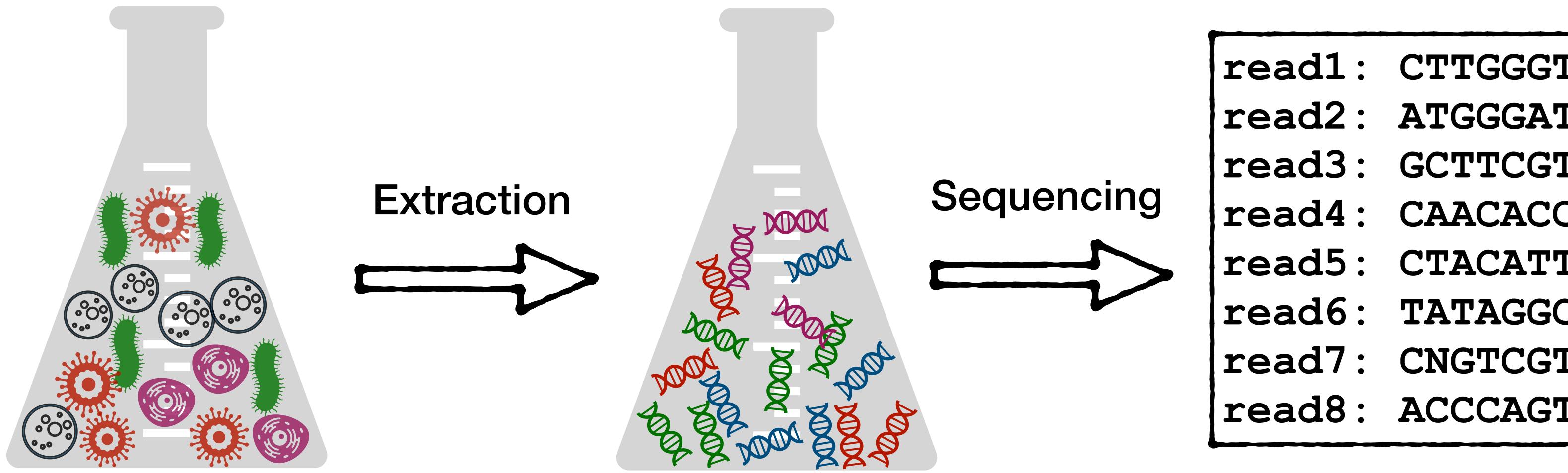


Memory-bound and taxonomy-aware k-mer selection for large reference databases

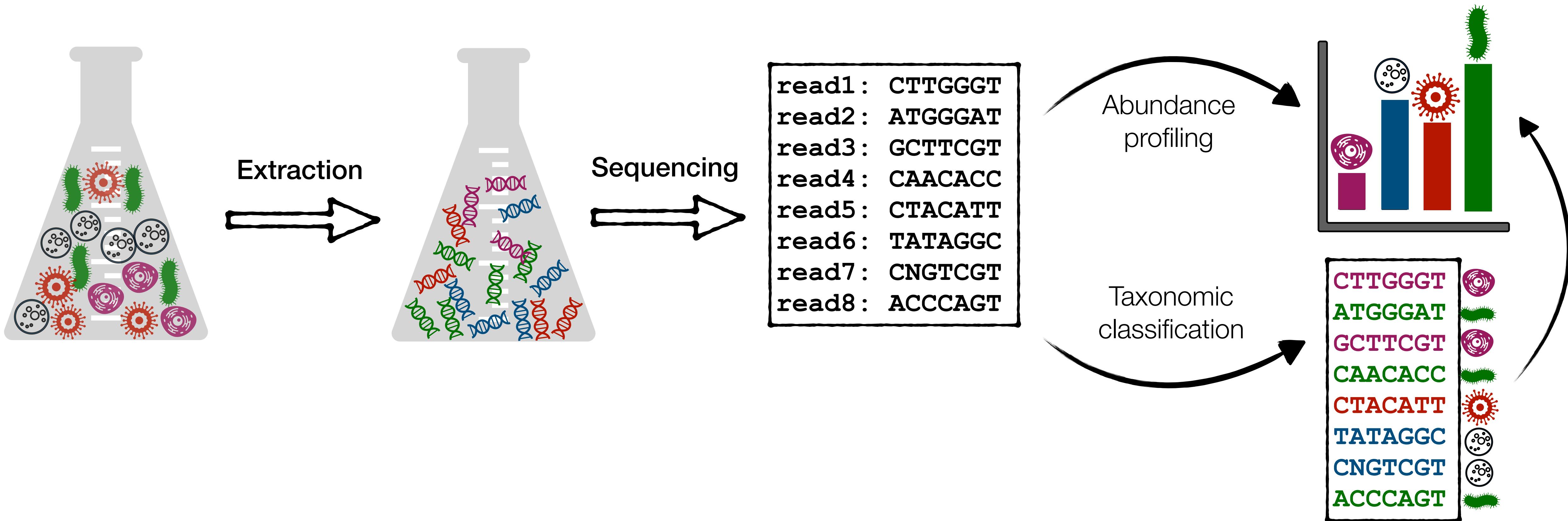
Ali Osman Berk Şapçı & Siavash Mirarab
UC San Diego



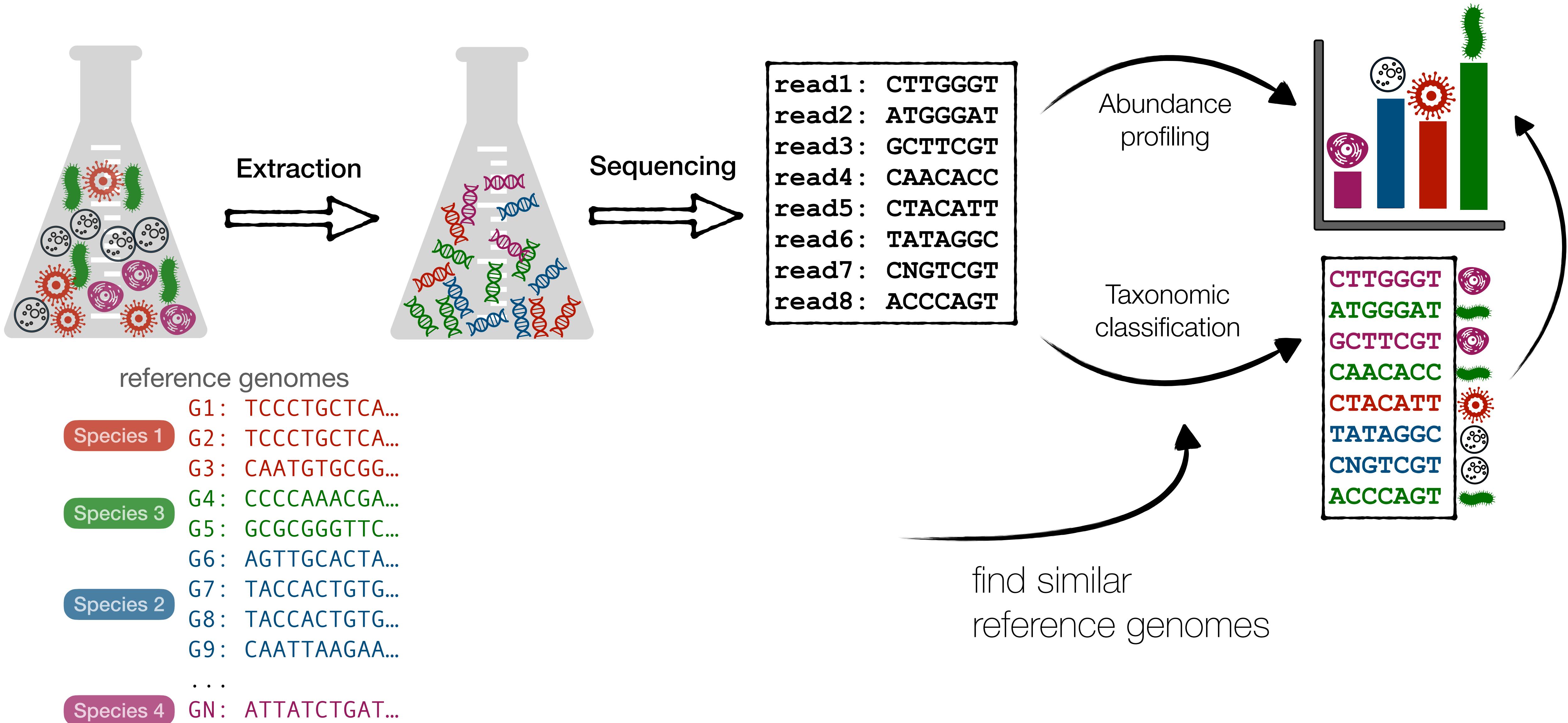
Identifying metagenomic sequences



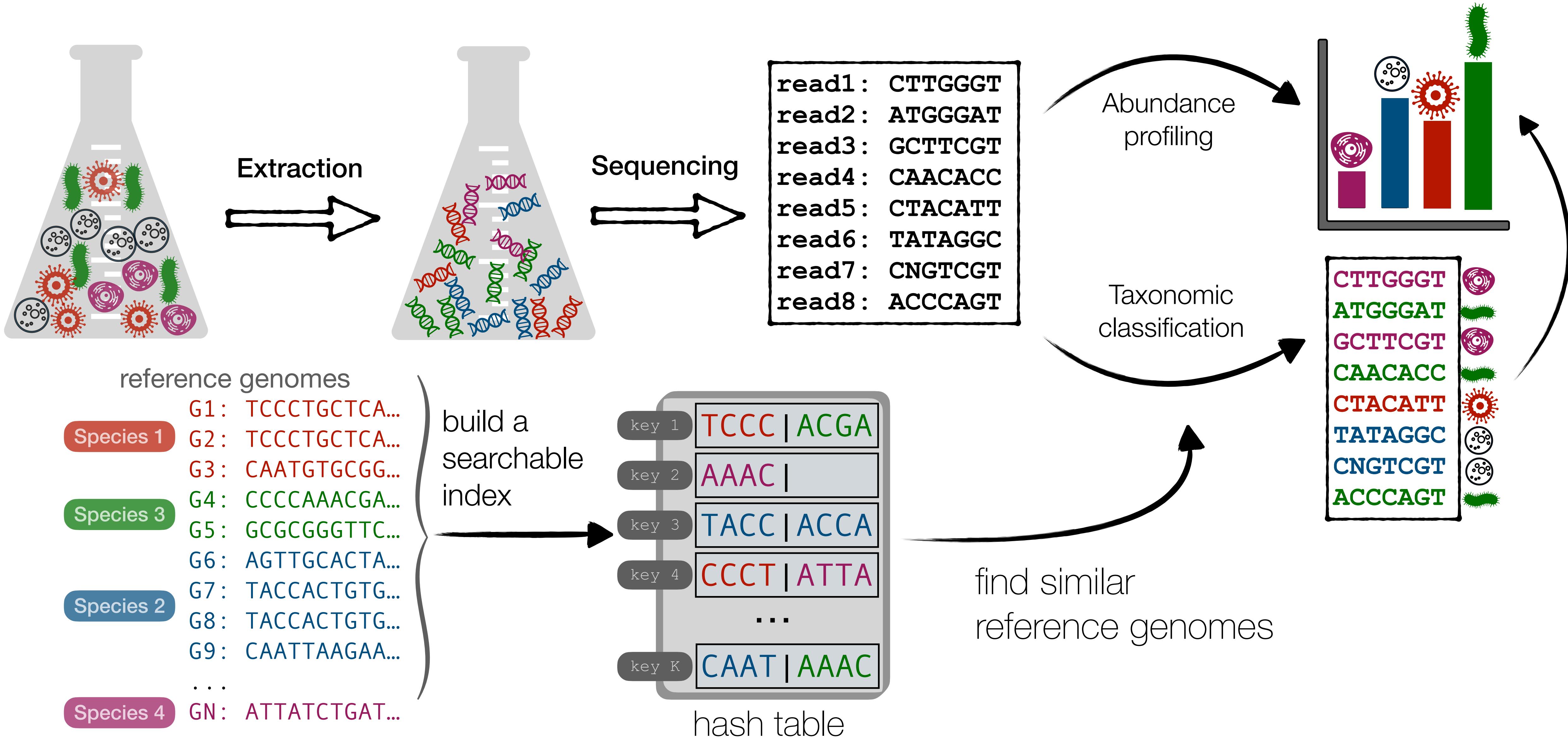
Identifying metagenomic sequences



Identifying metagenomic sequences



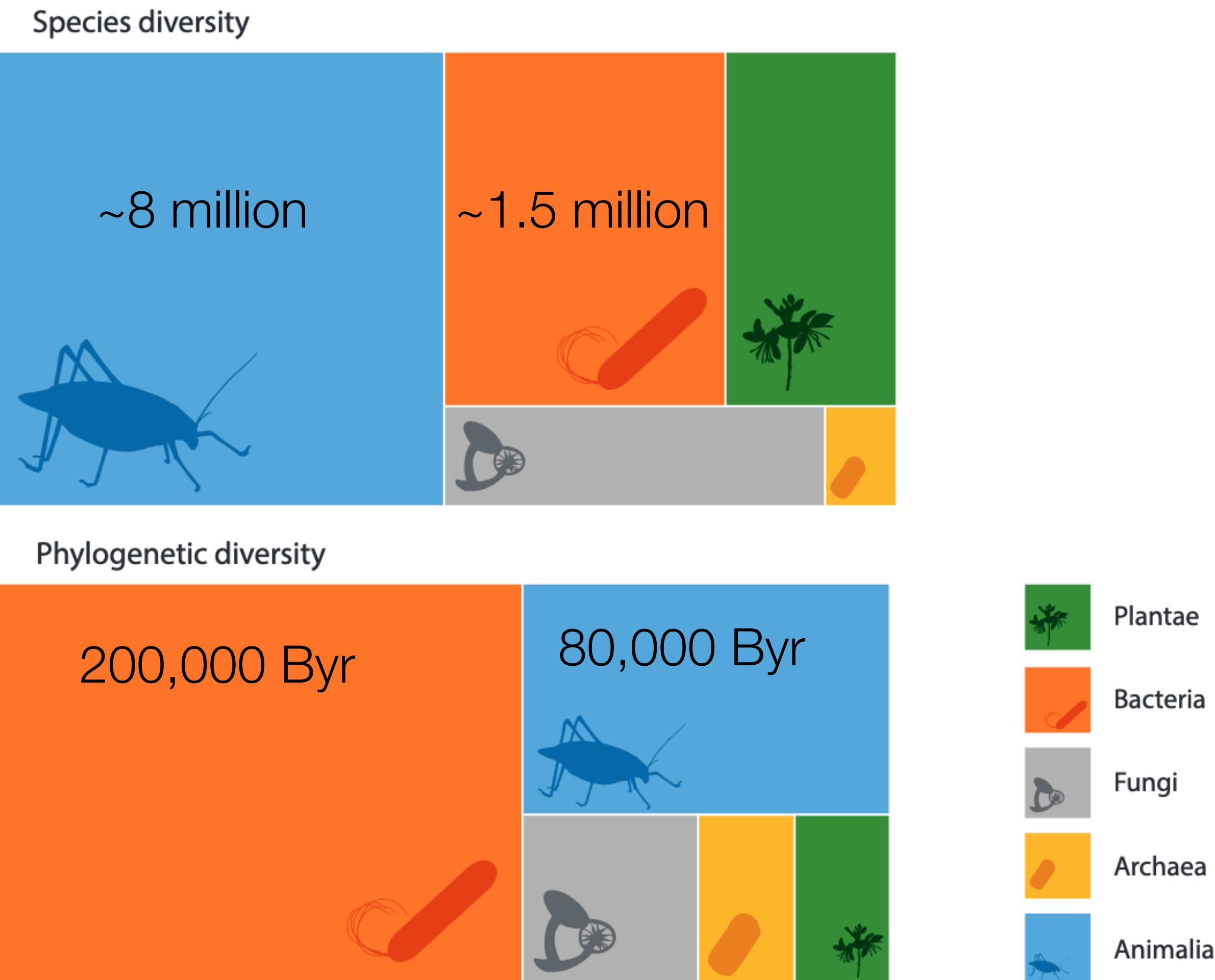
Identifying metagenomic sequences



Novel sequences challenge popular tools

- Reference databases (and indexes) **remain incomplete** compared to all species...

and there is a rich diversity within species!

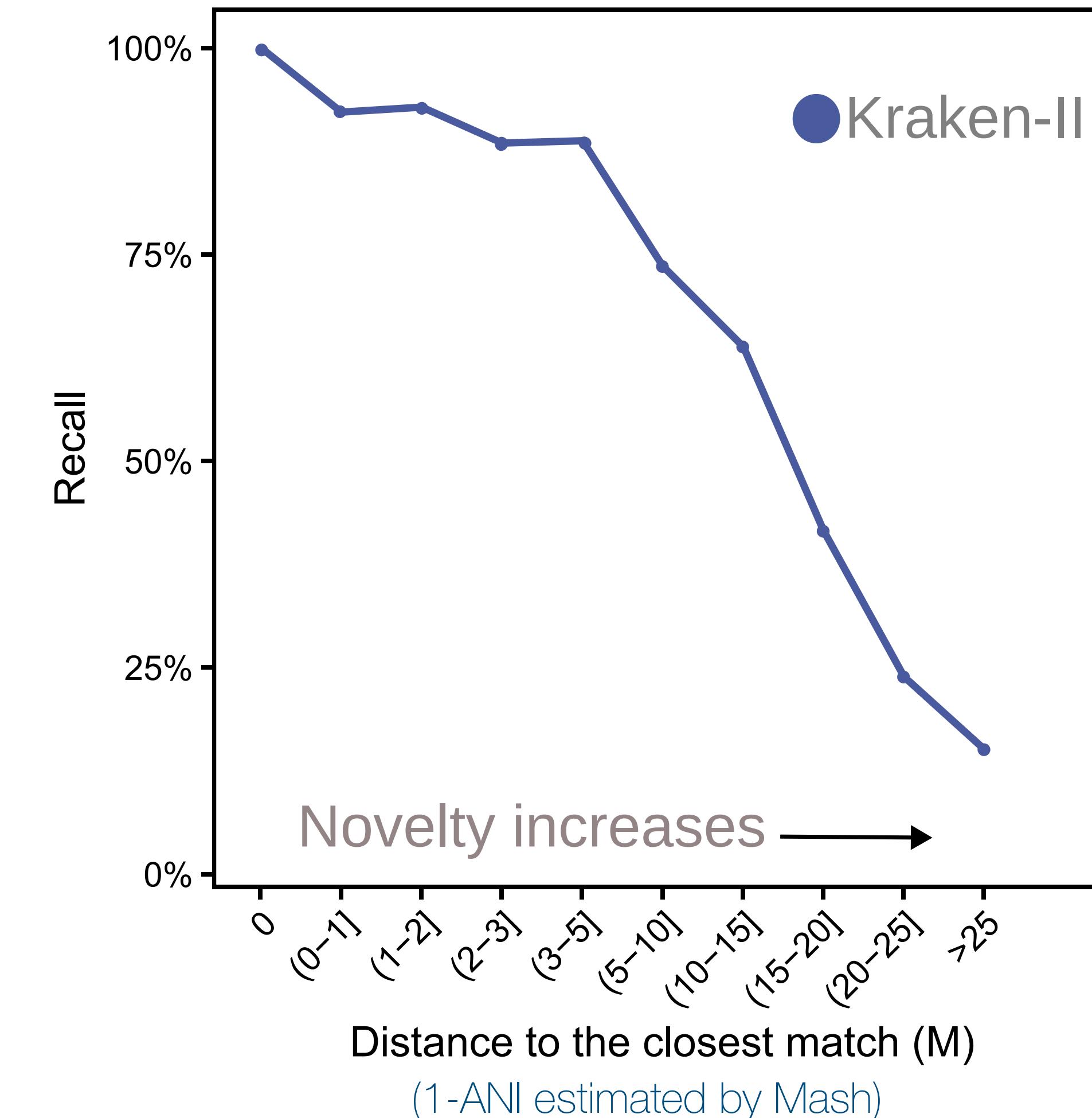


Novel sequences challenge popular tools

- Reference databases (and indexes) **remain incomplete** compared to all species...

and there is a rich diversity within species!

- Novel sequences:** sequences which lack a close matching reference genome



Solutions for identifying novel queries w/ limited resources

- ▶ find distant matches → increase sensitivity of the search
- ▶ enhance the reference set → utilize more genomes & larger databases

Solutions for identifying novel queries w/ limited resources

- ▶ find distant matches → increase sensitivity of the search
- ▶ enhance the reference set → utilize more genomes & larger databases

Computing the Hamming distances of inexact matches

CONSULT-II: accurate taxonomic identification and profiling using locality-sensitive hashing

Ali Osman Berk Şapçı  ¹, Eleonora Rachman  ¹, Siavash Mirarab  ^{1,2,*}

Solutions for identifying novel queries w/ limited resources

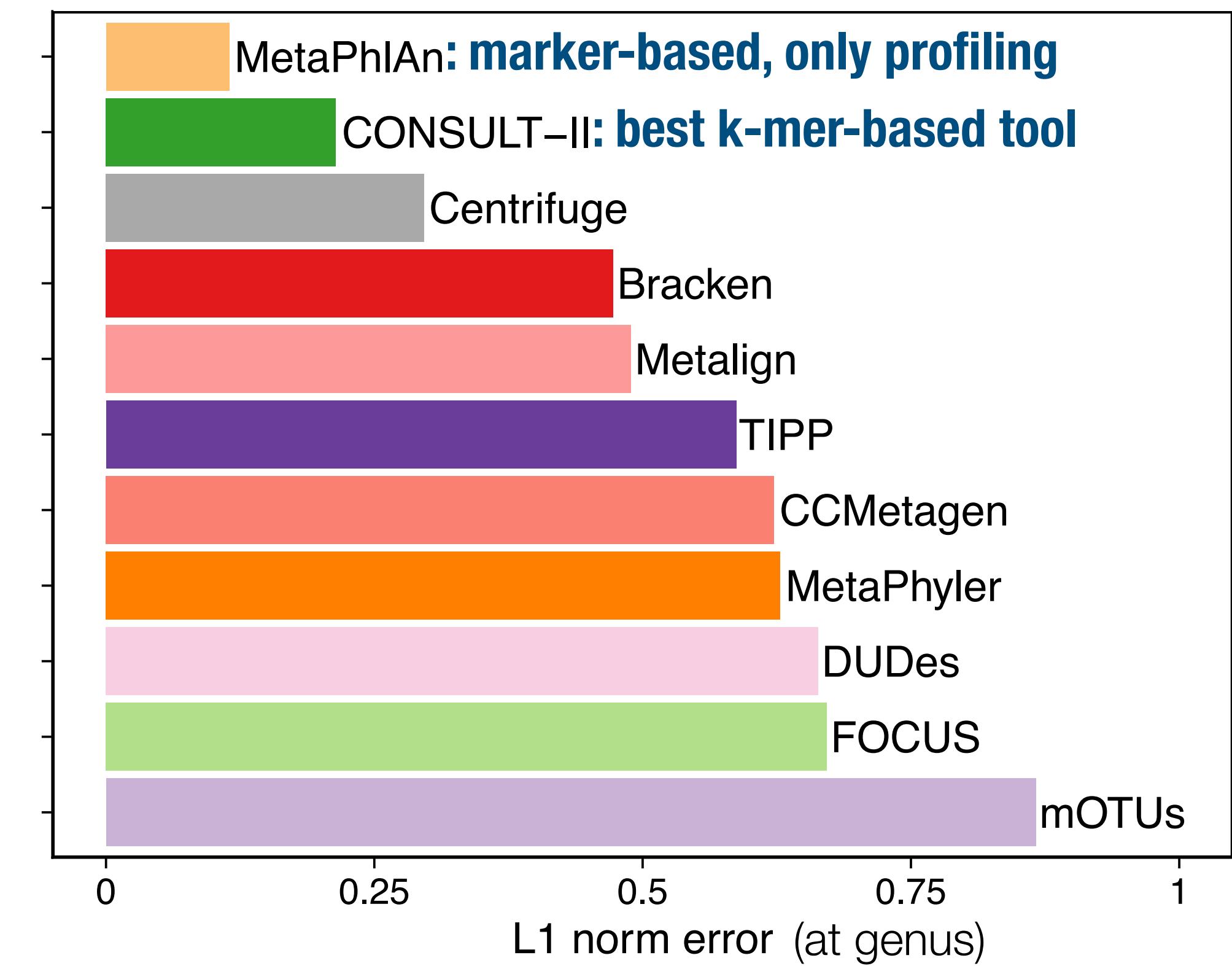
- ▶ find distant matches → increase sensitivity of the search
- ▶ enhance the reference set → utilize more genomes & larger databases

Computing the Hamming distances of inexact matches

CONSULT-II: accurate taxonomic identification and profiling using locality-sensitive hashing

Ali Osman Berk Şapçı  ¹, Eleonora Rachtmann  ¹, Siavash Mirarab  ^{1,2,*}

Strain-madness dataset [CAMI-II]



(using a RefSeq snapshot from 2019 with ~130k genomes)

Can we use more reference genomes?

- ▶ find distant matches → increase sensitivity of the search
- ▶ enhance the reference set → utilize more genomes & larger databases

Can we use more reference genomes?

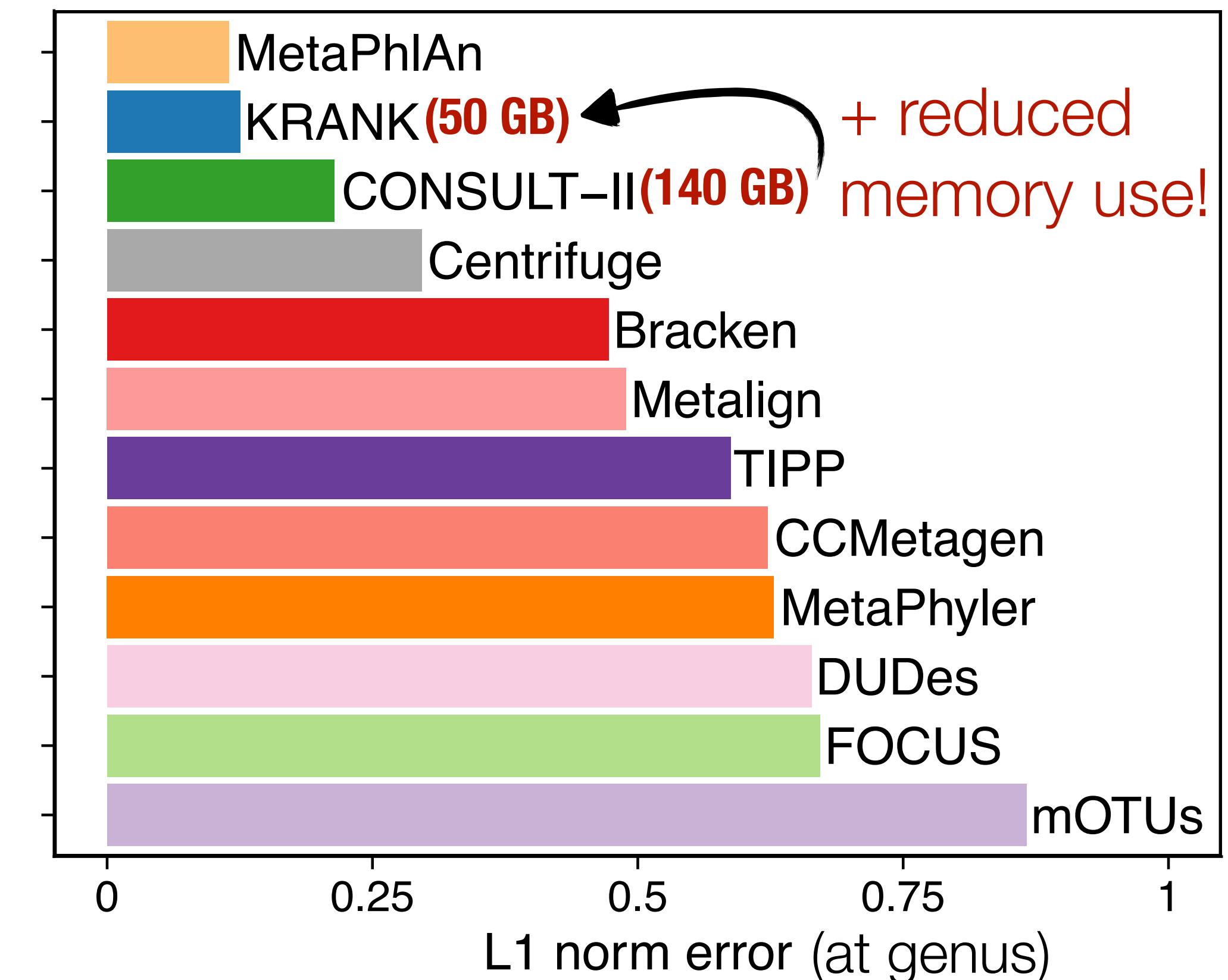
- ▶ find distant matches → increase sensitivity of the search
- ▶ enhance the reference set → utilize more genomes & larger databases

- **Challenge:** very large & diverse databases have too many k -mers to fit in the memory
 - ▶ Limited to a selected subset
- **This talk:** – KRANK
 - ▶ Selecting a representative subset of k -mers + classification/profiling using CONSULT-II

Can we use more reference genomes?

- ▶ find distant matches → increase sensitivity of the search
- ▶ enhance the reference set → utilize more genomes & larger databases

Strain-madness dataset [CAMI-II]

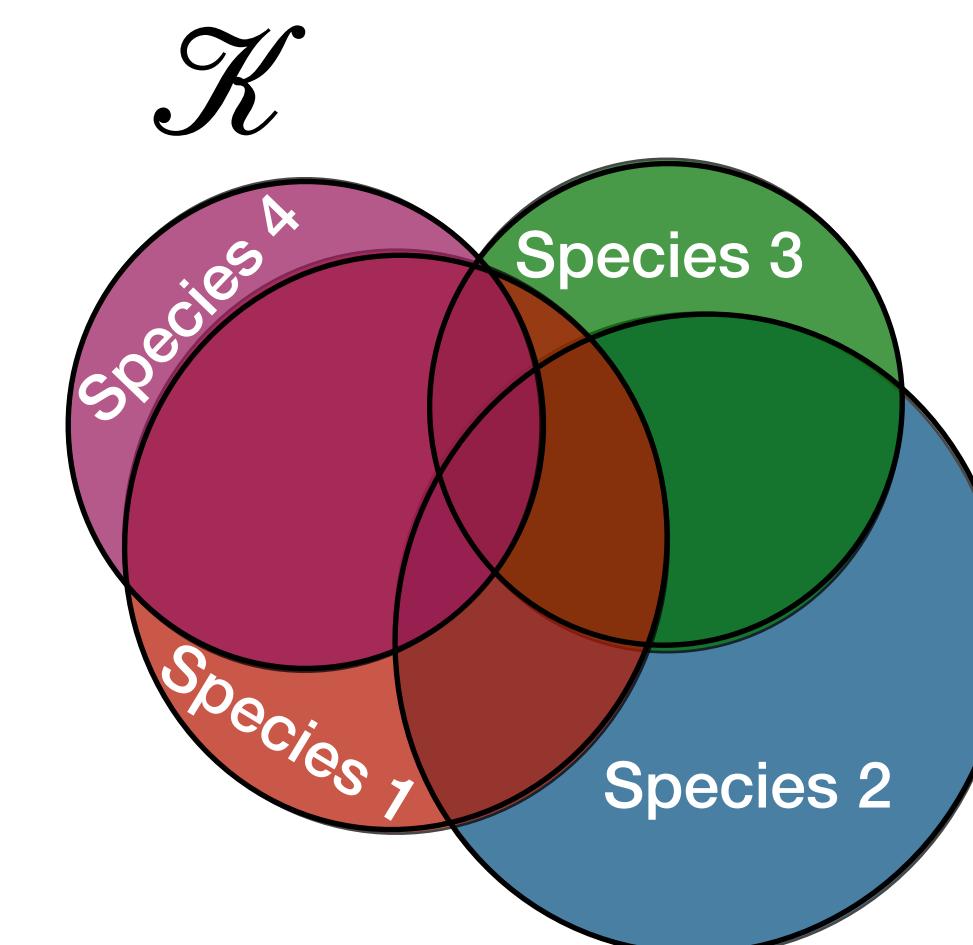


- **Challenge:** very large & diverse databases have too many k -mers to fit in the memory
 - ▶ Limited to a selected subset
- **This talk:** – KRANK
 - ▶ Selecting a representative subset of k -mers + classification/profiling using CONSULT-II

Problem statement

- Given:
 1. k -mer set \mathcal{K} of a large collection of genomes
 2. limited budget $M < |\mathcal{K}|$
 3. taxonomy

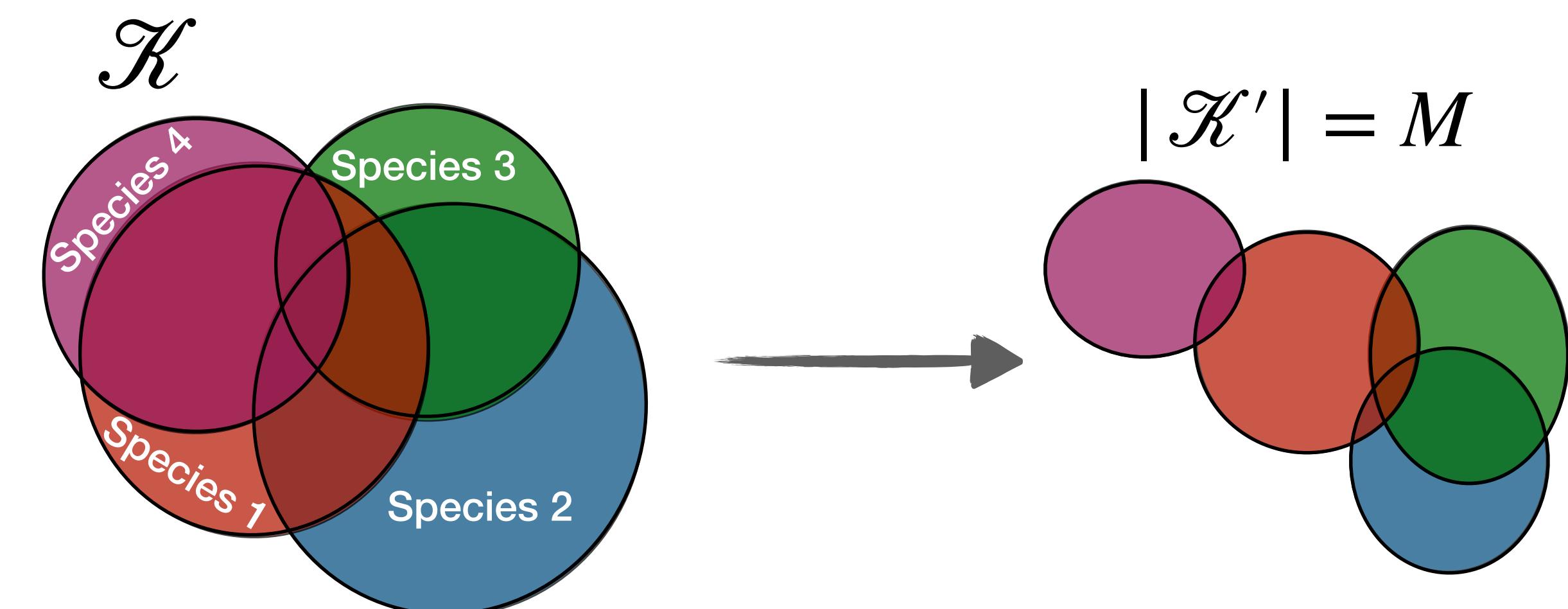
Species 1	G1: TCCCTGCTCAGTGGTATATGGTTTGCTA...
Species 3	G2: TCCCTGCTCAGCCCCATATGGTTTGCTA...
Species 2	G3: CAATGTGCGGATGGCGTTACGACTTACTGG...
Species 4	G4: CCCCCAAACGATGCTGAAGGCTCAGGTTACA...
Species 1	G5: GCGCGGGTTCCCGCCCTAACCCGGGCCGA...
Species 2	G6: AGTTGCACTACTTCTGCGACCCAAATGCAC...
Species 3	G7: TACCACTGTGTTCGTGTCACTAGGACGGG...
Species 4	G8: TACCACTGTGTTCGTGTCACTAGGACGGG...
Species 1	G9: CAATTAAGAATACTTATATTATTGTACAC...
...	...
Species 4	GN: ATTATCTGATTATATTGATTAGTA...



Problem statement

- Given:
 1. k -mer set \mathcal{K} of a large collection of genomes
 2. limited budget $M < |\mathcal{K}|$
 3. taxonomy
- Select a subset with size M such that the collection is well represented

Species 1	G1: TCCCTGCTCAGTGGTATATGGTTTGCTA...
Species 3	G2: TCCCTGCTCAGCCCCATATGGTTTGCTA...
Species 2	G3: CAATGTGCGGATGGCGTTACGACTTACTGG...
Species 4	G4: CCCCCAAACGATGCTGAAGGCTCAGGTTACA...
	G5: GCGCGGGTTCCCGCCCTAACCCGGGCCGA...
	G6: AGTTGCACTACTTCTGCGACCCAAATGCAC...
	G7: TACCACTGTGTTCGTGTCACTAGGACGGG...
	G8: TACCACTGTGTTCGTGTCACTAGGACGGG...
	G9: CAATTAAGAATACCTTATATTATTGTACAC...
	...
Species 4	GN: ATTATCTGATTTATATTATGATTTAGTA...

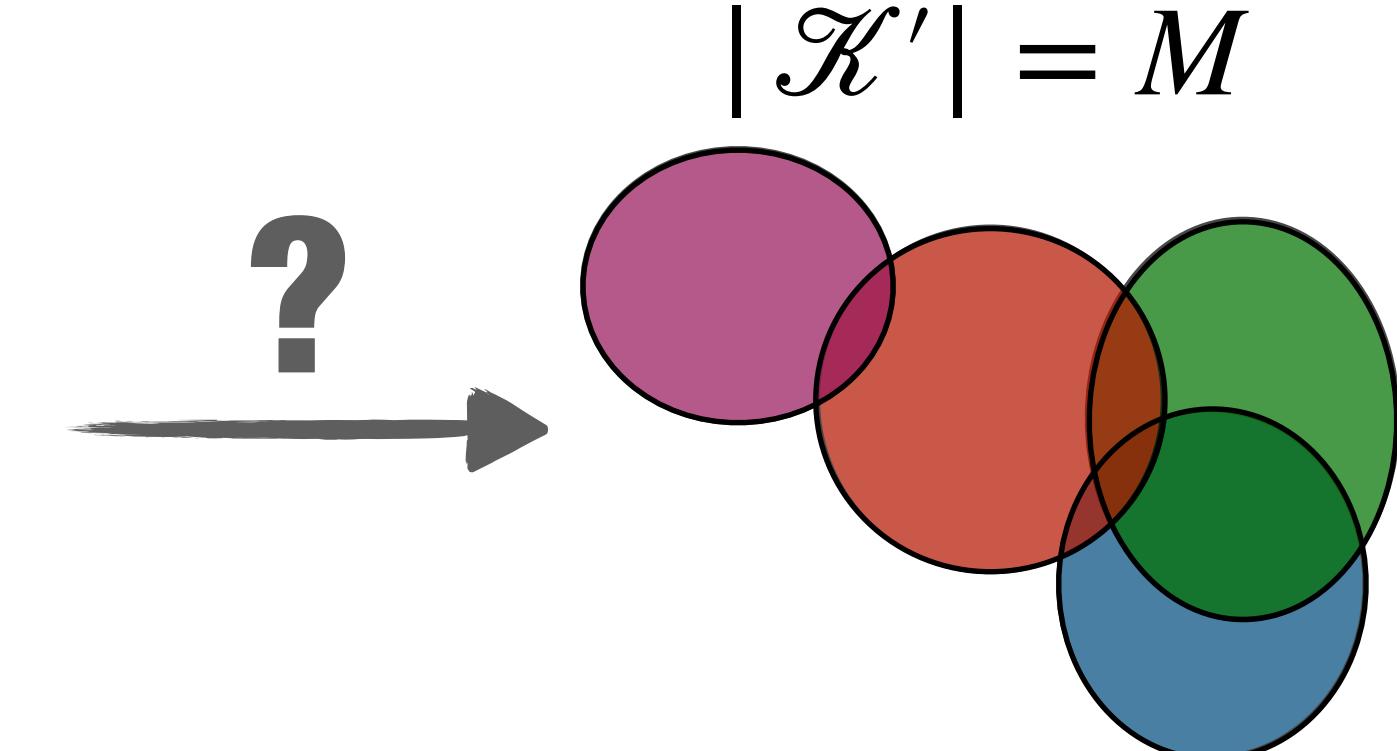
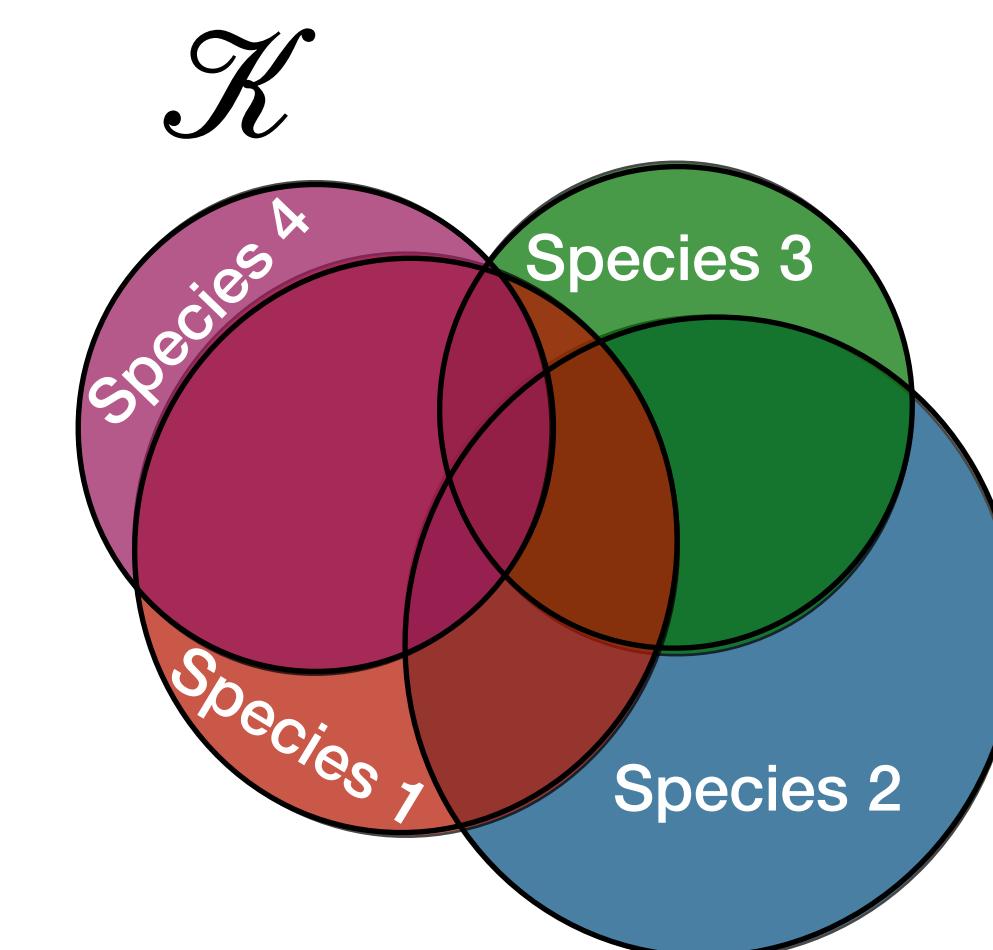


Problem statement

- Given:
 1. k -mer set \mathcal{K} of a large collection of genomes
 2. limited budget $M < |\mathcal{K}|$
 3. taxonomy
- Select a subset with size M such that the collection is well represented

high accuracy in
taxonomic identification

Species 1	G1: TCCCTGCTCAGTGGTATATGGTTTGCTA...
Species 3	G2: TCCCTGCTCAGCCCCATATGGTTTTGCTA...
Species 2	G3: CAATGTGCGGATGGCGTTACGACTTACTGG...
Species 4	G4: CCCCCAAACGATGCTGAAGGCTCAGGTTACA...
	G5: GCGCGGGTTCCCGCCCTAACCCGGGCCGA...
	G6: AGTTGCACTACTTCTGCGACCCAAATGCAC...
	G7: TACCACTGTGTTCGTGTCACTAGGACGGG...
	G8: TACCACTGTGTTCGTGTCACTAGGACGGG...
	G9: CAATTAAAGAATACCTTATATTATTGTACAC...
	...
Species 4	GN: ATTATCTGATTTATATTATGATTTAGTA...



Reducing the reference set by selecting k-mers

G1: TCCCTGC
CCCTGCT
CCTGCTC
CTGCTCA...

G2: TCGCTAC
CGCTACG
GCTACGC
CTACGCG...

G3: CAATGTG
AATGTGC
ATGTGCG
TGTGCGG...

G5: GCGCGGG
CGCGGGT
GCGGGTT
CGGGTTC...

G4: CCCCCAA
CCCAAAC
CCAAACG
CAAACGT...

Reducing the reference set by selecting k-mers

- **Baseline:** random selection

G1: TCCCTGC
CCCTGCT
CCTGCTC
CTGCTCA...

G2: TCGCTAC
CGCTACG
GCTACGC
CTACGCG...

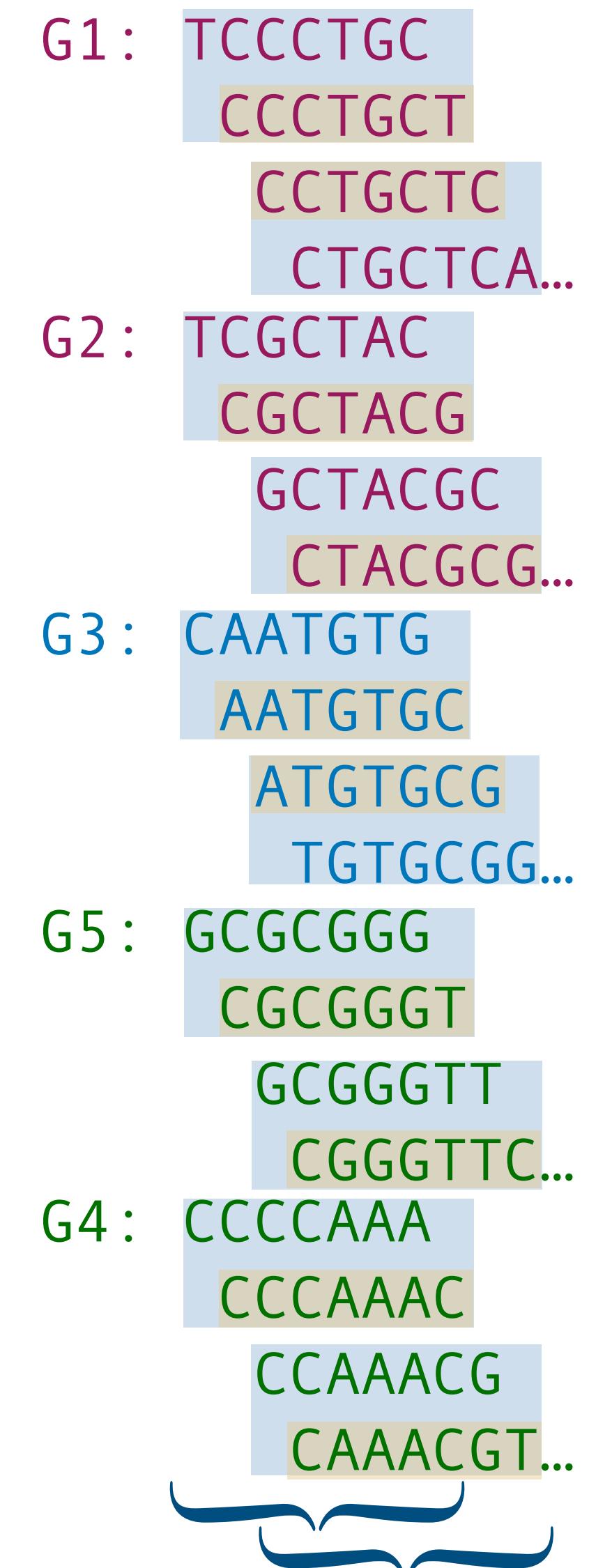
G3: CAATGTG
AATGTGC
ATGTGCG
TGTGCGG...

G5: GCGCGGG
CGCGGGT
GCGGGTT
CGGGTTC...

G4: CCCCAA
CCCAAAC
CCAAACG
CAAACGT...

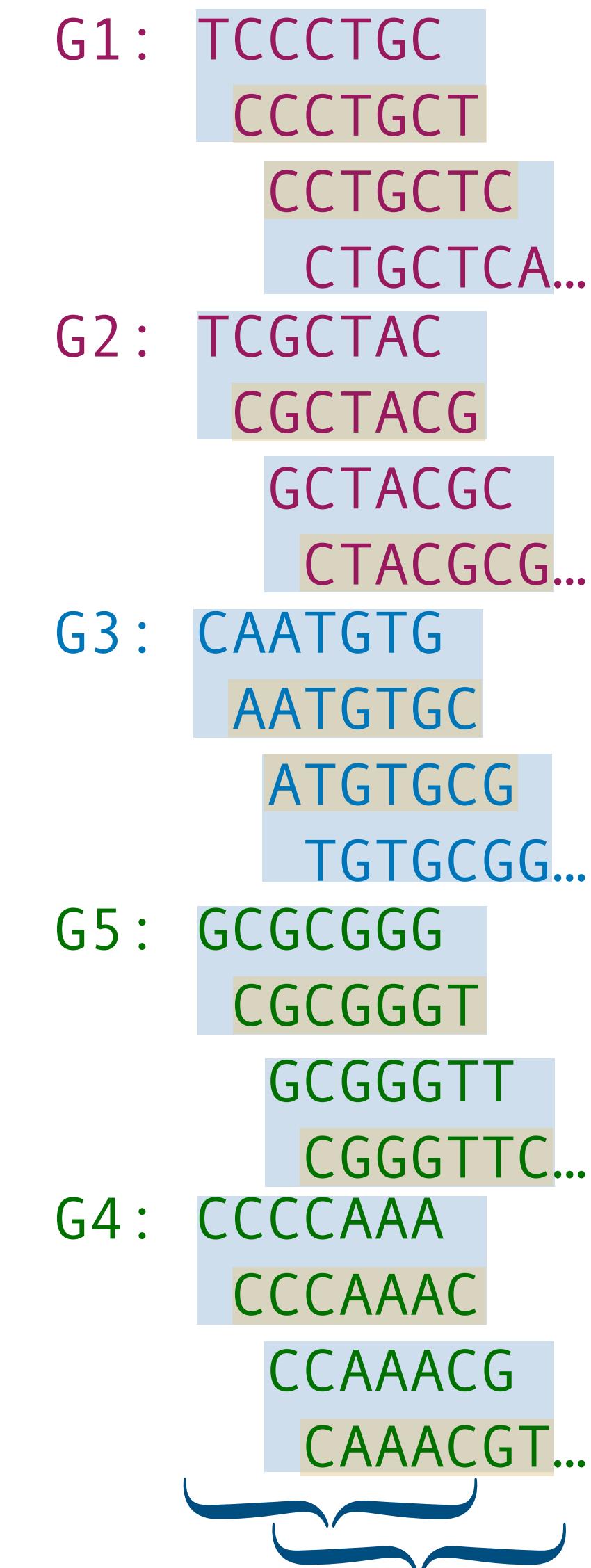
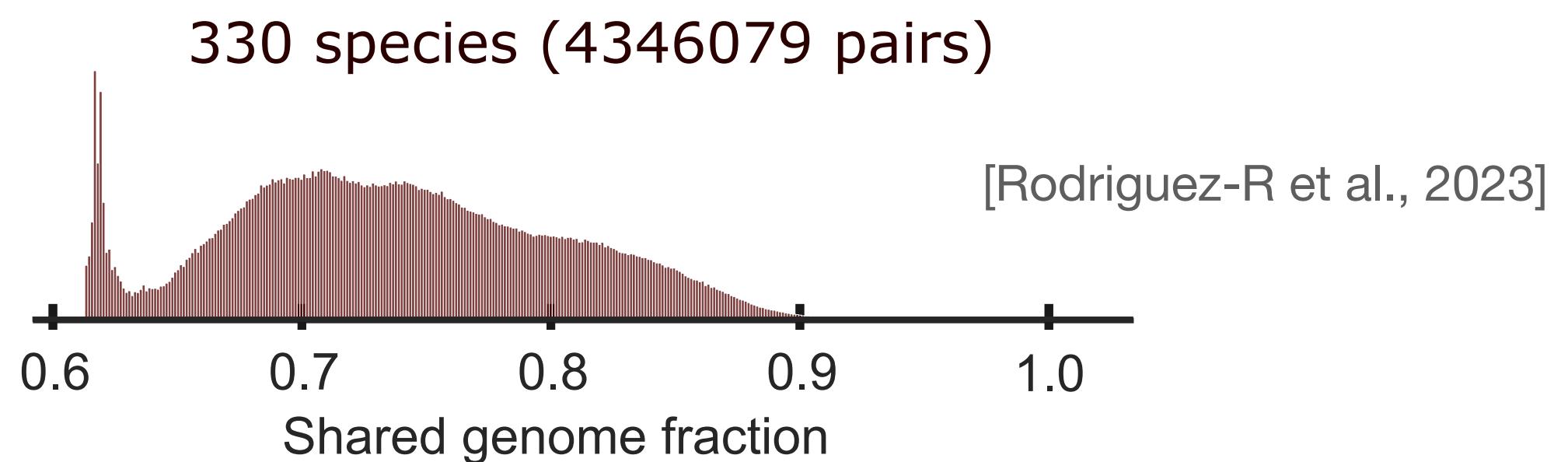
Reducing the reference set by selecting k-mers

- **Baseline:** random selection
- **Minimizers:** selecting one among overlapping k-mers with a sliding window



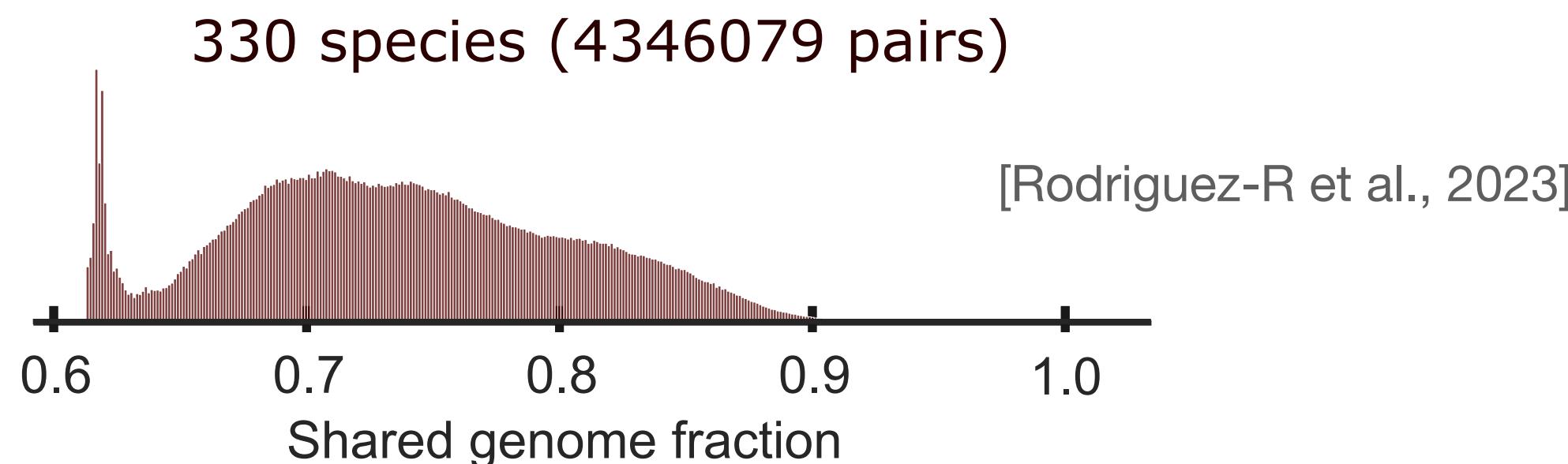
Reducing the reference set by selecting k-mers

- **Baseline:** random selection
- **Minimizers:** selecting one among overlapping k -mers with a sliding window
- Even with minimizers, number of distinct k -mers grows fast with the number of genomes

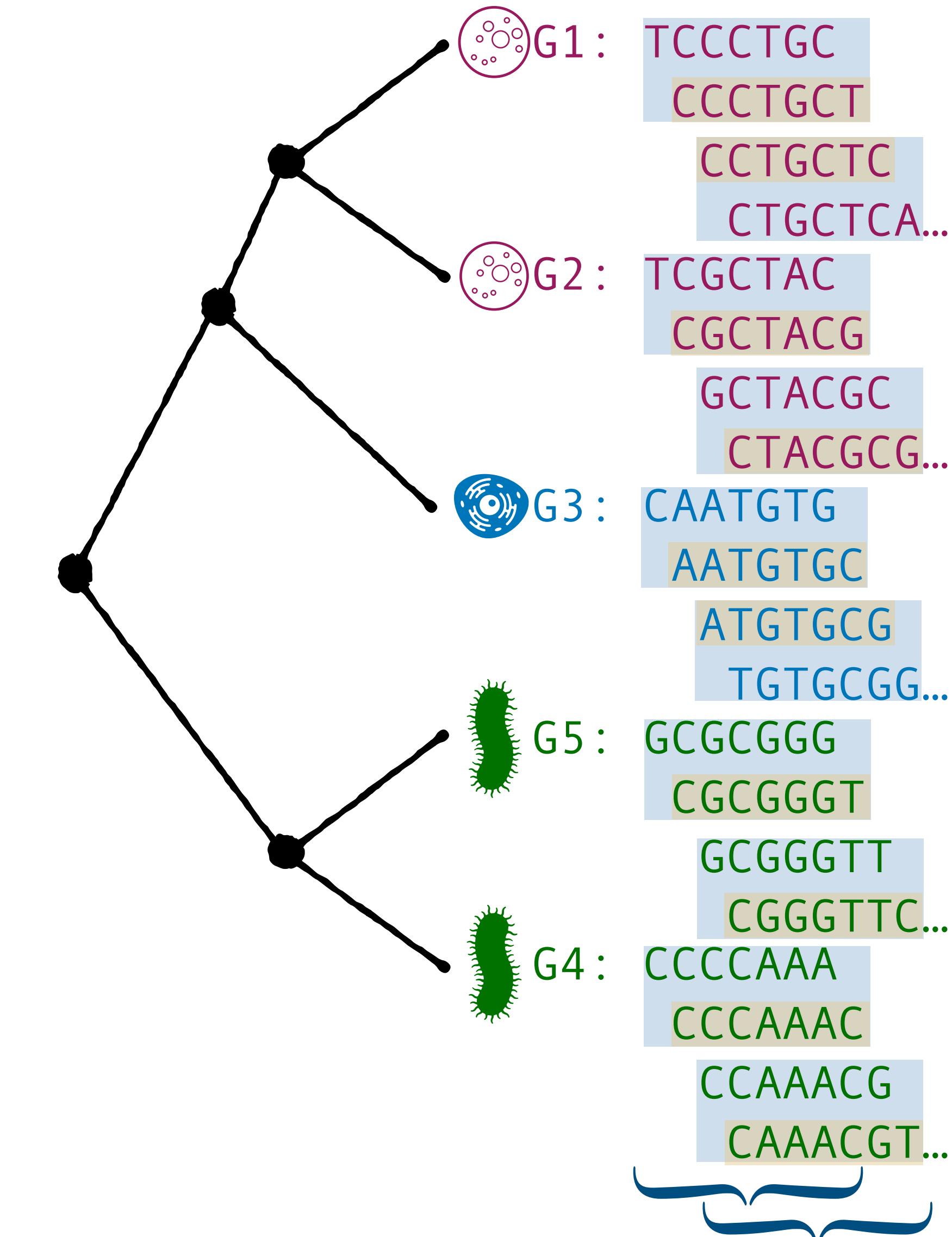


Reducing the reference set by selecting k-mers

- **Baseline:** random selection
- **Minimizers:** selecting one among overlapping k -mers with a sliding window
- Even with minimizers, number of distinct k -mers grows fast with the number of genomes

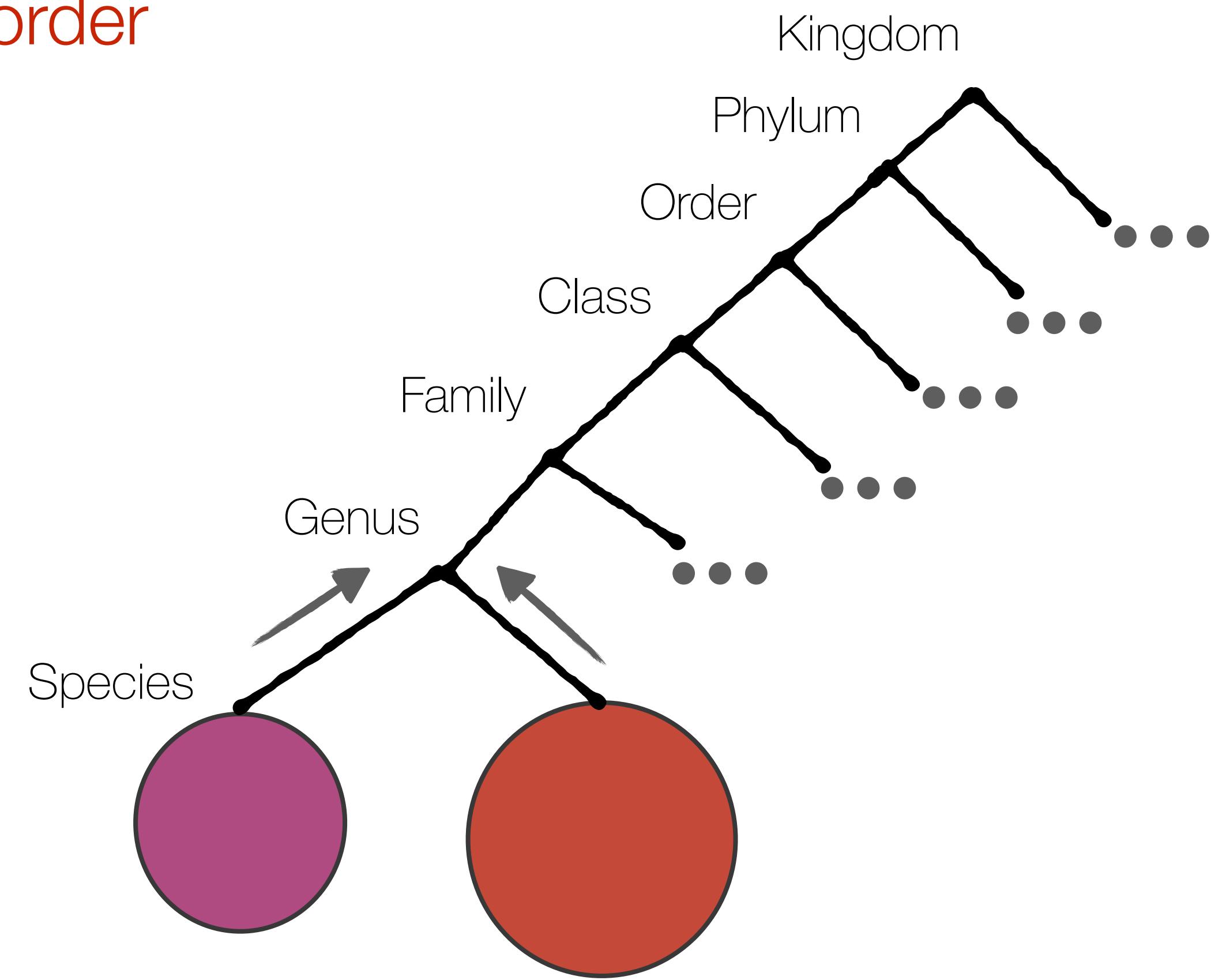
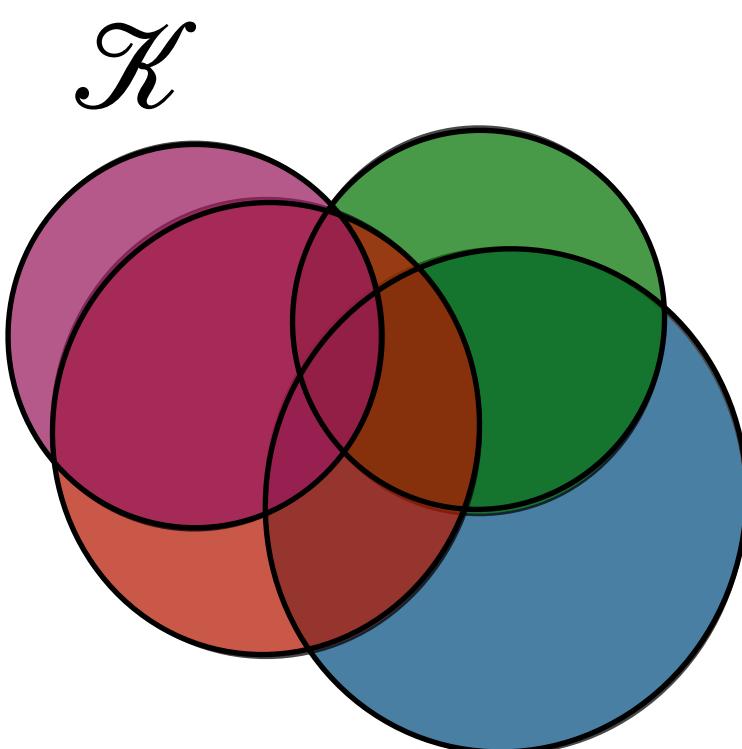


- Additionally, exploit the evolutionary dimension



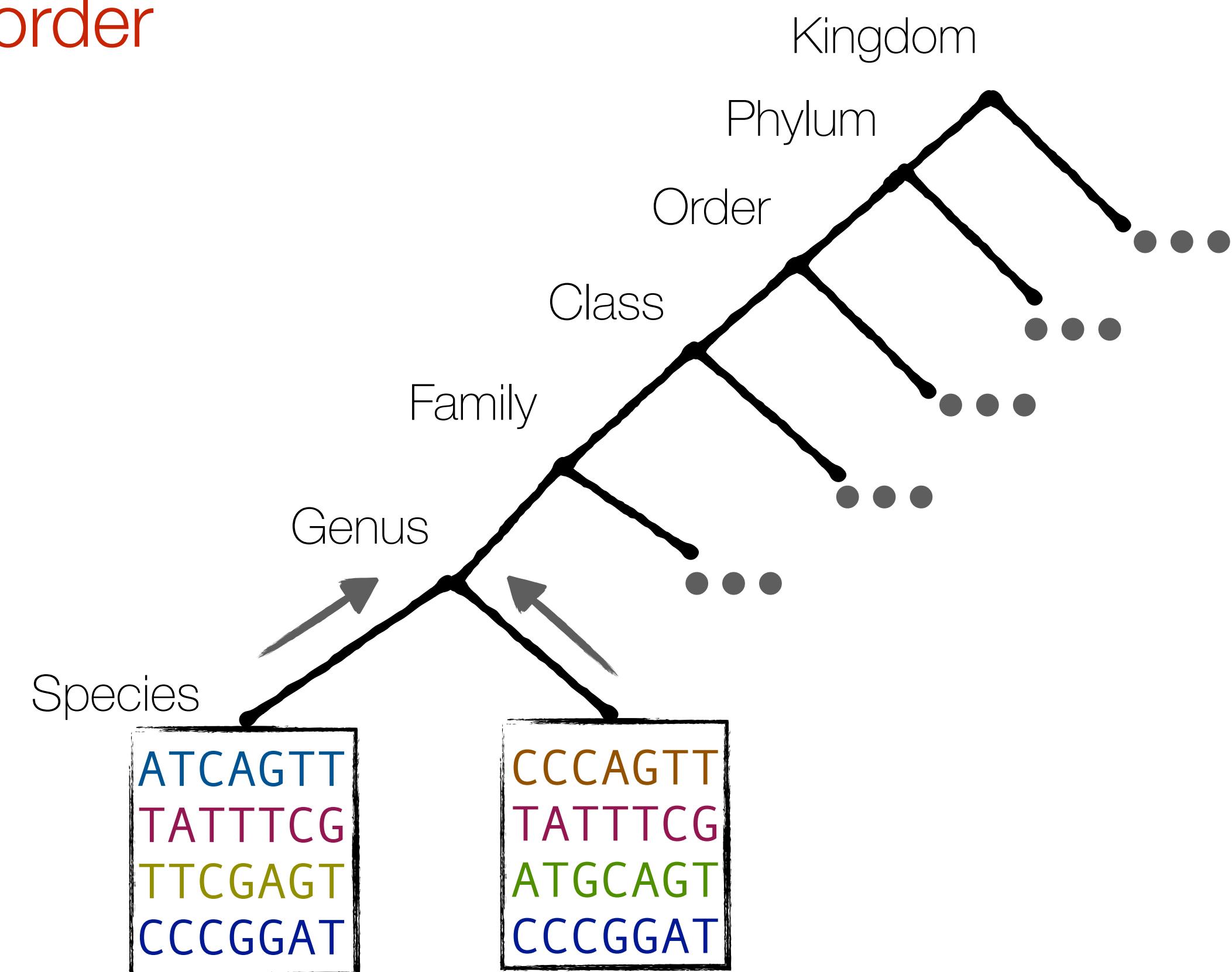
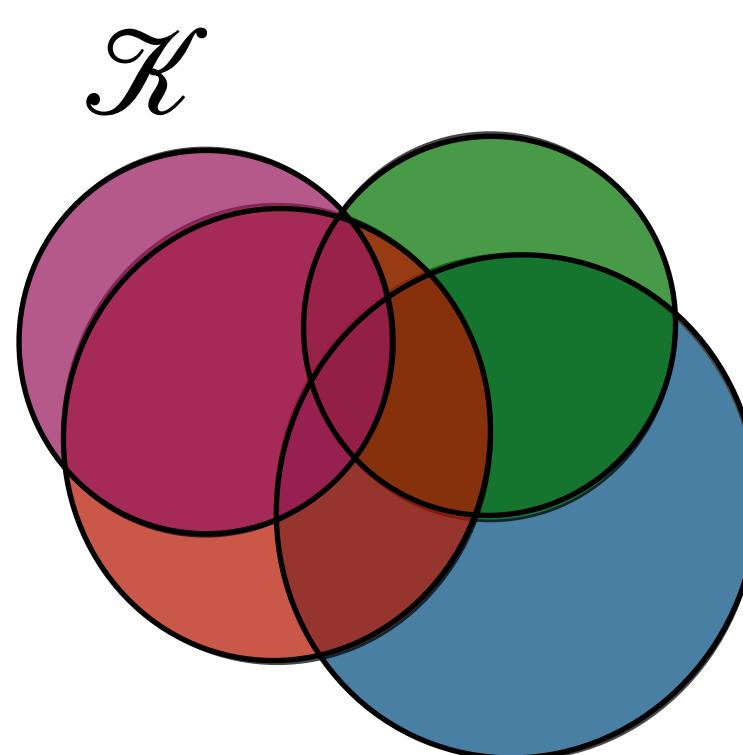
KRANK selects a representative k -mer subset in a memory-bound manner!

Core idea: instead of computing all intersections;
hierarchical subsampling through a **post order traversal** of the taxonomic tree



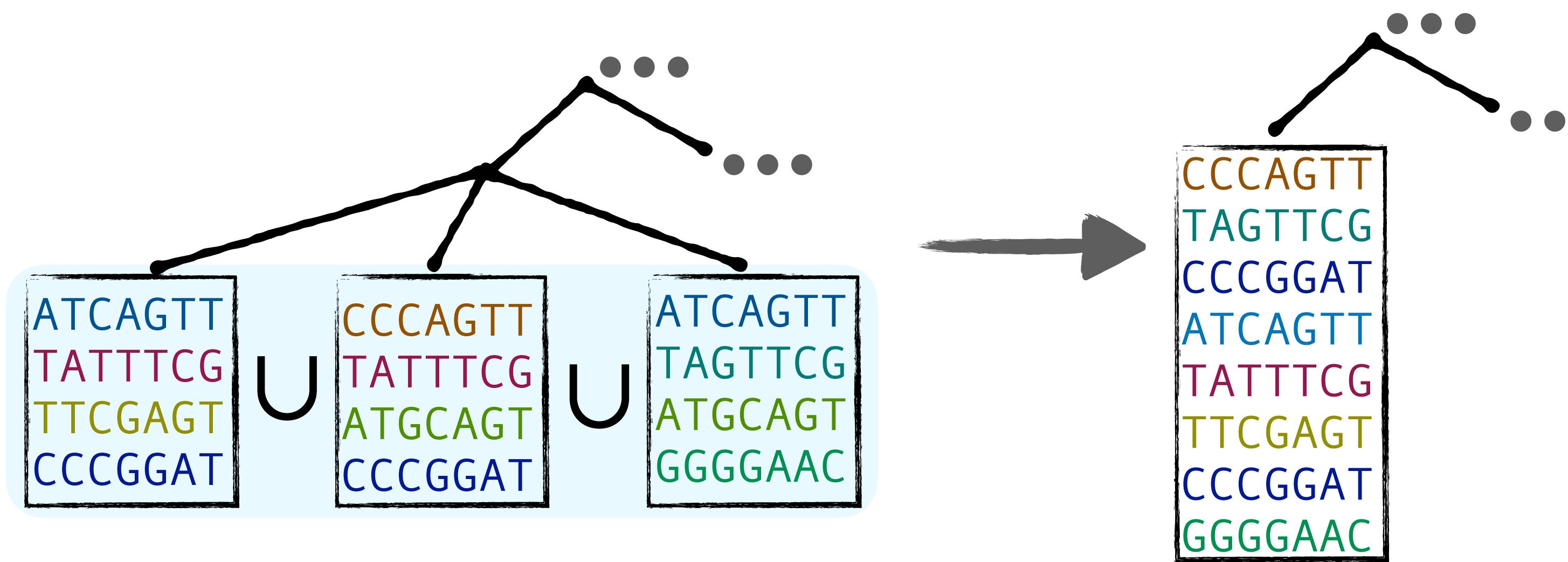
KRANK selects a representative k -mer subset in a memory-bound manner!

Core idea: instead of computing all intersections;
hierarchical subsampling through a **post order**
traversal of the taxonomic tree



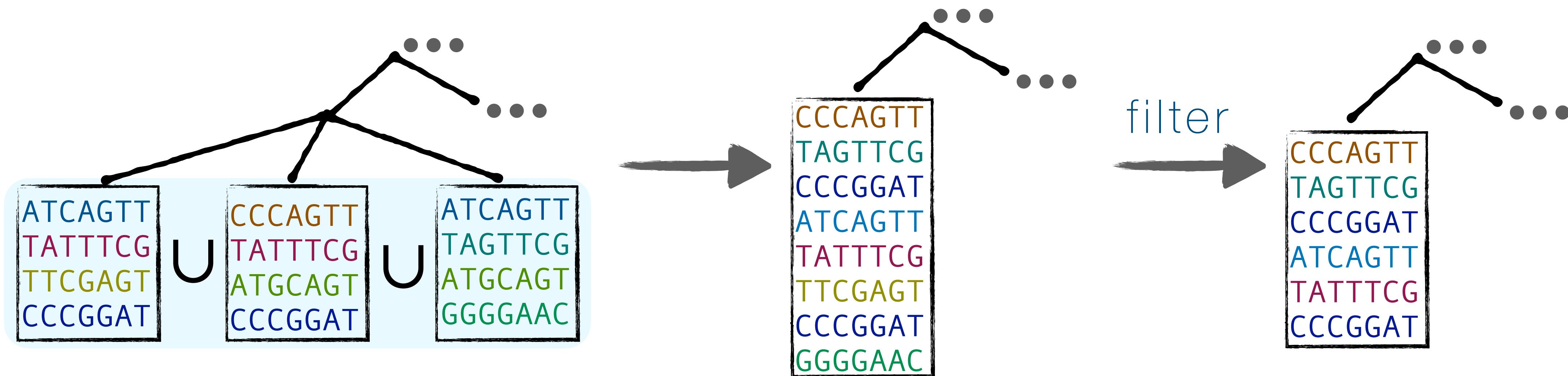
Gradual filtering of k-mers at internal nodes

- Recursively take the union of sibling taxa



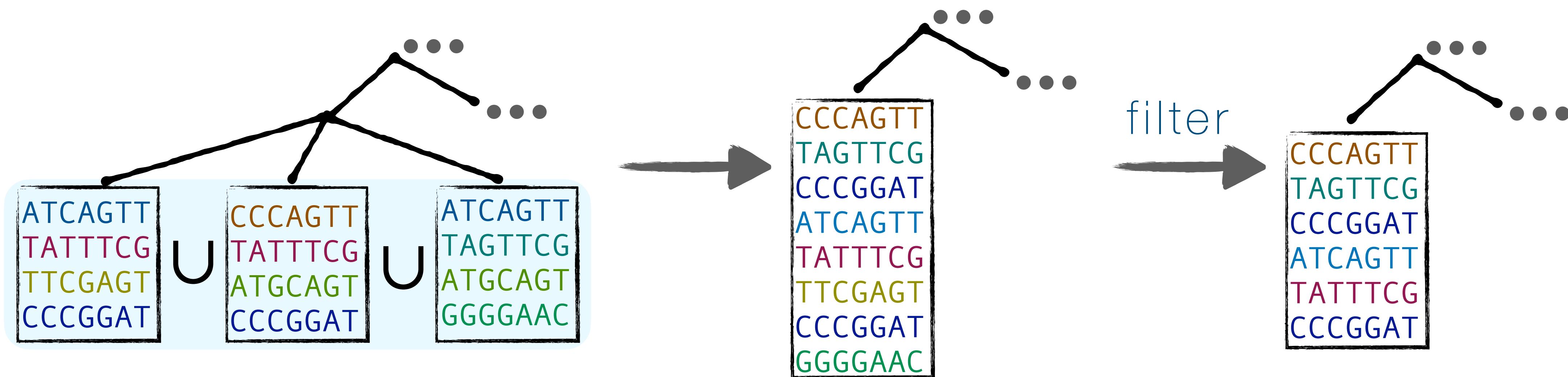
Gradual filtering of k-mers at internal nodes

- Recursively take the union of sibling taxa
- Filter some number of k -mers based on a *ranking*



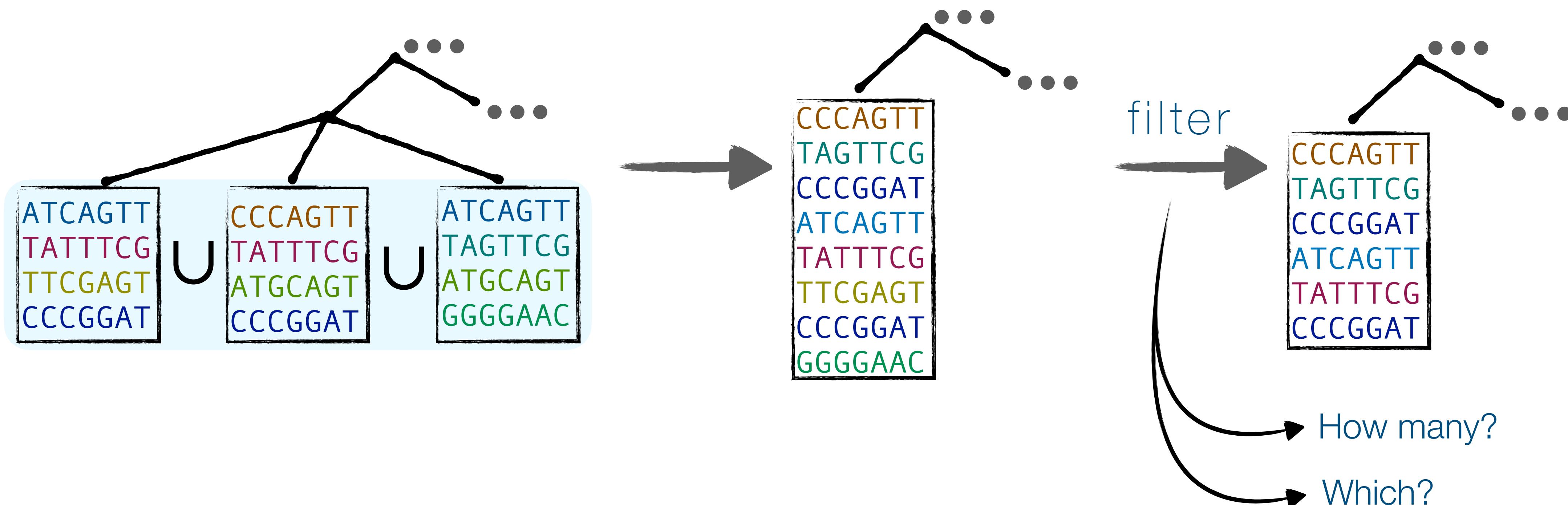
Gradual filtering of k-mers at internal nodes

- Recursively take the union of sibling taxa
- Filter some number of k -mers based on a *ranking*
- At the root, we obtain the final library with size M



Gradual filtering of k-mers at internal nodes

- Recursively take the union of sibling taxa
- Filter some number of k -mers based on a *ranking*
- At the root, we obtain the final library with size M



Q1: How many k -mers should we remove from each node/taxon?

Q2: How do we rank k -mers to assess which one(s) should be kept?

- **Baseline:** no gradual filtering — `wait` & select M randomly at the `root`

- **Baseline:** no gradual filtering — **wait** & select M randomly at the **root**

Given total budget M ,

$\mathbb{E}[\# \text{ of selected } k\text{-mers for a taxon } t]$ is

$$M \frac{|\mathcal{K}_t|}{|\mathcal{K}|}$$

The diagram consists of two curved arrows. The top arrow originates from the term $|\mathcal{K}_t|$ in the equation and points to the text "set of k -mers under the taxon t ". The bottom arrow originates from the term $|\mathcal{K}|$ in the equation and points to the text "set of all reference k -mers".

set of k -mers
under the taxon t

set of all
reference k -mers

- **Baseline:** no gradual filtering — wait & select M randomly at the root

Given total budget M ,

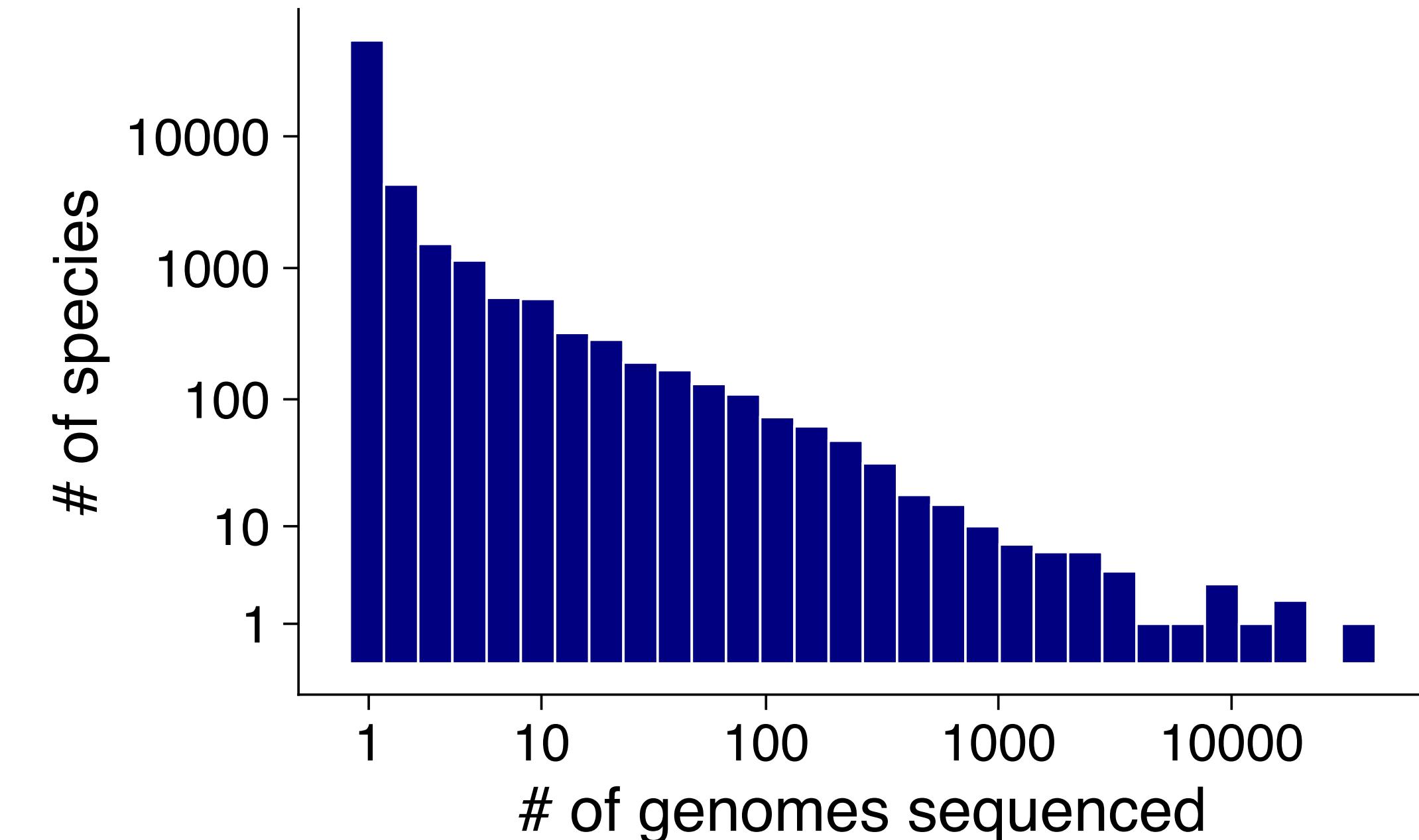
$\mathbb{E}[\# \text{ of selected } k\text{-mers for a taxon } t]$ is

$$M \frac{|\mathcal{K}_t|}{|\mathcal{K}|}$$

set of k -mers
under the taxon t

set of all
reference k -mers

- Proportional contribution →
 - ▶ taxa with low sampling get little representation
 - ▶ highly-sampled groups dominates (e.g., *E. coli*)



Gradual filtering is making some decisions earlier

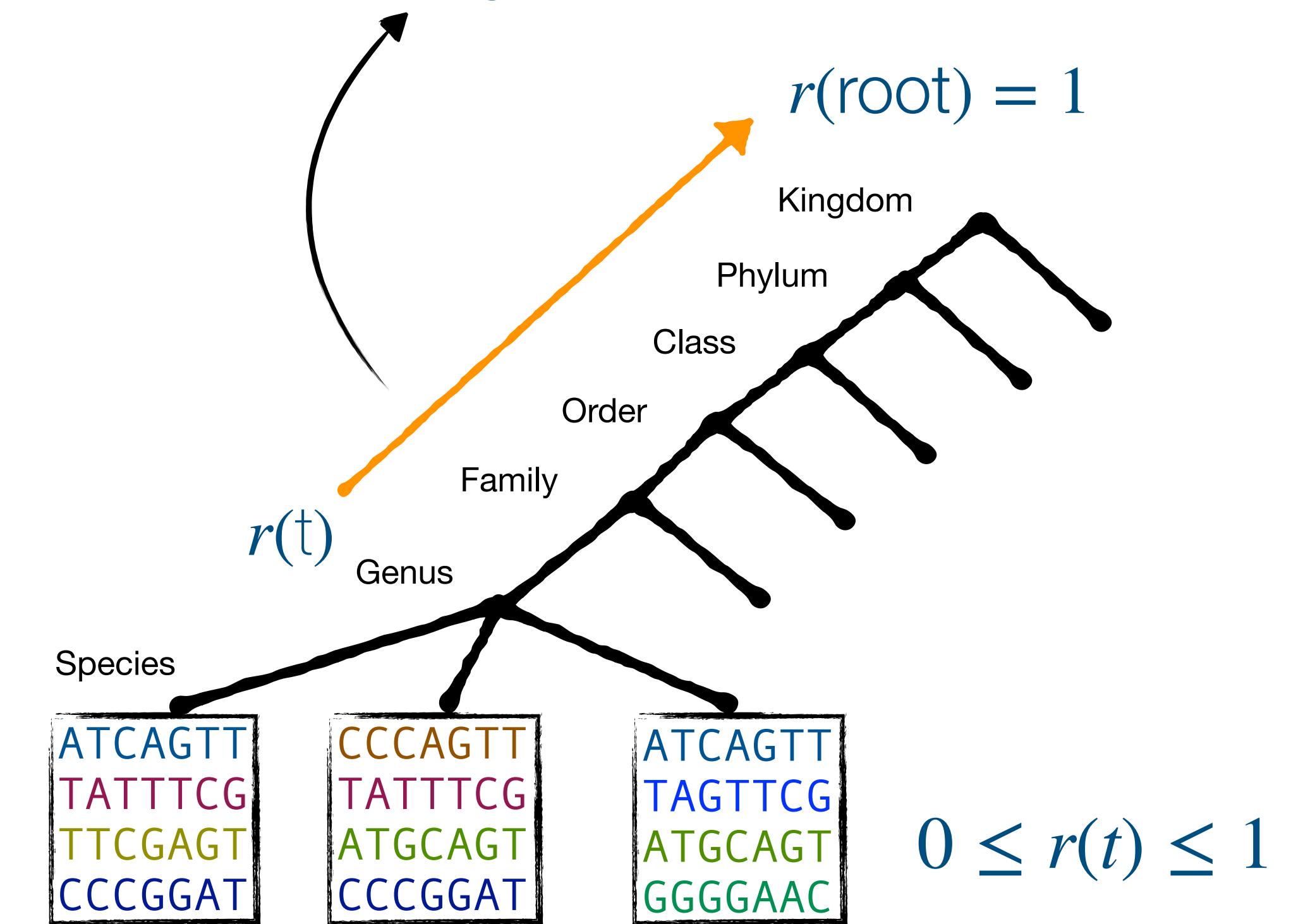
Goal: remove k -mers from bloated taxa earlier & delay decisions for smaller taxa

Gradual filtering is making some decisions earlier

Goal: remove k -mers from bloated taxa earlier & delay decisions for smaller taxa

- Adaptive size constraint, $r(t)M$, on internal nodes

increases as we go up in the tree!

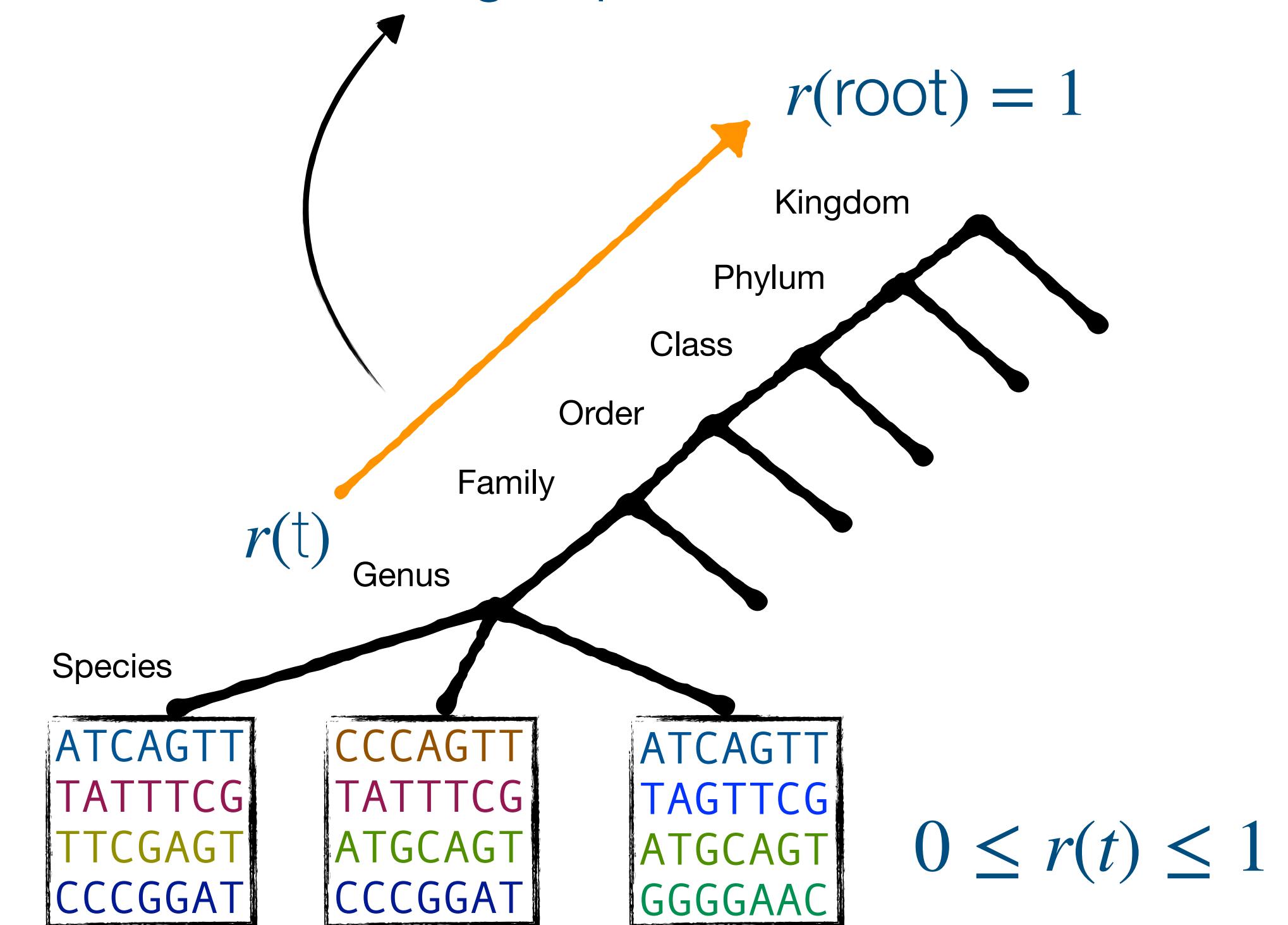


Gradual filtering is making some decisions earlier

Goal: remove k -mers from bloated taxa earlier & delay decisions for smaller taxa

- Adaptive size constraint, $r(t)M$, on internal nodes
- $r(t)$ is a heuristic: square root of ratio of k -mers under t

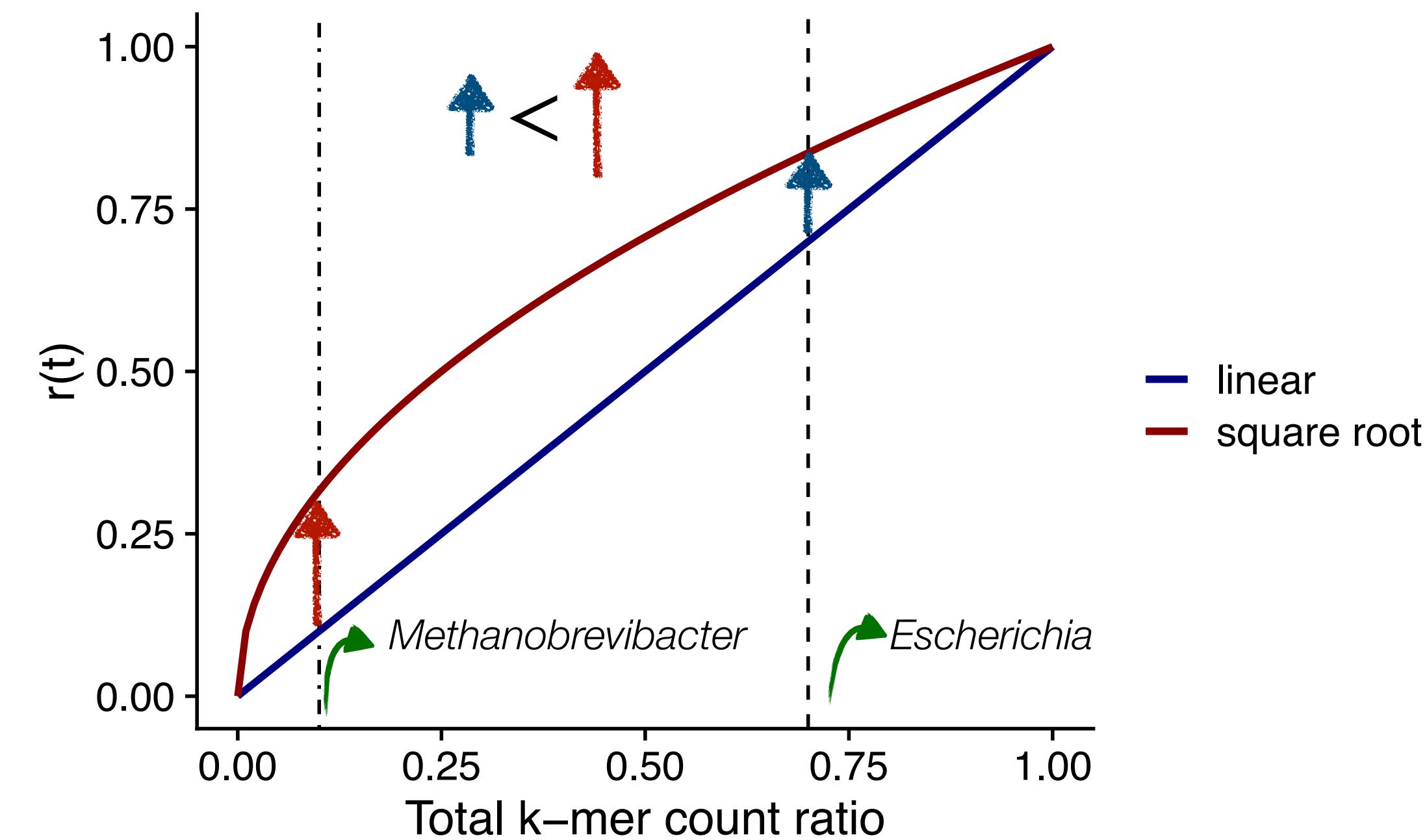
increases as we go up in the tree!



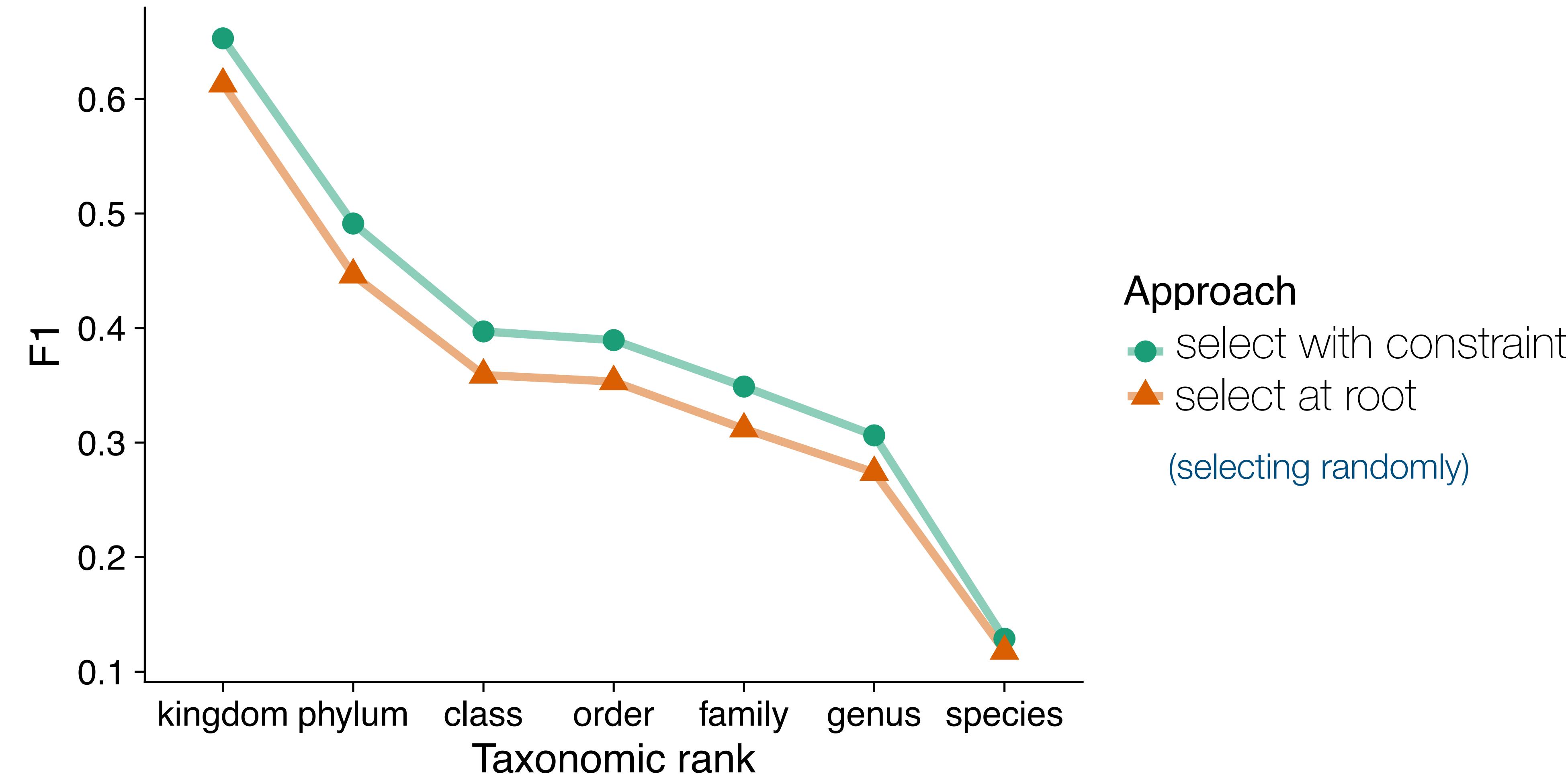
Gradual filtering is making some decisions earlier

Goal: remove k -mers from bloated taxa earlier & delay decisions for smaller taxa

- Adaptive size constraint, $r(t)M$, on internal nodes
- $r(t)$ is a heuristic: square root of ratio of k -mers under t
- Concavity of $r(t)$ favors taxa with fewer k -mers
(less diversity or sparsely sampled)



Adaptive size constraint improves classification



(empirical analysis using 3.2Gb, in WoL-v1 with 9k species, 10k genomes)

Q1: How many k -mers should we remove from each node/taxon?

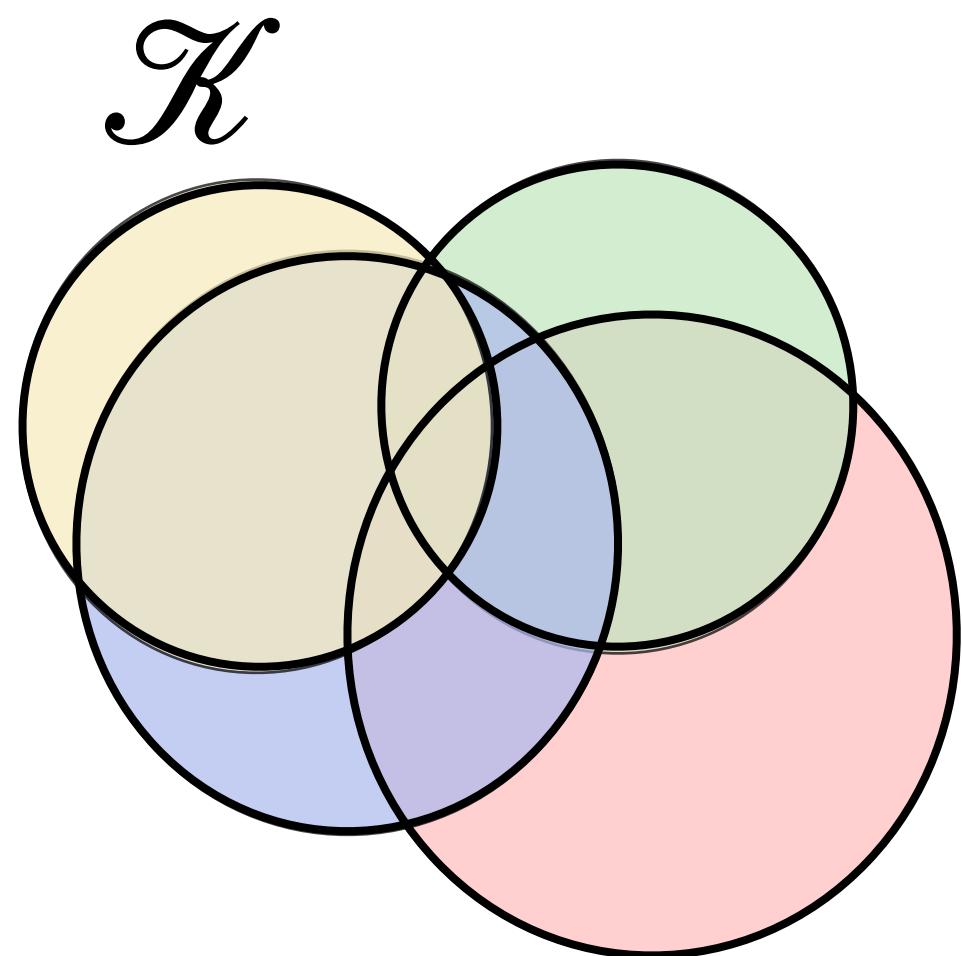
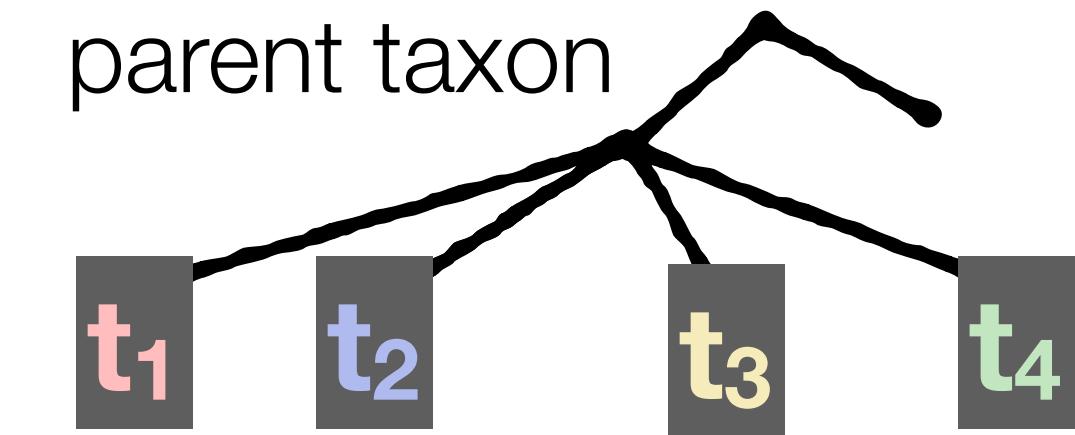
Q2: How do we rank k -mers to assess which one(s) should be kept?

Which k-mers would provide better representation?

Baseline: selecting randomly until the constraint is satisfied

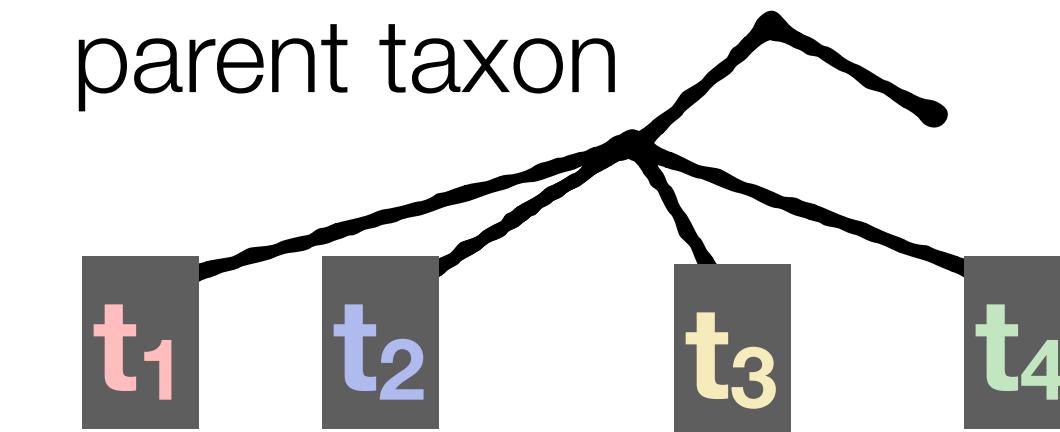
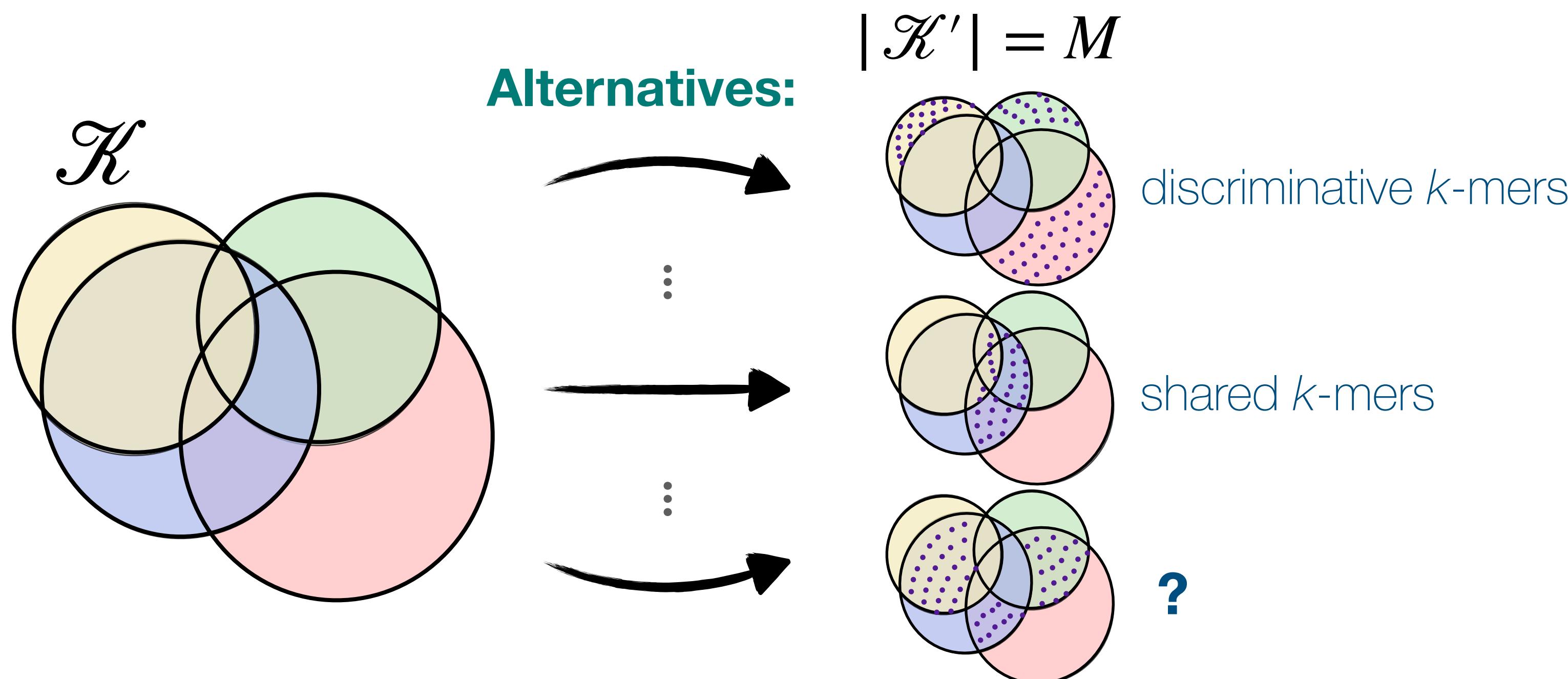
Which k-mers would provide better representation?

Baseline: selecting randomly until the constraint is satisfied



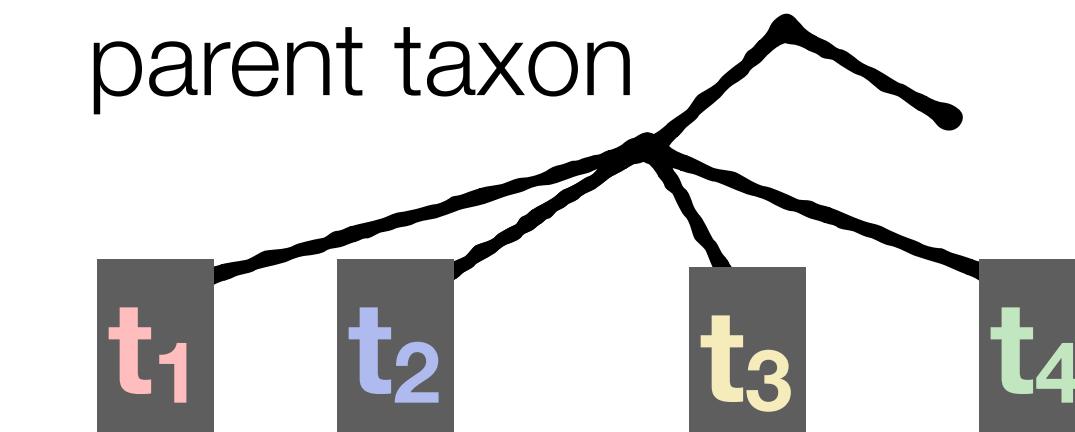
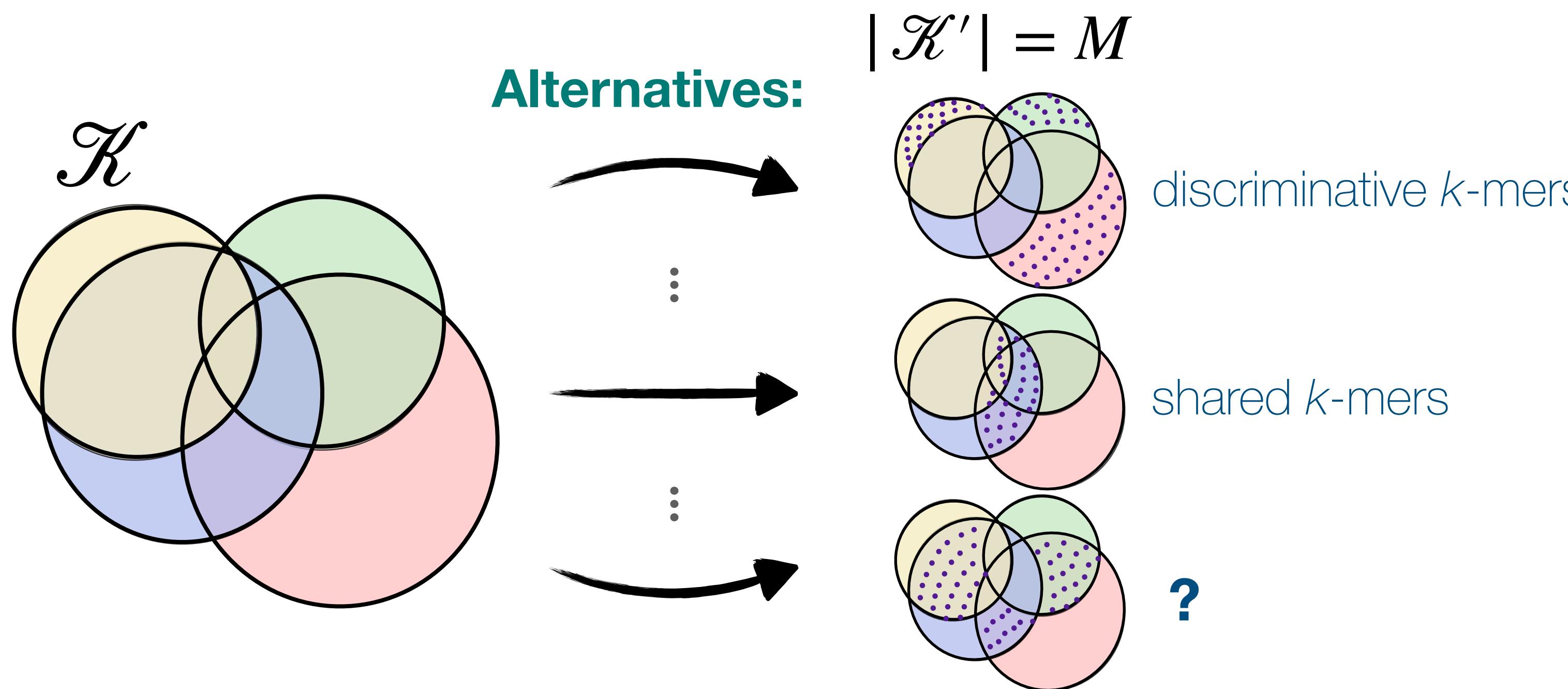
Which k-mers would provide better representation?

Baseline: selecting randomly until the constraint is satisfied



Which k-mers would provide better representation?

Baseline: selecting randomly until the constraint is satisfied

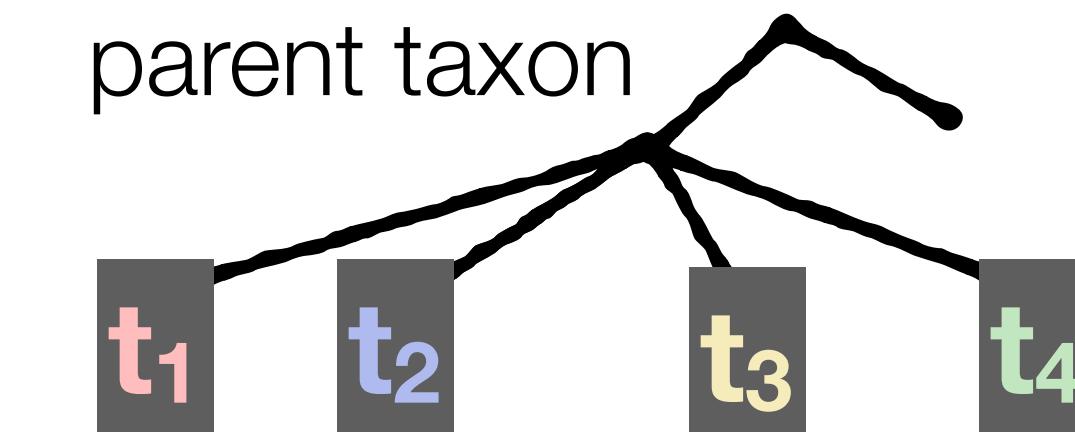
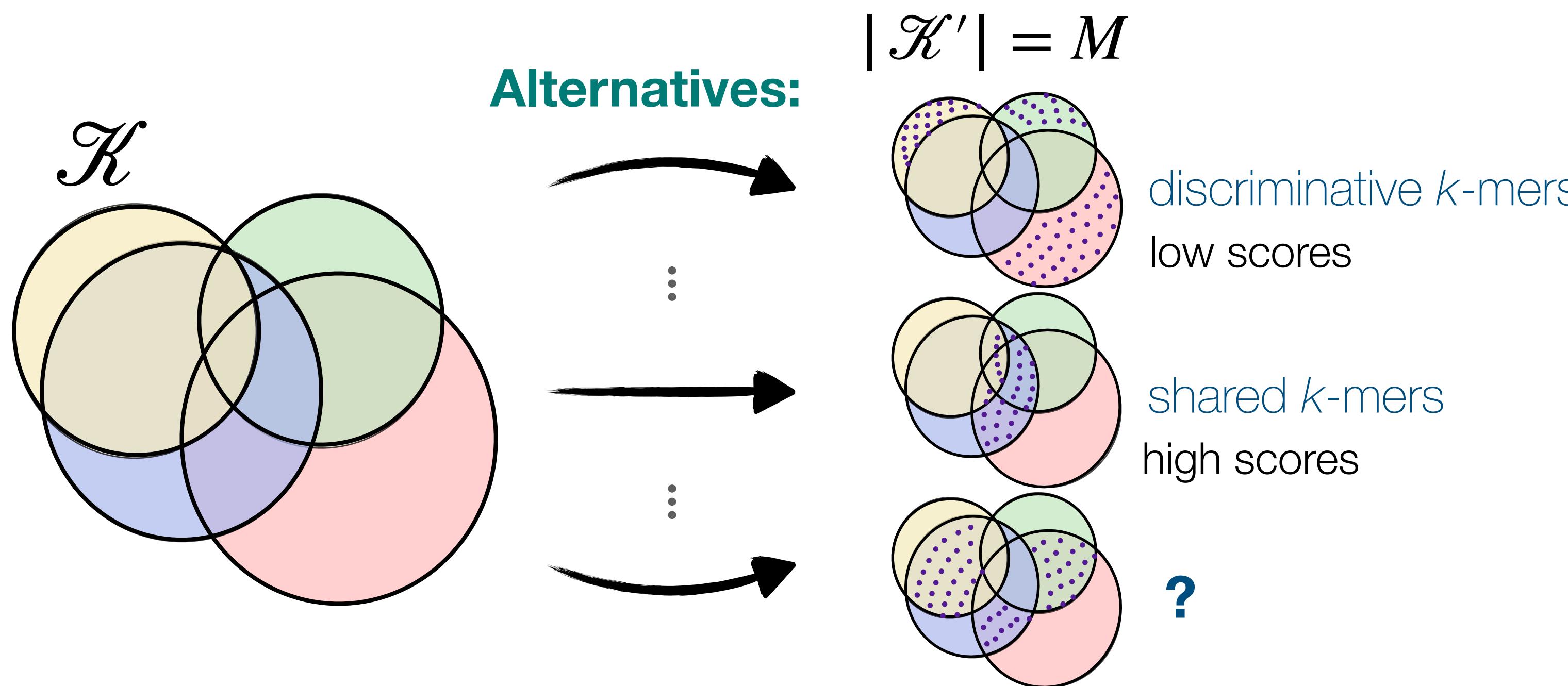


of species under t with k -mer x

	x_1	x_2	x_3	...	$x_{ \mathcal{K}' }$
t_1	4	7	0	...	3
t_2	0	0	2	...	0
t_3	0	0	1	...	1
t_4	2	2	1	...	0
Score:	6	9	4	...	4

Which k-mers would provide better representation?

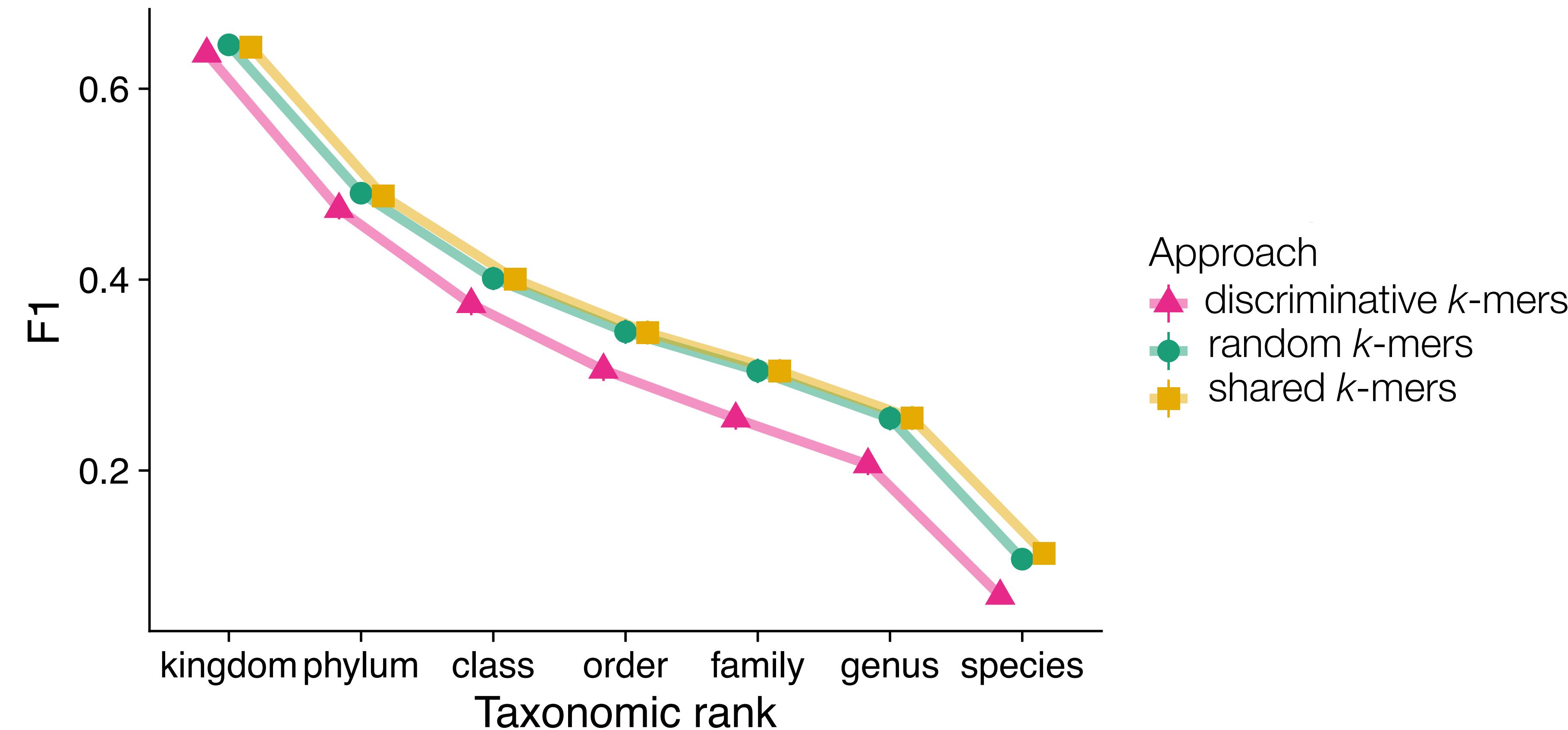
Baseline: selecting randomly until the constraint is satisfied



of species under t with k -mer x

	x_1	x_2	x_3	...	$x_{ \mathcal{K}' }$
t_1	4	7	0	...	3
t_2	0	0	2	...	0
t_3	0	0	1	...	1
t_4	2	2	1	...	0
Score:	6	9	4	...	4

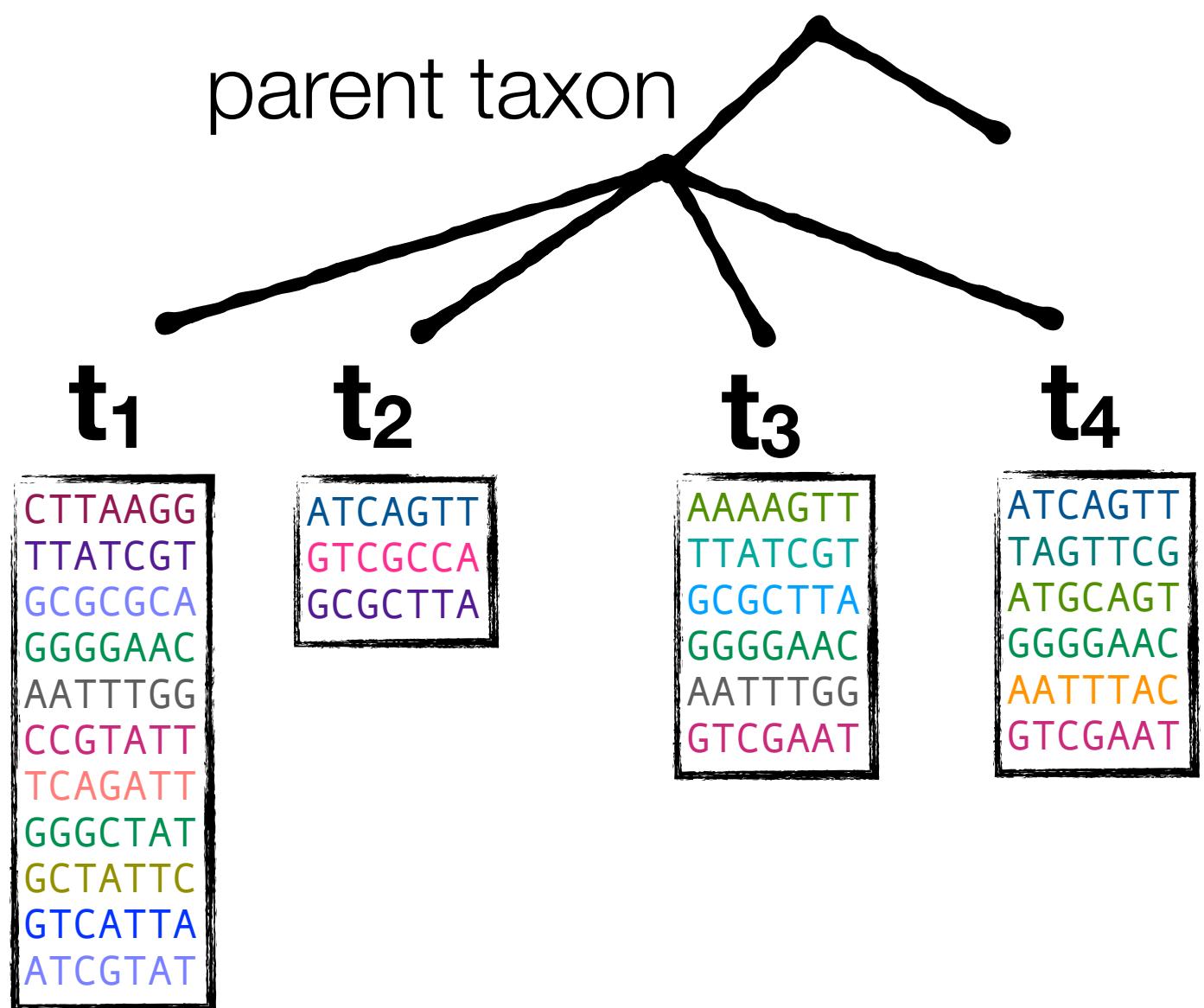
Neither discriminative nor shared k-mers improve the baseline



(empirical analysis using 3.2Gb, in WoL-v1 with 9k species, 10k genomes)

Incorporating taxon coverage in ranking

Intuition: keep shared k -mers but ensure no group is left uncovered



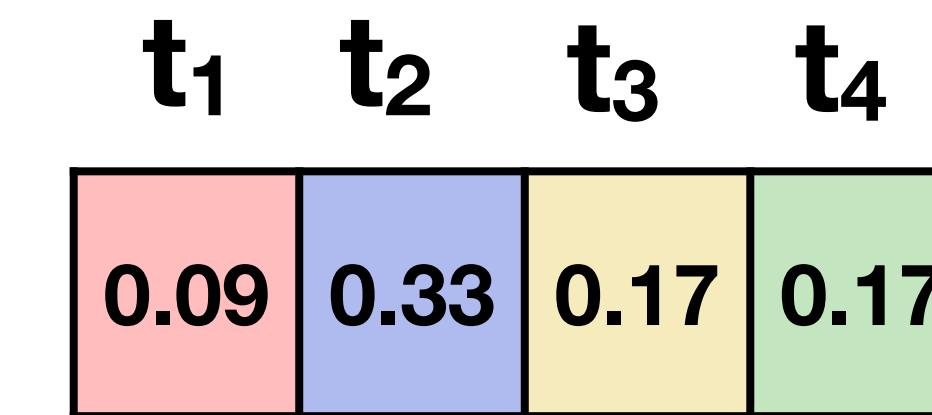
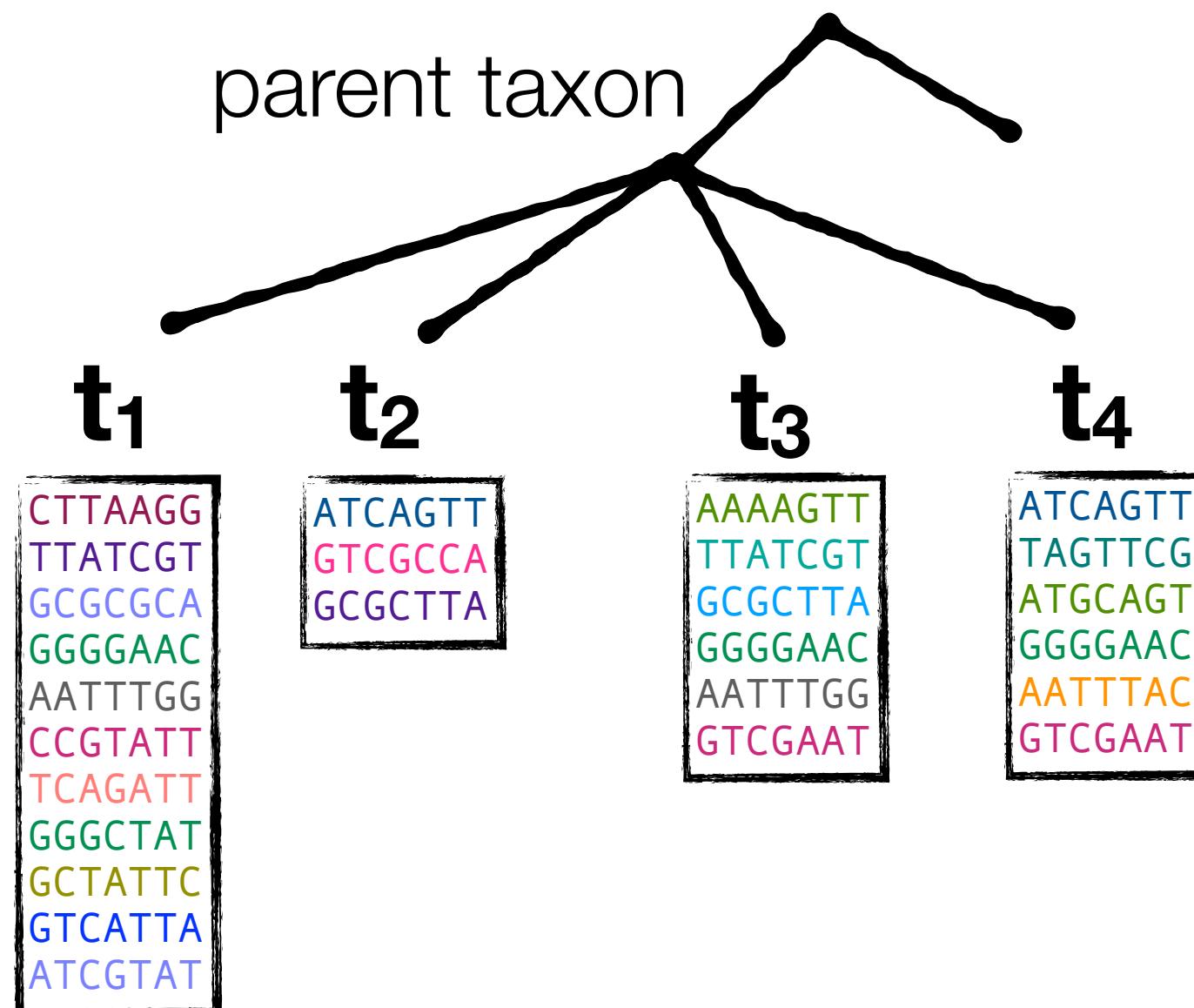
t_1 : Afford to remove more!

t_2 : Needs to be prioritized!

Incorporating taxon coverage in ranking

Intuition: keep shared k -mers but ensure no group is left uncovered

Scalable heuristic: down-weight the impact of taxa that are highly covered among surviving k -mers

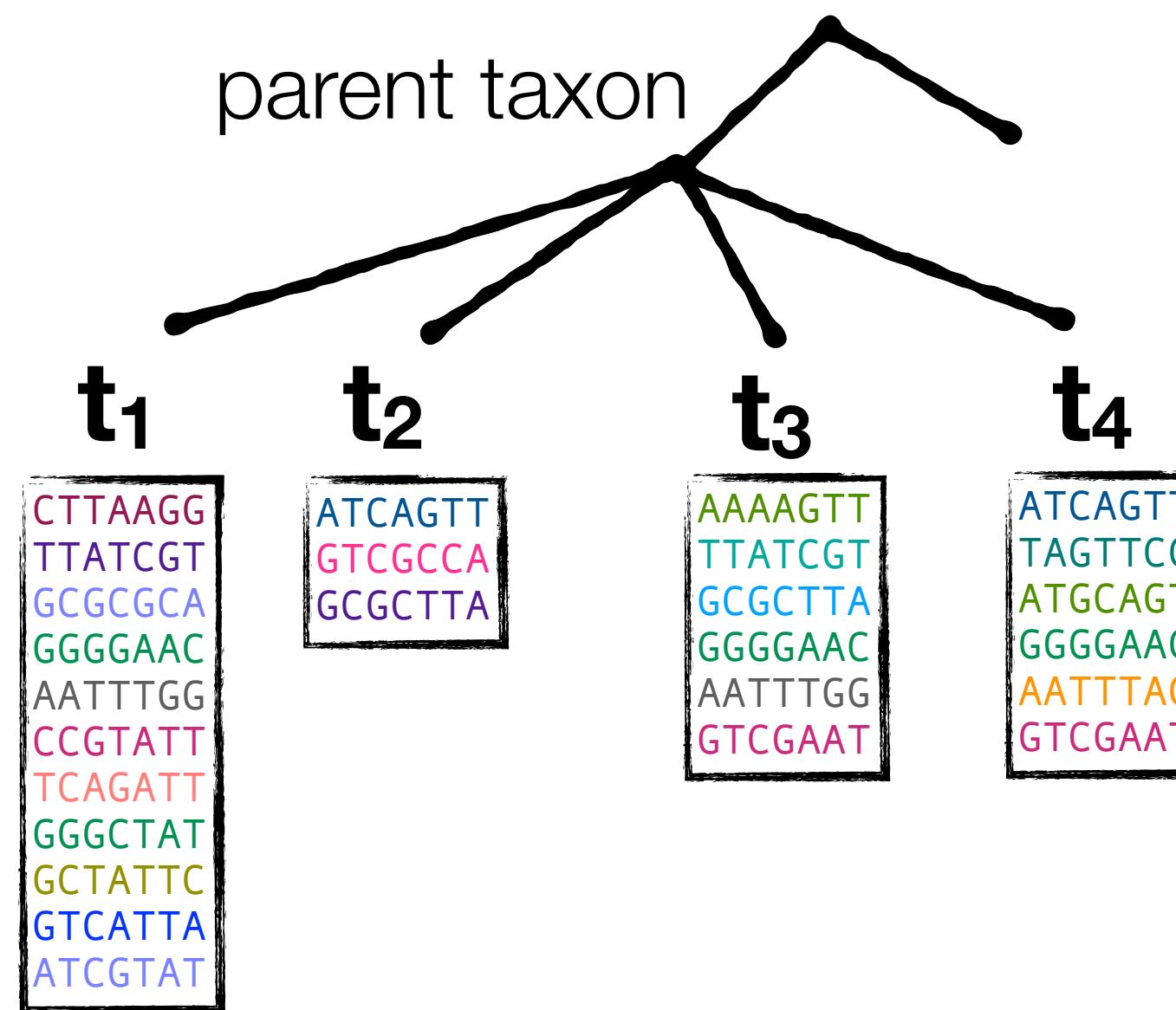


t_1 : Afford to remove more!

t_2 : Needs to be prioritized!

Incorporating taxon coverage in ranking

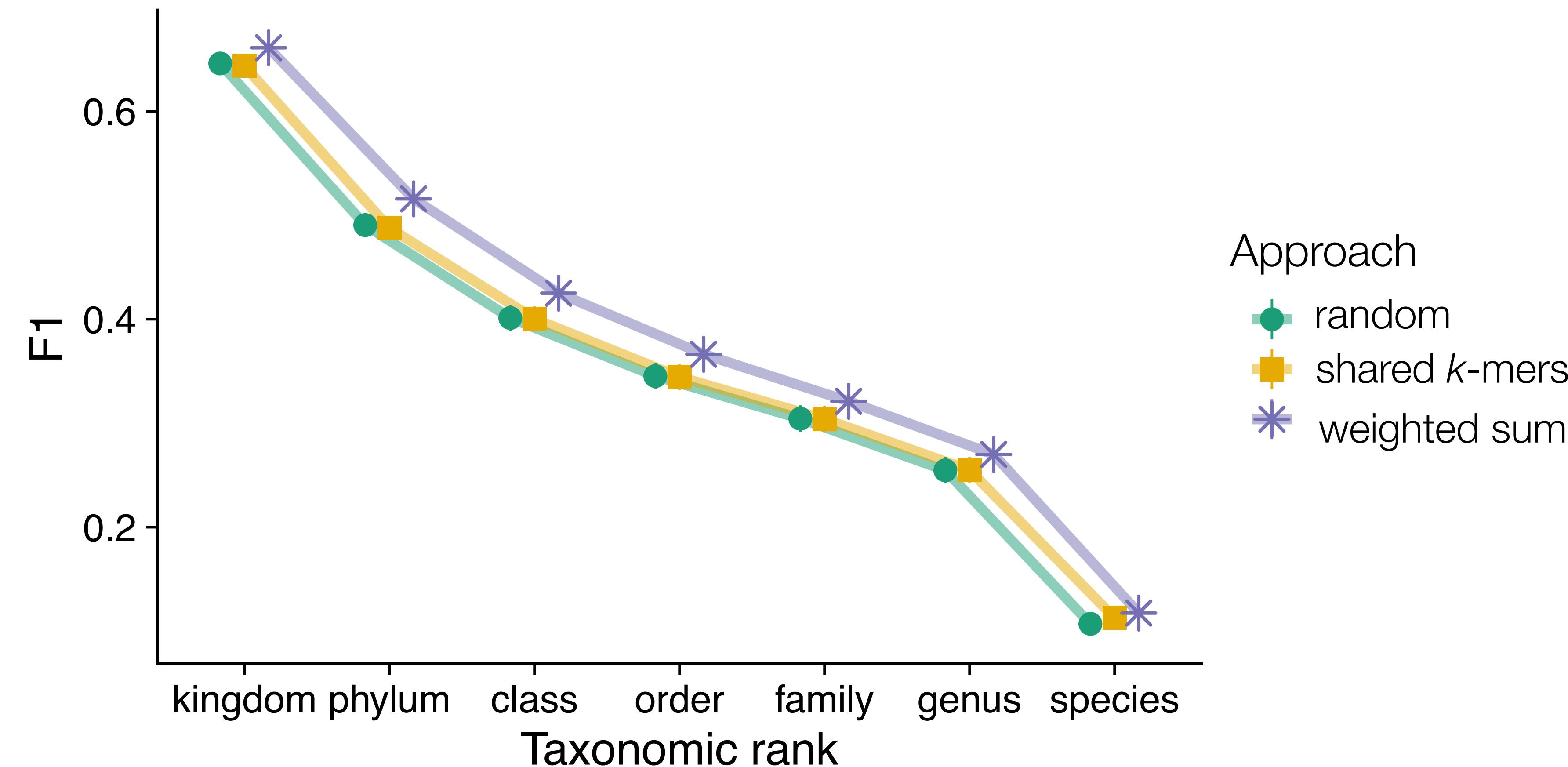
Intuition: keep shared k -mers but ensure no group is left uncovered



Scalable heuristic: down-weight the impact of taxa that are highly covered among surviving k -mers

		# of species under t with k -mer x						
		x_1	x_2	x_3	...	$x_{ \mathcal{K} }$		
weights of taxa	t_1	0.09	4	7	0	...	3	
		0.33	0	0	2	...	0	
•		0.17	0	0	1	...	1	
		0.17	2	2	1	...	0	
Score:		0.7	0.97	1	...	0.44		

Neither discriminative nor shared k-mers improve the baseline

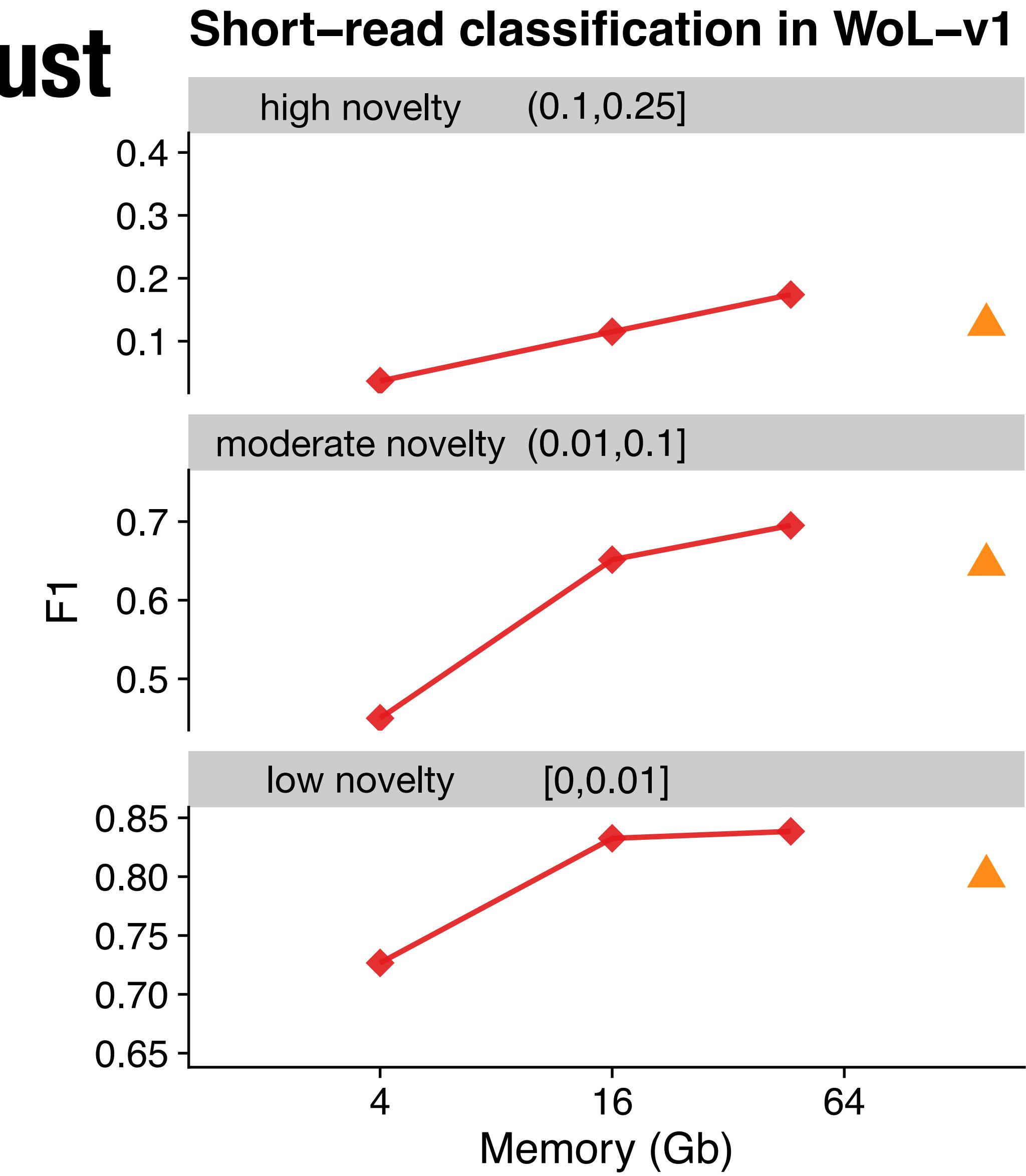


(empirical analysis using 3.2Gb, in WoL-v1 with 9k species, 10k genomes)

- **KRANK** puts all these heuristics together:
 - ▶ weighted-sum ranking + adaptive size constraint
 - ▶ other minor tricks
 - ▶ highly optimized and scalable implementation

KRANK builds lightweight and robust reference libraries

- Simulated reads across different novelty levels

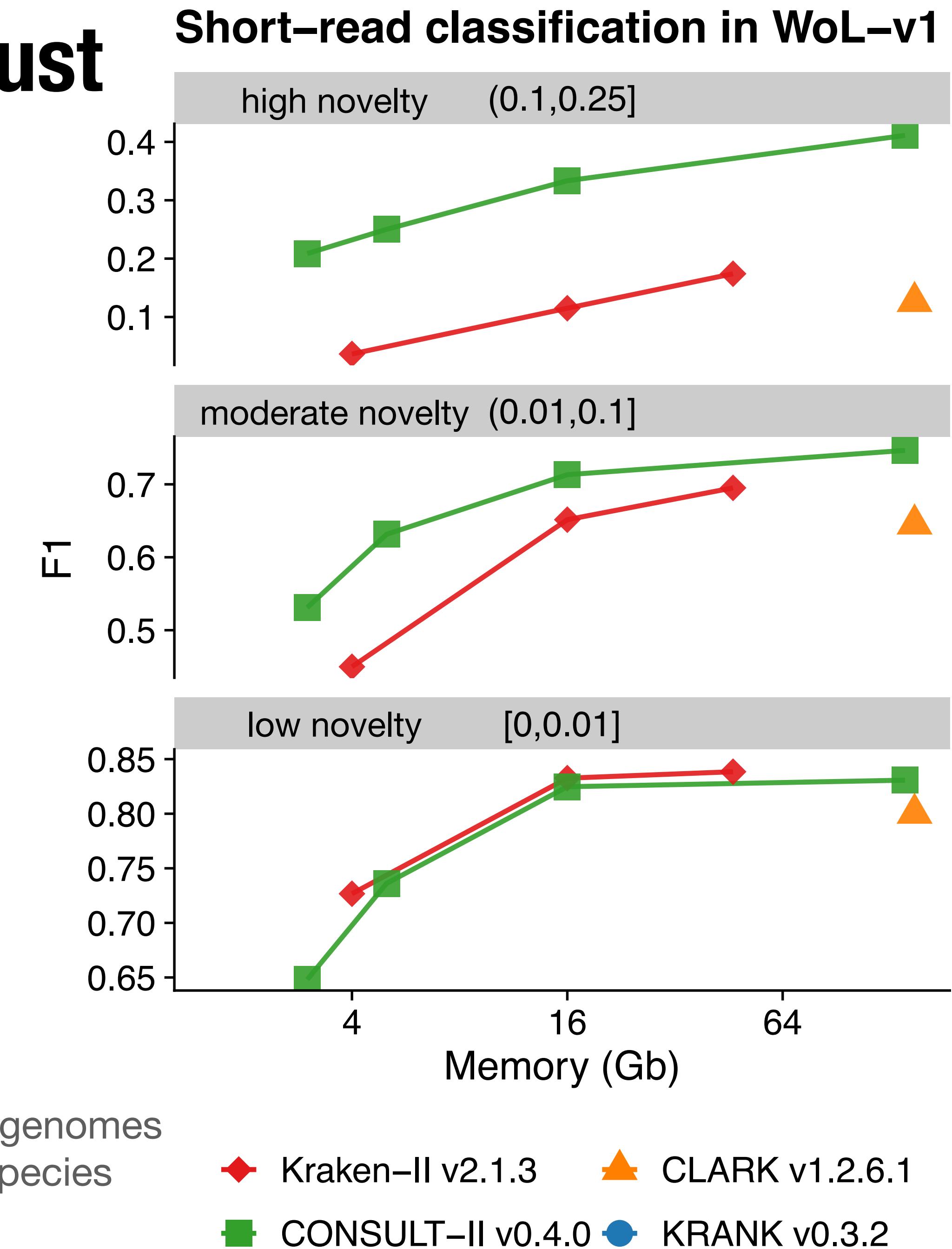


10k genomes
9k species

◆ Kraken-II v2.1.3 ▲ CLARK v1.2.6.1
■ CONSULT-II v0.4.0 ● KRANK v0.3.2

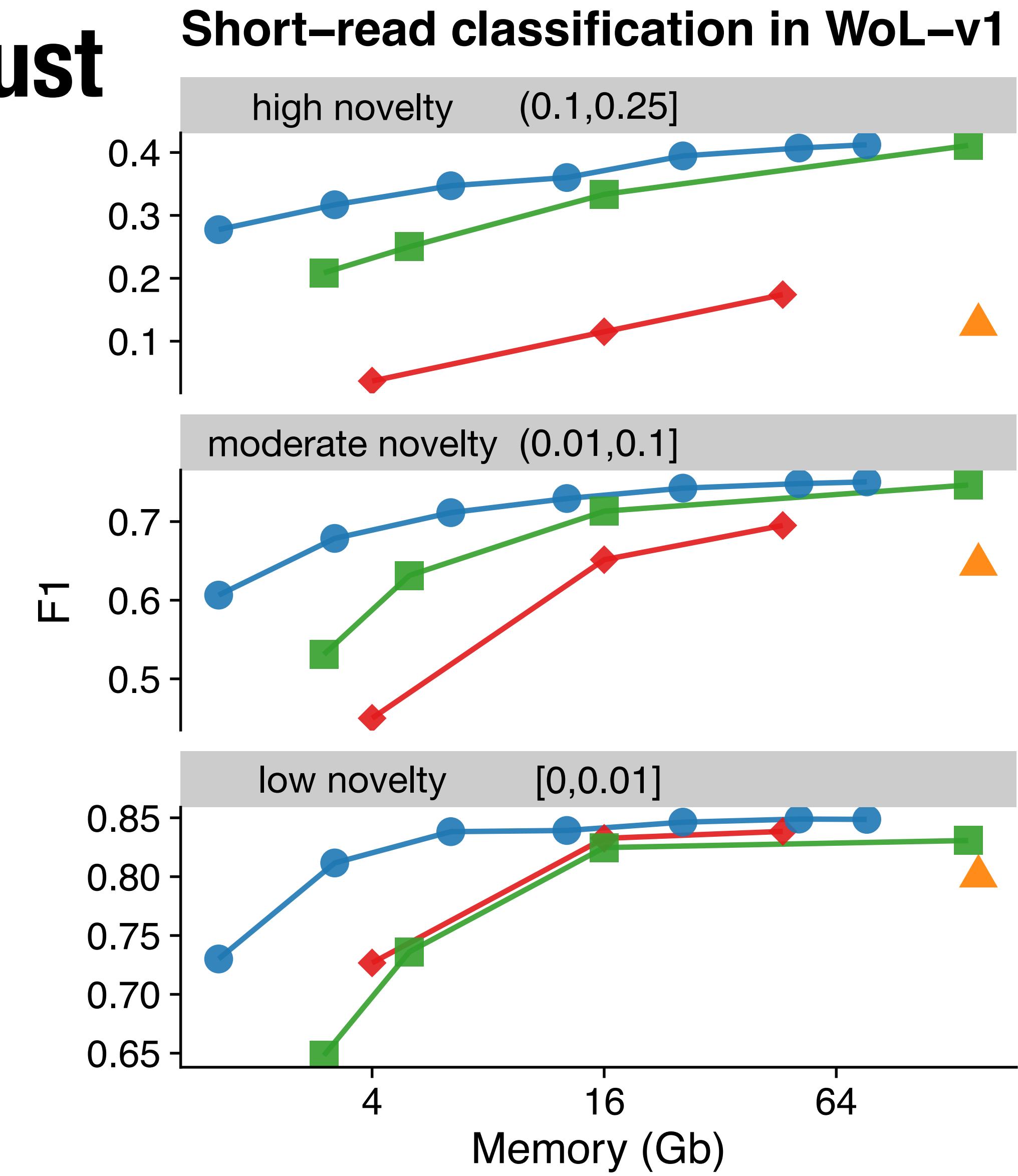
KRANK builds lightweight and robust reference libraries

- Simulated reads across different novelty levels
- Adjusting the memory usage and observing the impact on the performance



KRANK builds lightweight and robust reference libraries

- Simulated reads across different novelty levels
- Adjusting the memory usage and observing the impact on the performance
- KRANK preserves the same level of robust performance with much smaller k -mer subsets



10k genomes
9k species

◆ Kraken-II v2.1.3 ▲ CLARK v1.2.6.1
■ CONSULT-II v0.4.0 ● KRAMK v0.3.2

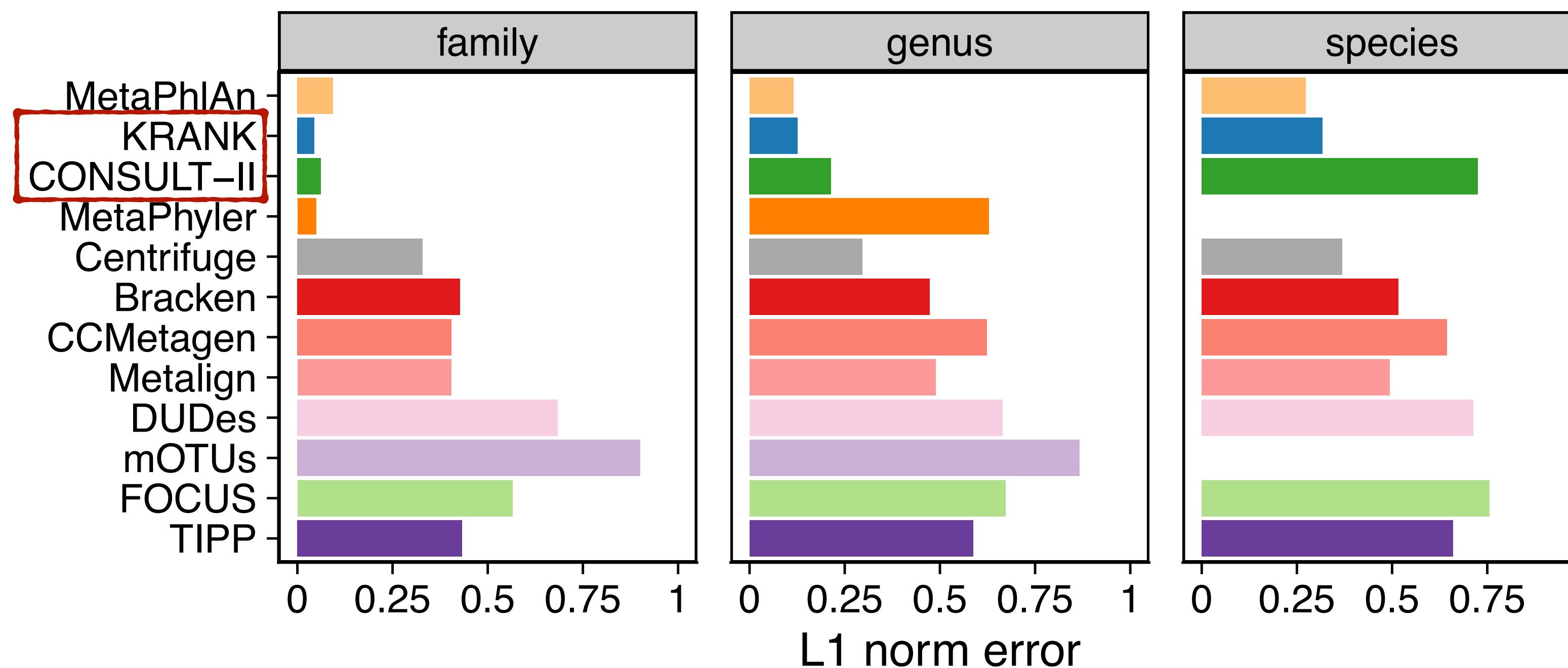
Boosting the performance in CAMI-II with a smaller subset

- Library construction: 3-hours (36 nodes × 14 cores) for RefSeq genomes (2019)

Boosting the performance in CAMI-II with a smaller subset

- Library construction: 3-hours (36 nodes \times 14 cores) for RefSeq genomes (2019)
- Consistently improves CONSULT-II across all ranks

Strain–madness dataset of CAMI-II

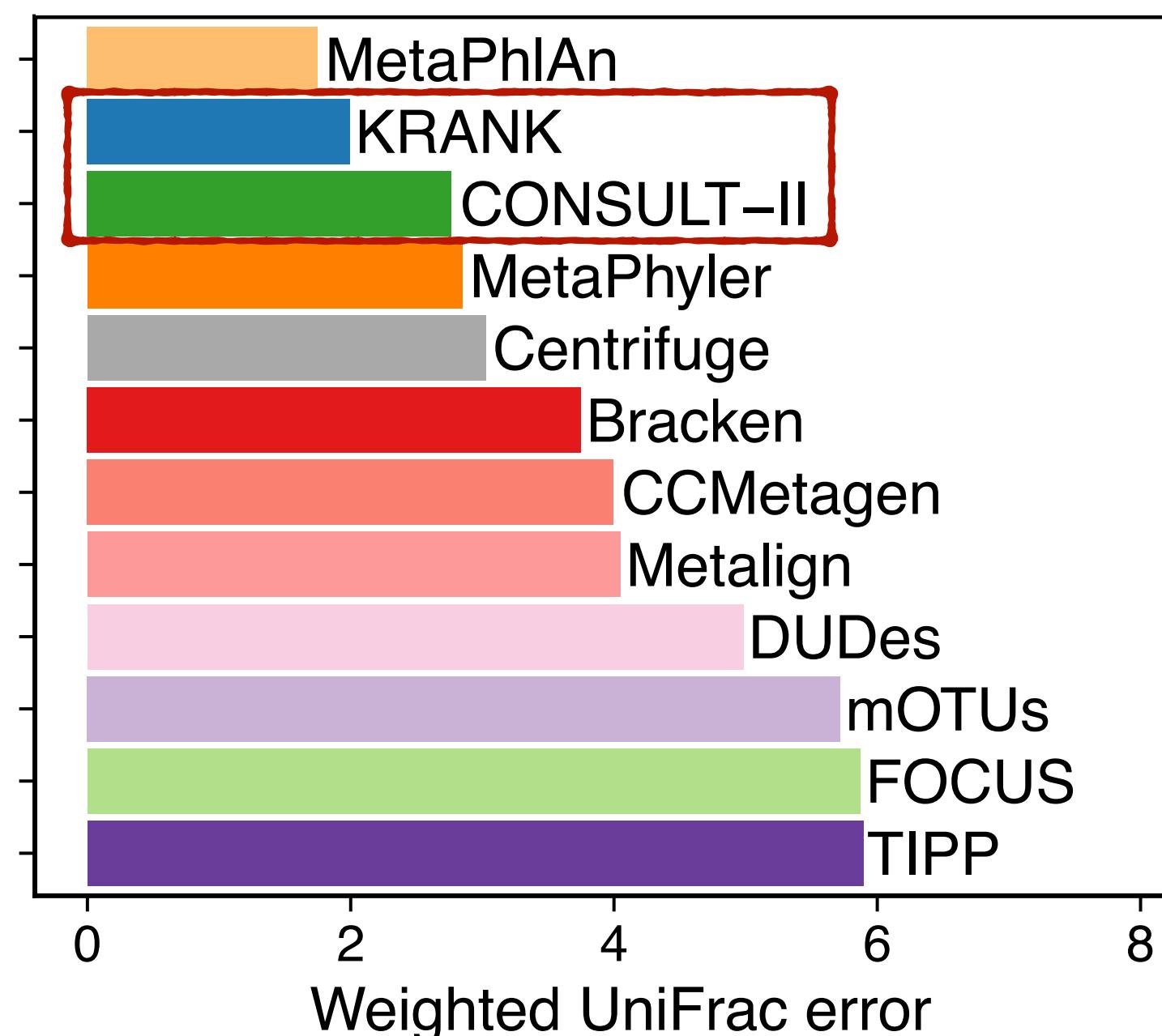


CONSULT-II: 140Gb
KRANK: 51Gb

Boosting the performance in CAMI-II with a smaller subset

- Library construction: 3-hours (36 nodes × 14 cores) for RefSeq genomes (2019)
- Consistently improves CONSULT-II across all ranks
- Second-best tool according to rank-invariant UniFrac error

Strain–madness dataset of CAMI-II



CONSULT-II: 140Gb
KRANK: 51Gb

- KRANK uses taxonomy to subsample large k -mer databases
 - ▶ based on **carefully chosen heuristics**
 - ▶ used in combination with minimizers
- Future work includes:
 - ▶ exploring **alternatives** strategy a more **principled approach**
 - better modeling of imbalance
 - using a phylogenetic tree
 - ▶ pairing KRANK with other classification methods
 - ▶ pairing with sketching algorithms

- KRANK uses taxonomy to subsample large k -mer databases
 - ▶ based on **carefully chosen heuristics**
 - ▶ used in combination with minimizers
- Future work includes:
 - ▶ exploring **alternatives** strategy a more **principled approach**
 - better modeling of imbalance
 - using a phylogenetic tree
 - ▶ pairing KRANK with other classification methods
 - ▶ pairing with sketching algorithms



Extra Slides

The case against discriminative k-mers

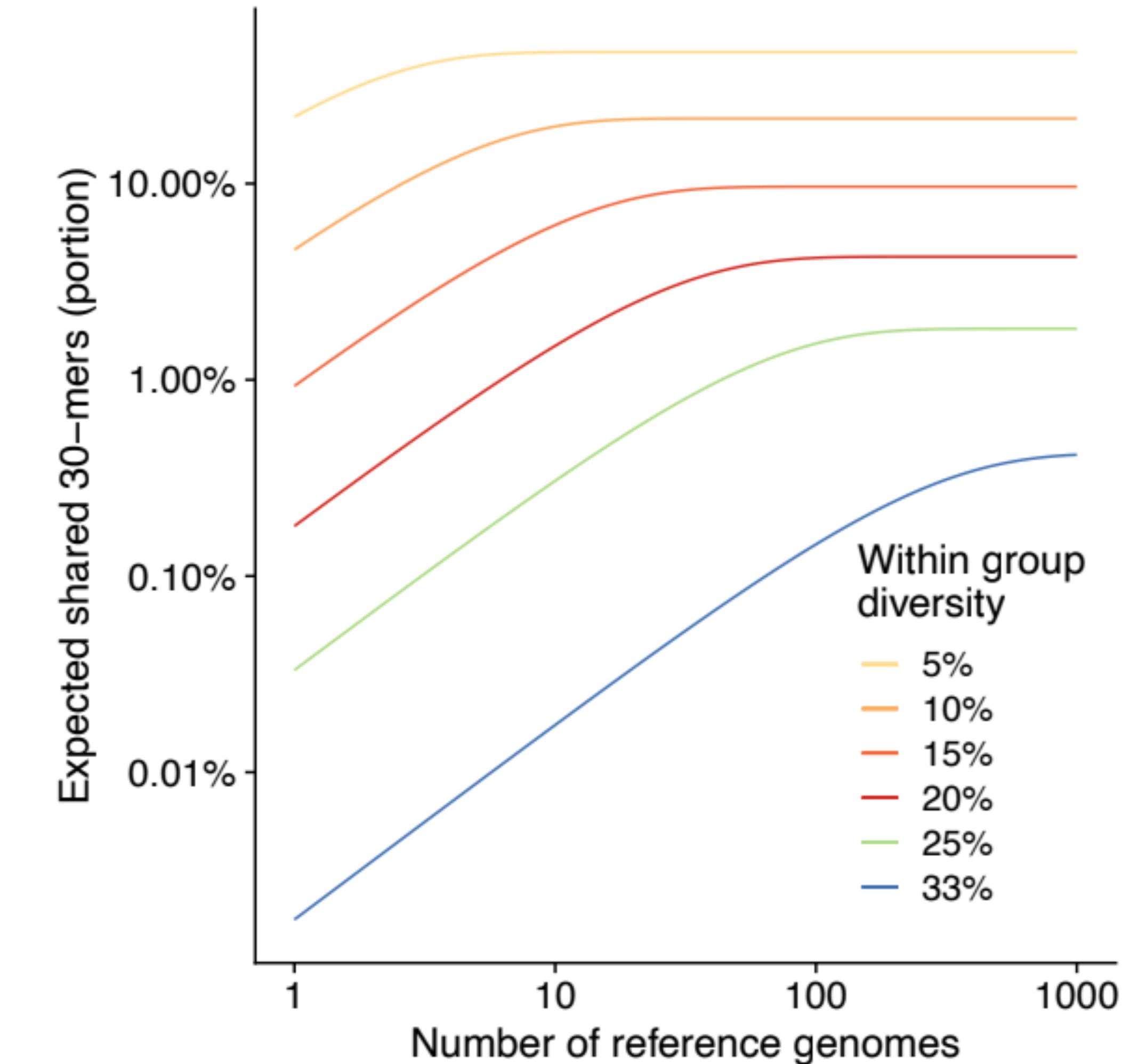
- **Problem:** considerably small portion of k-mers are shared within a group!
(it gets worse for upper ranks)
- **Claim:** Removing common k-mers will make it difficult to find matches!

Given a query genome, what is the expected portion of shared k-mers in a reference set with N genomes within $2d$ distance?

$$\frac{(1 - d)^k \left(1 - (1 - (1 - d)^k)^N \right)}{}$$

k-mer from the ancestor
stays same

k-mer from the ancestor
changes in all N



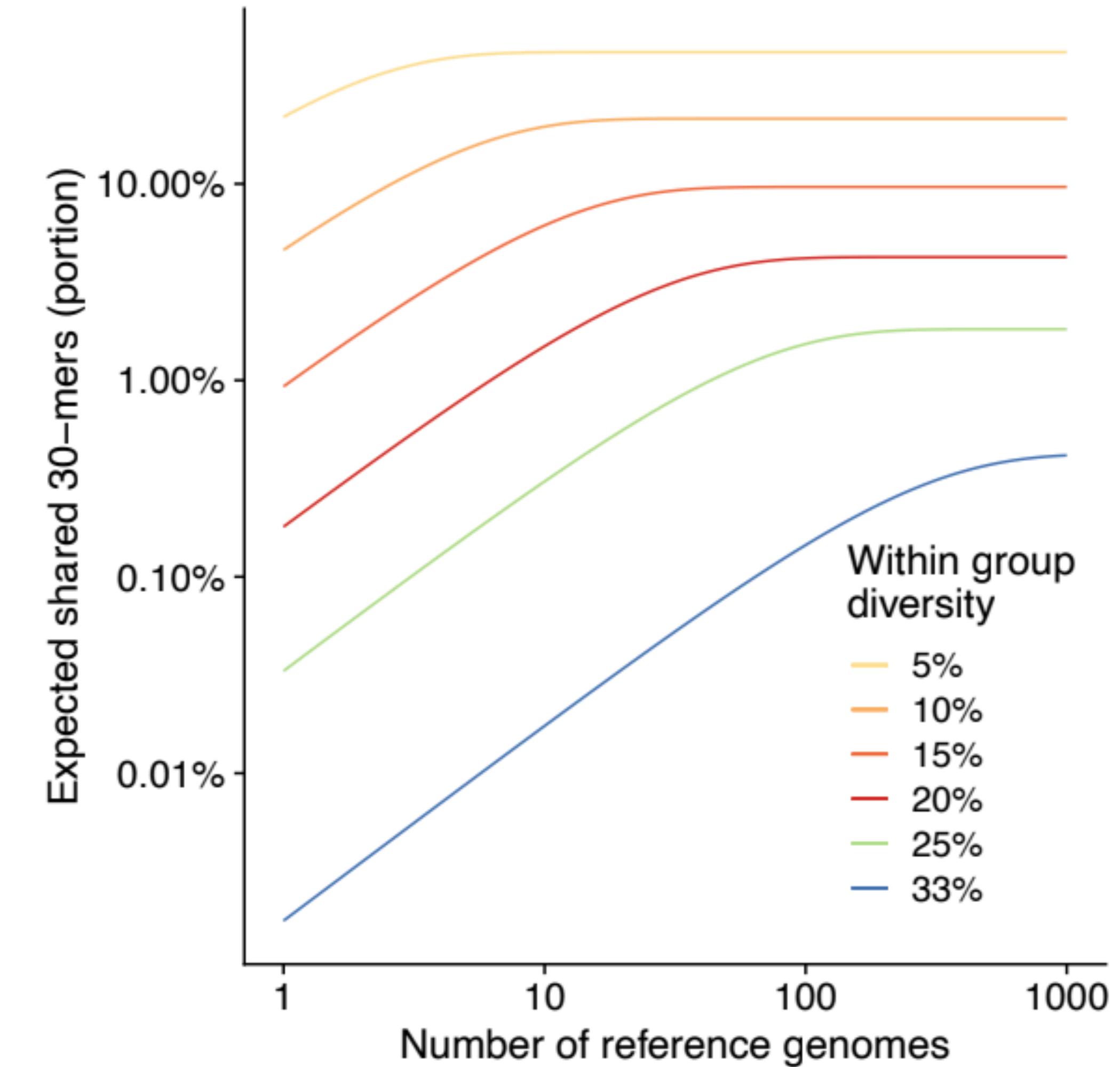
The case against discriminative k-mers

- **Problem:** considerably small portion of k-mers are shared within a group!
(it gets worse for upper ranks)
- **Claim:** Removing common k-mers will make it difficult to find matches!

Example: within $d = 20\%$ diversity (~genus)



- ▶ $N = 5$: 0.7% of query 30-mers,
- ▶ $N \rightarrow \infty$: 4.2% of query 30-mers,
will be found in at least one reference.



Bonus: compact k-mer encodings

CONSULT-II used 2 bits per letter: 64bit for 32-mers.

We only compute HD between k -mers that have the same hash value!

We do not need h positions used to compute LSH; they are already the same!



Just drop LSH positions and store the rest: $k = 32, h = 16 \rightarrow 32\text{bit}$

Improvements are pronounced at higher ranks

- KRANK 13Gb competes with CONSULT-II 144Gb.
- Novel queries were accurately classified at higher ranks.
- With little memory, KRANK+CONSULT-II is highly sensitive.

