Meta-colored compacted de Bruijn graphs

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Joint work with

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University of Maryland

The colored k-mer indexing problem

- A k-mer is a sub-string of length k of some string R.
- We are given a collection $\mathcal{R} = \{R_1, ..., R_N\}$ of reference sequences. Each R_i is a (long) sequence over the DNA alphabet {A,C,G,T}.
- Problem. We want to build an *index* for \mathcal{R} so that we can retrieve the set $Color(x) = \{i \mid x \in R_i\}$ efficiently for any k-mer x. Note that $Color(x) = \emptyset$ if $x \notin \mathcal{R}$.

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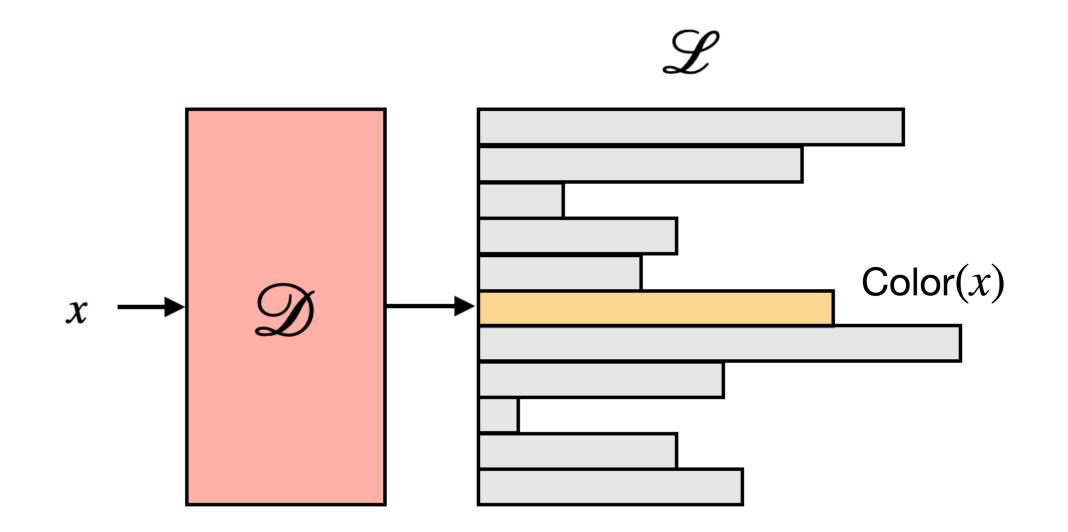
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- A lot of hype in the indexing community for the case where \mathcal{R} is a pangenome, i.e., a collection of related genomes.
- **Applications.** This problem is relevant for applications where sequences are first matched against known references (i.e., mapping/alignment algorithms): single-cell RNA-seq, metagenomics, etc.

Modular indexing layout

- All the distinct k-mers in $\mathscr{R} = \{R_1, ..., R_N\}$ are stored in the **dictionary** \mathscr{D} .
- What we want for a k-mer x is the map:

$$x \to \operatorname{Color}(x) = \{i \mid x \in R_i\}.$$

The collection of all Color(x) is the **inverted index** \mathscr{L} .



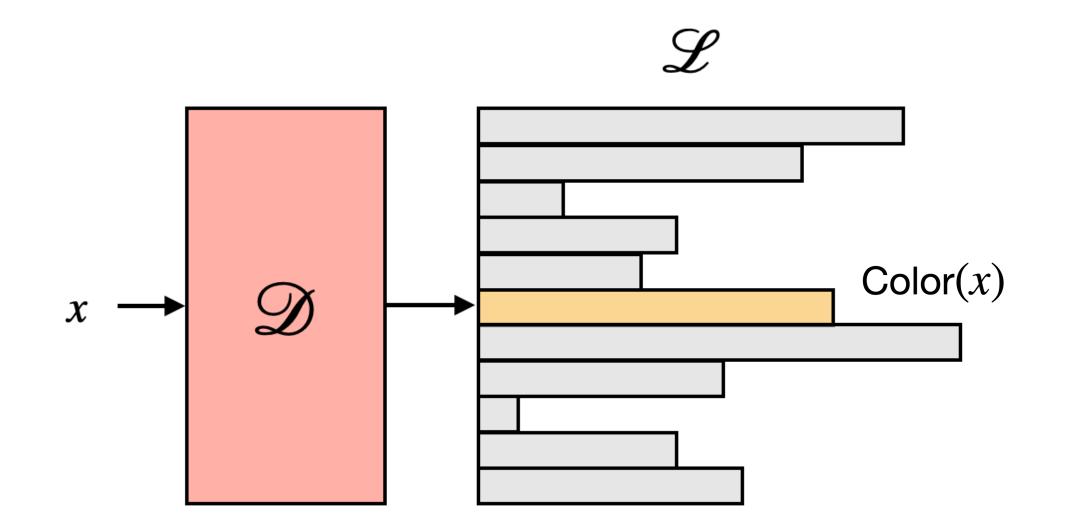
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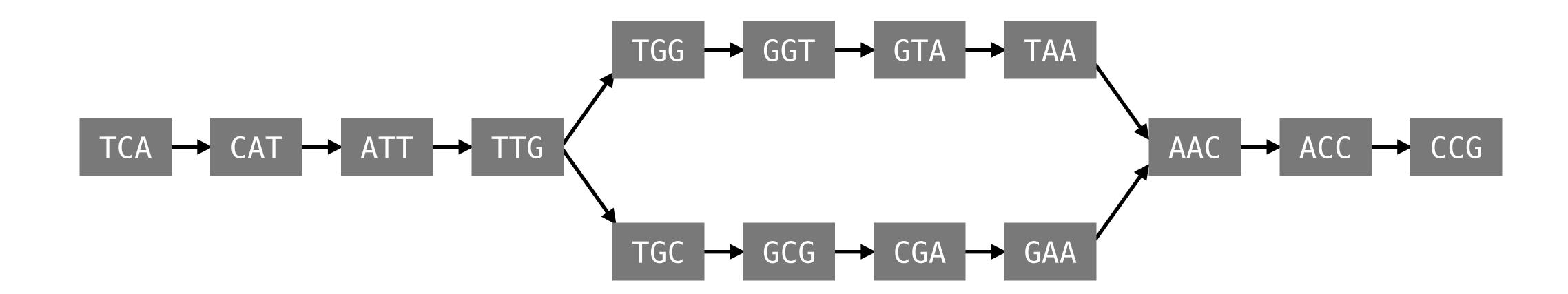


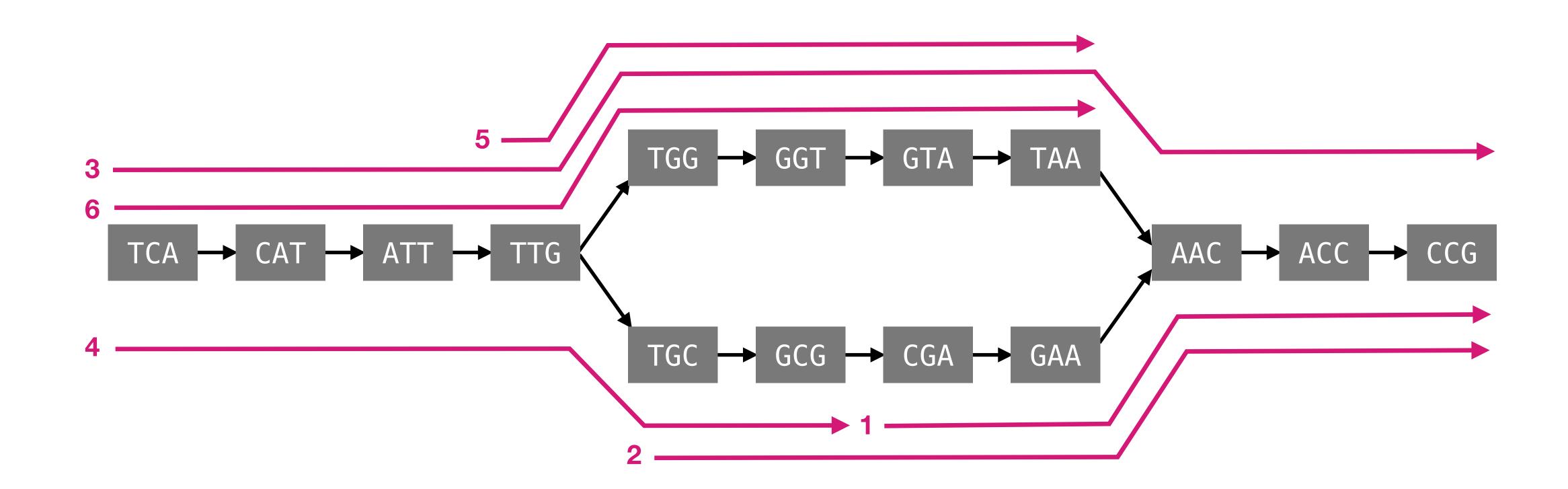
• Our problem reduces to that of representing two data structures, ${\mathscr D}$ and ${\mathscr L}$.

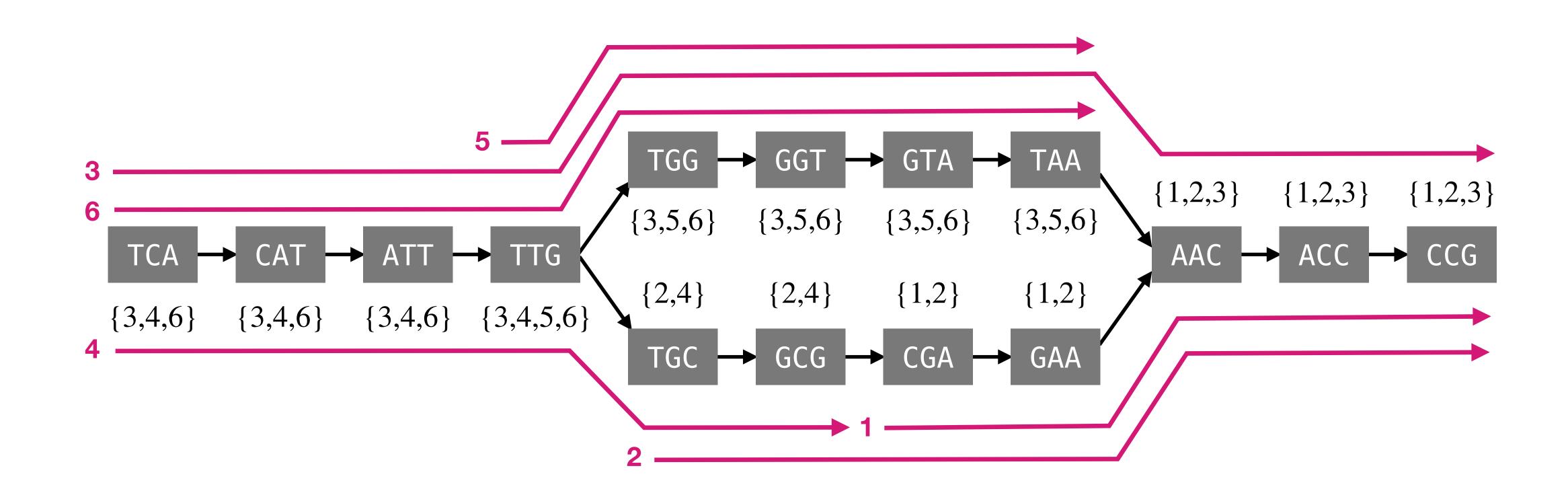


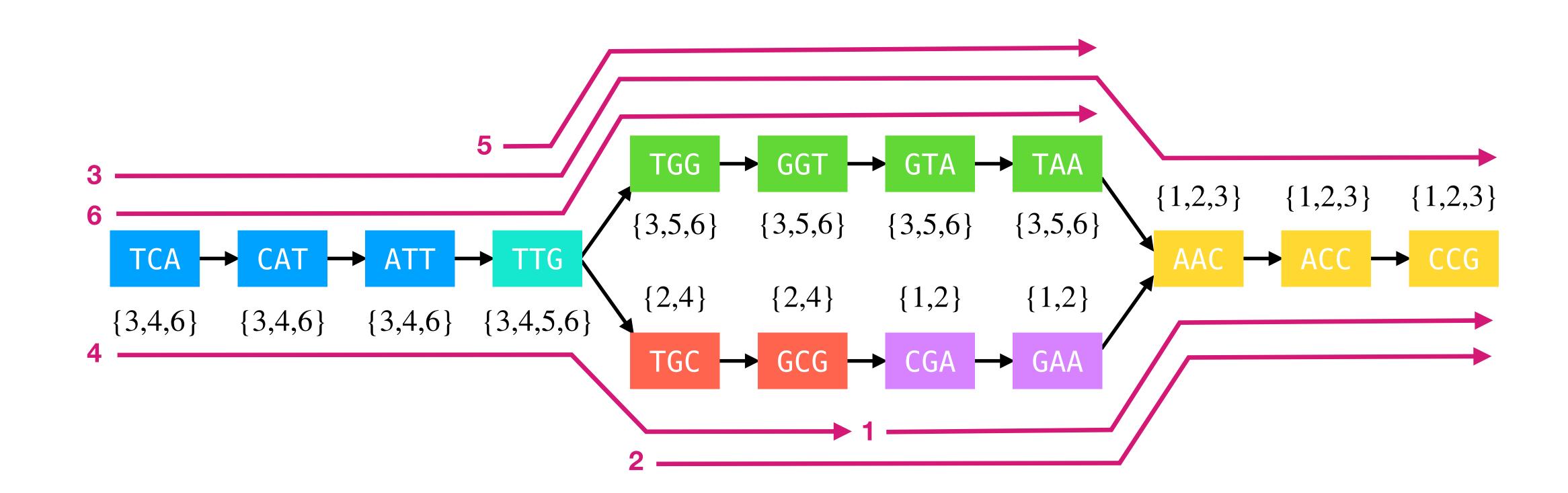
de Bruijn graphs

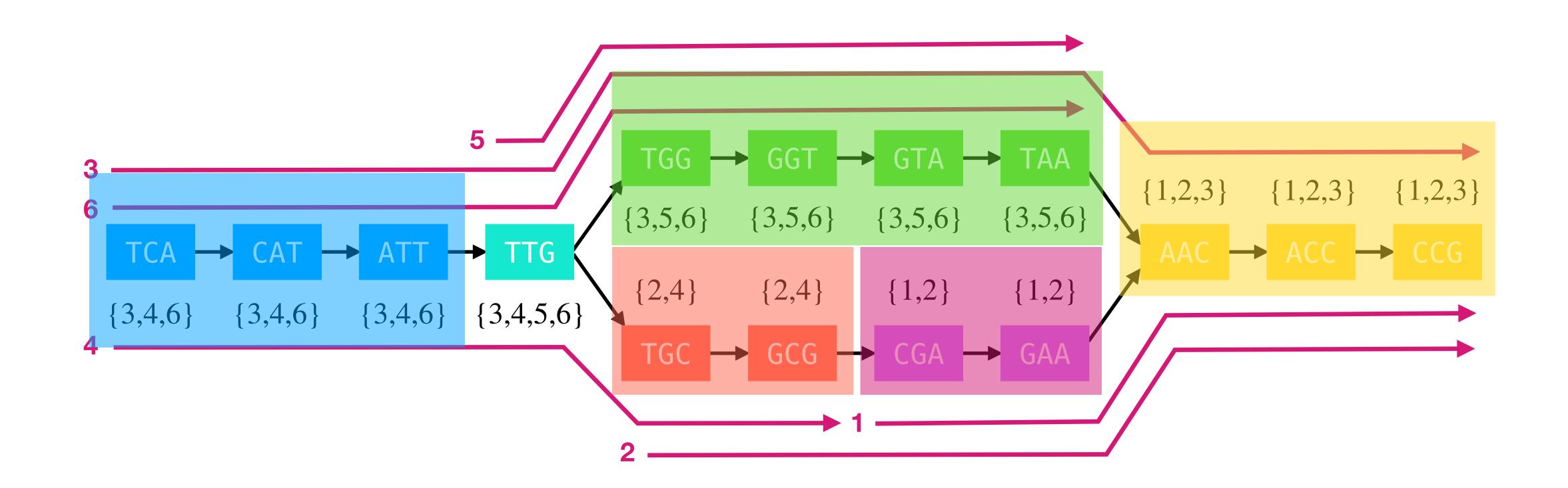
- The dictionary \mathscr{D} is a set of k-mers with (k-1)-symbol overlaps.
- One-to-one correspondence between \mathscr{D} and a *de Bruijn* graph (dBG).
- Example for k = 3.





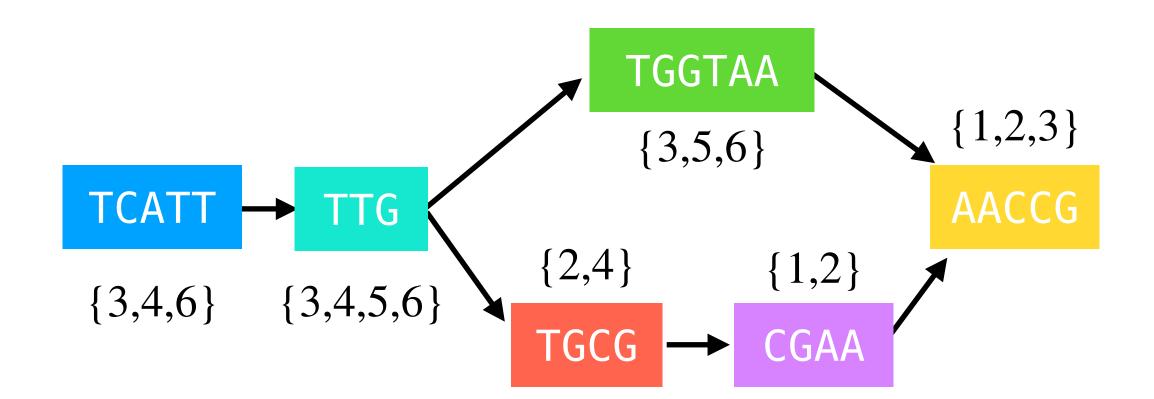






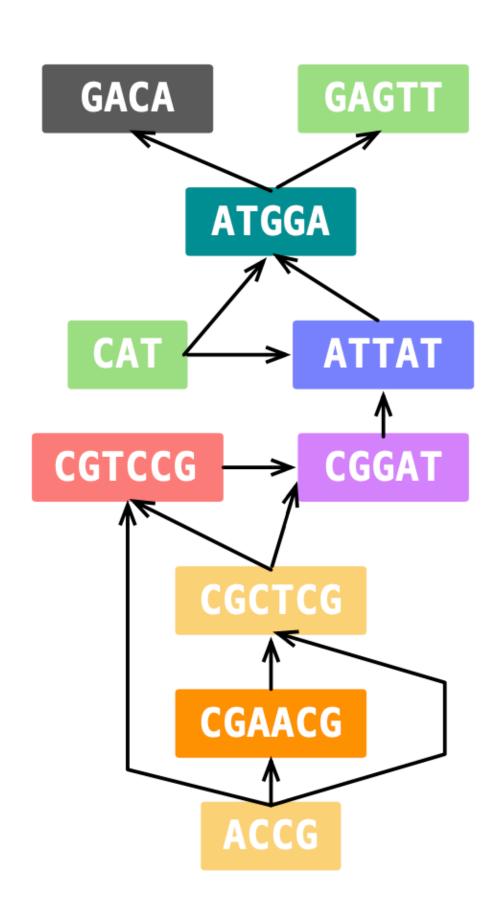
Colored compacted de Bruijn graphs

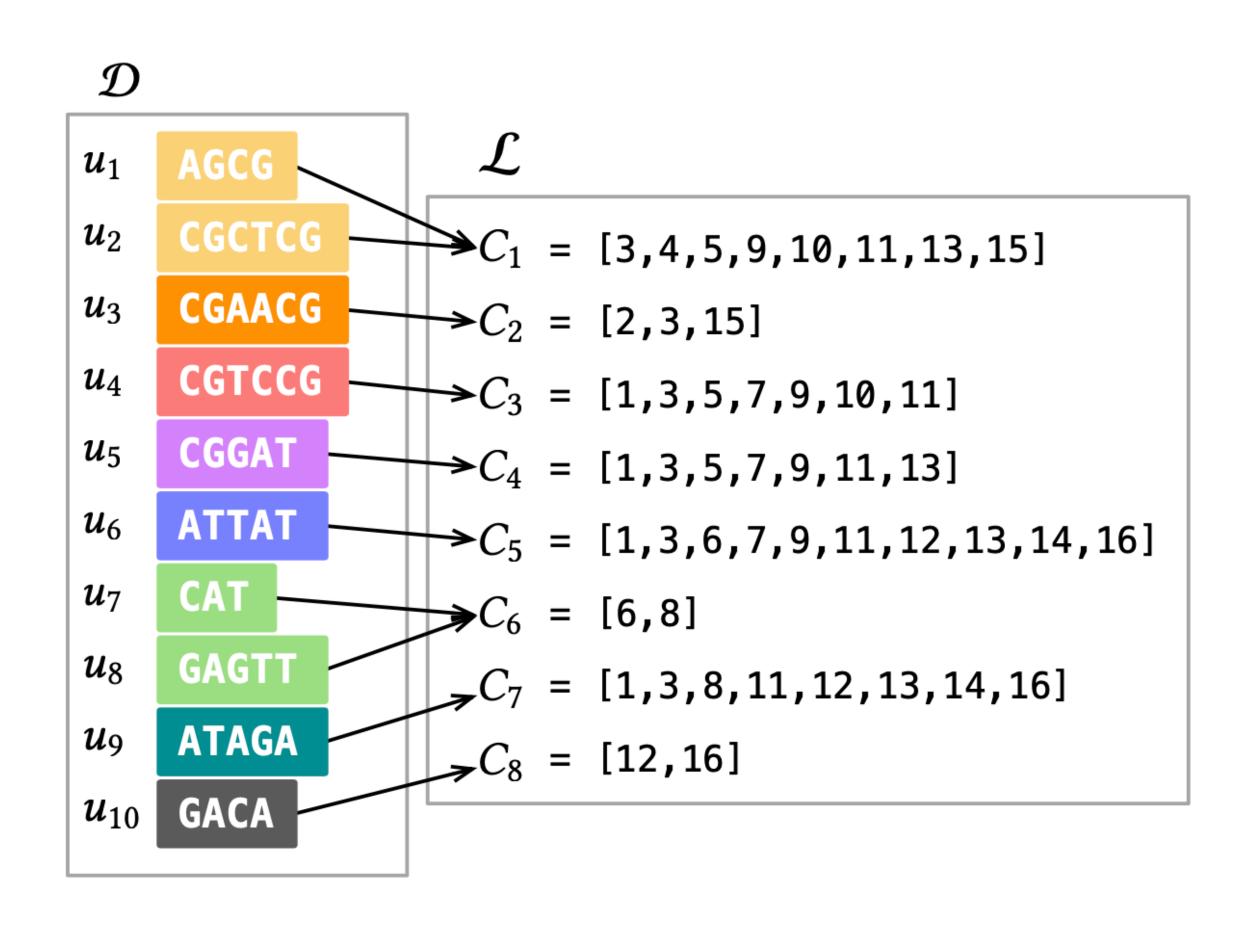
- Example for k = 3 and N = 6 references.
- Nodes having the same color along non-branching paths are collapsed into (monochromatic) unitigs.



Colored compacted de Bruijn graphs

Another, larger, example for N = 16 references.





Properties of colored compacted dBGs

- 1. Unitigs spell references in $\mathcal{R}. \to We$ can represent the set of unitigs instead of the set of k-mers. Better space and cache locality.
- 2. **Unitigs are monochromatic.** \rightarrow We store a color set for each unitig, rather than for each k-mer. We need an efficient map from k-mers to unitigs.
- 3. **Unitigs co-occur.** → Distinct unitigs often have the same color, i.e., they co-occur in the same subset of references. We have way less distinct colors than unitigs. We need an efficient map from unitigs to colors.

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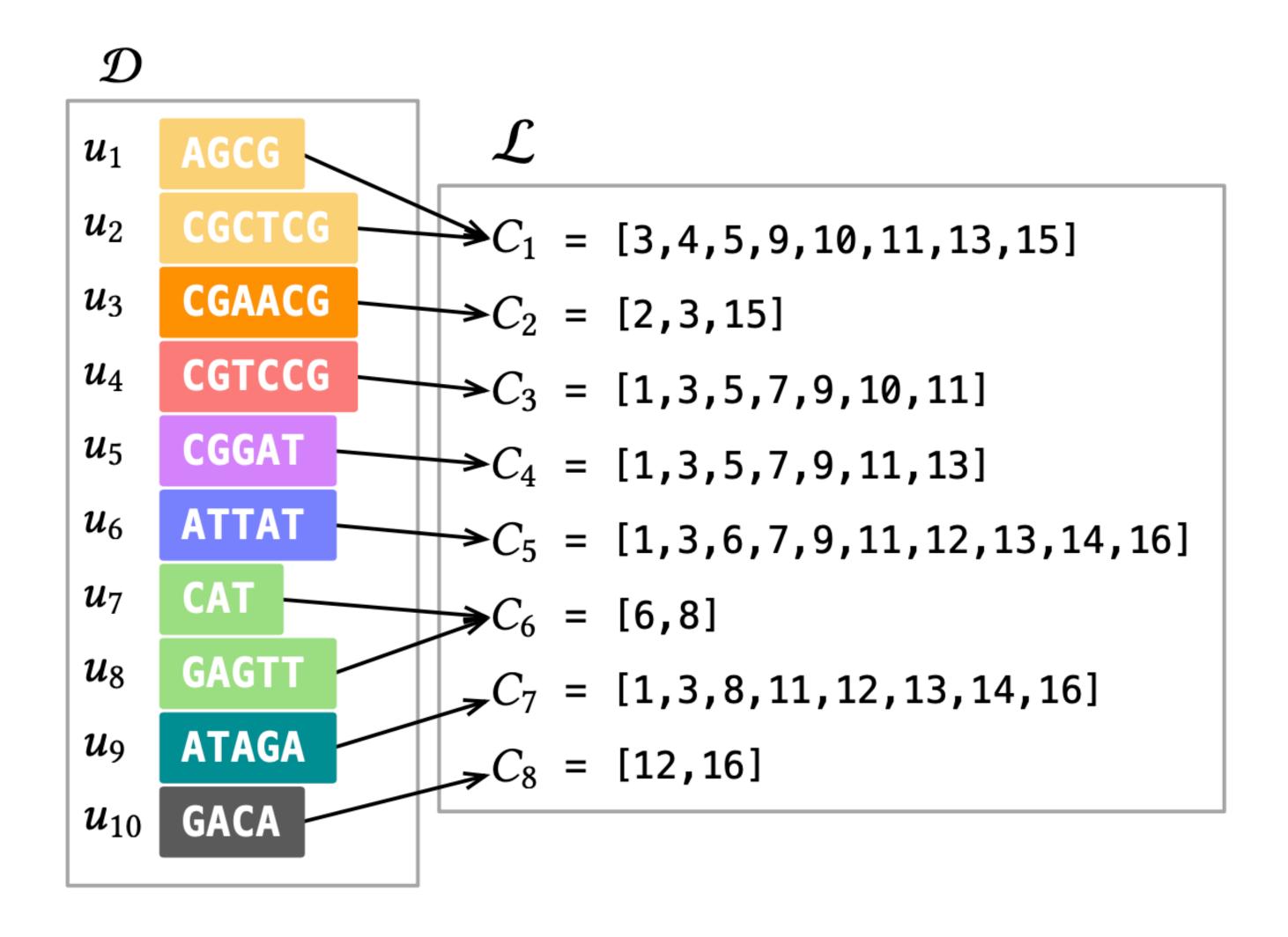
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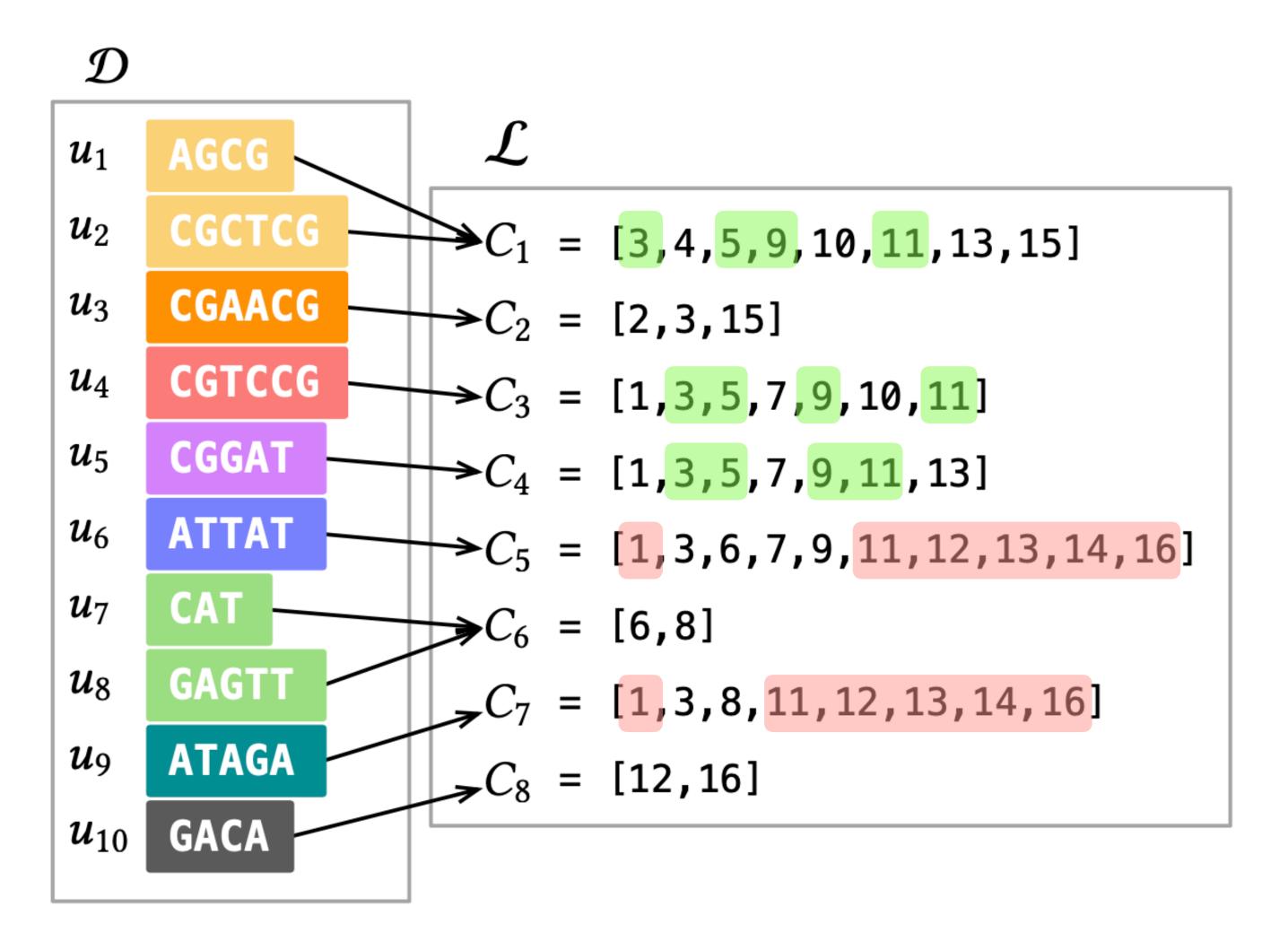
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4. Colors are similar when indexing pangenomes. → Opportunity to achieve much better compression if colors are not compressed *individually* (each set independently of the others) but *common patterns are factored out and compressed once*.

Colors are similar when indexing pangenomes

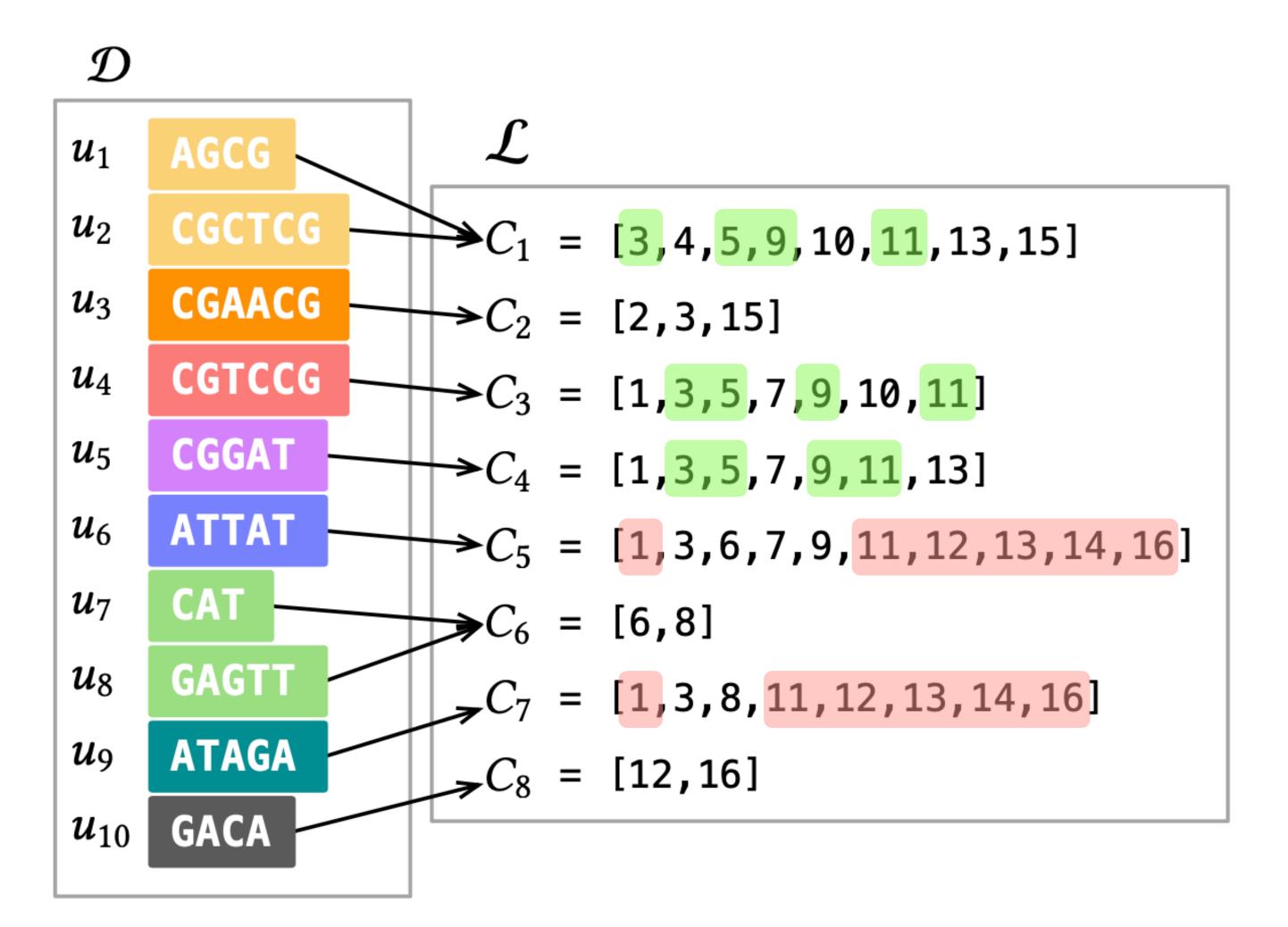


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- The pattern {3,5,9,11} is currently represented three times.
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- Q. How to factor out this redundancy?

Introducing meta and partial colors

- Recall that N is the number of references in the collection \mathcal{R} .
- Two steps:
 - 1. We determine a **partition** of $[N] = \{1,...,N\}$ so that references in the same partition are *similar*.
 - **Intuition:** Similar references induce similar colors and thus *share patterns in the colors* → the number of **distinct partial colors** in a partition is small → factor out the redundancy.
 - 2. We render each original color as a sequence of references or meta colors to those partial colors.

$$C_1 = [3,4,5,9,10,11,13,15]$$
 $C_2 = [2,3,15]$
 $C_3 = [1,3,5,7,9,10,11]$
 $C_4 = [1,3,5,7,9,11,13]$
 $C_5 = [1,3,6,7,9,11,12,13,14,16]$
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• Example for N = 16 references and 4 partitions.

 \mathcal{L}

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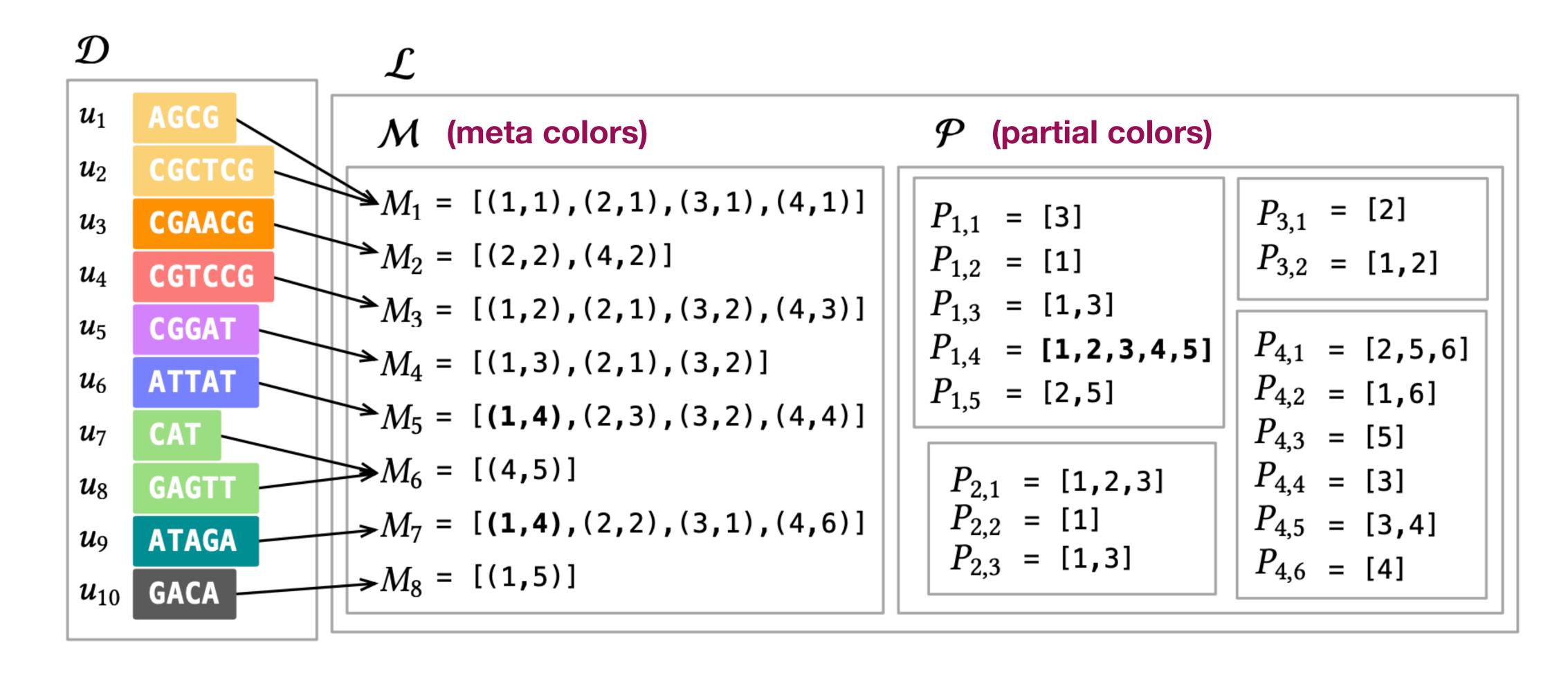
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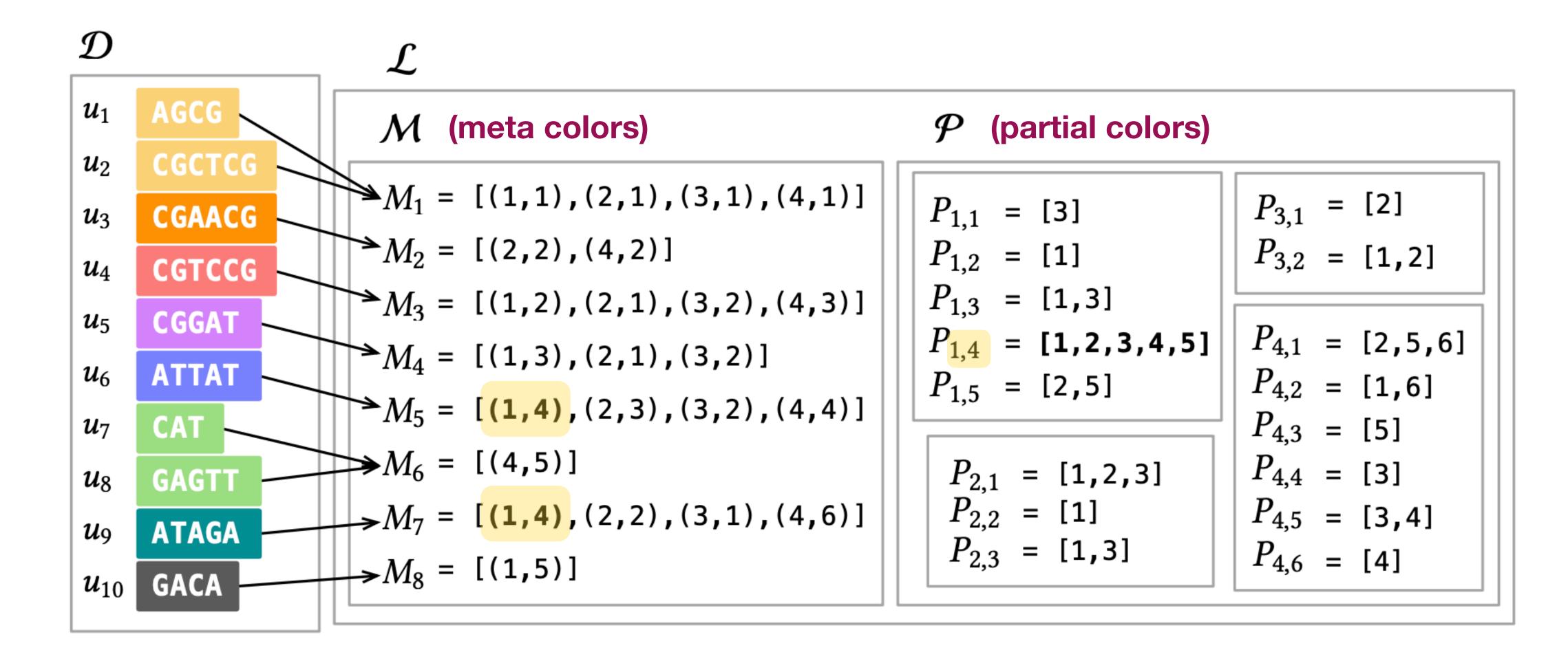
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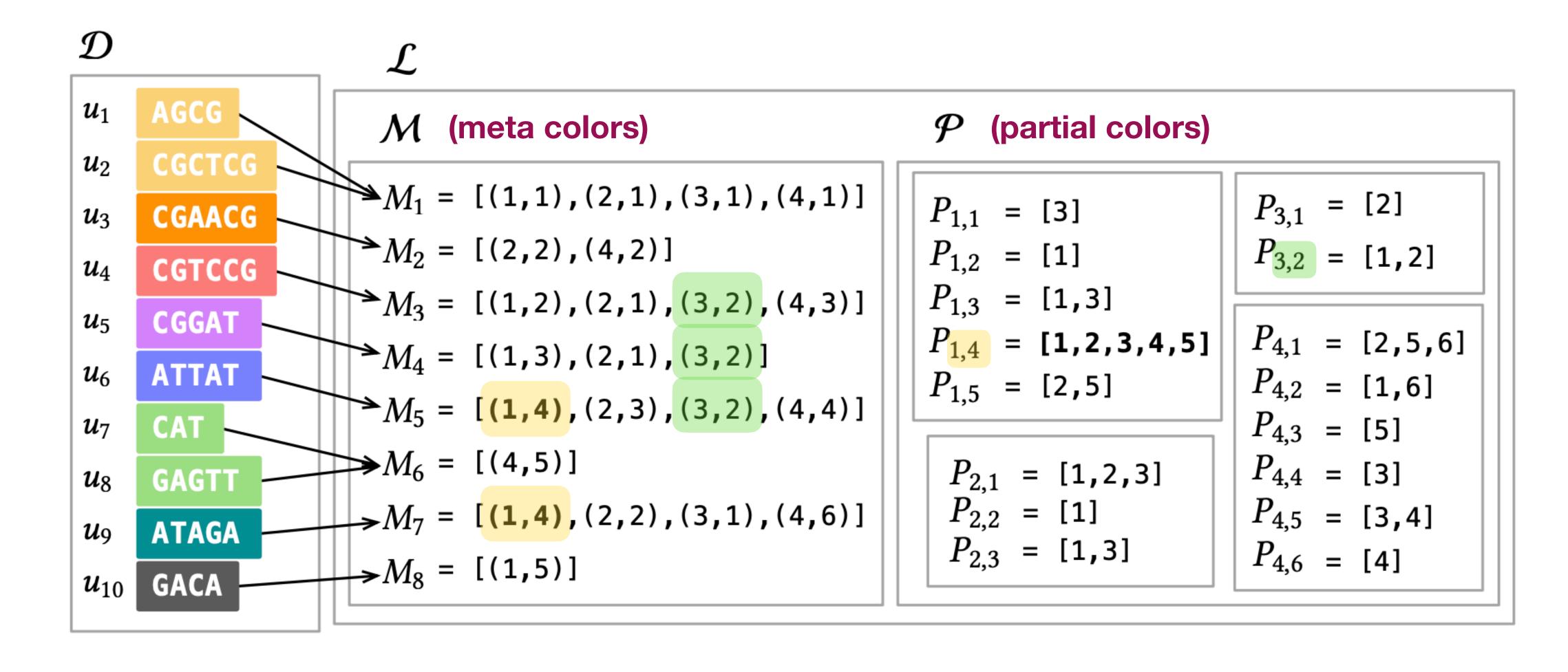
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[6]
[6,8]
[-5]
[1,2,3]
[1]
[1,3]







Results

- We applied the meta/partial color optimisation to Fulgor [Fan et al., ALMOB 2024].
- We call it the *meta-colored* compacted dBG (Mac-dBG, or Fulgor-v2).
- Code: https://github.com/jermp/fulgor.
- Results on some large pangenomes of different complexities.

	E. Coli (EC)		S.	Enteric	a (SE)		Gut bacteria (GB)
Genomes	3,682	5,000	10,000	50,000	100,000	150,000	30,691
Distinct colors $(\times 10^6)$	5.59	2.69	4.24	13.92	19.36	23.61	227.80
Integers in colors $(\times 10^9)$	5.74	5.77	15.68	133.49	303.53	490.04	10.04
k-mers in dBG ($\times 10^6$)	170.65	104.69	239.88	806.23	1,018.69	$1,\!194.44$	13,936.86
Unitigs in dBG $(\times 10^6)$	9.31	4.95	8.24	30.64	41.16	49.60	566.39

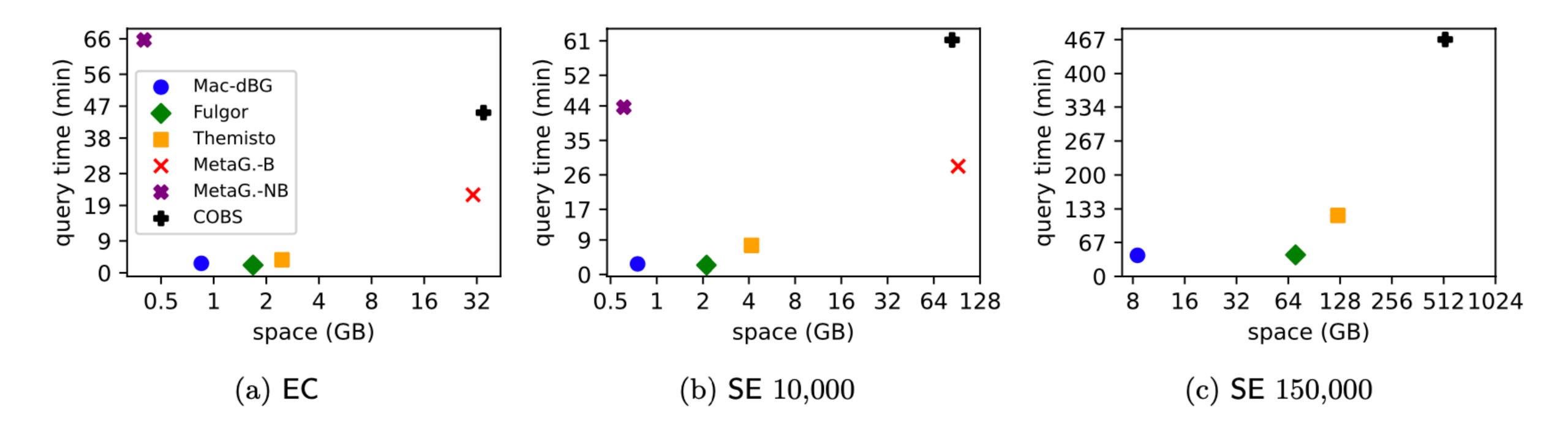
Index space in GB

	Genomes	Mac-dBG			Fulgor			Themisto			MetaGraph			COBS
	General	$\overline{\mathrm{dBG}}$	Colors	Total	$\overline{\mathrm{dBG}}$	Colors	Total	$\overline{\mathrm{dBG}}$	Colors	Total	$\overline{\mathrm{dBG}}$	Colors	Total	$\overline{\text{Total}}$
EC	3,682	0.29	0.52	0.81	0.29	1.36	1.65	0.22	1.85	2.08	0.10	0.23	0.33	7.53
	5,000	0.16	0.16	0.32	0.16	0.59	0.75	0.14	1.29	1.43	0.07	0.19	0.26	9.11
	10,000	0.35	0.33	0.68	0.35	1.66	2.01	0.32	3.50	3.81	0.13	0.38	0.51	18.68
SE	50,000	1.26	2.14	3.40	1.26	17.03	18.30	1.07	32.42	33.48	0.36	1.95	2.31	88.61
	100,000	1.72	3.83	5.55	1.72	40.70	42.44	1.35	75.94	77.28	0.45	3.50	3.95	173.58
	$150,\!000$	2.03	5.37	7.40	2.03	68.60	70.66	1.58	125.16	126.74				265.49
GB	30,691	21.31	7.85	29.16	21.31	15.45	36.85	18.33	30.88	49.21	5.23	4.77	10.00	21.23

Pseudoalignment efficiency

Genomes Rate		Mac-dBG Fulg		gor Themi		isto	sto MetaGB		MetaGNB		COBS			
			mm:ss	GB	mm:ss	GB	h:mm:ss	GB	mm:ss	GB	h:mm:ss	GB	h:mm:ss	GB
EC	3,682	98.99	2:40	0.85	2:10	1.68	0:03:40	2.46	22:00	30.44	1:05:41	0.40	0:45:11	34.93
	5,000	89.49	1:16	0.37	1:16	0.82	0:03:50	1.82	14:14	36.54	0:20:32	0.33	0:38:34	41.93
	10,000	89.71	2:45	0.75	2:26	2.11	0:07:35	4.16	28:15	92.18	0:43:40	0.61	1:01:14	84.20
SE	50,000	91.25	14:00	3.65	19:15	18.53	0:42:02	33.14		—	4:30:03	2.72	3:54:18	408.82
	100,000	91.41	26:48	6.29	27:30	42.78	1:22:00	75.93		—	9:40:06	4.82	8:07:29	522.56
	150,000	91.52	41:30	8.51	42:30	70.55	2:00:13	124.27		—		_	7:47:14	522.63
GB	30,691	92.91	01:03	28.51	01:10	30.02	0:01:20	48.47	28:55	15.86	0:22:05	9.91	0:34:45	225.57

Overall space vs. time trade-off



Conclusions

- SSHash to obtain an efficient map from k-mers to unitigs.
- Permute unitigs in color order to enable a space-efficient mapping from unitigs to colors.
- Factorize the redundancy in large color matrixes via meta/partial colors.
- Result: the meta-colored dBG embodies a superior space/time trade-off compared to the state of the art. Space improvement can be dramatic but query efficiency not harmed.
- Take-away: No reason not to use meta-colored dBGs to compress and index pangenomes!
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