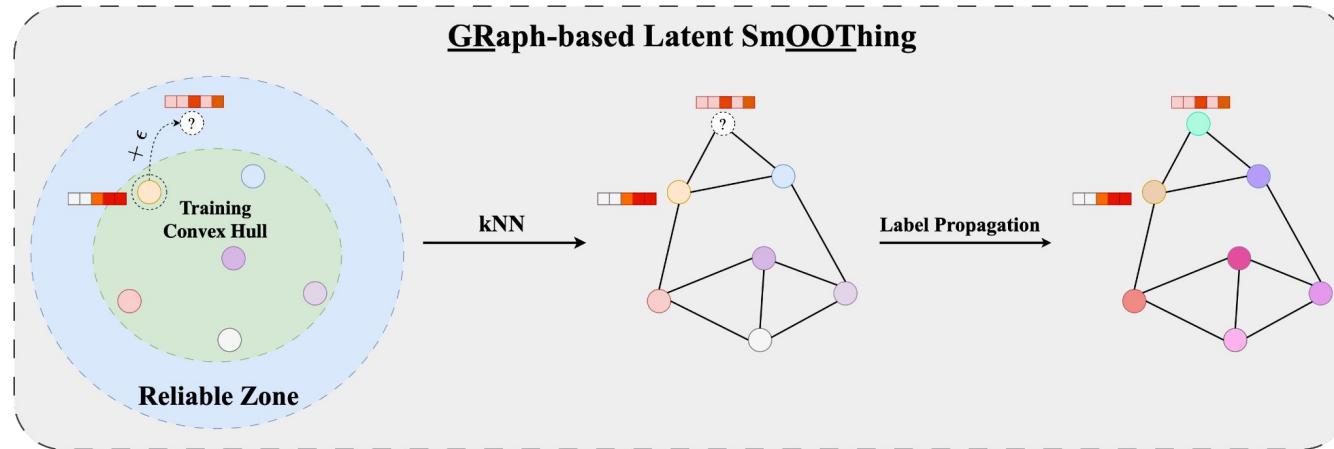
# Method: GROOT



1. Introduce **mutations** into latent sample.
2. Construct **kNN graph** in the latent space.
3. Assign pseudo labels for new samples and **smoothen** the landscape.



# Why reliable?

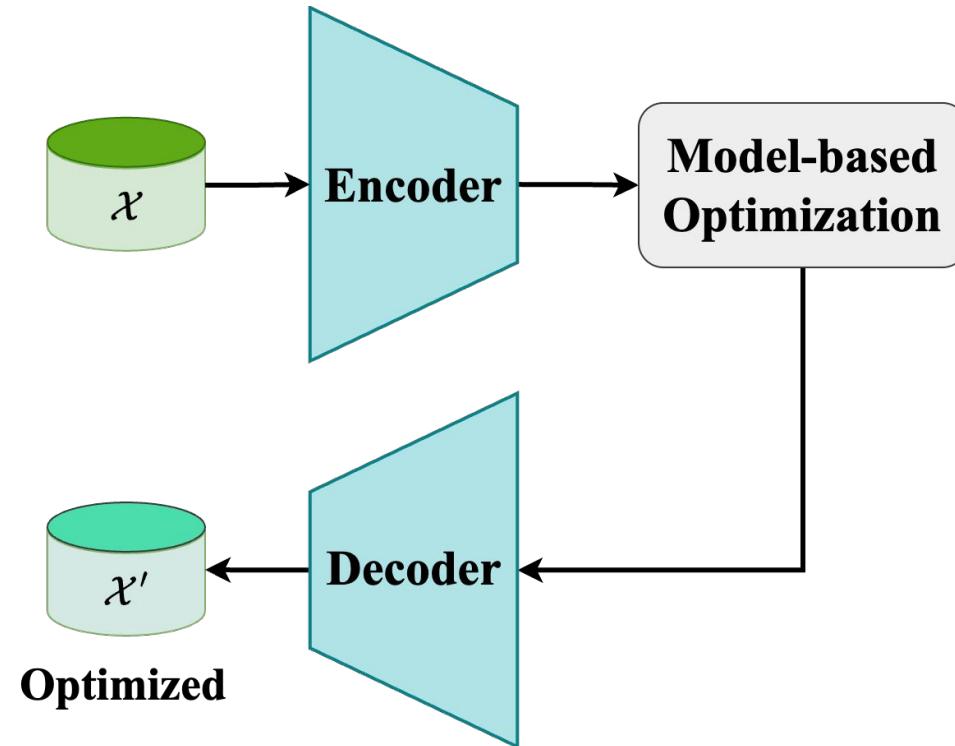


**Question:** Are assigned pseudo labels reliable?

$$\mathbb{E}[D(z, \text{Conv}(\mathbb{X}))] < 2(1 - \beta)\sqrt{d}$$

Distance from synthesized samples and training set are constrained and controllable

# Method: MBO



1. **Encode** initial sequences  $X \rightarrow$  latent embeddings.
2. **MBO search**: surrogate explores the latent space for points with maximal predicted fitness.
3. **Decode** optimized embeddings  $\rightarrow$  novel sequences  $X'$  ready for validation.

# Data Preparation



## Dataset and Task Definition

Task	Difficulty	Fitness Range (%)	Mutational Gap	Best Fitness	$ \mathcal{D} $
AAV	Harder1	< 30th	13	0.33	1157
	Harder2	< 20th	13	0.29	920
	Harder3	< 10th	13	0.24	476
GFP	Harder1	< 30th	8	0.10	1129
	Harder2	< 20th	8	0.01	792
	Harder3	< 10th	8	0.01	397

# Experimental Results



Method	AAV harder1 task			AAV harder2 task			AAV harder3 task		
	Fitness ↑	Diversity	Novelty	Fitness ↑	Diversity	Novelty	Fitness ↑	Diversity	Novelty
AdaLead	0.38 (0.0)	5.5 (0.5)	7.0 (0.7)	0.43 (0.0)	4.2 (0.7)	7.8 (0.8)	0.37 (0.0)	6.22 (0.9)	8.0 (1.2)
CbAS	0.02 (0.0)	22.9 (0.1)	18.5 (0.5)	0.01 (0.0)	23.2 (0.1)	19.3 (0.4)	0.01 (0.0)	23.2 (0.1)	19.3 (0.4)
BO	0.00 (0.0)	20.4 (0.3)	21.8 (0.4)	0.01 (0.0)	20.4 (0.0)	22.0 (0.0)	0.01 (0.0)	20.6 (0.3)	22.0 (0.0)
GFN-AL	0.00 (0.0)	15.4 (6.2)	21.6 (0.5)	0.00 (0.0)	8.1 (3.5)	21.6 (1.0)	0.00 (0.0)	7.6 (0.8)	22.6 (1.4)
PEX	0.23 (0.0)	6.4 (0.5)	3.8 (0.7)	0.30 (0.0)	7.8 (0.4)	5.0 (0.0)	0.26 (0.0)	7.3 (0.7)	4.4 (0.5)
GGS	0.30 (0.0)	13.6 (0.2)	14.5 (0.3)	0.27 (0.0)	16.0 (0.0)	19.4 (0.0)	0.38 (0.0)	7.0 (0.1)	9.6 (0.1)
ReLSO	0.15 (0.0)	20.9 (0.0)	13.0 (0.0)	0.17 (0.0)	20.3 (0.0)	13.0 (0.0)	0.22 (0.0)	17.8 (0.0)	11.0 (0.0)
S-ReLSO	0.24 (0.0)	11.5 (0.0)	13.0 (0.0)	0.28 (0.0)	16.4 (0.0)	6.5 (0.0)	0.27 (0.0)	17.7 (0.0)	11.0 (0.0)
<b>GROOT (GA)</b>	0.37 (0.0)	13.6 (0.9)	10.0 (0.7)	0.36 (0.0)	13.7 (1.1)	10.1 (0.9)	0.34 (0.1)	14.0 (2.2)	10.0 (1.4)
<b>GROOT</b>	<b>0.46 (0.1)</b>	9.8 (1.6)	12.2 (0.5)	<b>0.45 (0.0)</b>	9.9 (0.8)	13.0 (0.0)	<b>0.42 (0.1)</b>	11.0 (2.0)	13.0 (0.0)

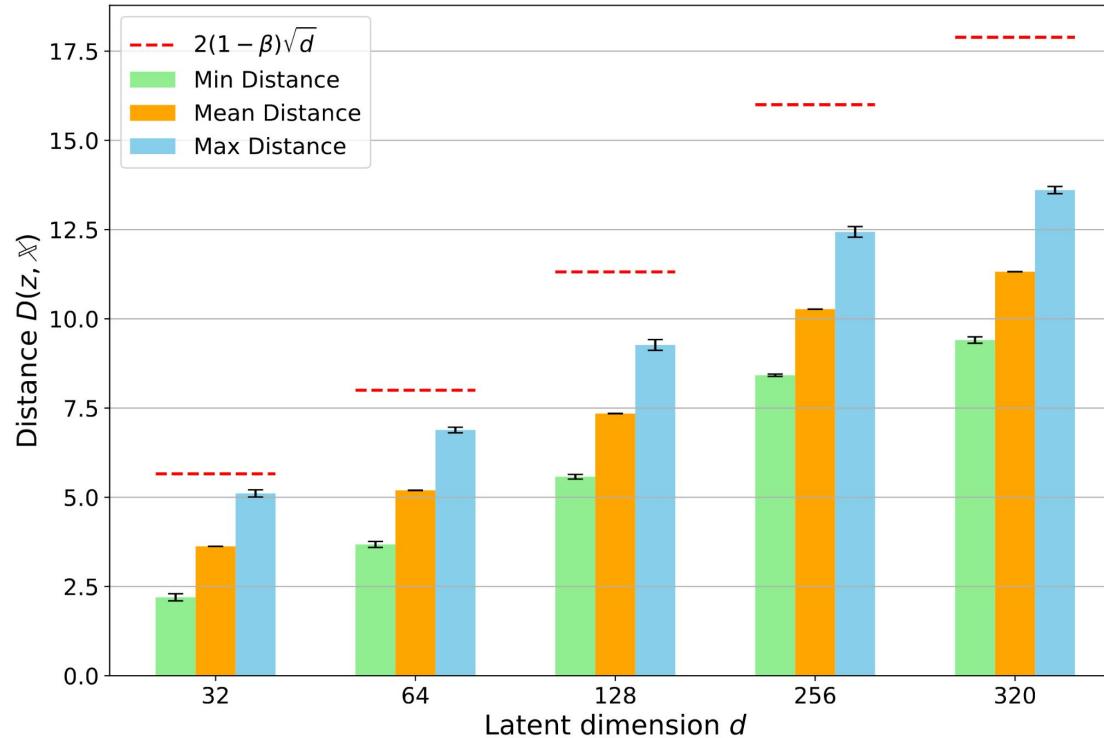
  

Method	GFP harder1 task			GFP harder2 task			GFP harder3 task		
	Fitness ↑	Diversity	Novelty	Fitness ↑	Diversity	Novelty	Fitness ↑	Diversity	Novelty
AdaLead	0.39 (0.0)	8.4 (3.2)	9.0 (1.2)	0.4 (0.0)	7.3 (2.8)	9.8 (0.4)	0.42 (0.0)	6.4 (2.3)	9.0 (1.2)
CbAS	-0.08 (0.0)	172.2 (35.7)	201.5 (1.5)	-0.09 (0.0)	158.4 (34.8)	202.0 (0.7)	-0.08 (0.0)	186.4 (33.4)	201.5 (0.9)
GFN-AL	0.21 (0.1)	74.3 (55.3)	219.2 (3.3)	0.14 (0.2)	27.0 (9.5)	223.5 (2.4)	0.21 (0.0)	37.5 (21.7)	219.8 (4.3)
PEX	0.13 (0.0)	12.6 (1.2)	7.1 (1.1)	0.17 (0.0)	12.6 (1.2)	7.1 (1.1)	0.19 (0.0)	12.2 (1.1)	7.8 (1.7)
GGS	0.67 (0.0)	4.7 (0.2)	9.1 (0.1)	0.60 (0.0)	5.4 (0.2)	9.8 (0.1)	0.00 (0.0)	15.7 (0.4)	19.0 (2.2)
ReLSO	$0.94(0.0)^\dagger$	0.0 (0.0)	8.0 (0.0)	$0.94(0.0)^\dagger$	0.0 (0.0)	8.0 (0.0)	$0.94(0.0)^\dagger$	0.0 (0.0)	8.0 (0.0)
S-ReLSO	$0.94(0.0)^\dagger$	0.0 (0.0)	8.0 (0.0)	$0.94(0.0)^\dagger$	0.0 (0.0)	8.0 (0.0)	$0.94(0.0)^\dagger$	0.0 (0.0)	8.0 (0.0)
<b>GROOT</b>	<b>0.88 (0.0)</b>	3.0 (0.2)	7.0 (0.0)	<b>0.87 (0.0)</b>	3.0 (0.1)	7.5 (0.5)	<b>0.62 (0.2)</b>	7.6 (1.5)	8.6 (1.5)

† indicates that the generated population has collapsed (i.e., producing only a single sequence).

**In-silico Evaluator:** An independent oracle whose checkpoint are taken from [2].

# Empirical Validation on Upper Bound



# Effectiveness of GROOT



Task	Difficulty	Smoothed	Fitness ↑	Diversity	Novelty
AAV	Harder1	No	0.12	20.0	10.0
		Yes	<b>0.46</b>	9.8	12.2
	Harder2	No	0.11	20.0	9.6
		Yes	<b>0.45</b>	9.9	13.0
GFP	Harder3	No	0.12	20.1	10.0
		Yes	<b>0.42</b>	11.0	13.0
	Harder1	No	-0.12	71.0	42.2
		Yes	<b>0.88</b>	3.0	7.0
GFP	Harder2	No	-0.18	69.5	41.1
		Yes	<b>0.87</b>	3.0	7.5
GFP	Harder3	No	-0.17	64.0	37.0
		Yes	<b>0.62</b>	7.6	8.6



# THANK YOU!

