

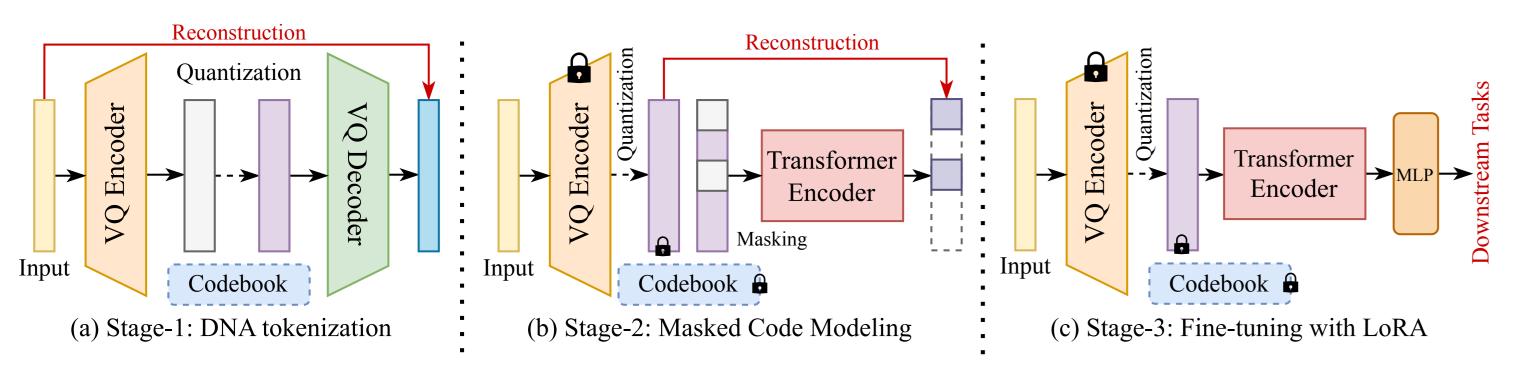
## VQDNA: Unleashing the Power of Vector Quantization for Multi-Species Genomic Sequence Modeling



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## Summary of Contributions

- We introduce genome vocabulary learning framework that learns a genome tokenizer with a discriminative vocabulary for pattern-aware genome language.
- An HRQ tokenizer is designed to progressively enrich the limited genome vocabulary with a hierarchy of varying scales of codebooks in a coarse-to-fine manner.
- Extensive experiments across 32 datasets verify the exceptional generalizability of VQDNA, including an empirical case study on SARS-CoV-2 mutations.



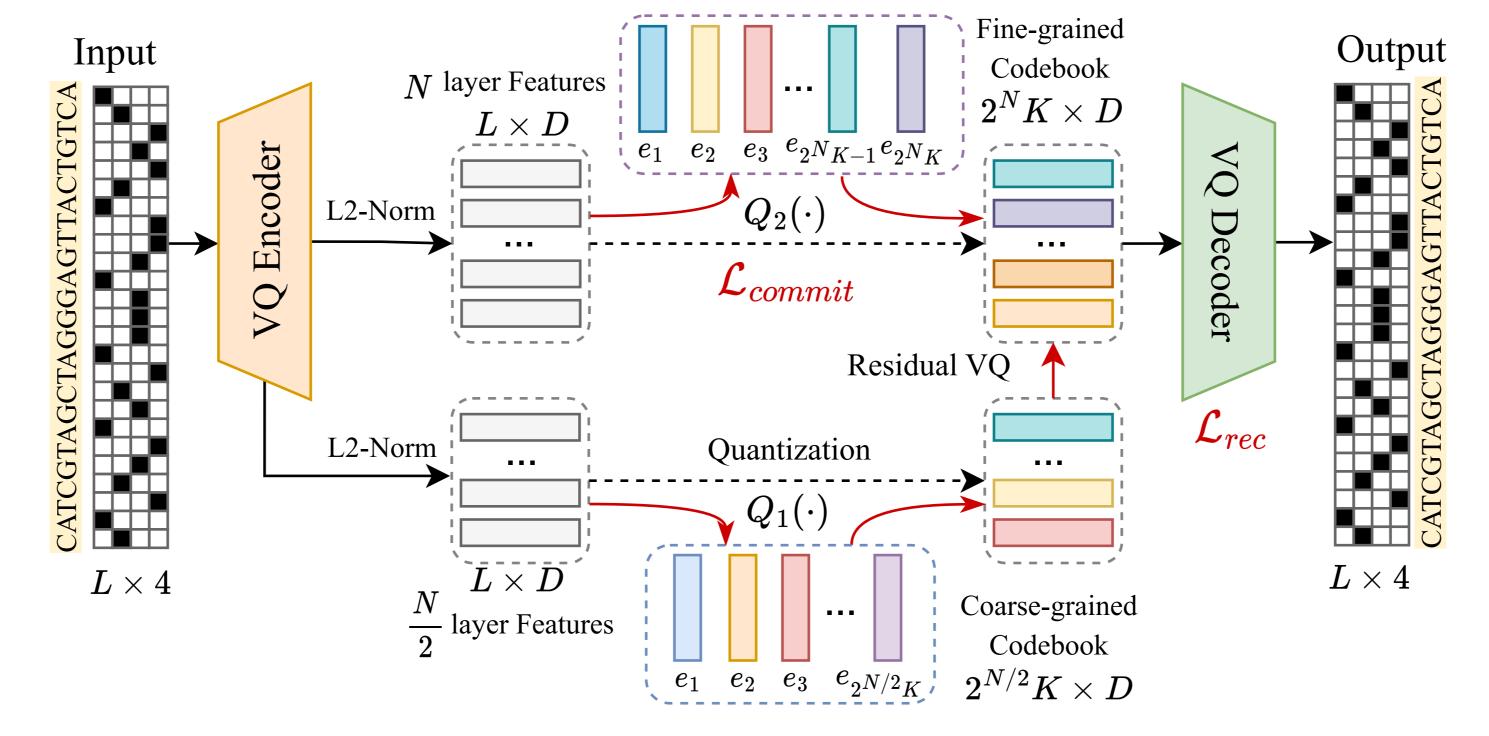
## Data-efficient Pipeline for Genome

Three-stage pipeline: (a) genome vocabulary learning, (b) masked code modeling, (c) parameter-efficient fine-tuning.

• Semantic Vocabulary: Expanding 4 nucleotides to 4K learnable words (VQ dictionary). Using VQVAE as the baseline version of VQDNA, quantize embeddings by the code mapping function Q(.,.) with a codebook with  $K \text{ words}, \mathcal{C} = \{(k, e(k))\}_{k \in [K]}, \text{ where } e(k) \in \mathbb{R}^d:$ 

$$M_{i} = \mathcal{Q}(Z_{i}; \mathcal{C}) = \operatorname{argmin}_{k \in [K]} \|Z_{i} - e(k)\|_{2}$$

$$\mathcal{L}_{\text{VQ}} = \underbrace{\mathcal{L}_{CE}(X, \hat{X})}_{\mathcal{L}_{\text{rec}}} + \underbrace{\|\operatorname{sg}[Z] - \hat{Z}\|_{2}^{2}}_{\mathcal{L}_{\text{code}}} + \beta \underbrace{\|Z - \operatorname{sg}[\hat{Z}]\|_{2}^{2}}_{\mathcal{L}_{\text{commit}}}$$

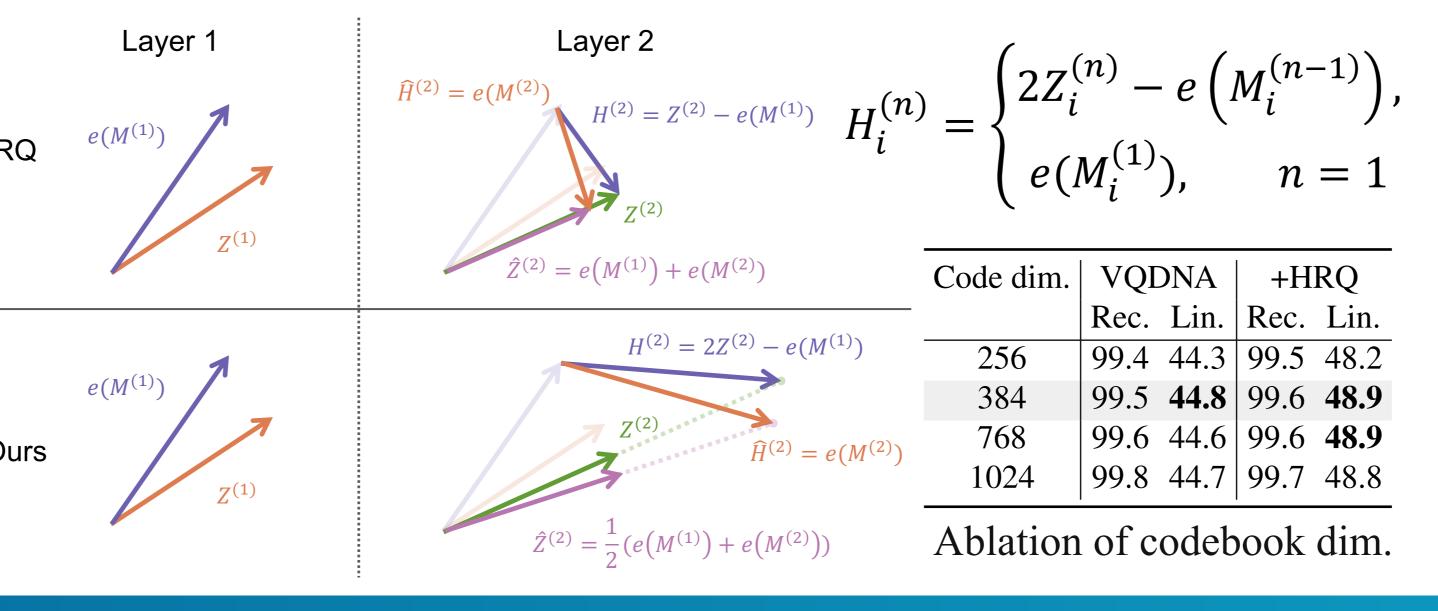


VQ-based Generation: Designing HRQ (hierarchical residual quantization) with two coarse-to-fine codebooks. The advanced hierarchical codebooks merging by vector subtraction instead of addation proposed by RQ:

$$M_{i}^{(n)} = Q\left(H_{i}^{(n)}; C^{(n)}\right),$$

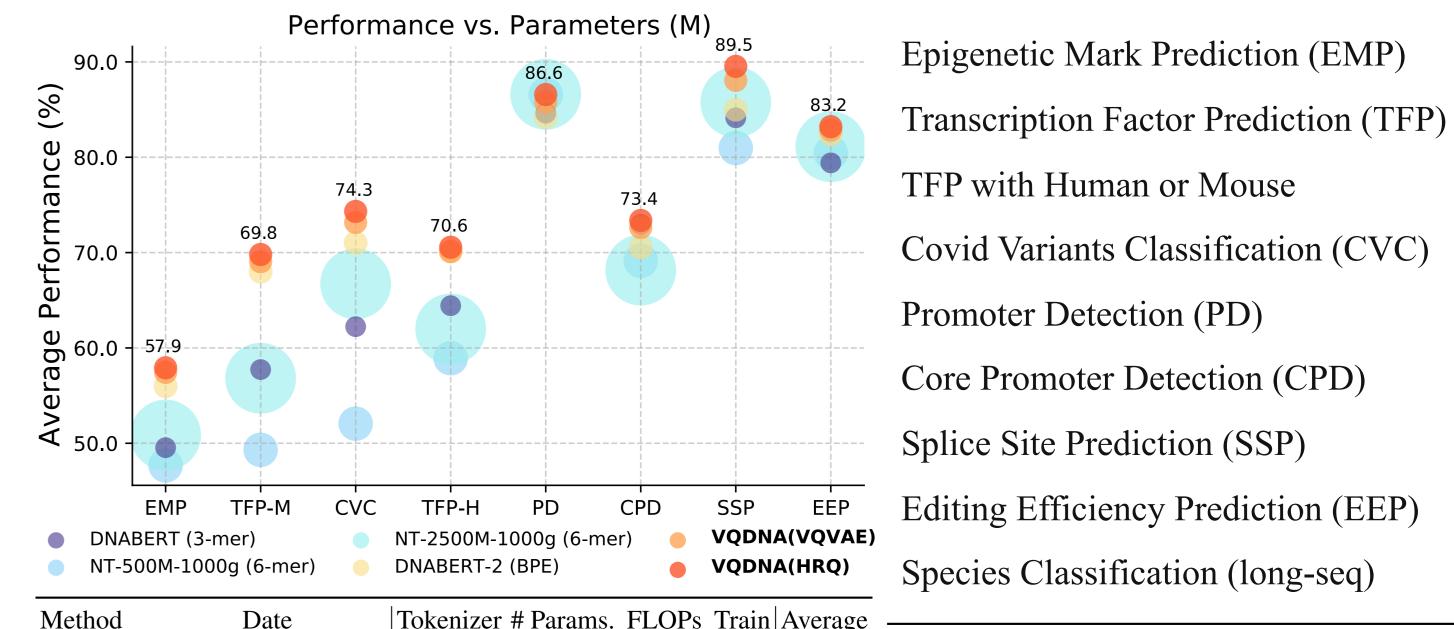
$$M_{i}^{(n)} = \operatorname{argmin}_{k \in [2^{n}K]} \left\| H_{i}^{(n)} - e(k^{(n)}) \right\|_{2}, M_{i}^{(n)} \in [2^{n}K]^{L}$$

$$\mathcal{L}_{HRQ} = \mathcal{L}_{CE}(X, \hat{X}) + \beta \sum_{n=1}^{N} \left\| Z^{(n)} - \operatorname{sg}[\hat{Z}^{(n)}] \right\|_{2}^{2}$$



## Experiment Results

• Comparison experiments across 32 genome datasets.



Covid Variants Classification (CVC) Promoter Detection (PD) Core Promoter Detection (CPD) Splice Site Prediction (SSP) Editing Efficiency Prediction (EEP)

nod	Date	Tokenizer	# Params.	FLOPs	Train	Average	_
			(M)	(G)	(B)	Rank	N
ABERT	BioInfo'2021	3-mer	86	3.3	122	5	Ι
500M-1000g	arXiv'2023	6-mer	480	3.2	50	6	N
2500M-1000g	arXiv'2023	6-mer	2537	19.4	300	4	F
ABERT-2	ICLR'2024	BPE	117	1.0	262	3	Ι
ONA	Ours	VQVAE	86+16	1.1+0.5	262	<u>2</u>	1
ONA	Ours	HRO	86+17	1 1+0 6	262	1	7

• Case study:

Alpha (B.1.1.7)

3 Delta (B.1.617.2)

2 Beta (B.1.351)

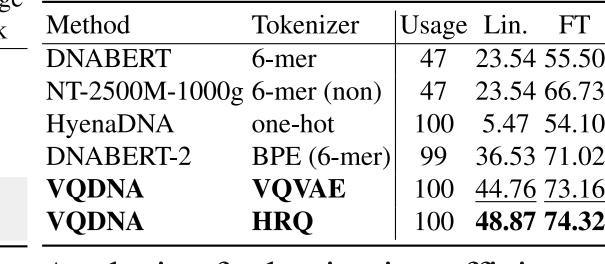
4 Eta (B.1.525)

5 <u>Gamma (P.1)</u>

6 Lota (B.1.526)

8 <u>Lambda (C.37)</u>

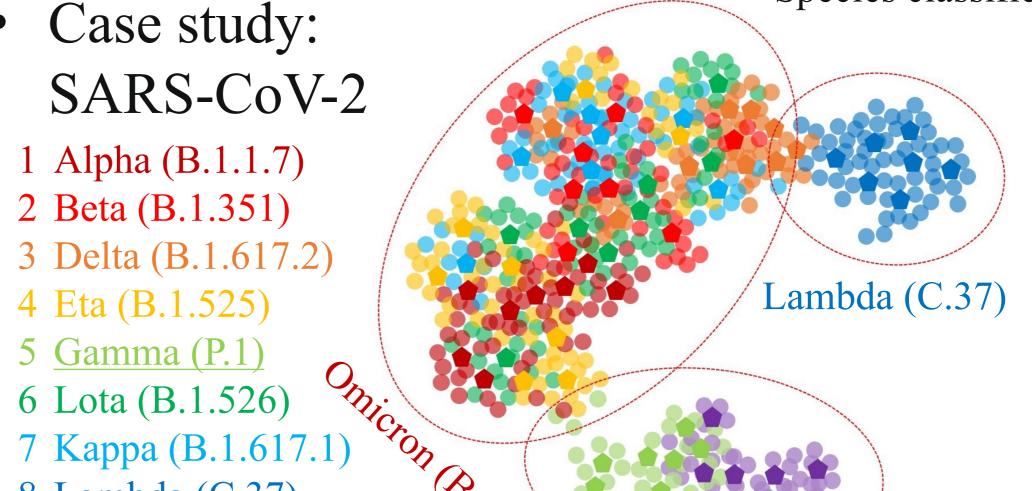
9 Zeta (P.2)



Average performance ranking on GUE datasets. Analysis of tokenization efficiency.

ode size	_			_	Code dim.		Method	1k	20k	32k	250k	450k
	Rec. L					Rec. Lin.	HyenaDNA	61.13	87.42	93.42	97.90	99.40
	98.2 42	- 1				99.4 44.3	DNABERT			91.93		N/A
256	98.8 43	3.6	99.1	47.7	384	99.5 <b>44.8</b>						1 1/1 1
512	99.5 4	4.8	99.6	48.9	768	99.6 44.6	DNABERT-2			99.28		N/A
1024	<b>99.6</b> 44	4.5	99.8	48.2	1024	99.8 44.7	VQDNA (HRQ)	61.57	88.05	99.46	N/A	N/A
'												

Species classification (1k to 1M tokens)



Method CVC **DNABERT** NT-500M-1000g NT-2500M-1000g | 66.73 **DNABERT-2** VQDNA VQDNA (HRQ) **74.32** 

Virus classification

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