

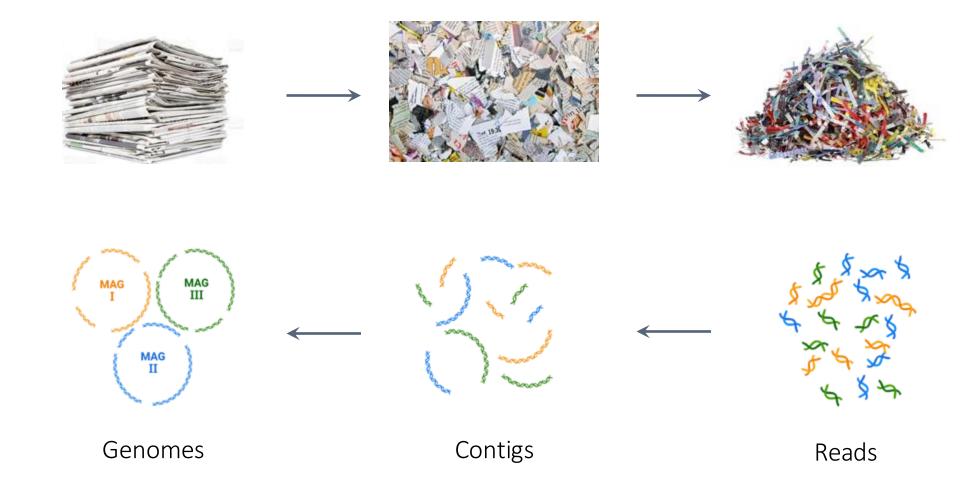


# Revisiting K-mer Profile for Effective and Scalable Genome Representation Learning

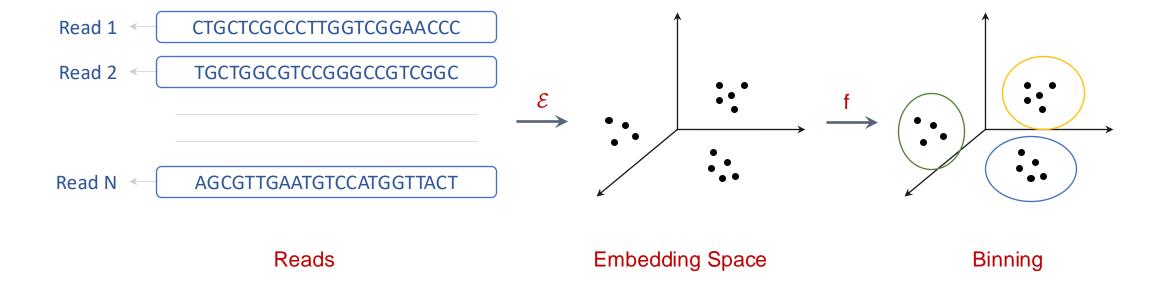
Abdulkadir Celikkanat Andres R. Masegosa and Thomas D. Nielsen

#### VILLUM FONDEN

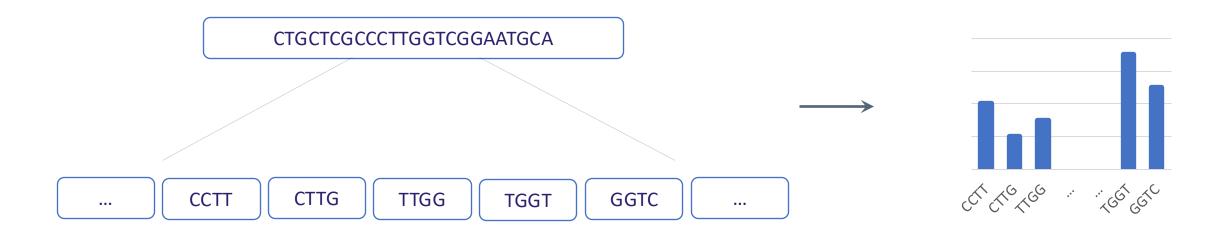
# Metagenomics Binning Problem



# Metagenomics Binning Problem



## k-mers / k-grams

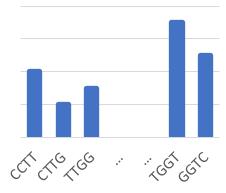


- *k-mers* are used to address several challenges:
  - Variable-length sequences.
  - The ambiguity in read direction
  - Complementary strands

#### Identifiable reads

CTGCTCGCCCTTGGTCGGAATGCA



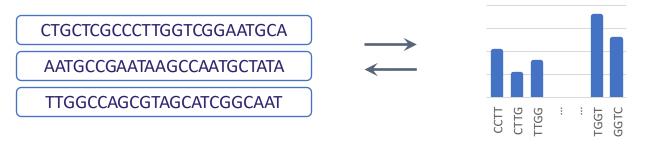


**Theorem.** Let  $\mathbf{r}$  be a read of length  $\ell$ . There exists no other distinct read having the same k-mer profile if and only if it does not satisfy any of the following conditions:

- 1.  $r_1 \cdots r_{k-1} = r_{\ell-k-2} \cdots r_{\ell}$  and  $r_i \neq r_1$  for some  $1 < i < \ell k 2$ .
- 2.  $r_i \cdots r_{i+k-2} = r_j \cdots r_{j+k-2}$  and  $r_g \cdots r_{g+k-2} = r_h \cdots r_{h+k-2}$  for some indices  $1 \le i < g < j < h \le \ell k + 2$  where  $r_{i+k-1} \cdots r_{g-1} \ne r_{j+k-1} \cdots r_{h-1}$ .
- 3.  $r_i \cdots r_{i+k-2} = r_j \cdots r_{j+k-2} = r_h \cdots r_{h+k-2}$  for some indices  $1 \le i < j < h \le \ell k + 2$  where  $r_{i+k-1} \cdots r_{j-1} \ne r_{j+k-1} \cdots r_{h-1}$ .
- *Identifiable reads* can be uniquely reconstructed from their given k-mer profile.

#### Identifiable reads

- Identifiable reads can be uniquely reconstructed from their given k-mer profile.
  - But using large values of k is impractical.



Lipschitz equivalent spaces.

**Proposition.** Let  $M_1=(\aleph_\ell,d_{\mathcal H})$  and  $M_2=(\mathbb N^{|\Sigma^k|},\|\cdot\|_1)$  be the metric spaces denoting the set of identifiable reads and their corresponding k-mer profiles equipped with edit and  $\ell_1$  distances, respectively. The k-mer profile function,  $c:M_1\to M_2$ , mapping given any read,  $\mathbf r$ , to its corresponding k-mer profile,  $c_{\mathbf r}:=c(\mathbf r)$ , is a Lipschitz equivalence, i.e. it satisfies

$$\forall \mathbf{r}, \mathbf{q} \in \Sigma^{\ell} \quad \alpha_l d_{\mathcal{H}}(\mathbf{r}, \mathbf{q}) \le ||c_{\mathbf{r}} - c_{\mathbf{q}}||_1 \le \alpha_u d_{\mathcal{H}}(\mathbf{r}, \mathbf{q})$$
(1)

for  $\alpha_l = 1/\ell$  and  $\alpha_u = k|\Sigma|^k$ , so  $M_1$  and  $M_2$  are Lipschitz equivalent.

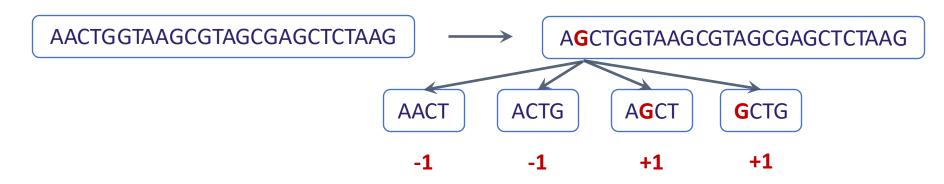
#### Linear read embeddings

**k-mer profile:** First, consider the definition of *k-mer profiles*:

$$\mathcal{E}_{kmer}(\mathbf{r}) \coloneqq \sum_{\mathbf{x} \in \Sigma^{k}} c_{\mathbf{r}}(\mathbf{x}) \mathbf{z}_{\mathbf{x}}$$

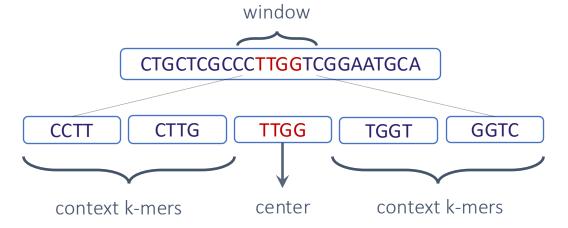
where  $\mathbf{z}_{x}$  represents the canonical basis vector for the k-mer  $\mathbf{x} \in \Sigma^{k}$ , i.e.  $(\mathbf{z}_{\mathbf{x}} \in \{(u_{1}, ..., u_{|\Sigma|^{k}}) \in \{0,1\}^{|\Sigma^{k}|}: \Sigma_{i} u_{i} = 1\})$ .

• k-mers are not independent!



#### Linear read embeddings

#### Poisson model:



•  $o_{{f x},{f y}}$  indicates the number of average co-appearances of k-mers i  ${f x}$  and  ${f y}$  per read within a window size  $\omega$ 

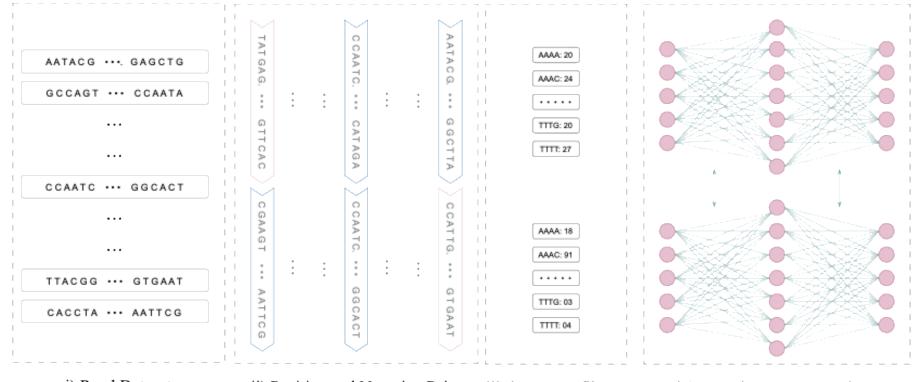
$$o_{\mathbf{x},\mathbf{y}} \sim Pois(\lambda_{\mathbf{x},\mathbf{y}})$$
  $\lambda_{\mathbf{x},\mathbf{y}} \coloneqq \exp(-\|\mathbf{z}_{\mathbf{x}} - \mathbf{z}_{\mathbf{y}}\|)$ 

• The embedding of read,  $\mathbf{r}$ , is given by

$$\mathcal{E}_{Pois}(\mathbf{r}) := \frac{1}{\sum_{\mathbf{x} \in \Sigma^k} c_{\mathbf{r}}(\mathbf{x}) \mathbf{z}_{\mathbf{x}}} \sum_{\mathbf{x} \in \Sigma^k} c_{\mathbf{r}}(\mathbf{x}) \mathbf{z}_{\mathbf{x}}$$

### Non-linear read embeddings

#### Non-linear model:



i) Read Dataset

ii) Positive and Negative Pairs

iii) k-mer Profiles

iv) Learning Representations

$$\mathcal{L}_{\text{NL}}\Big(\{y_{ij}\}_{(i,j)\in\mathcal{I}}|\Omega\Big) := -\frac{1}{|\mathcal{I}|}\sum_{(i,j)\in\mathcal{I}}y_{ij}\log p_{ij} + (1-y_{ij})\log(1-p_{ij}) \qquad p_{ij} = \exp\left(-\|\mathcal{E}_{\text{NL}}(\mathbf{r}_i) - \mathcal{E}_{\text{NL}}(\mathbf{r}_j)\|^2\right)$$

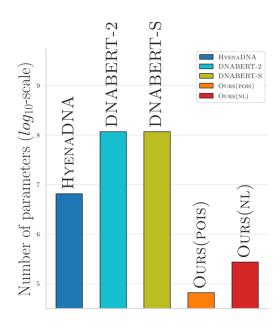
$$p_{ij} = \exp\left(-\|\mathcal{E}_{\scriptscriptstyle \mathrm{NL}}(\mathbf{r}_i) - \mathcal{E}_{\scriptscriptstyle \mathrm{NL}}(\mathbf{r}_j)\|^2\right)$$

#### **Experiments**



#### Conclusion

- We provide a theoretical analysis of the k-mer space, offering insights into why k-mers serve as powerful and informative features for genomic tasks.
- We show that scalable, lightweight models can provide competitive performance in the metagenomic binning task, highlighting their efficiency in handling complex datasets.
- We demonstrate that models based on k-mers remain viable alternatives to large-scale genome foundation models.





# Thank you!

For the implementation, datasets, and more details, please visit the address:

https://github.com/abdcelikkanat/revisitingkmers

