https://hao-ai-lab.github.io/dsc204a-f25/

DSC 204A: Scalable Data Systems
Fall 2025

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Large Message

Communication Model: $\alpha + n\,\beta, \beta = \frac{1}{B}$

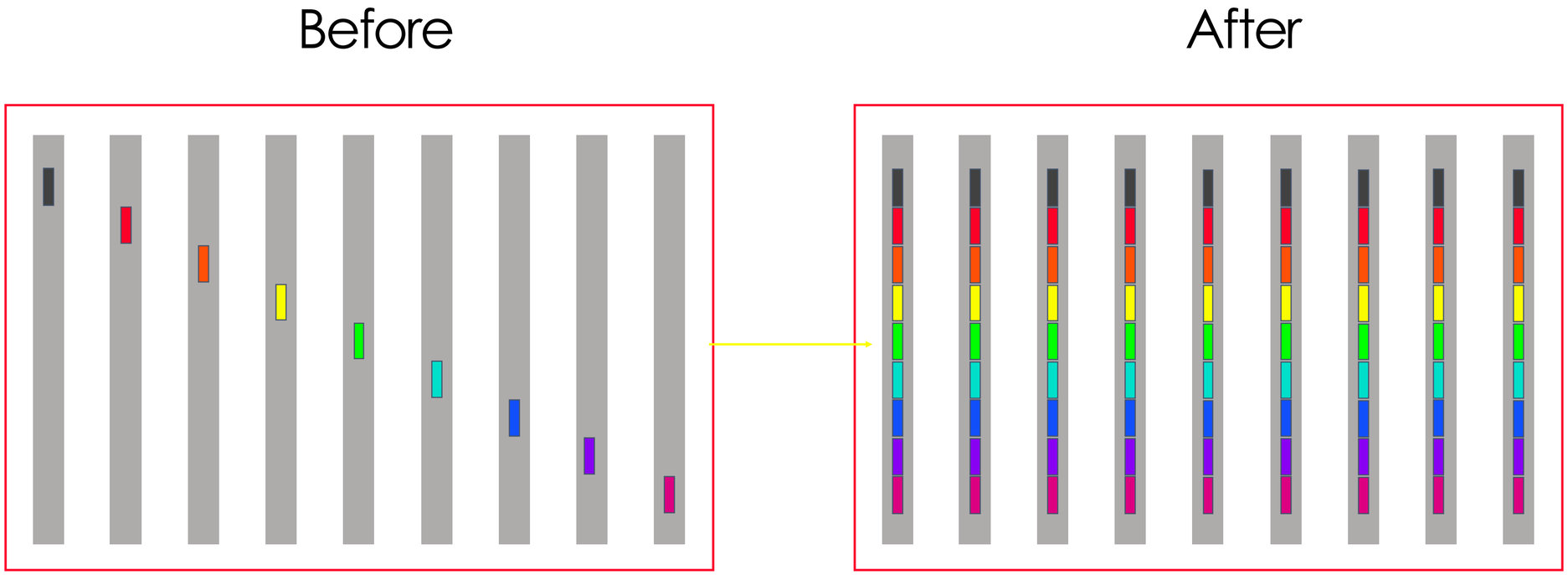
- The second term dominates – we want to minimize the second term
  - We want to utilize the bandwidth as much as possible

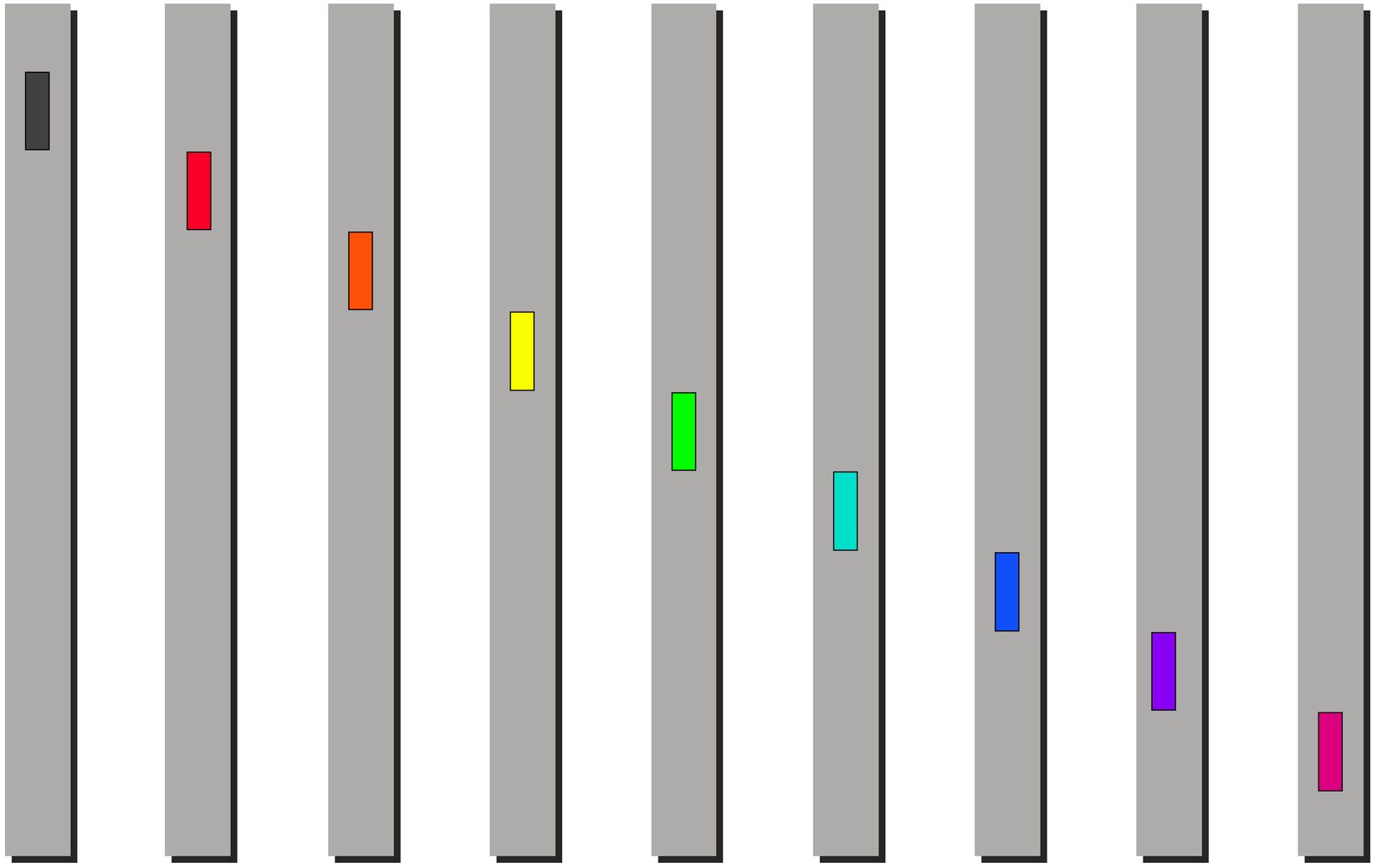
General principles

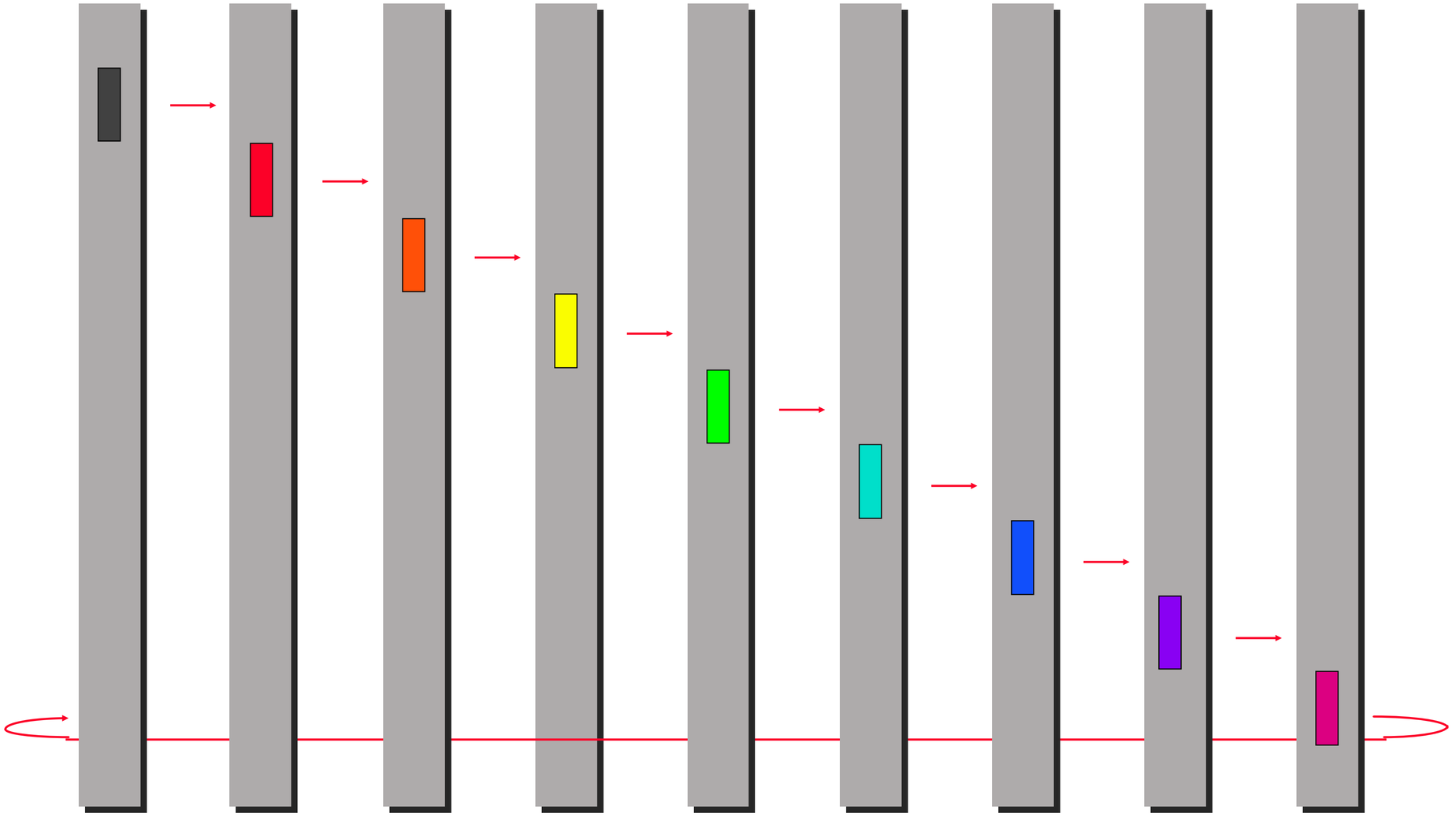
Ring algorithm has the following advantages

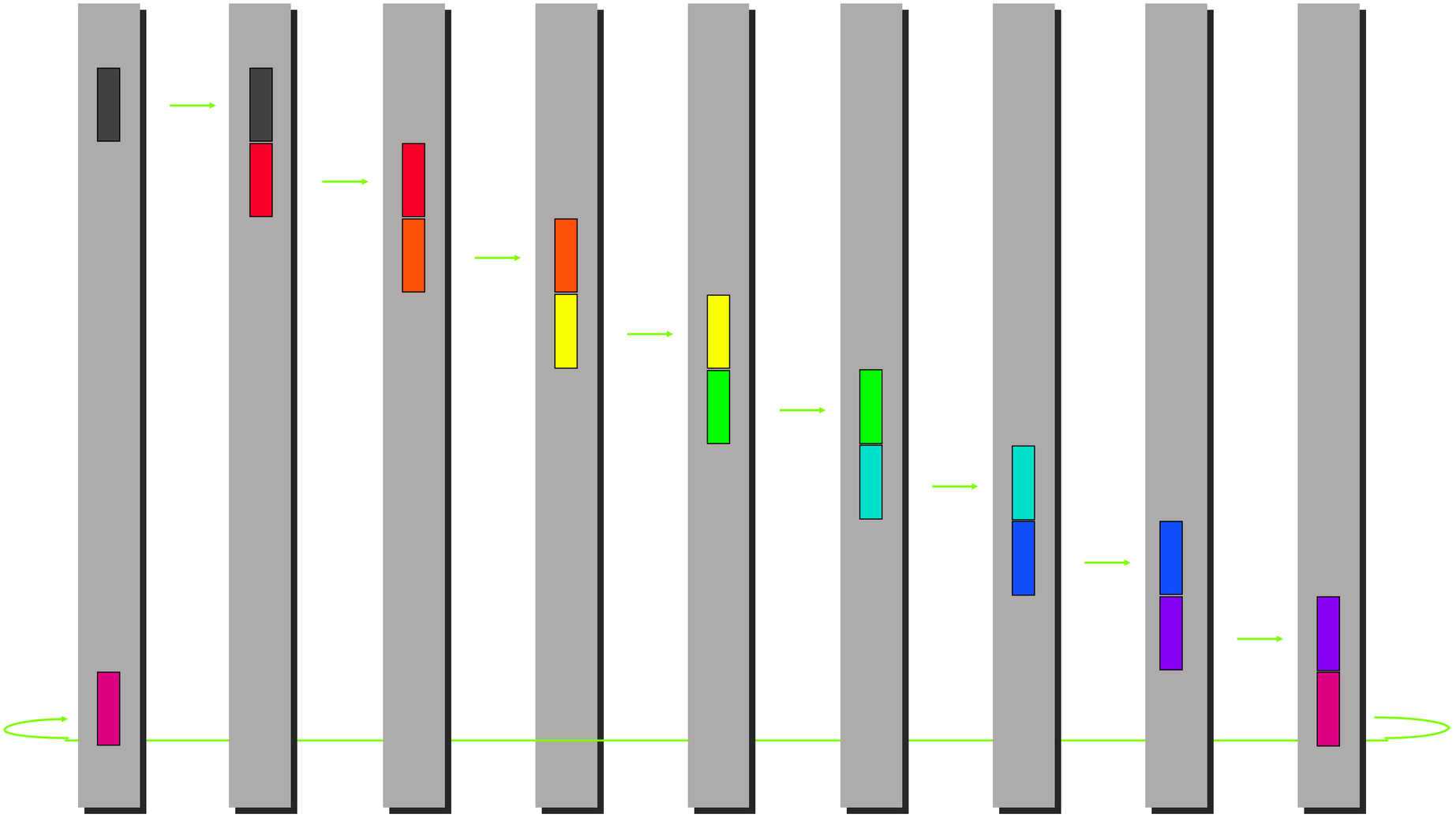
- Fully utilize the bandwidth (bandwidth optimal)
- implementation for arbitrary numbers of node

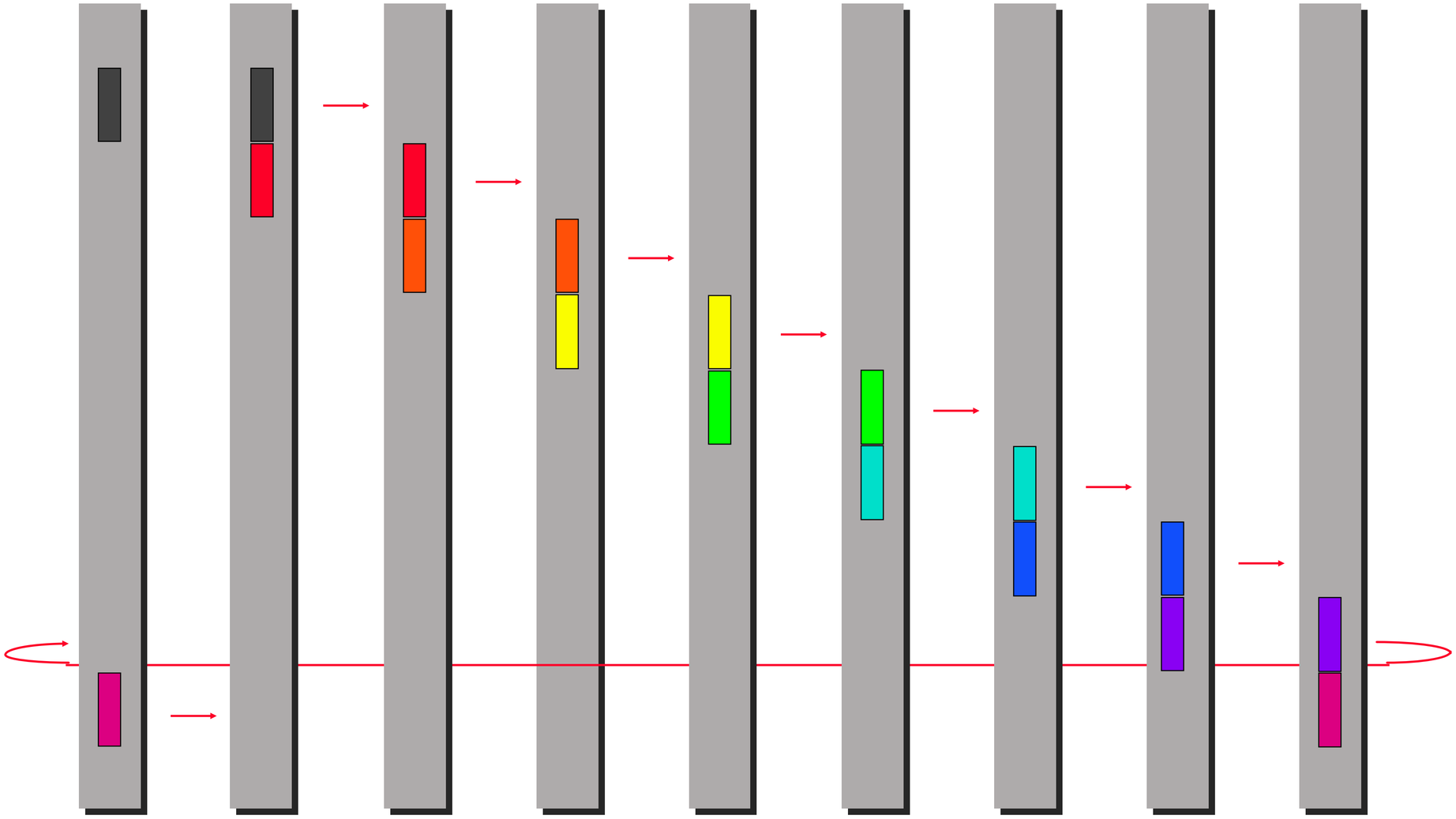
Allgather

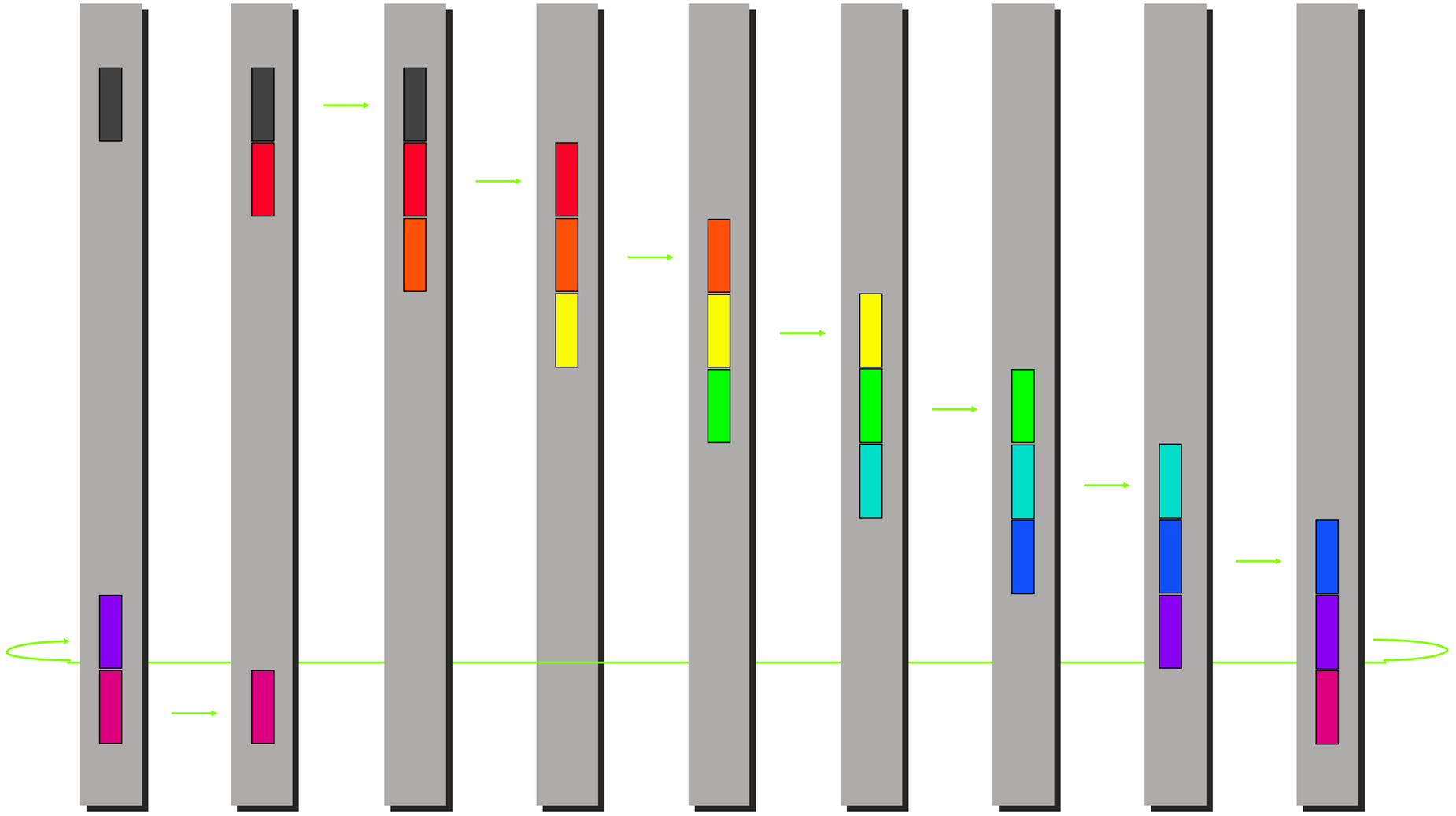


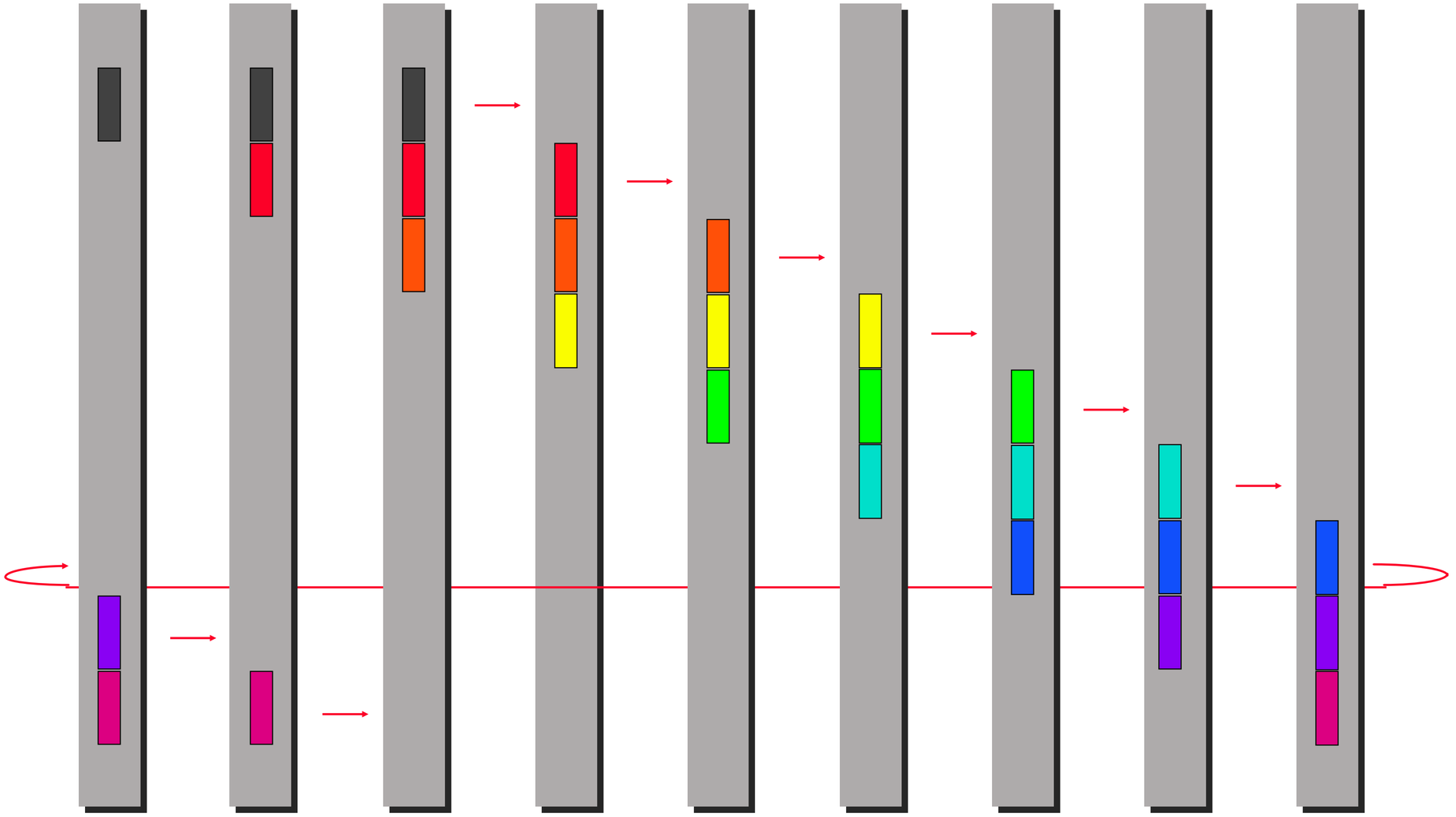


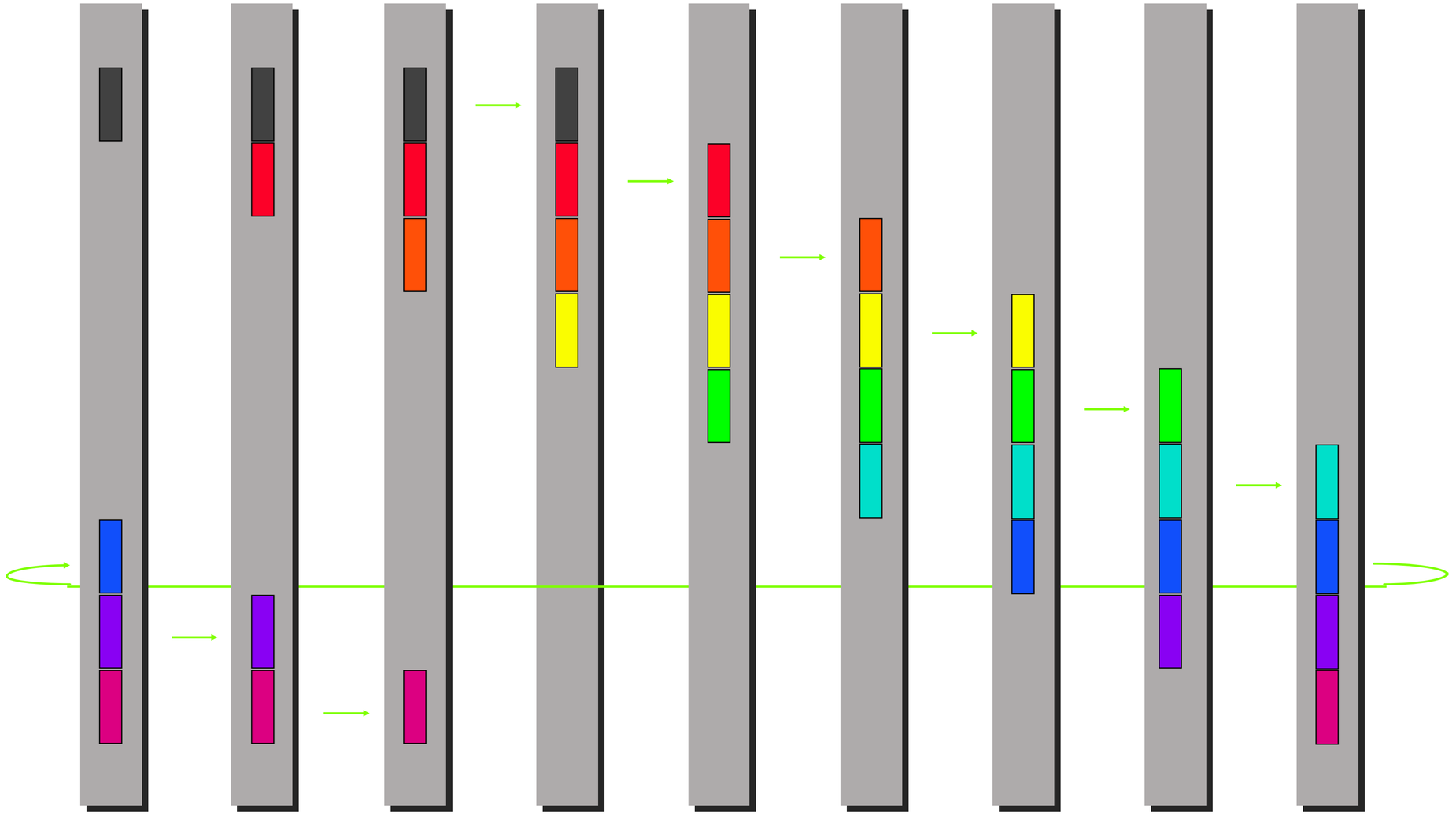


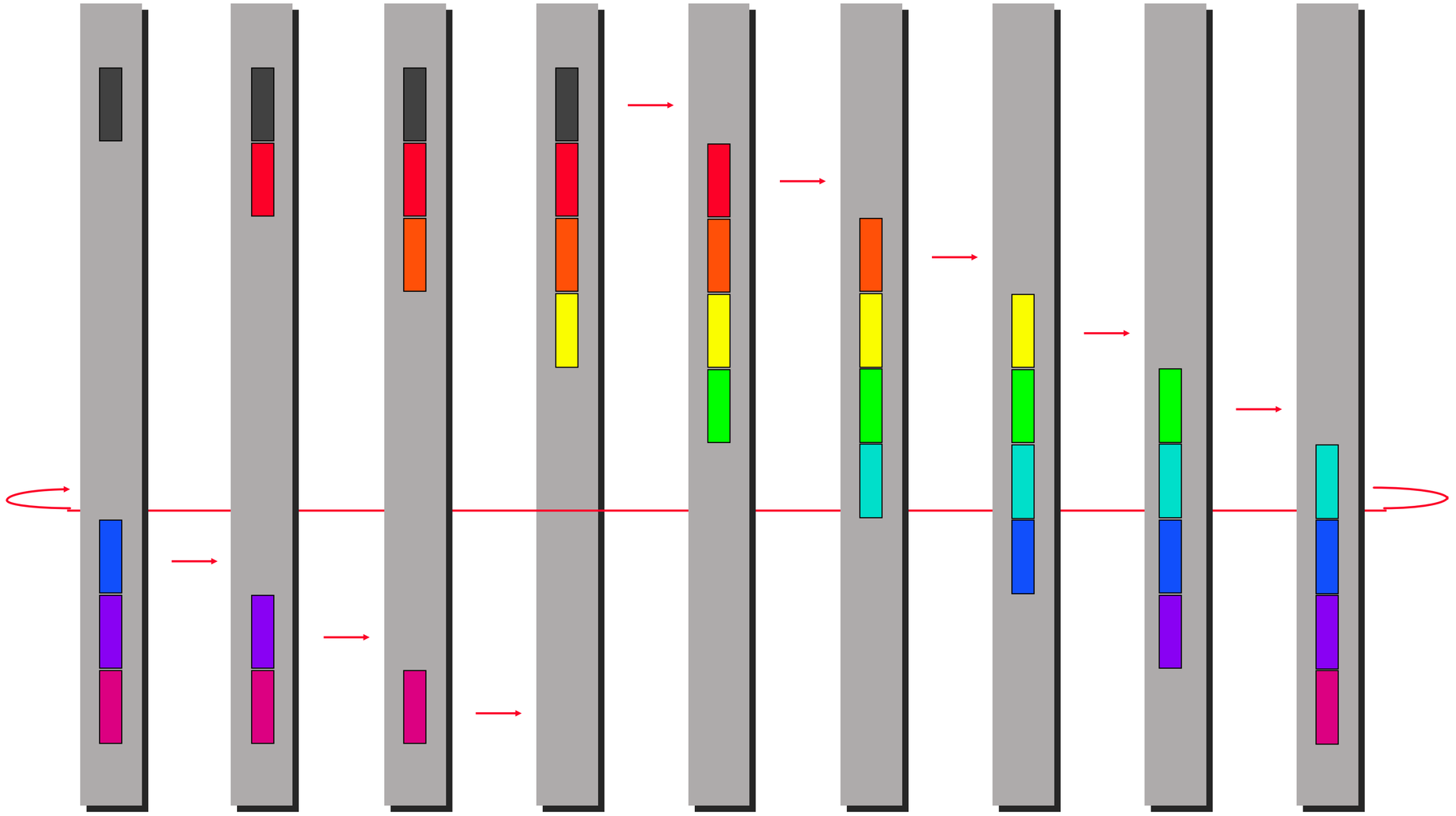


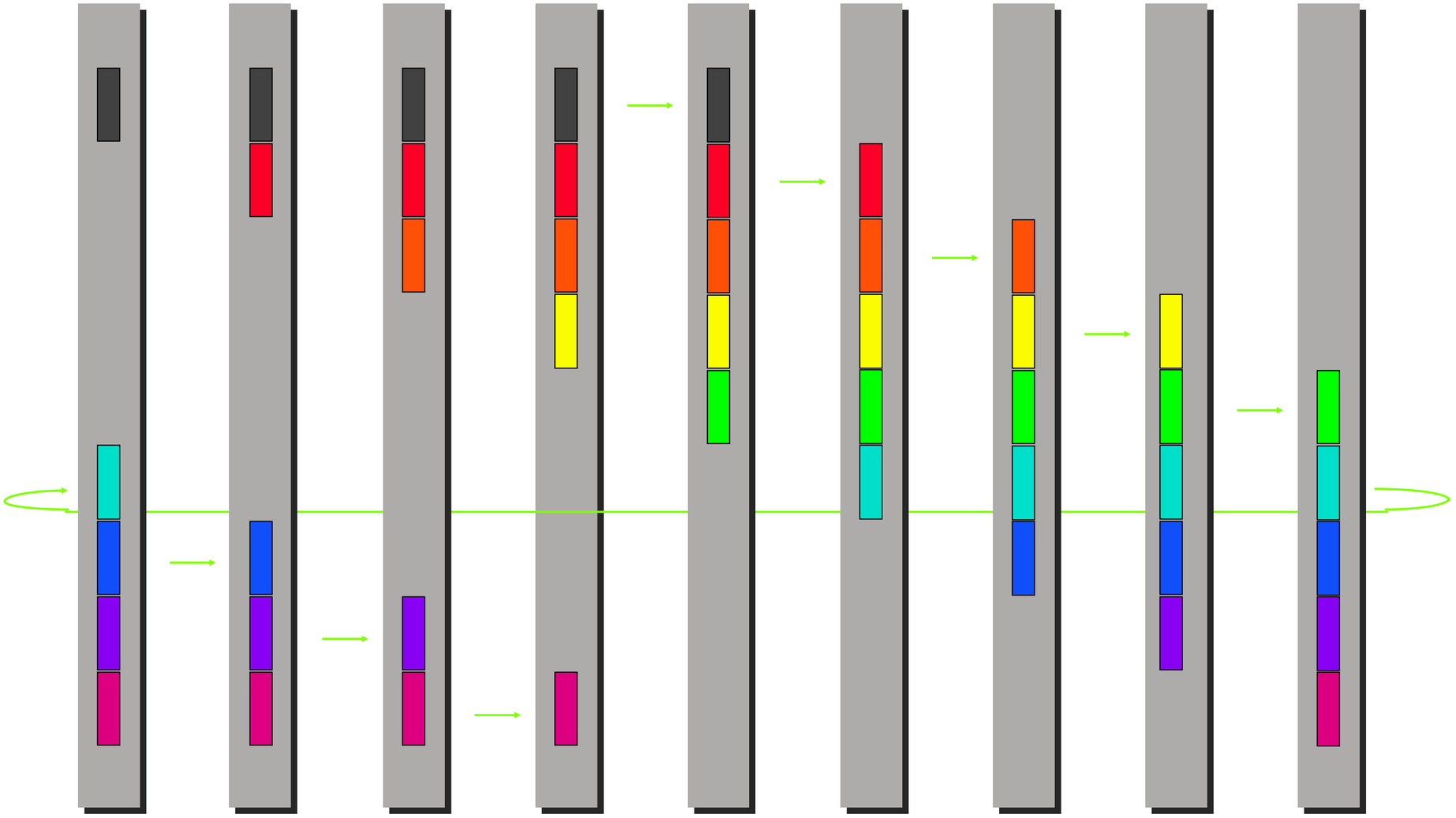


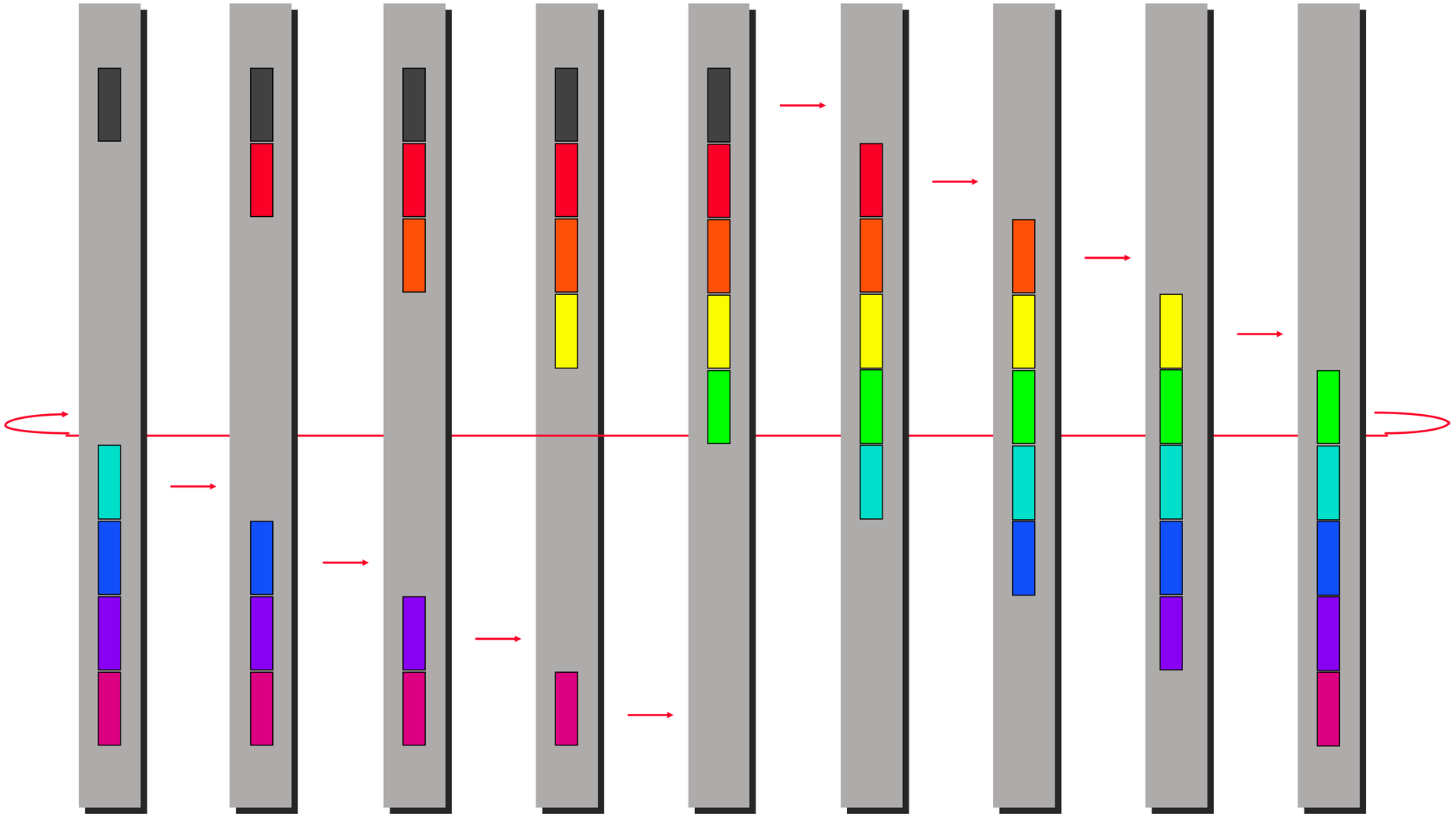


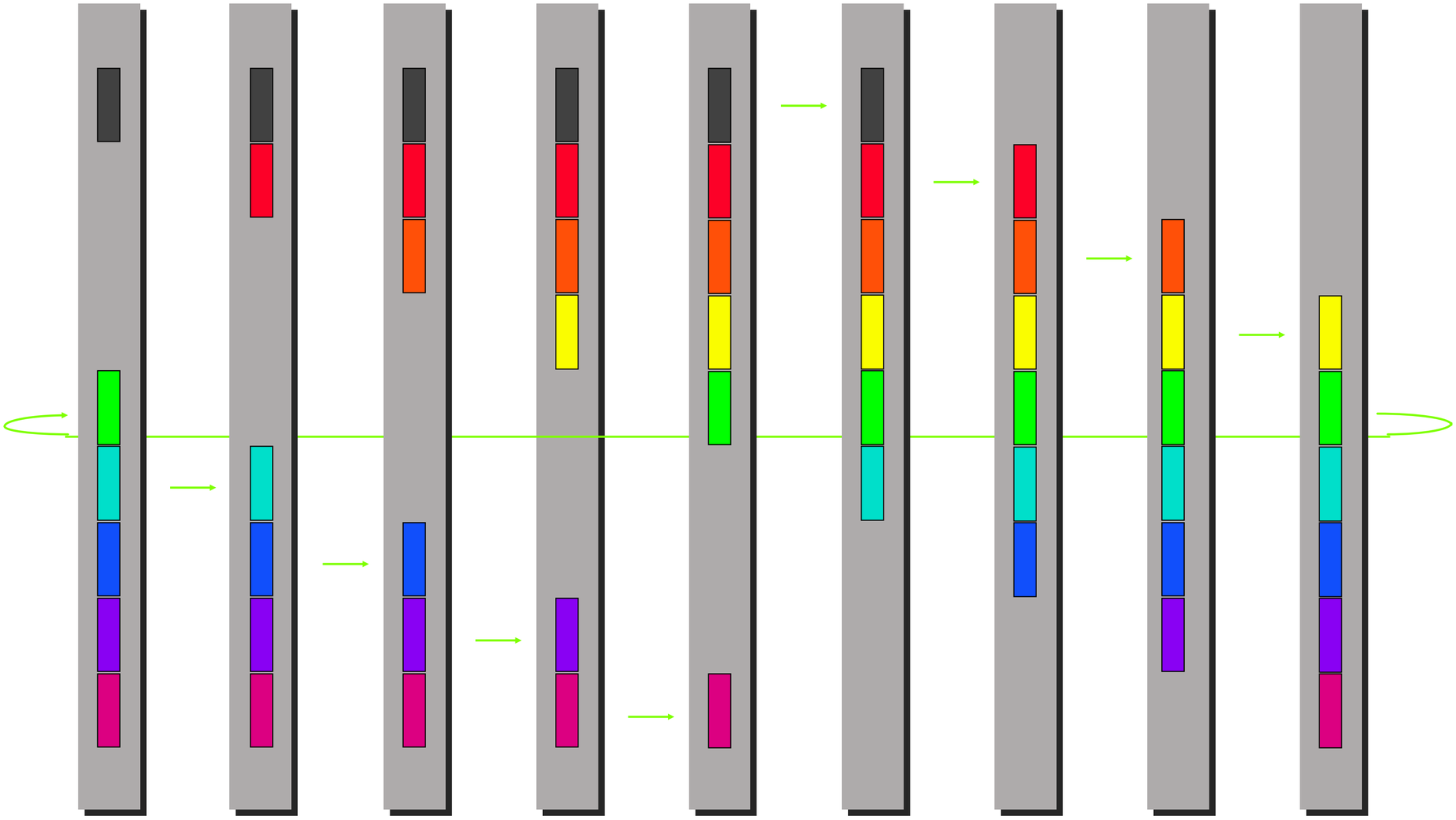


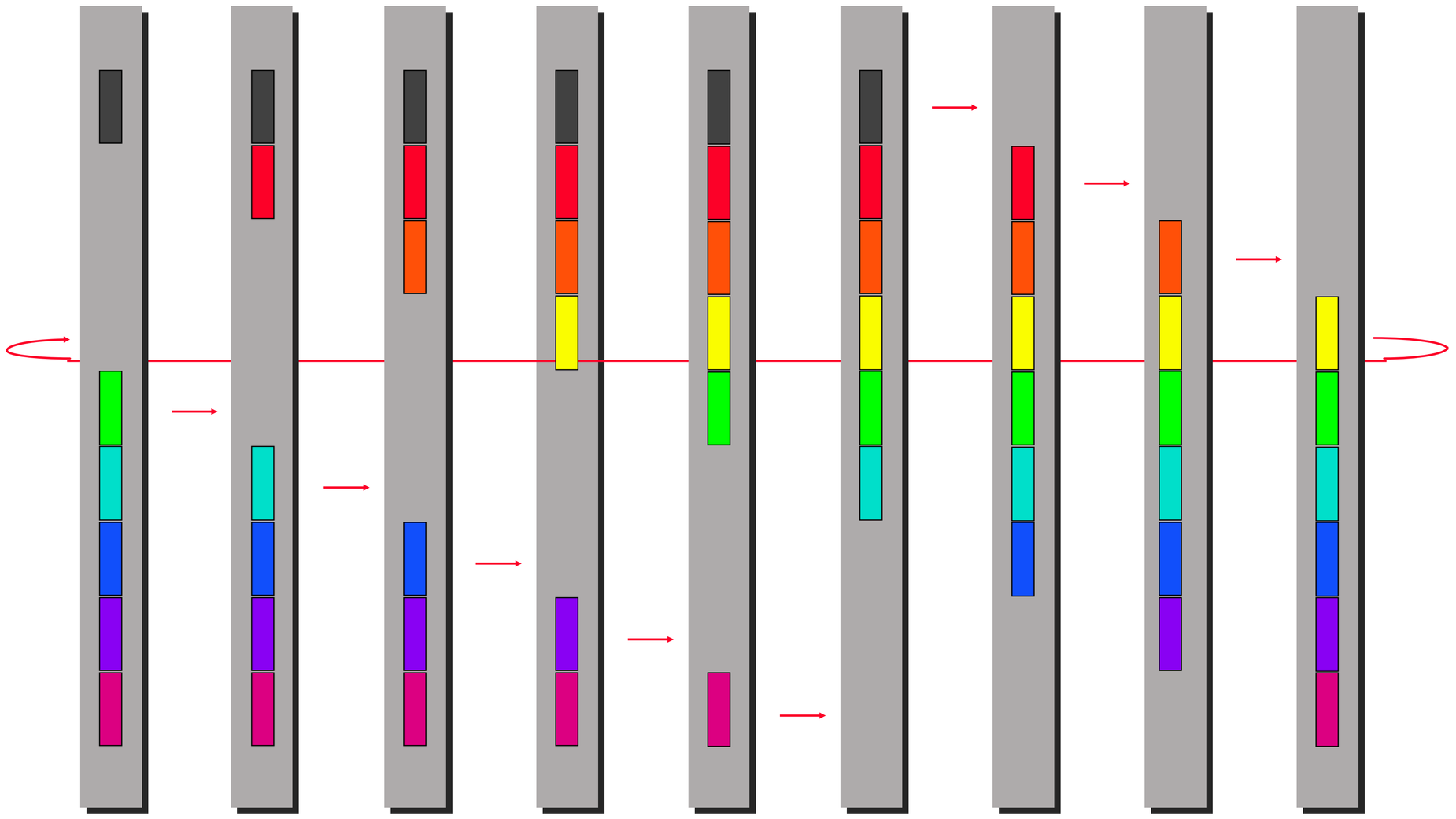


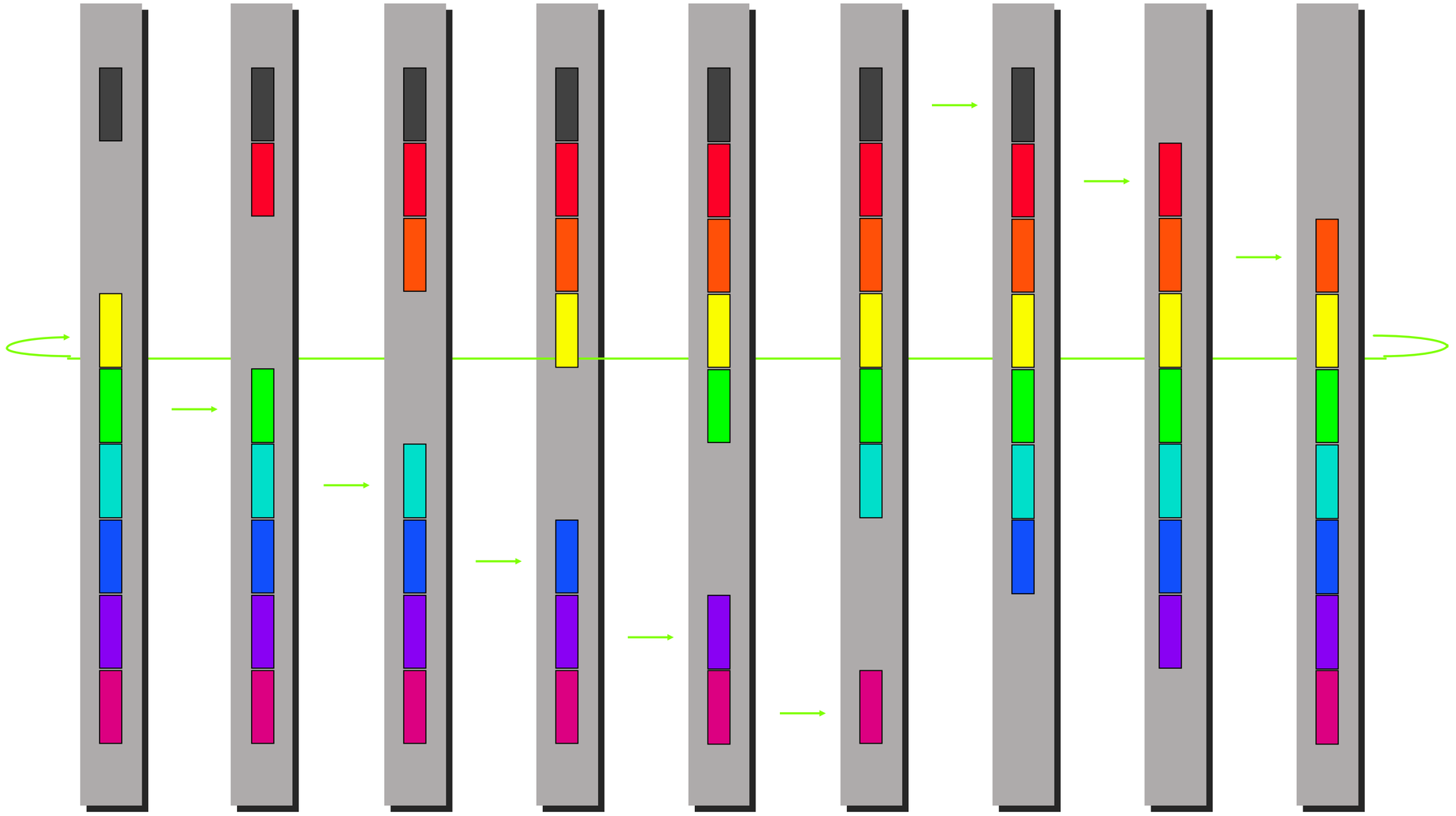


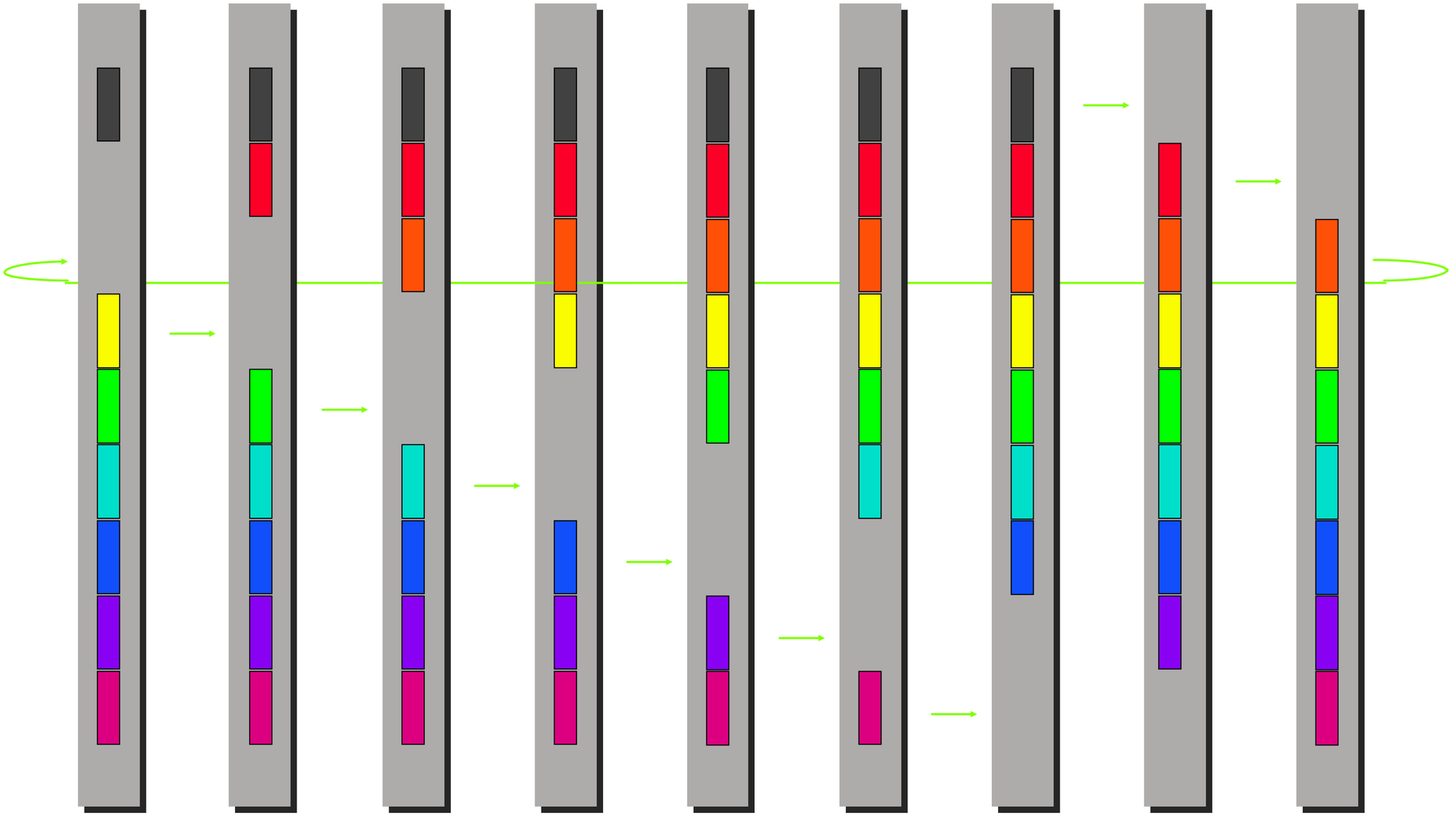


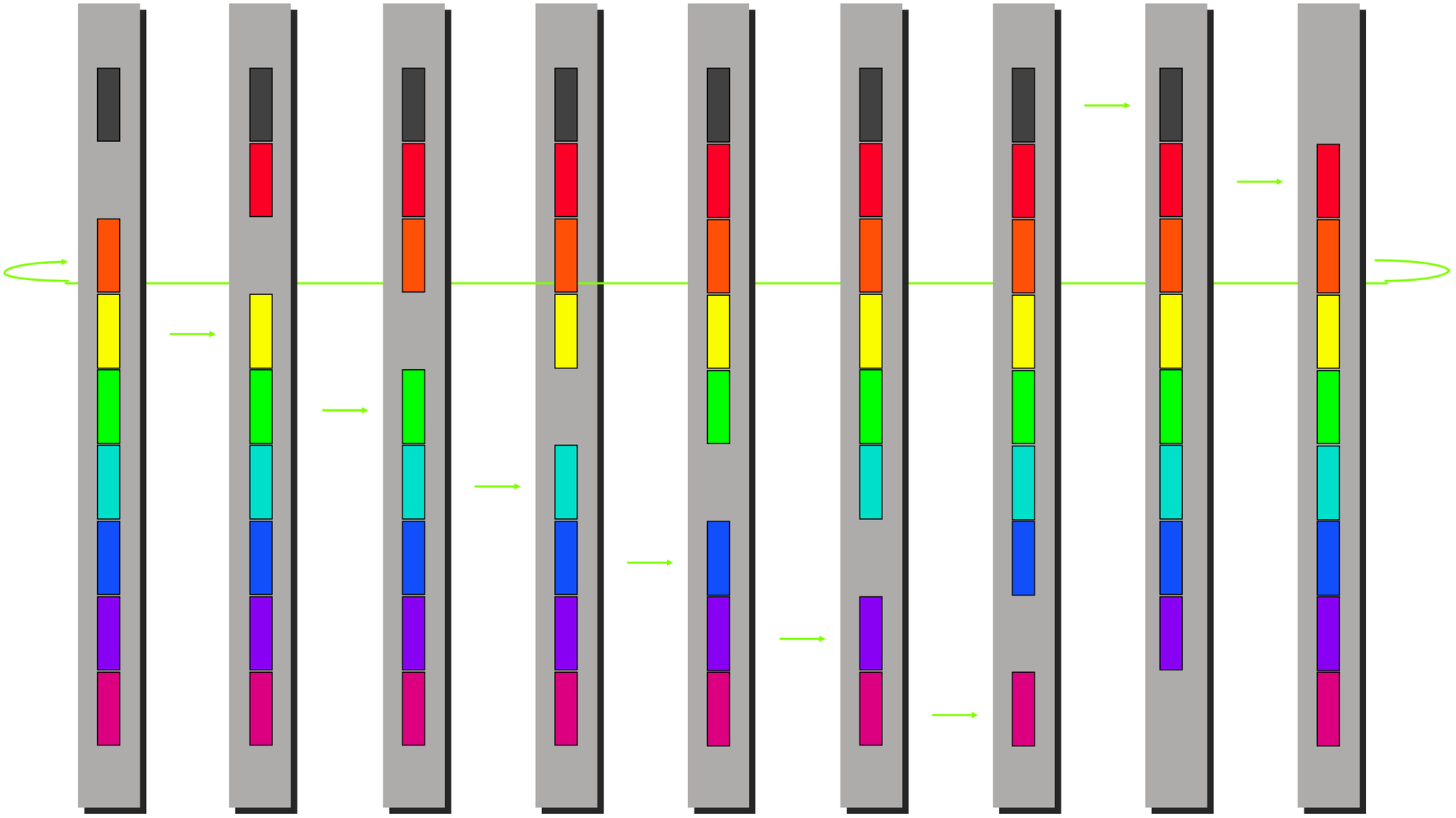


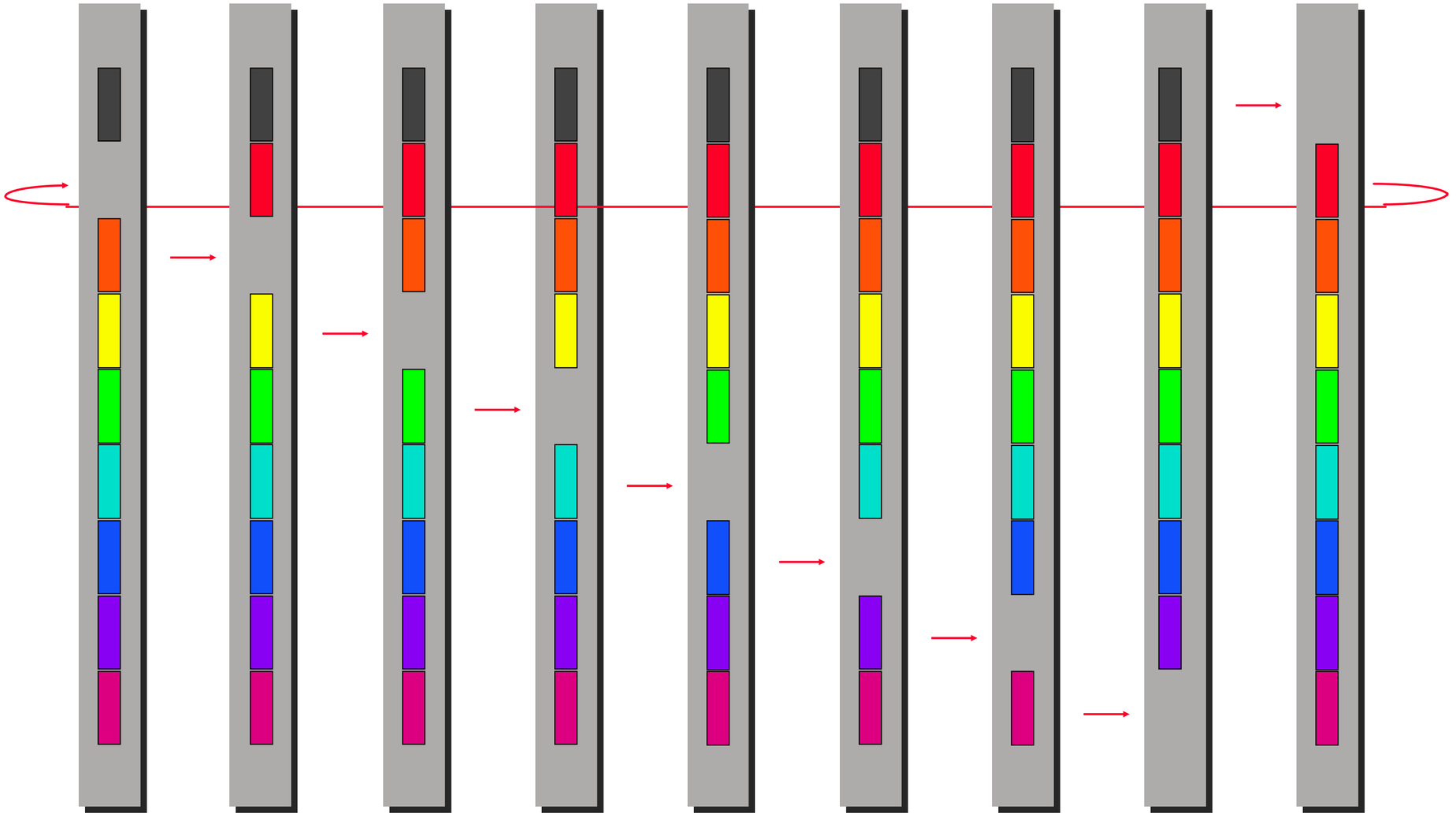


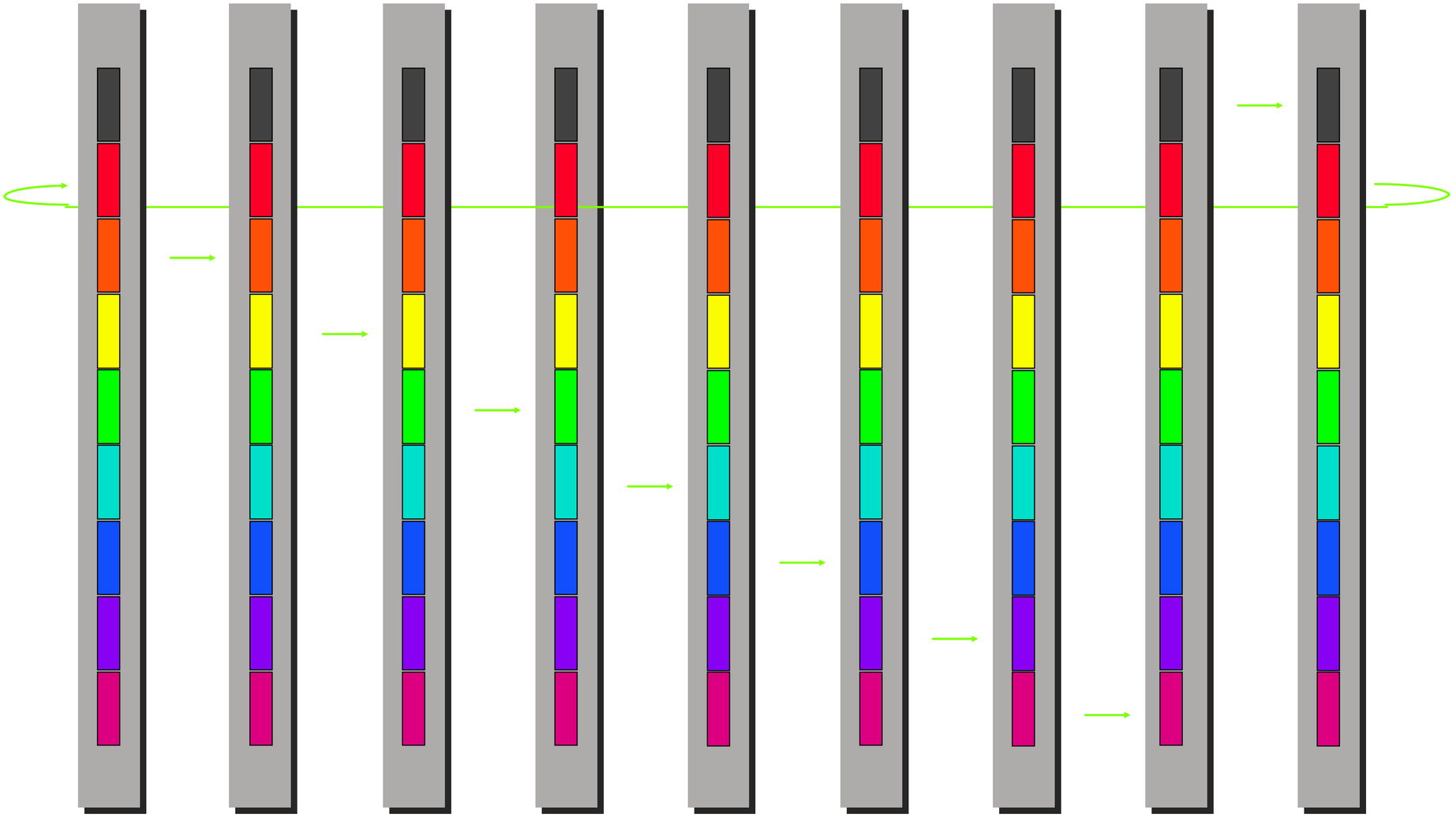


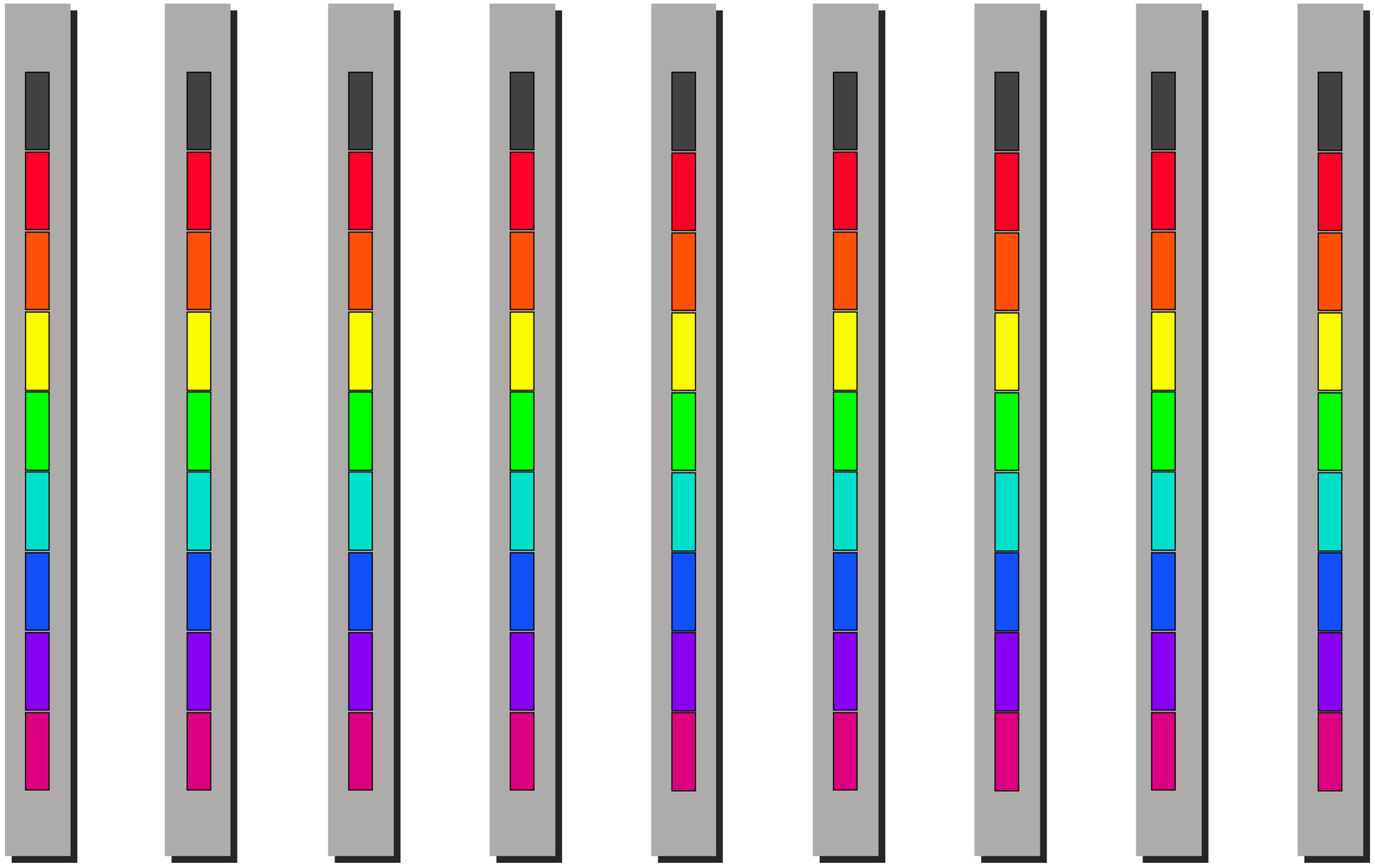




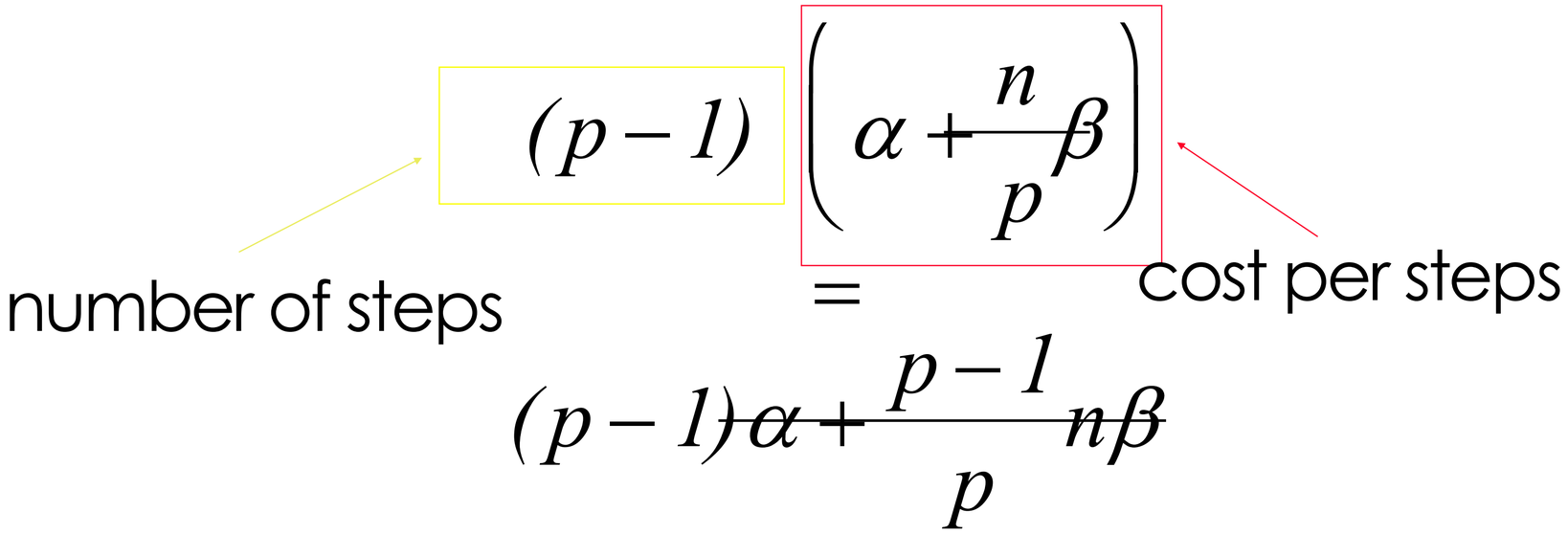




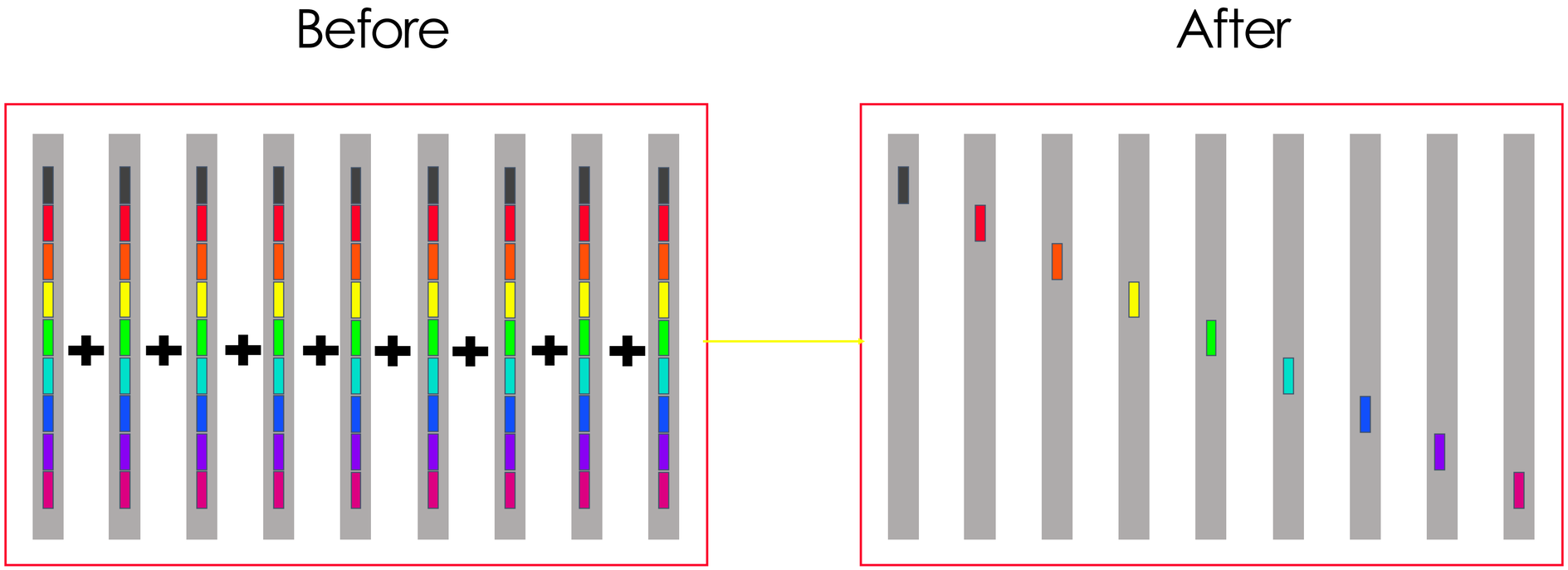


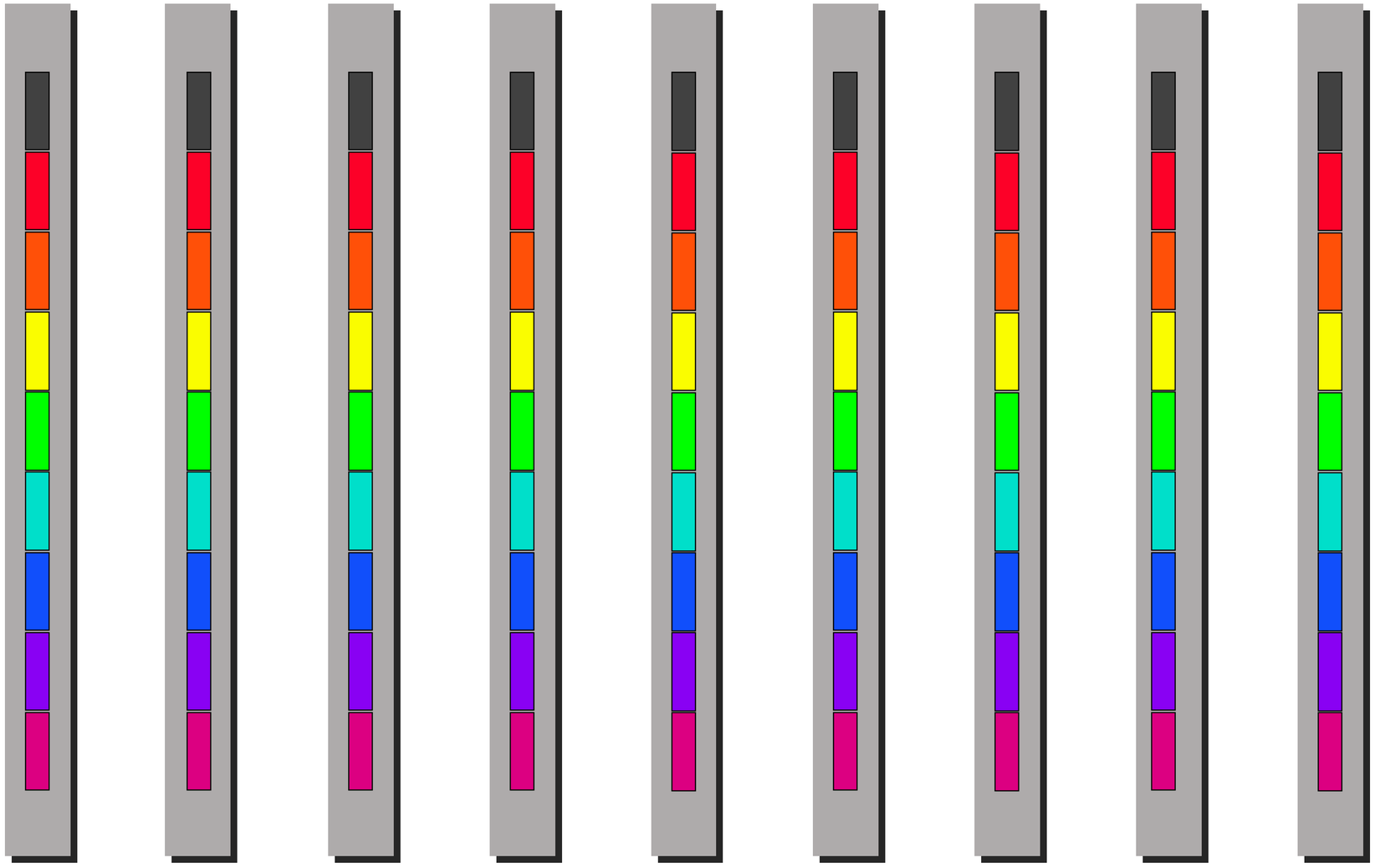


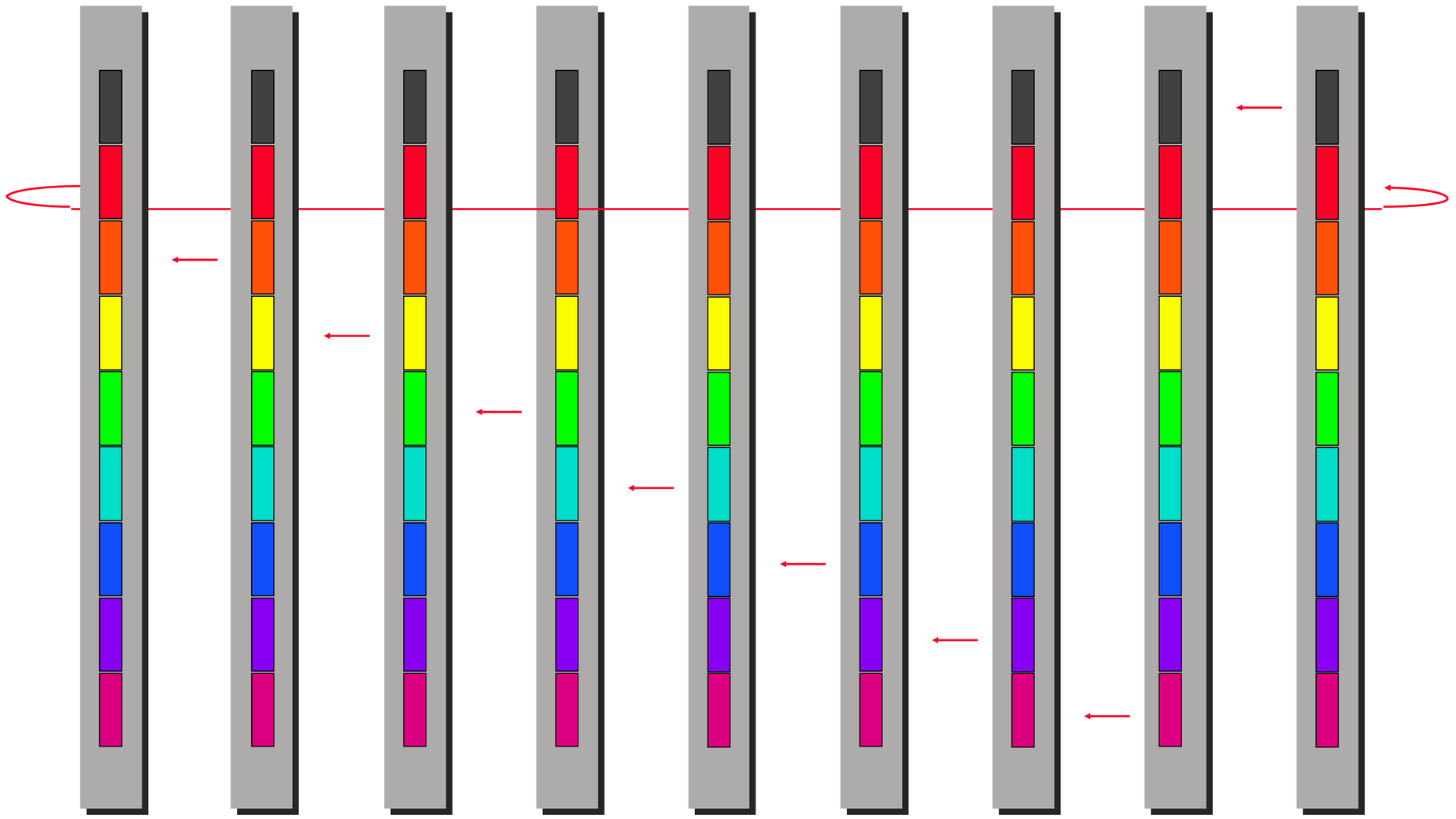
Cost of bucket Allgather

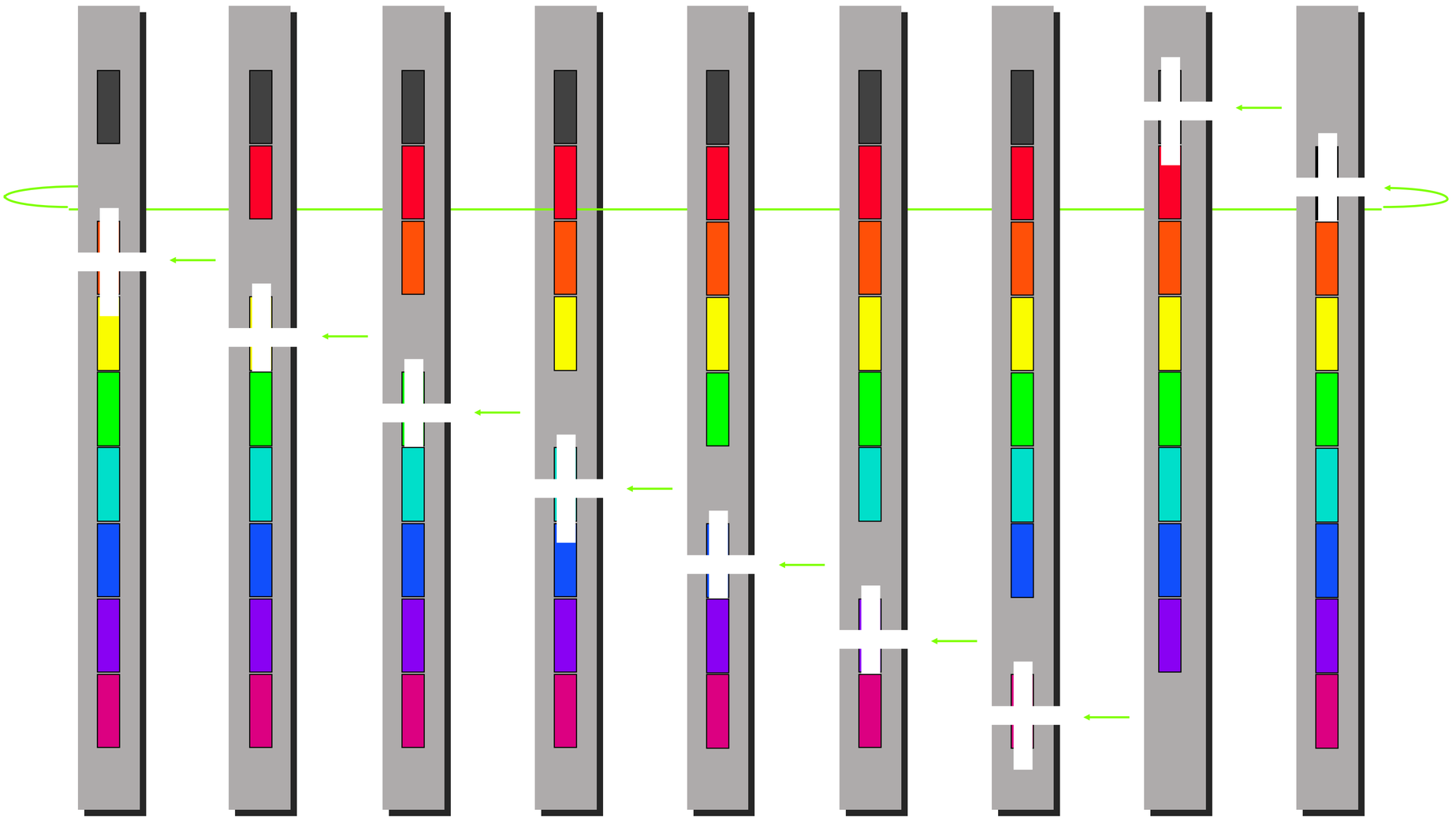


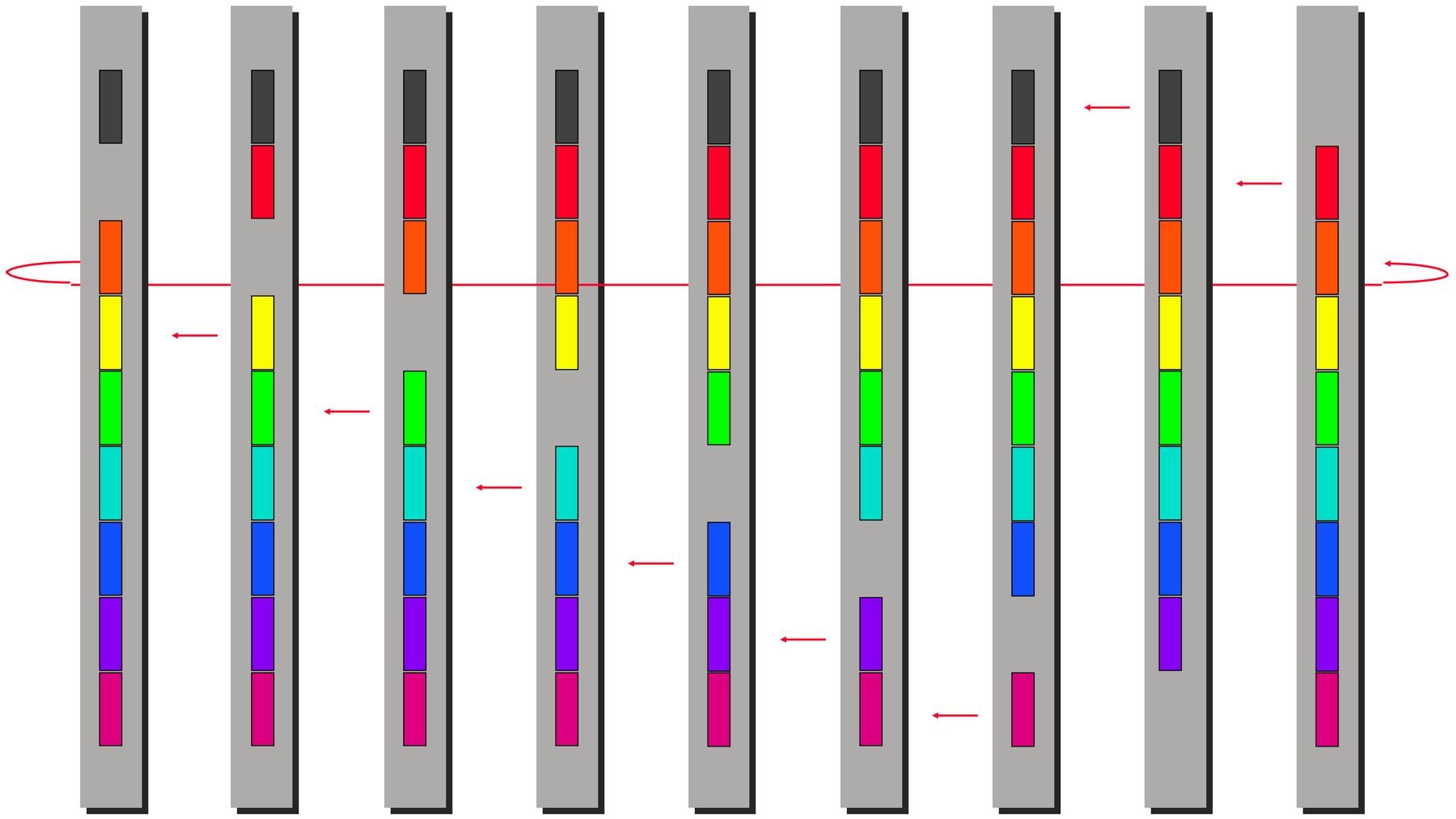
Reduce-scatter

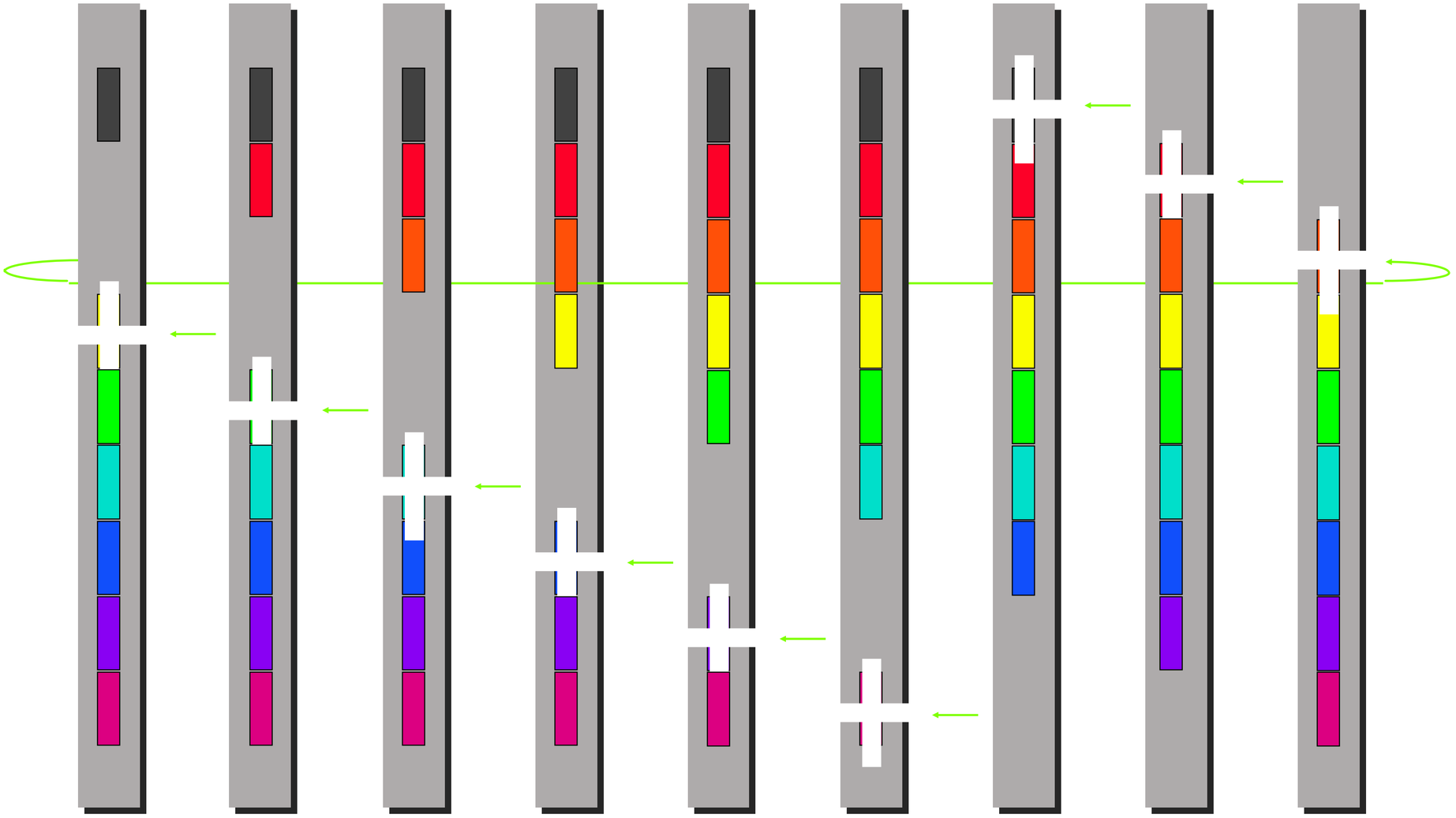


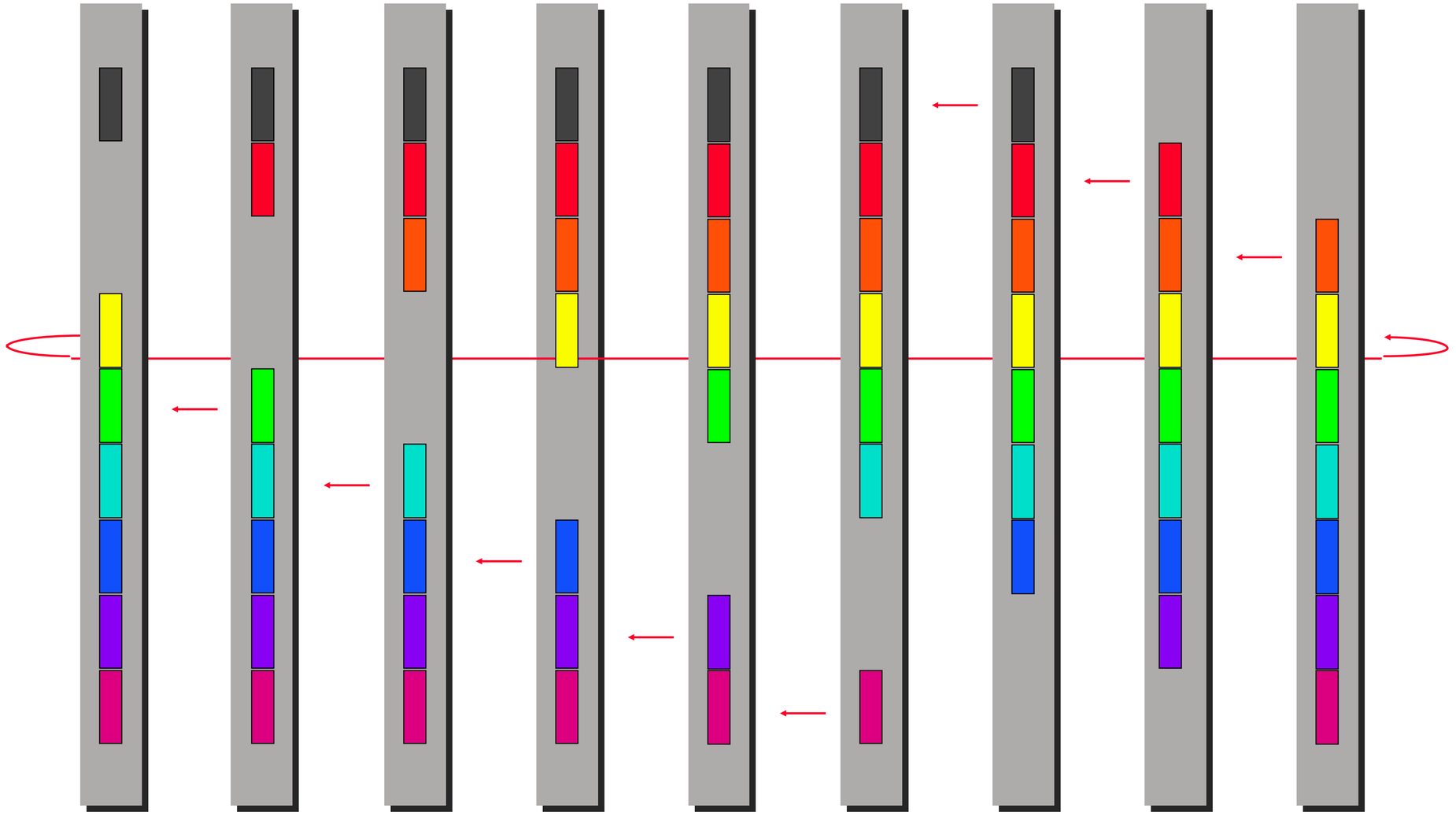


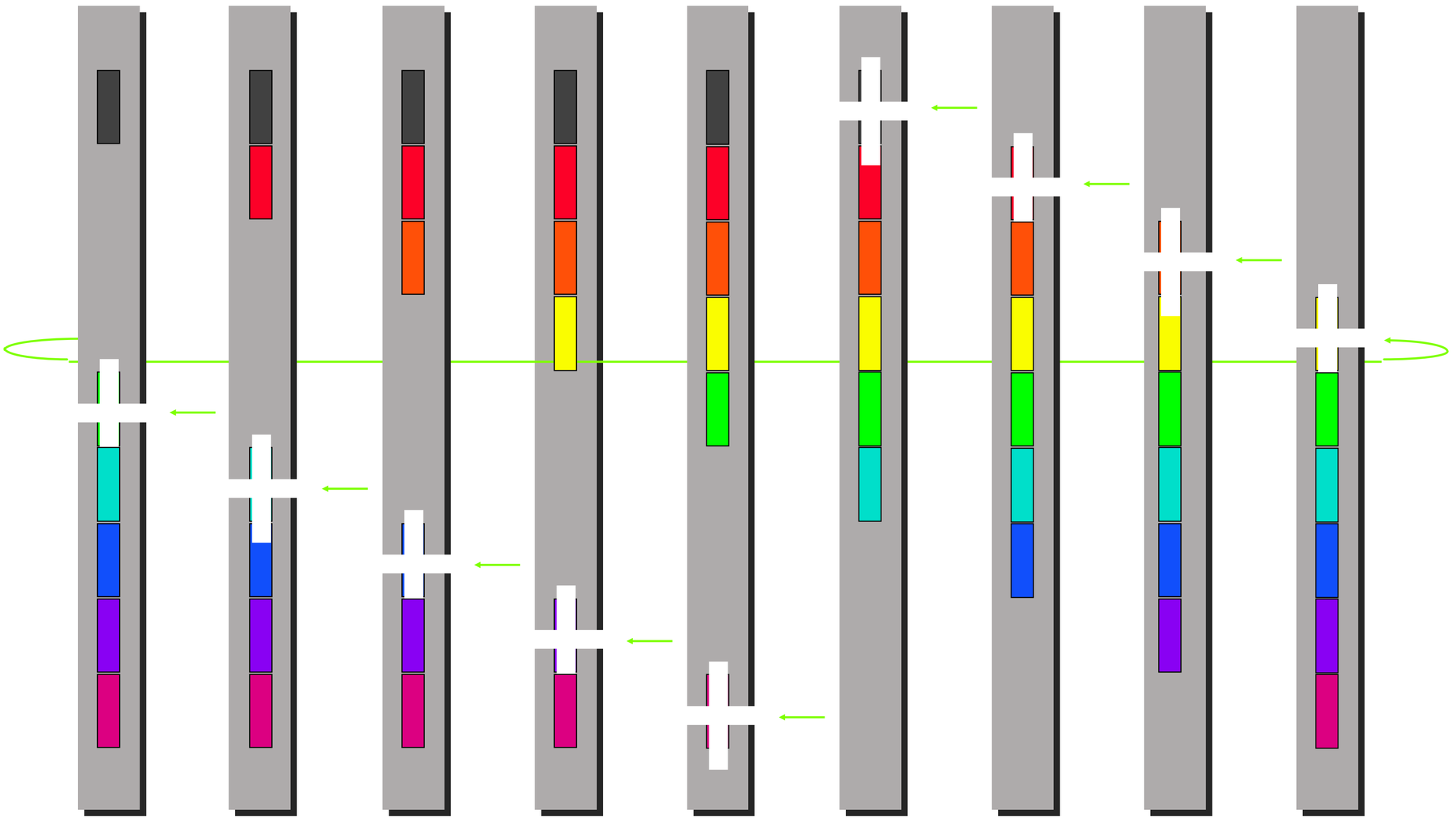


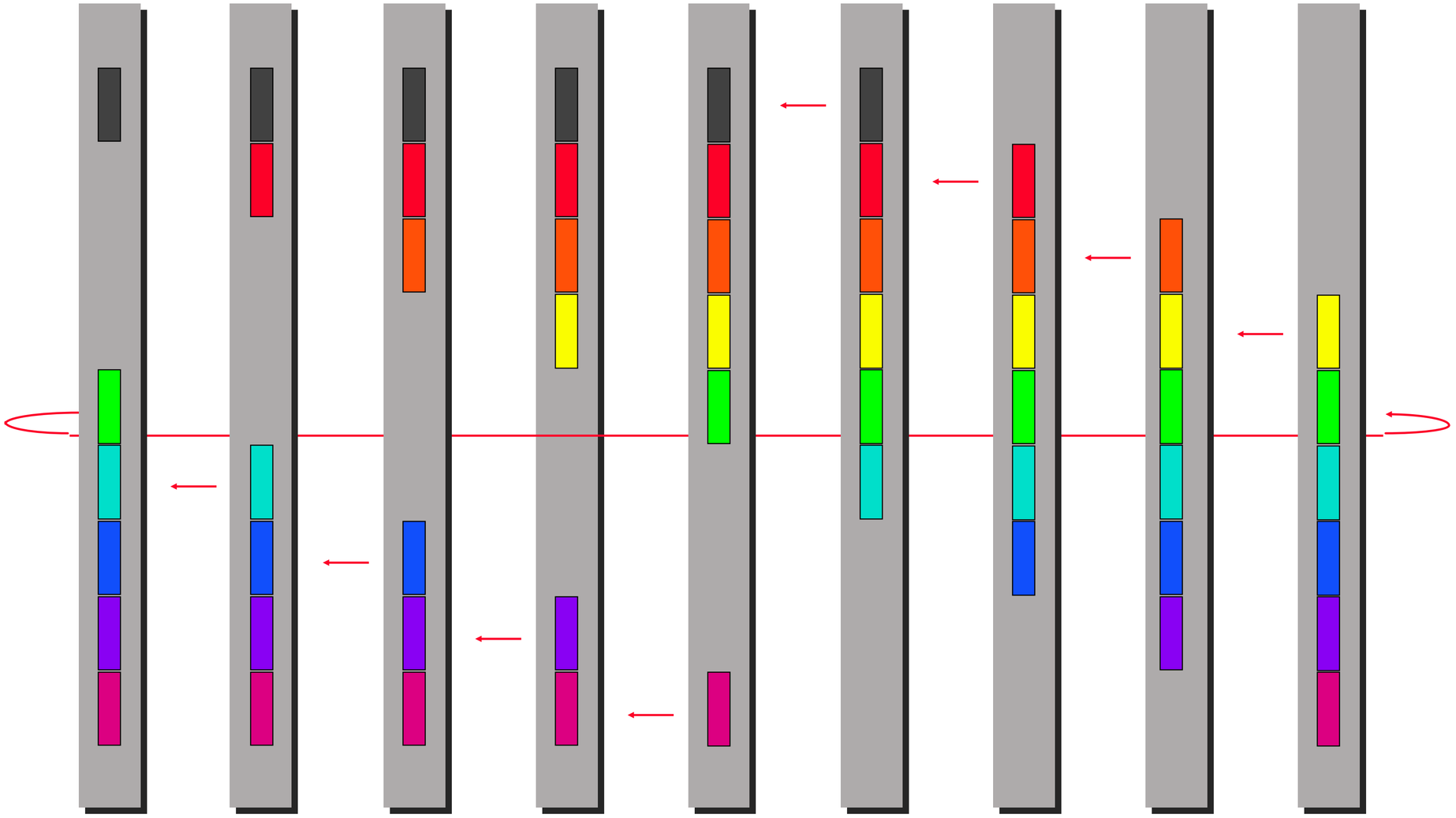


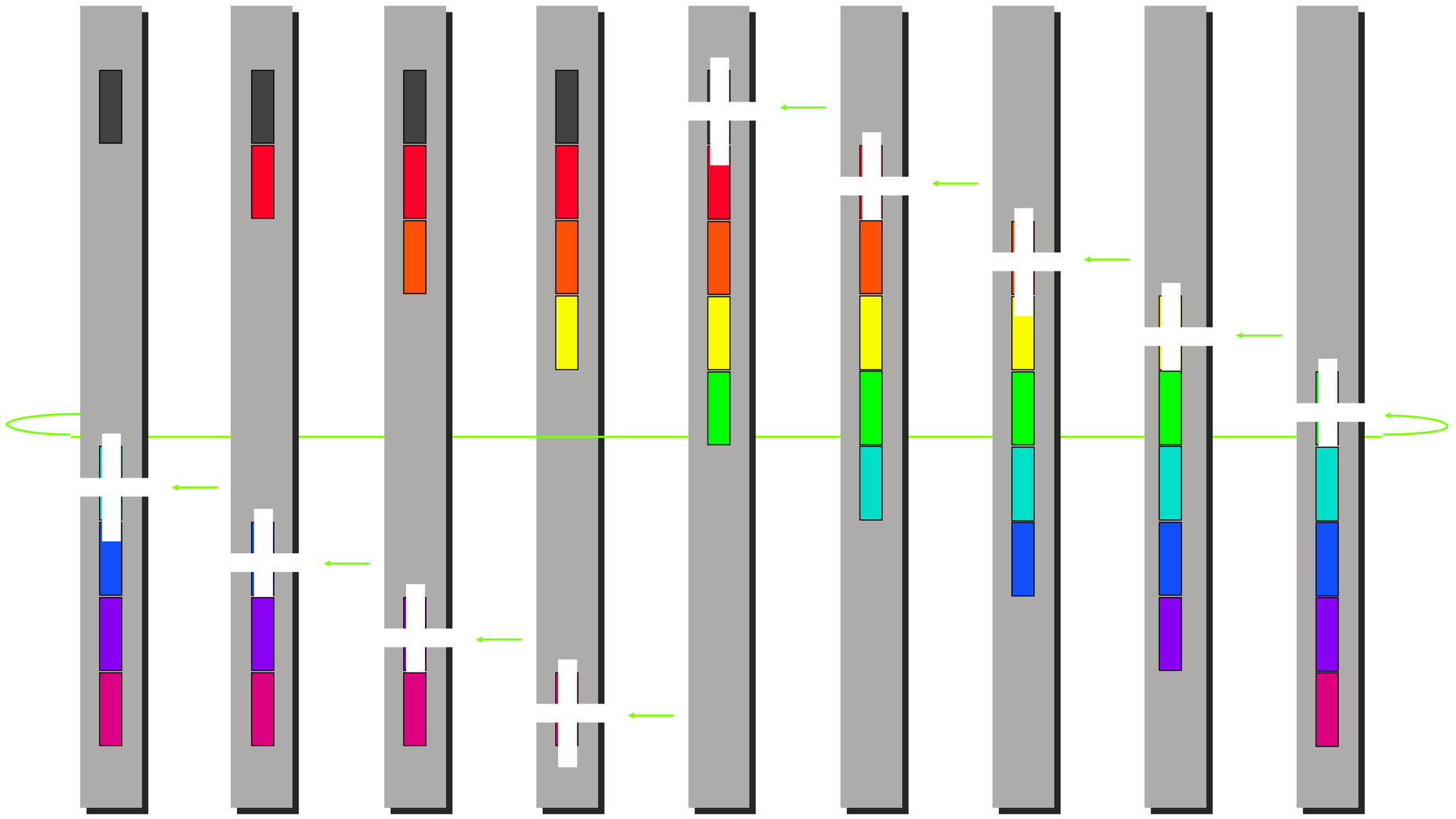


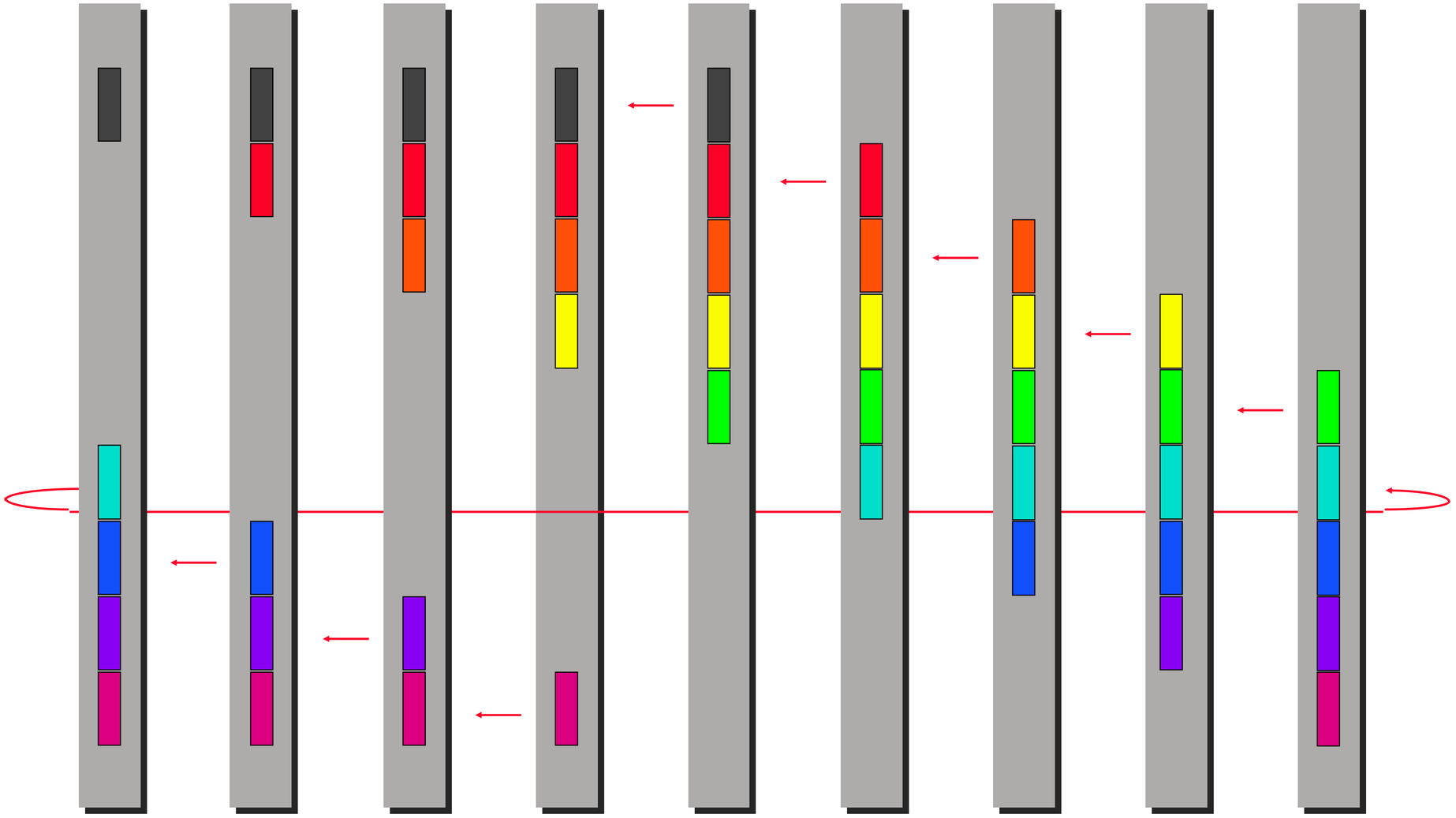


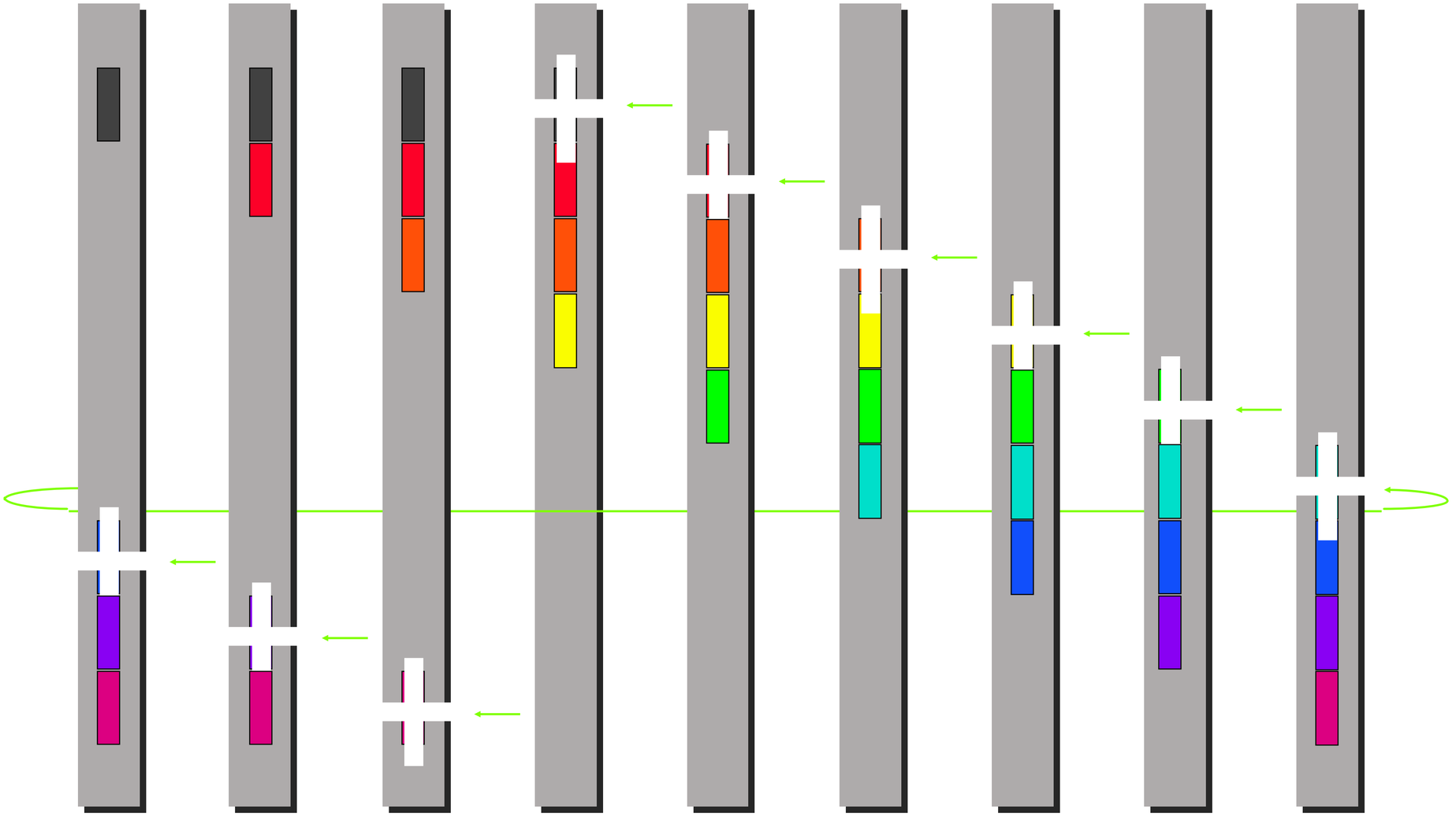


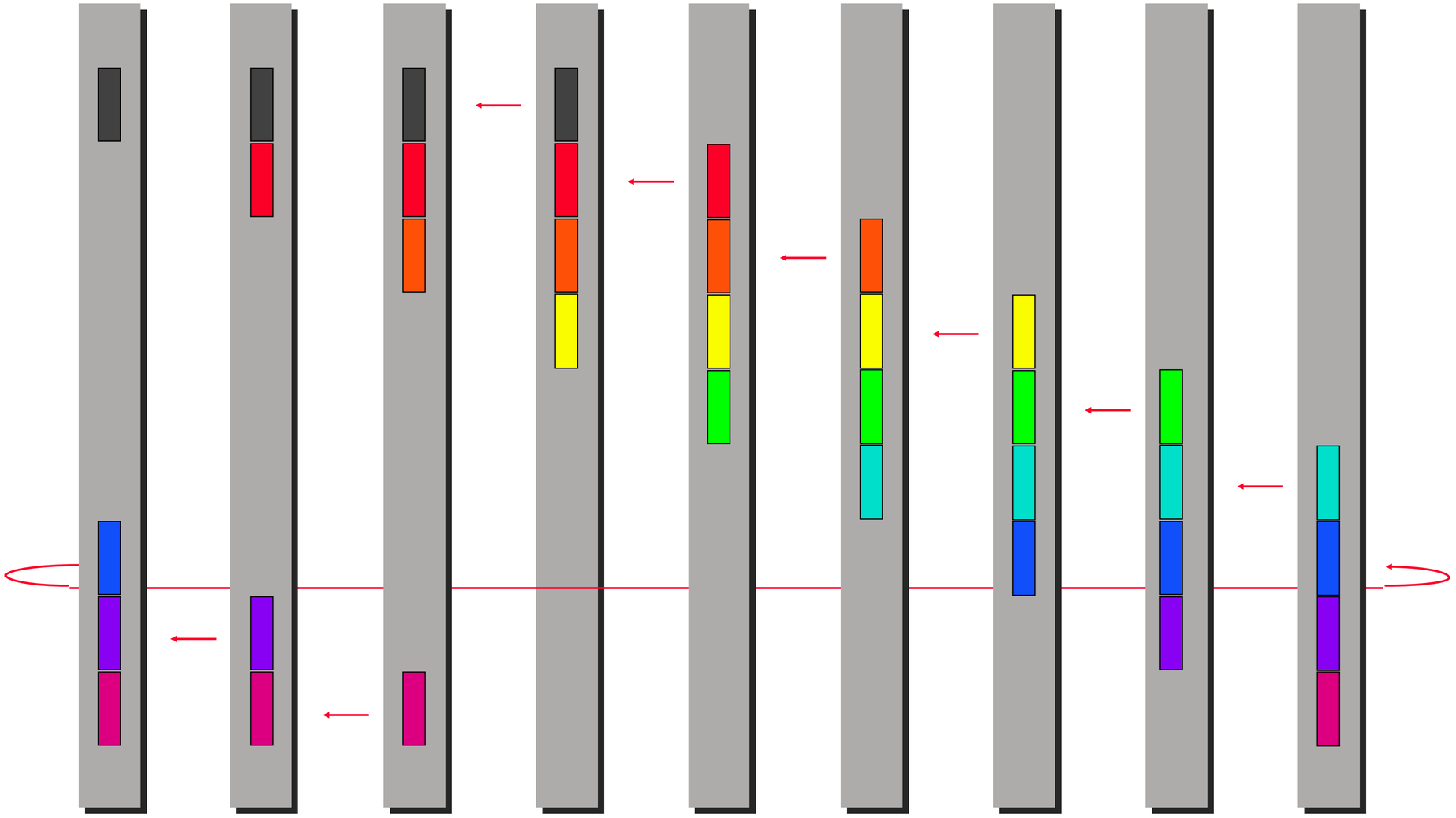


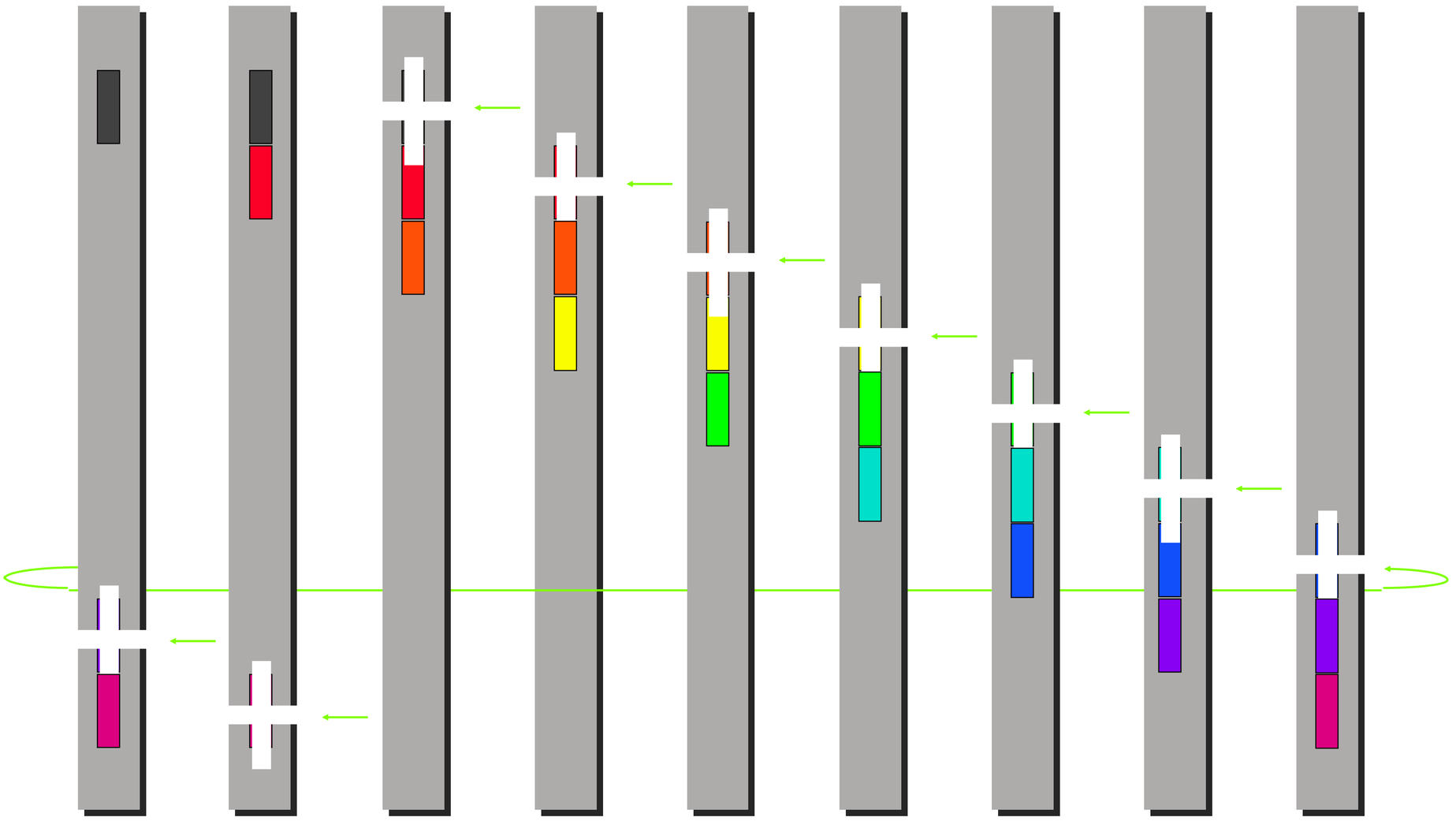


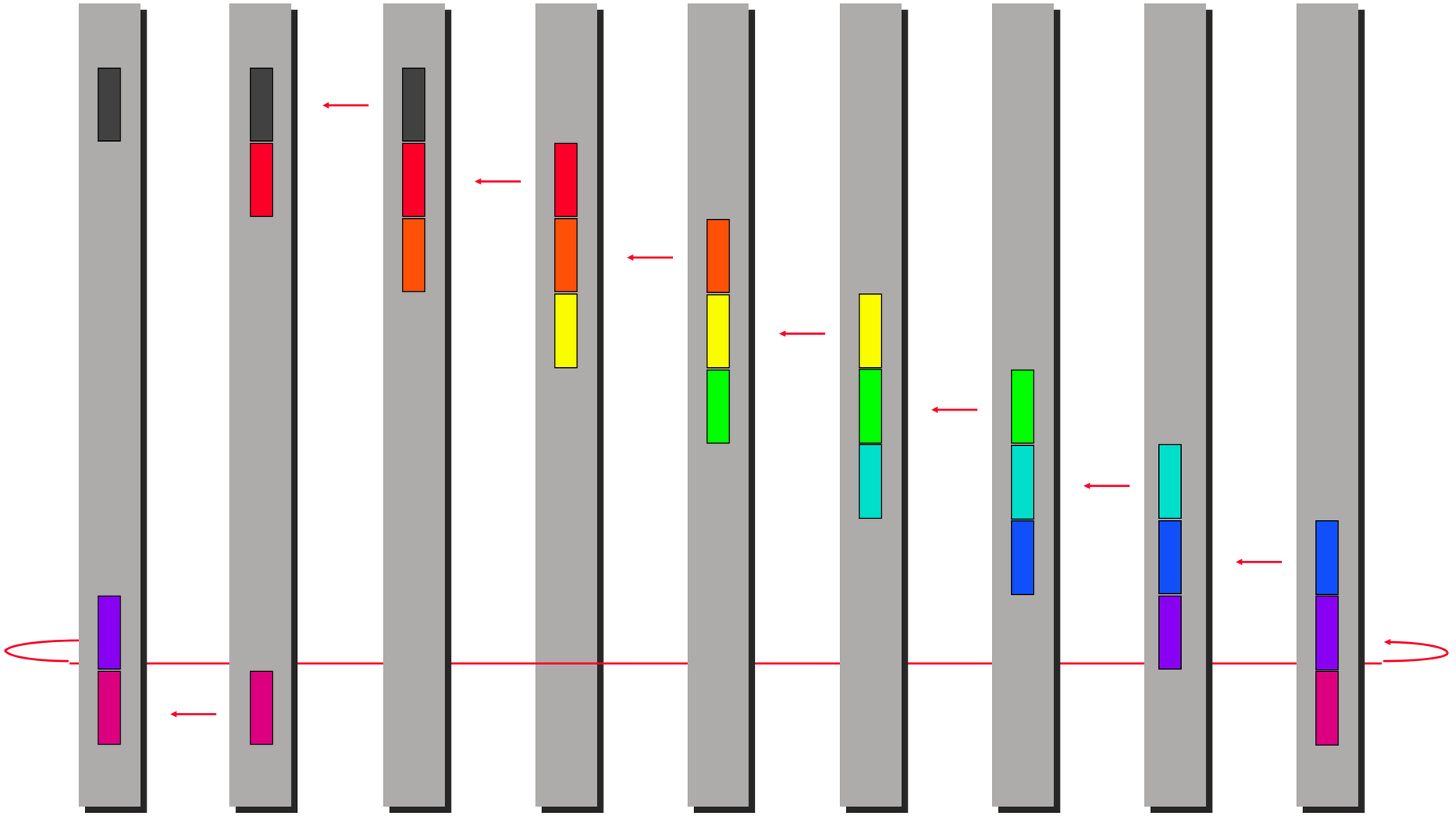


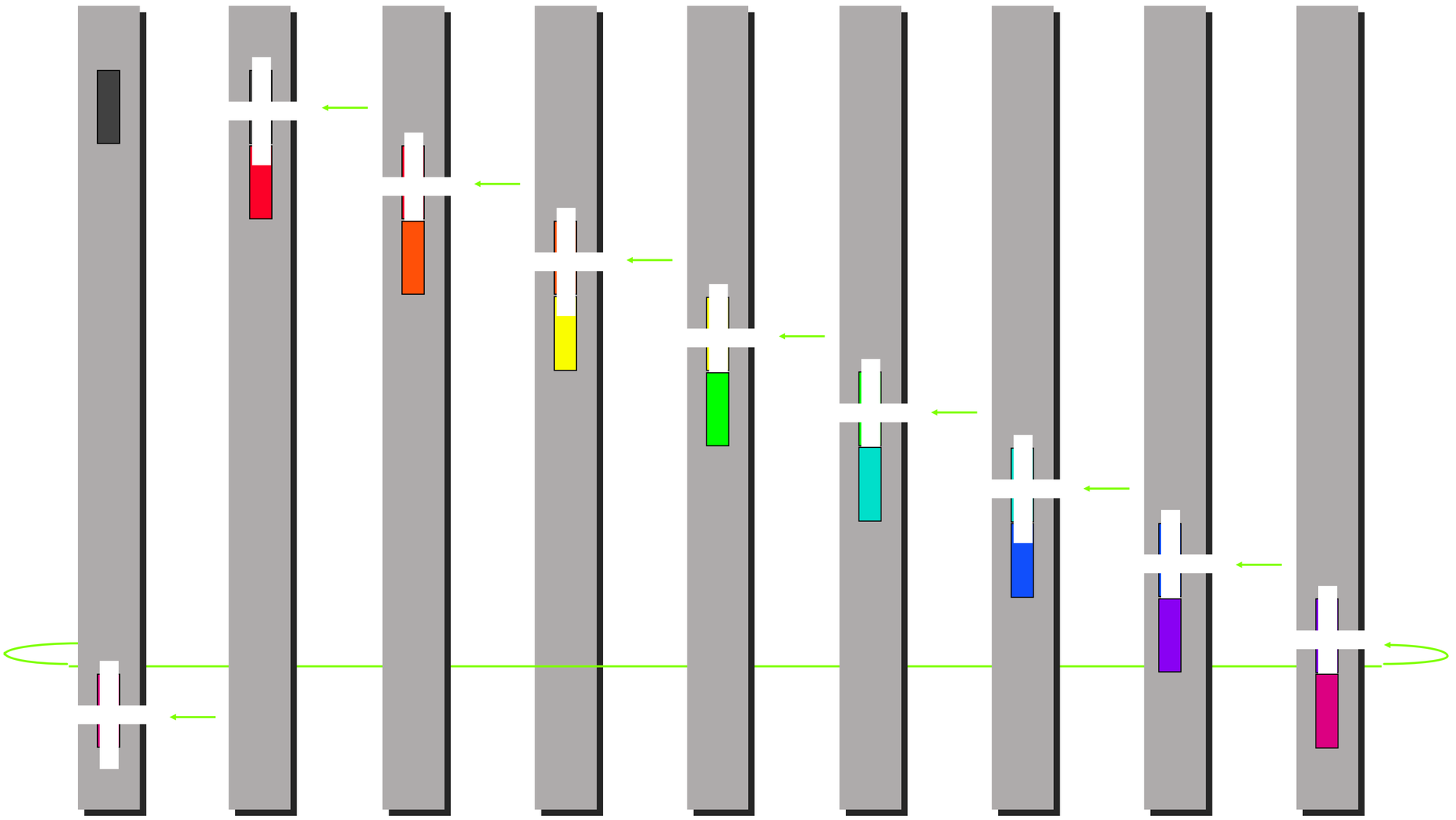


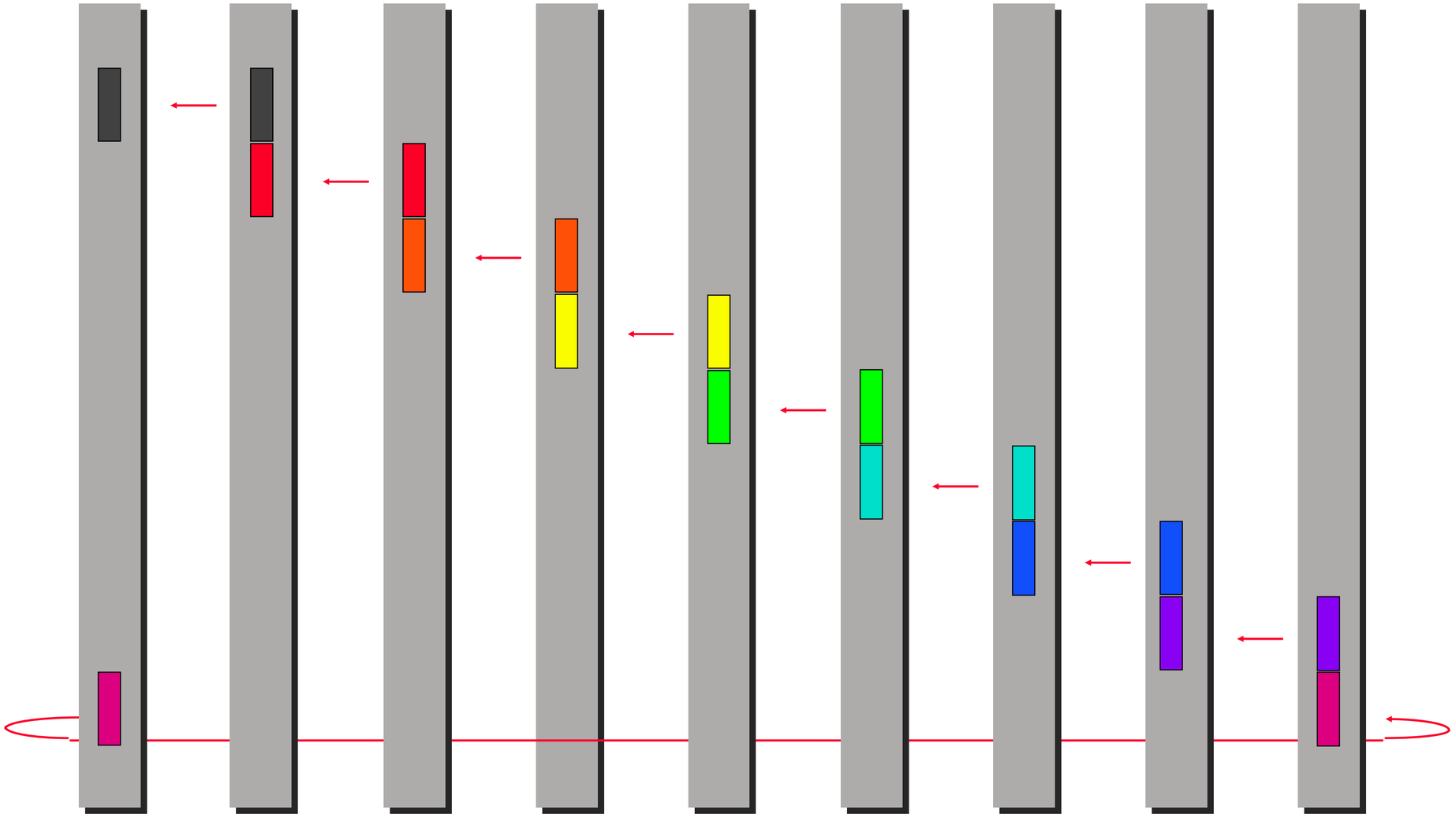


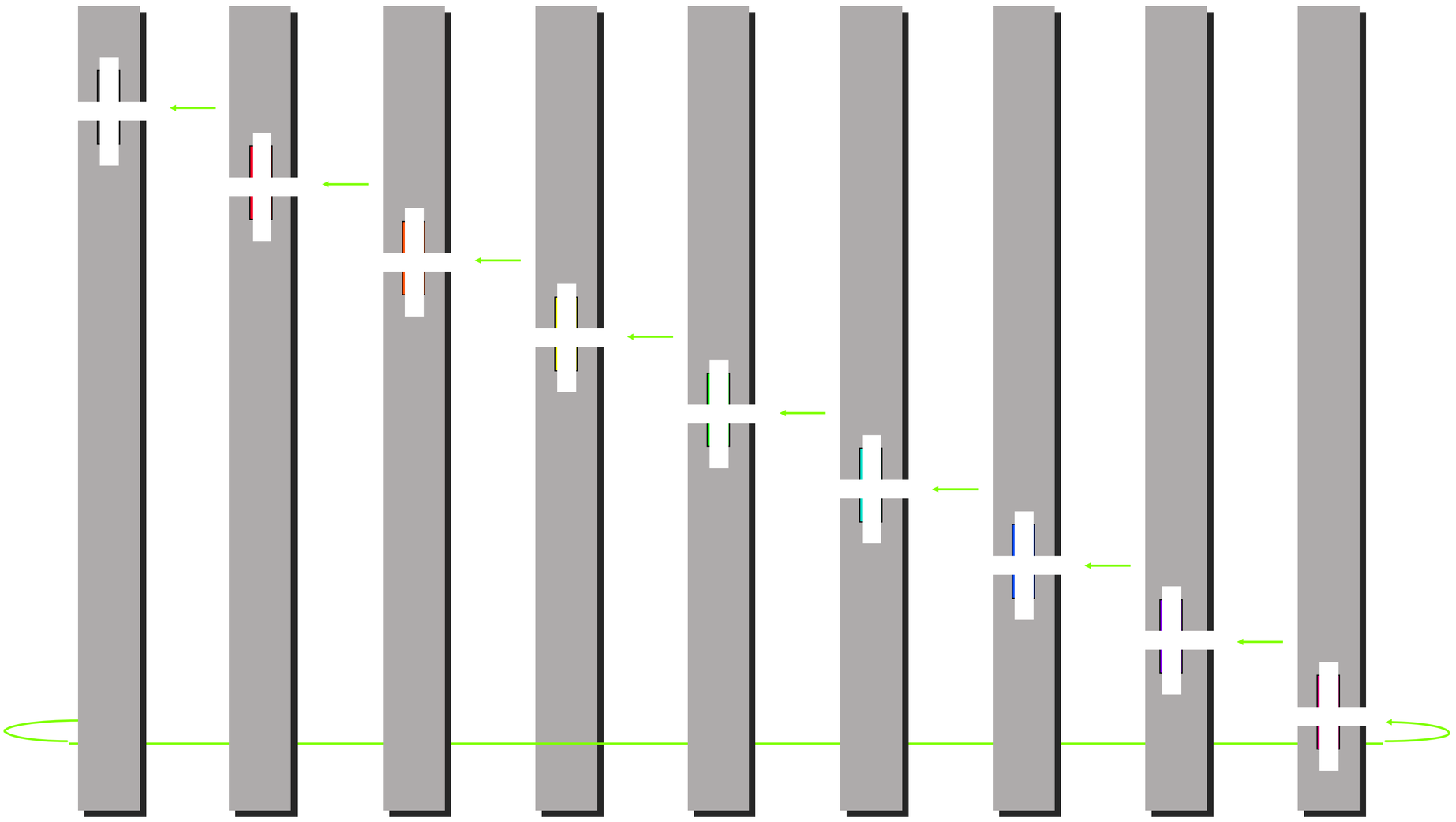


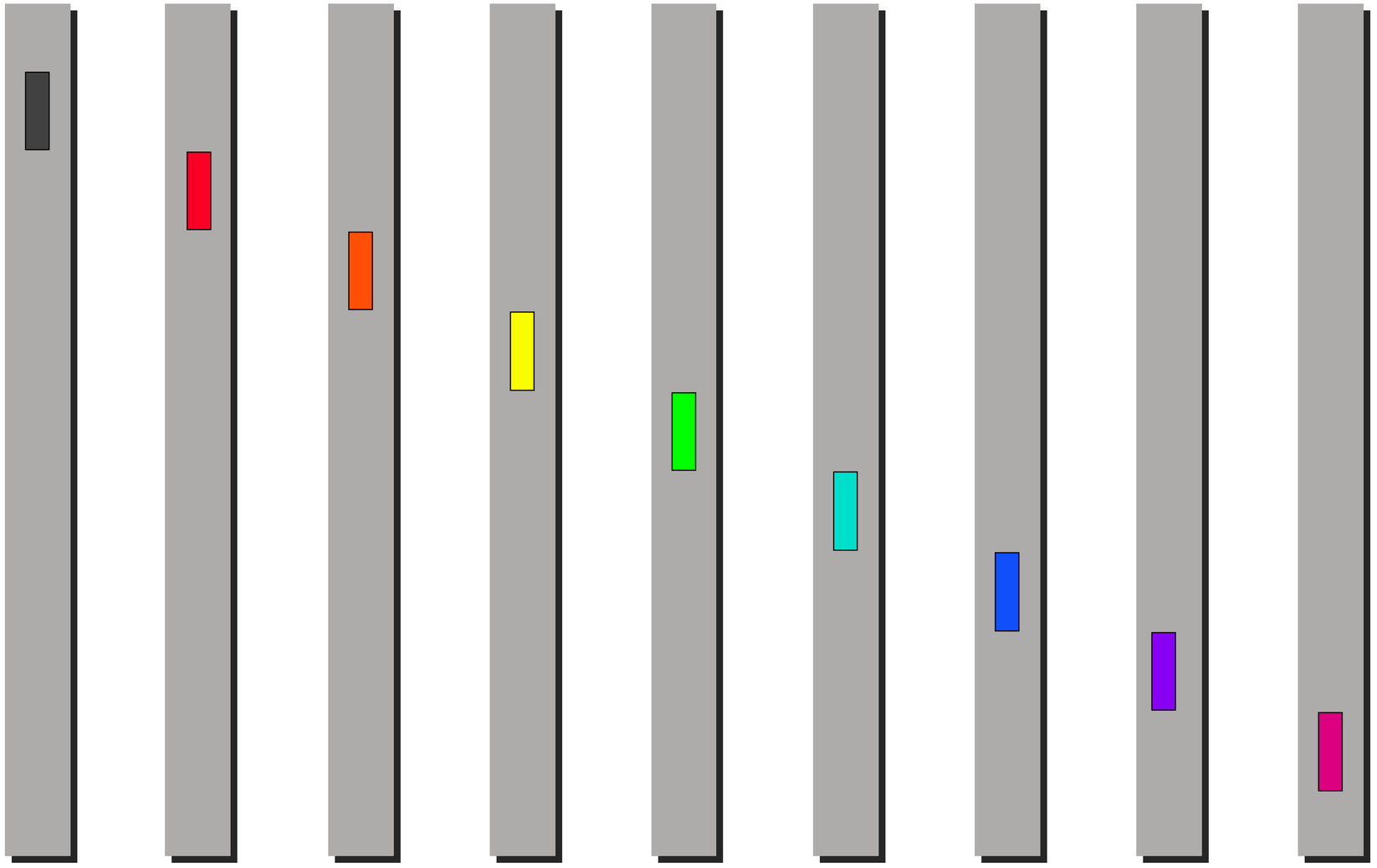




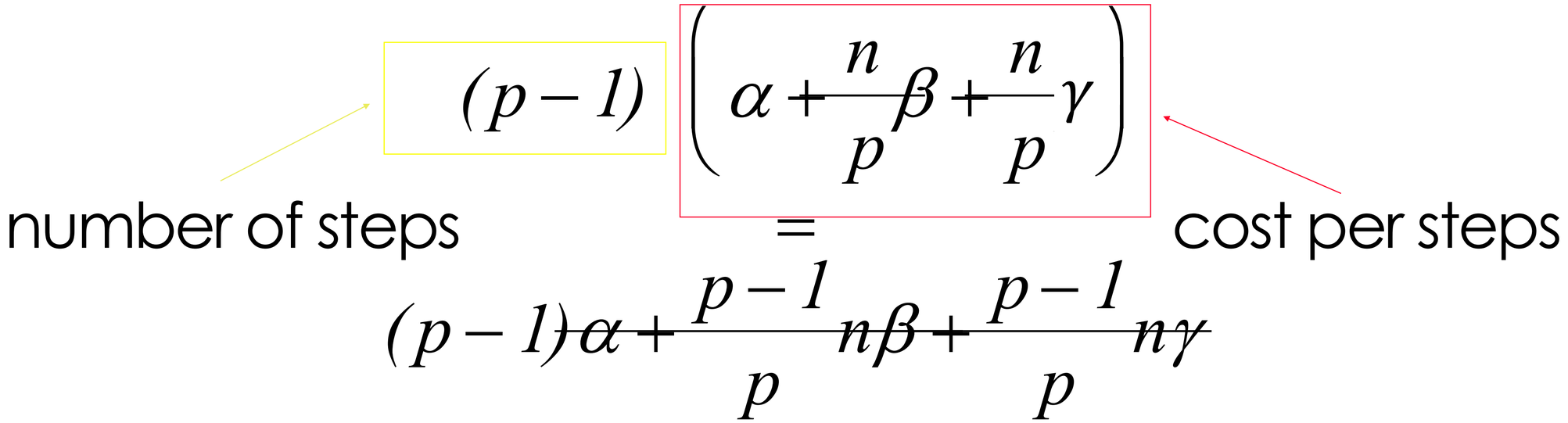






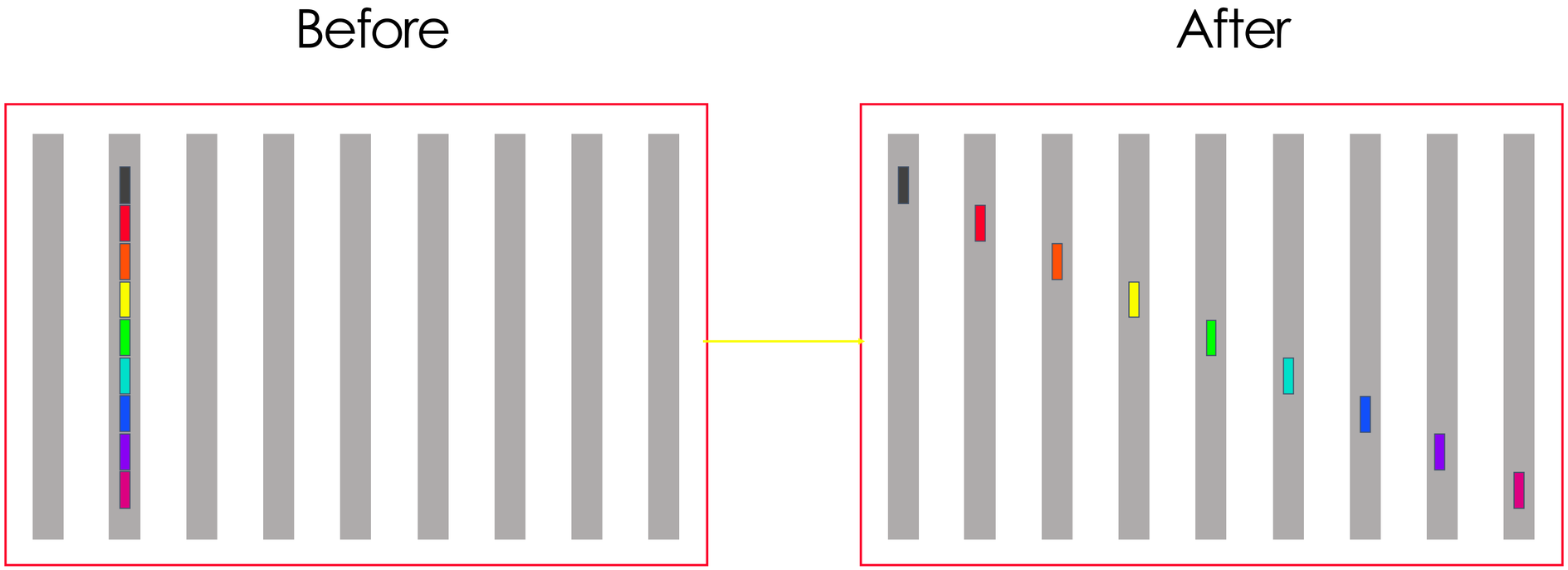


Cost


$(p-1)$
$\left(\alpha + \frac{n}{p}\beta + \frac{n}{p}\gamma\right)$
number of steps
=
cost per steps
$(p-1)\alpha + \frac{p-1}{p}n\beta + \frac{p-1}{p}n\gamma$

Scatter: Can Ring Be Better?

Notice: Scatter as implemented before using MST was optimal in Bandwidth as well (How to Prove?)

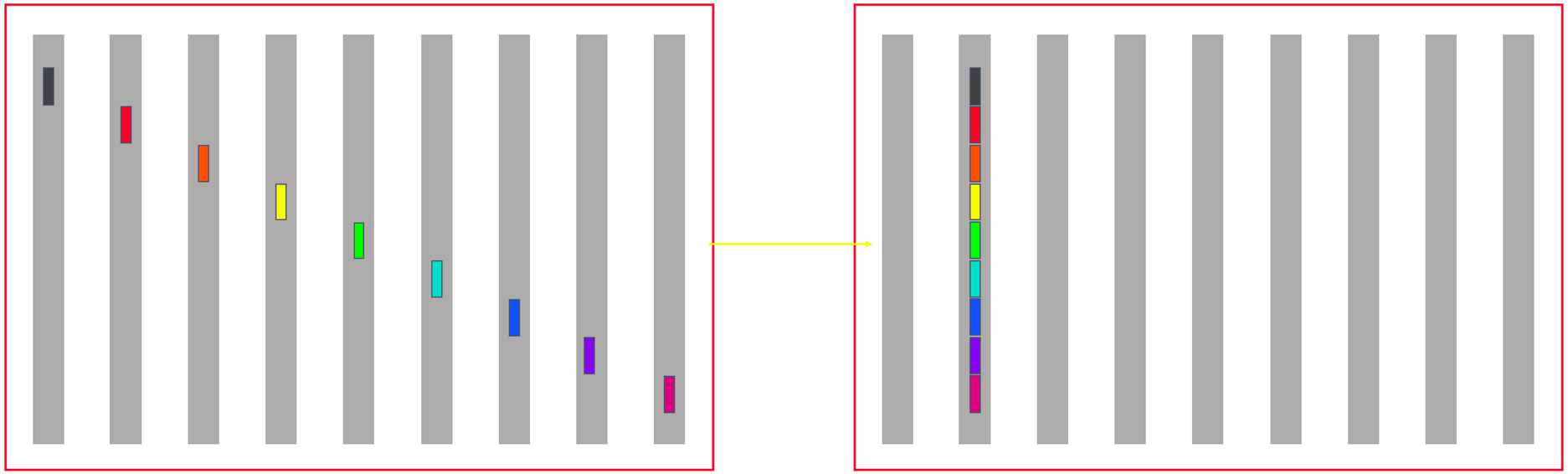


Gather

Notice: Gather as implemented before using MST was optimal in bandwidth as well（how to prove?）

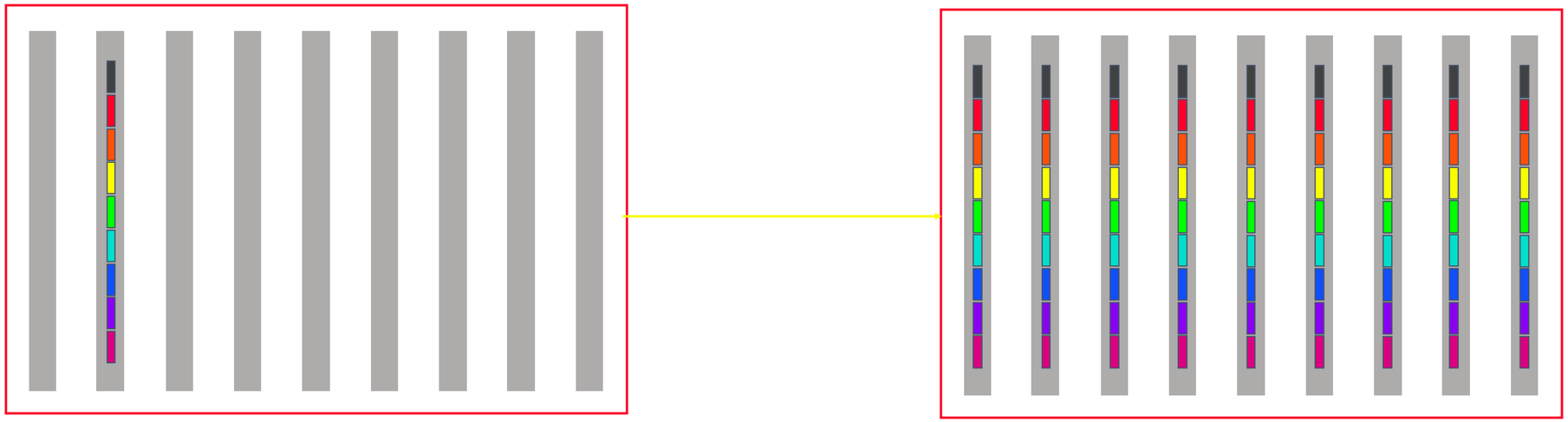
Before

After

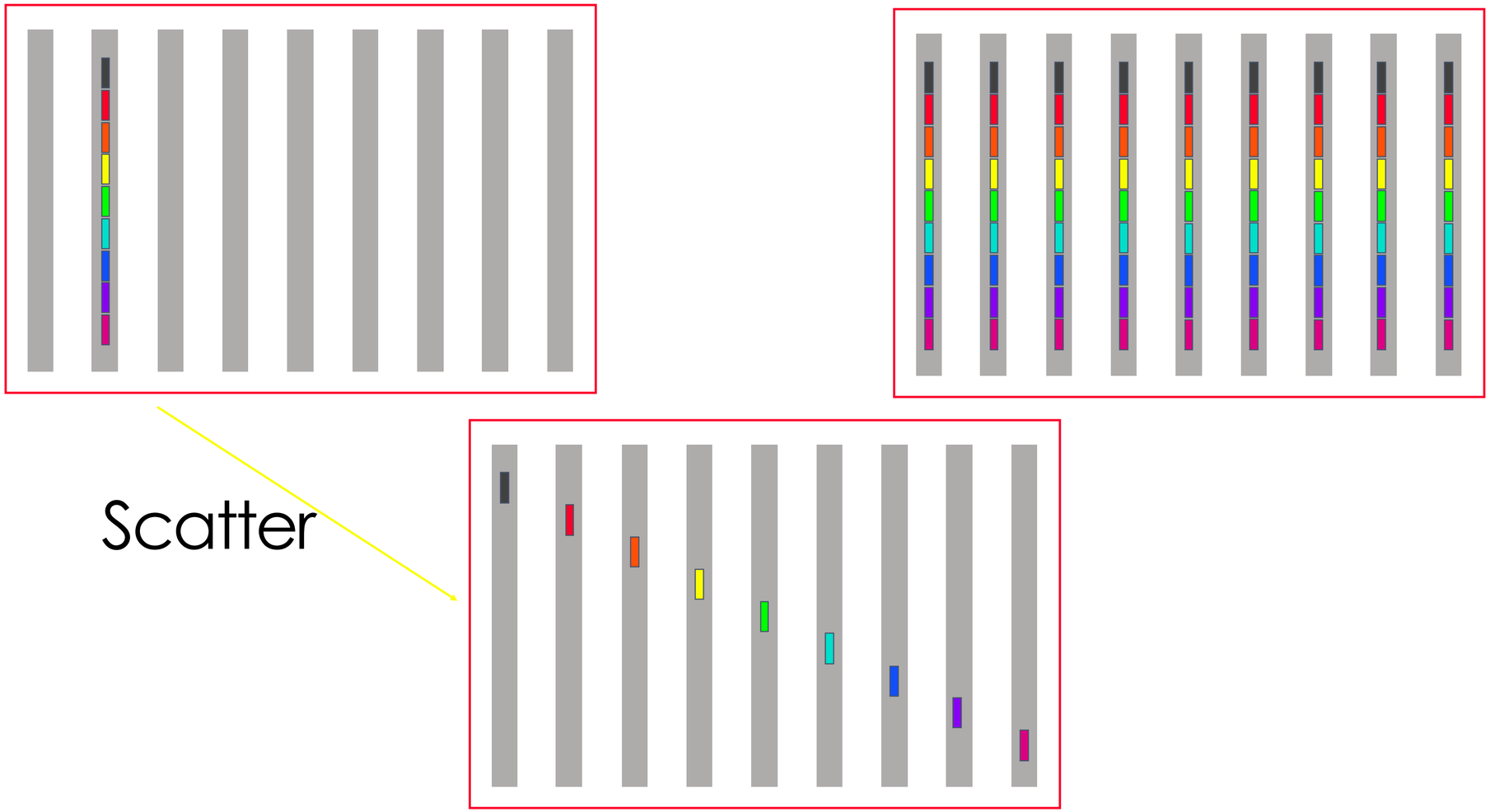


Using the building blocks

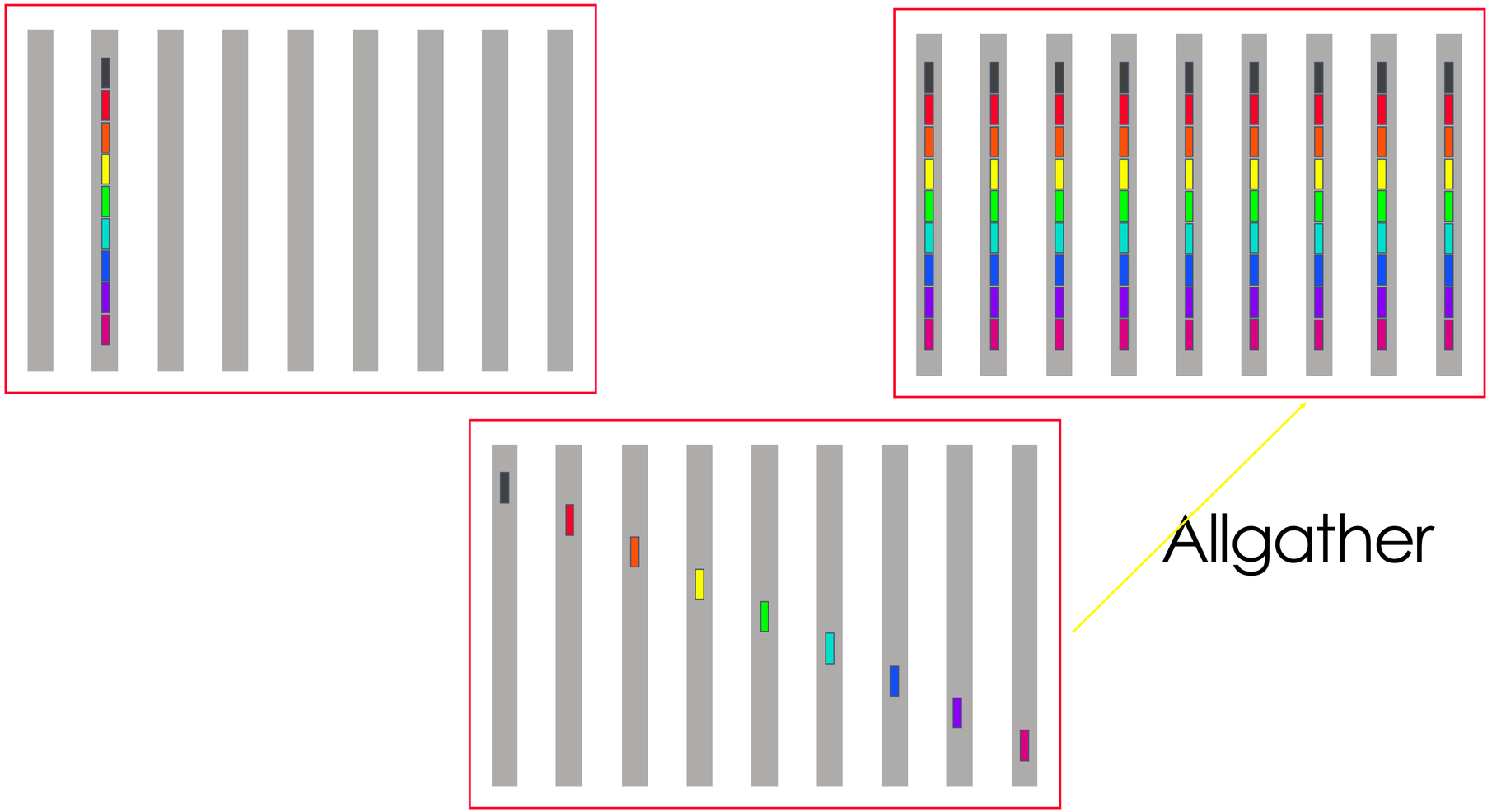
Broadcast (Large Message)



Broadcast (Large Message)



Broadcast (Large Message)



Cost of scatter/allgather broadcast

- Assumption: power of two number of nodes

scatter $\log(p)\alpha + \frac{p-1}{p} n\beta$

allgather $(p-1)\alpha + \frac{p-1}{p} n\beta$

$$\frac{(p-1)\alpha + \frac{p-1}{p} n\beta}{(\log(p) + p - 1)\alpha + 2\frac{p-1}{p} n\beta}$$

Cost of scatter/allgather broadcast

- Assumption: power of two number of nodes

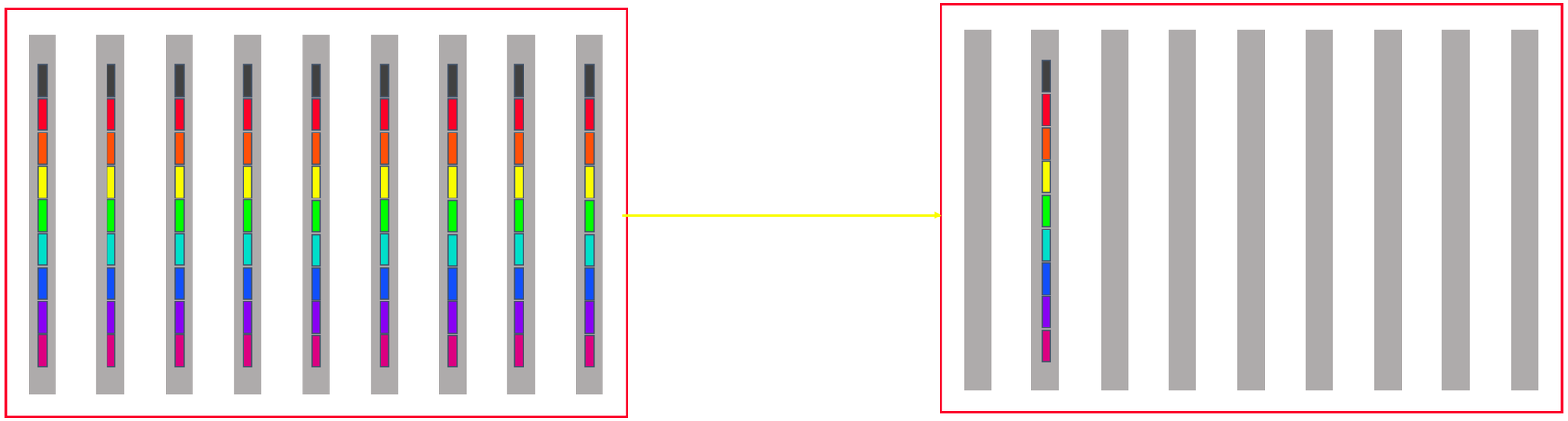
scatter $\log(p)\alpha + \frac{p-1}{p} n\beta$

allgather $(p-1)\alpha + \frac{p-1}{p} n\beta$

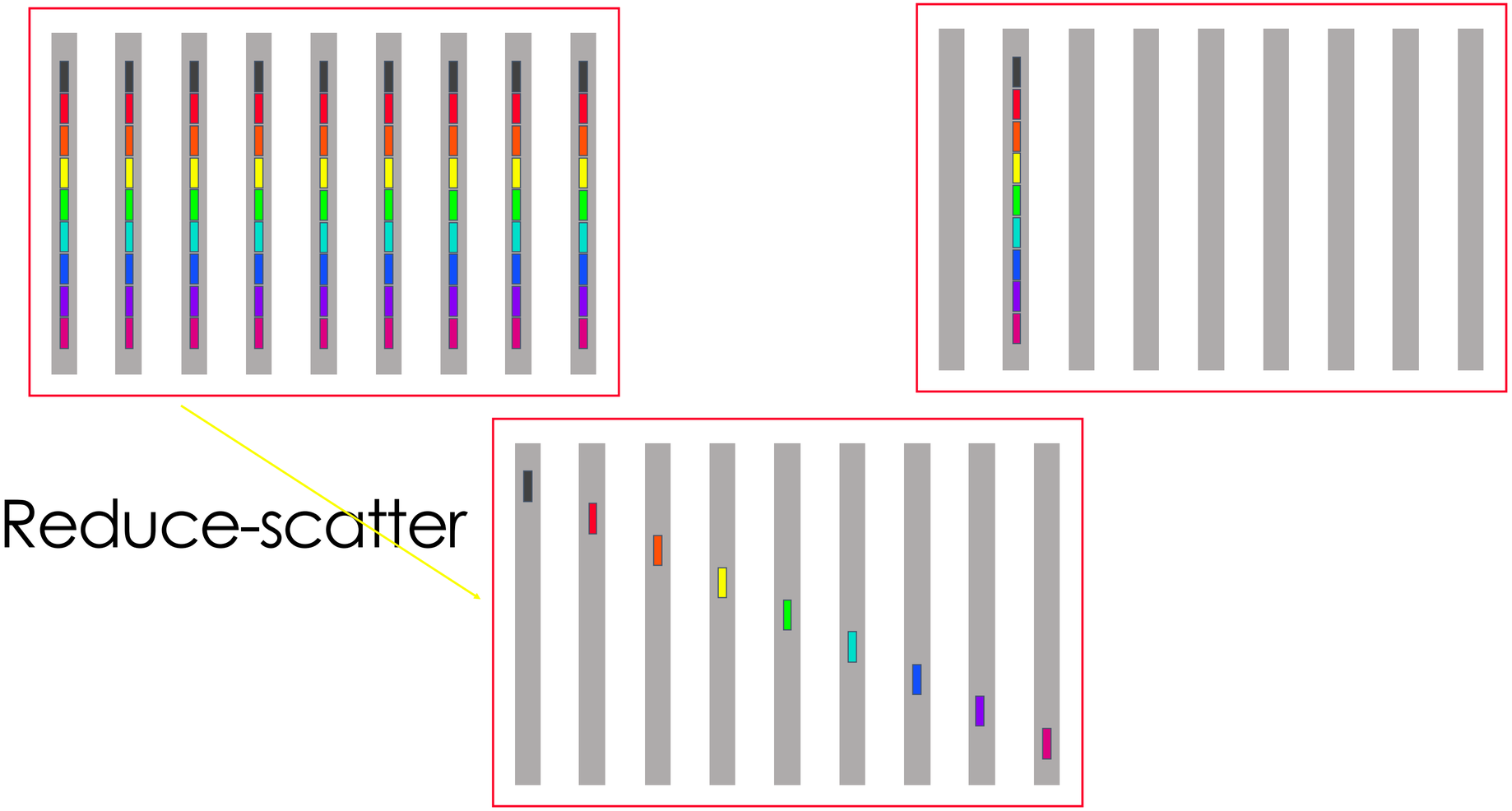
$$\frac{(p-1)\alpha + \frac{p-1}{p} n\beta}{(\log(p)+p-1)\alpha + 2\frac{p-1}{p} n\beta}$$

Vs. MST broadcast: $\lceil \log(p) \rceil \left(\alpha + n\beta\right)$

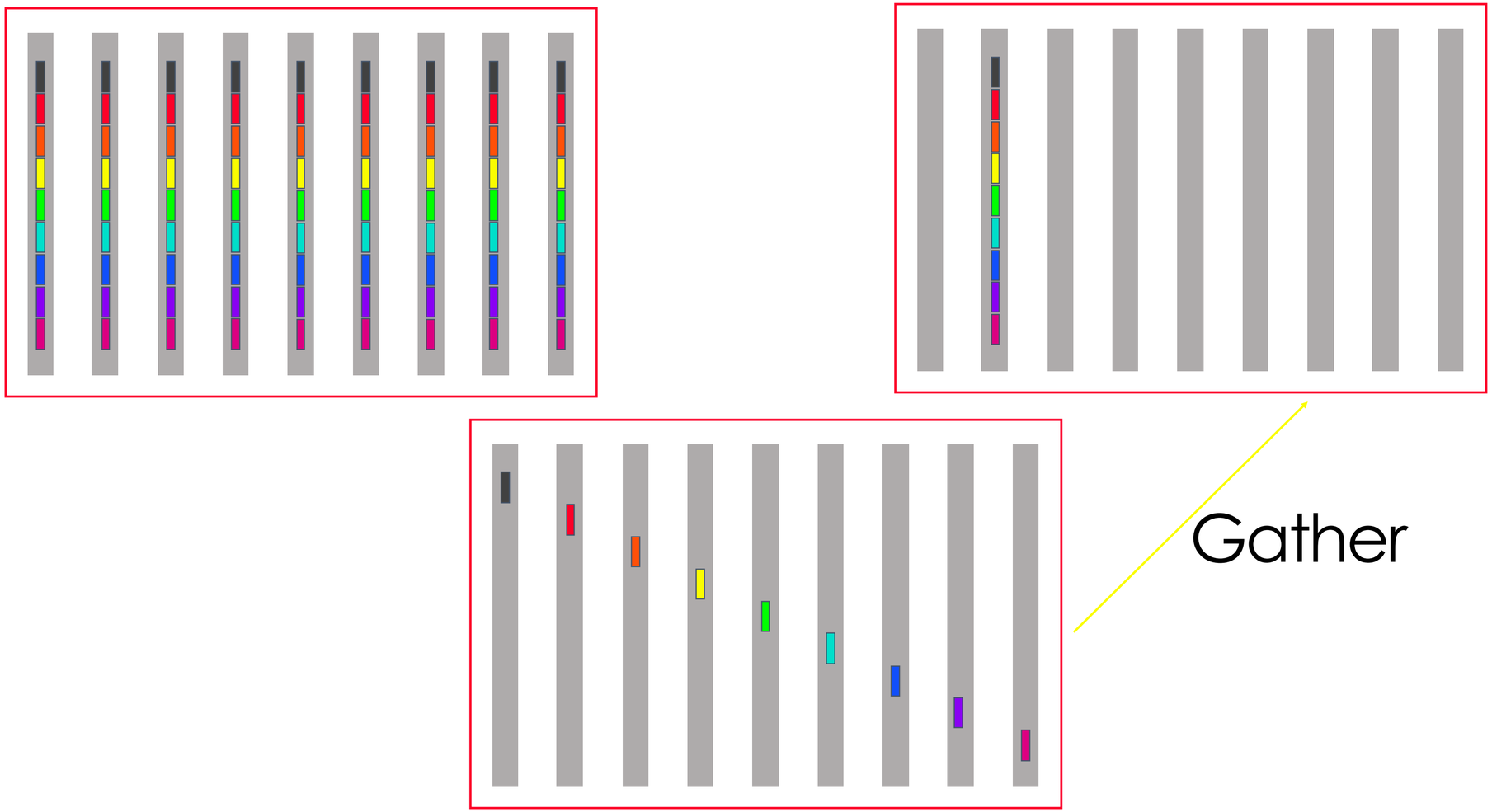
Reduce(-to-one) (Large Message)



Reduce (long vector)



Combine-to-one (long vector)



Cost of Reduce-scatter/Gather Reduce(-to-one)

- Assumption: power of two number of nodes

Reduce-scatter $(p-1)\alpha + \frac{p-1}{p} n\beta + \frac{p-1}{p} n\gamma$

gather $\log(p)\alpha + \frac{p-1}{p} n\beta$

$$\frac{\log(p)\alpha + \frac{p-1}{p} n\beta}{(\log(p)+p-1)\alpha + 2\frac{p-1}{p} n\beta + \frac{p-1}{p} n\gamma}$$

Cost of Reduce-scatter/Gather Reduce(-to-one)

- Assumption: power of two number of nodes

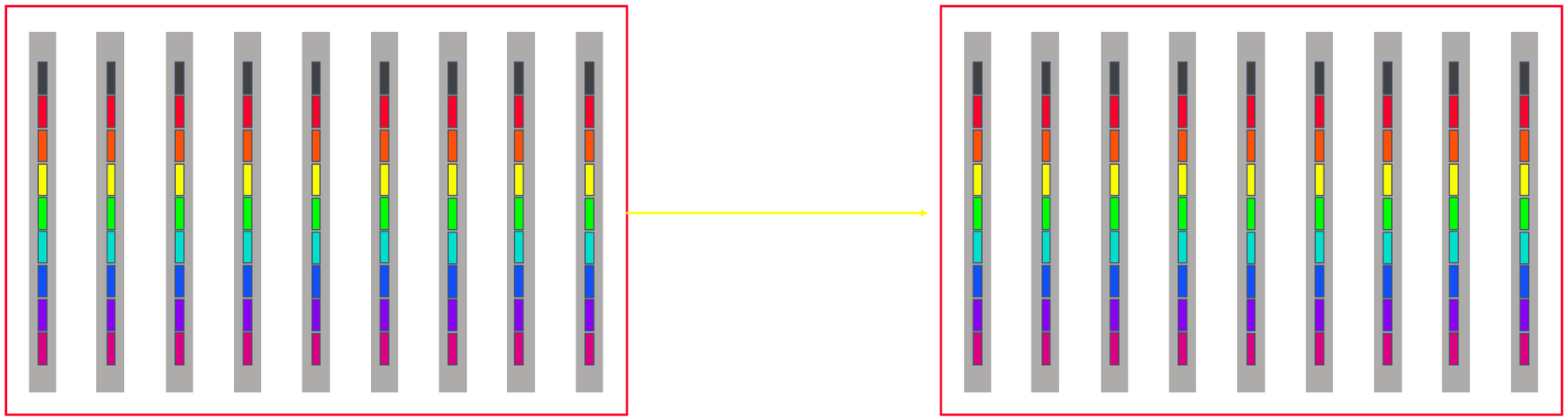
Reduce-scatter $(p-1)\alpha + \frac{p-1}{p} n\beta + \frac{p-1}{p} n\gamma$

gather $\log(p)\alpha + \frac{p-1}{p} n\beta$

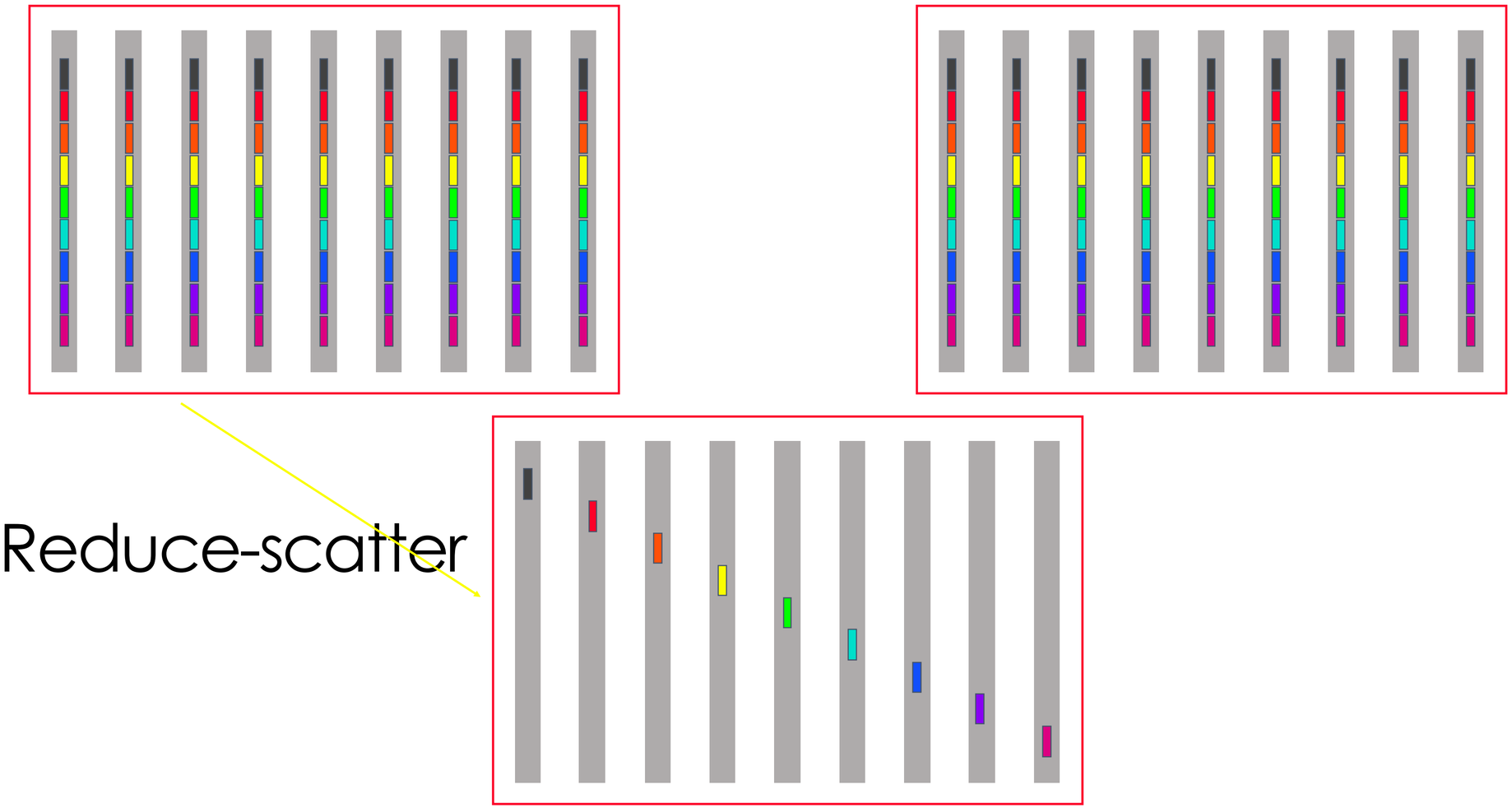
$$\frac{\log(p)\alpha + \frac{p-1}{p} n\beta}{(\log(p)+p-1)\alpha + 2\frac{p-1}{p} n\beta + \frac{p-1}{p} n\gamma}$$

Vs. MST reduce: $\lceil \log(p) \rceil \left(\alpha + n\beta + n\gamma\right)$

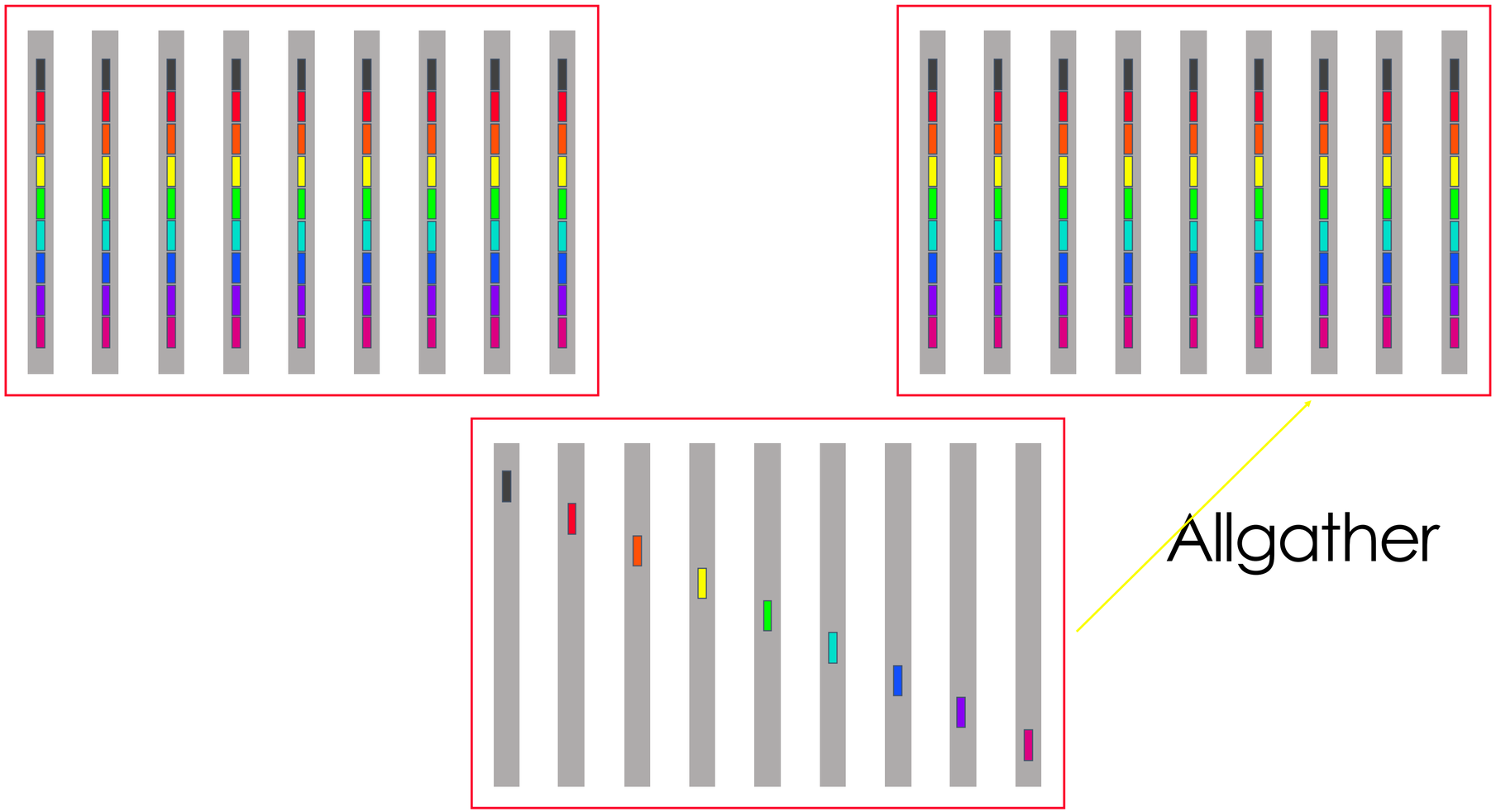
Allreduce (Large Message)



Allreduce (Large Message)



Allreduce
(long vector)



Cost of Reduce-scatter/Allgather Allreduce

- Assumption: power of two number of nodes

Reduce-scatter $(p-1)\alpha + \frac{p-1}{p} n\beta + \frac{p-1}{p} n\gamma$

Allgather $(p-1)\alpha + \frac{p-1}{p} n\beta$

$$\frac{(p-1)\alpha + \frac{p-1}{p} n\beta}{2(p-1)\alpha + 2\frac{p-1}{p} n\beta + \frac{p-1}{p} n\gamma}$$

Cost of Reduce-scatter/Allgather Allreduce

- Assumption: power of two number of nodes

Reduce-scatter $(p-1)\alpha + \frac{p-1}{p} n\beta + \frac{p-1}{p} n\gamma$

Allgather $(p-1)\alpha + \frac{p-1}{p} n\beta$

$$2(p-1)\alpha + 2\frac{p-1}{p} n\beta + \frac{p-1}{p} n\gamma$$

Vs. Reduce-broadcast allreduce $2\log(p)\alpha + 2\log(p)n\beta + \log(p)n\gamma$

Recap

Reduce-scatter

$$(p-1)\alpha + \frac{p-1}{p} n(\beta+\gamma)$$

Scatter

$$\log(p)\alpha + \frac{p-1}{p} n\beta$$

Gather

$$\log(p)\alpha + \frac{p-1}{p} n\beta$$

Allgather

$$(p-1)\alpha + \frac{p-1}{p} n\beta$$

Reduce(-to-one)

Allreduce

Broadcast

Recap

Reduce-scatter

$$(p-1)\alpha + \frac{p-1}{p} n(\beta+\gamma)$$

Scatter

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Allgather

$$(p-1)\alpha + \frac{p-1}{p} n\beta$$

Reduce(-to-one)

$$(p-1+\log(p))\alpha + \frac{p-1}{p} n(2\beta+\gamma)$$

Allreduce

Broadcast

Recap

Reduce-scatter

$$(p-1)\alpha + \frac{p-1}{p} n(\beta+\gamma)$$

Scatter

$$\log(p)\alpha + \frac{p-1}{p} n\beta$$

Gather

$$\log(p)\alpha + \frac{p-1}{p} n\beta$$

Allgather

$$(p-1)\alpha + \frac{p-1}{p} n\beta$$

Reduce(-to-one)

$$(p-1+\log(p))\alpha + \frac{p-1}{p} n(2\beta+\gamma)$$

Allreduce

$$2(p-1)\alpha + \frac{p-1}{p} n(2\beta+\gamma)$$

Broadcast

$$(\log(p)+p-1)\alpha + 2\frac{p-1}{p} n\beta$$

Recap

Reduce-scatter

$$(p-1)\alpha + \frac{p-1}{p} n(\beta+\gamma)$$

Scatter

$$\log(p)\alpha + \frac{p-1}{p} n\beta$$

Gather

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Allreduce

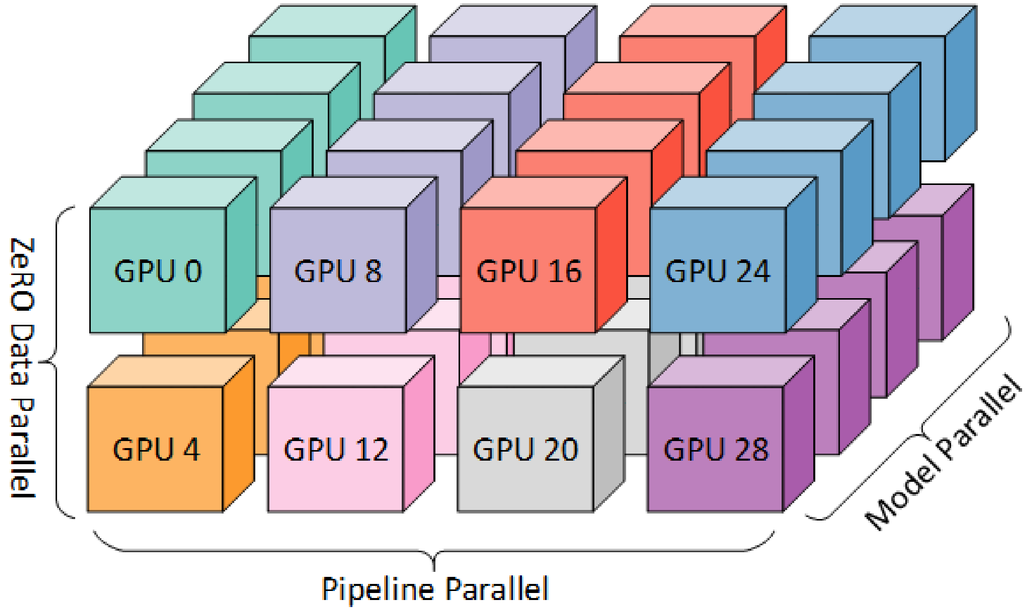
$$2(p-1)\alpha + \frac{p-1}{p} n(2\beta+\gamma)$$

Broadcast

$$(\log(p)+p-1)\alpha + 2\frac{p-1}{p} n\beta$$

A More Complicate Case

- Real Cluster to train ChatGPT:
  - If using GPU: 2D Mesh
  - If using TPU: 3D Mesh, see figure below



Summary and Question

- MST -> when alpha dominates
- Ring -> when n*beta dominates
- 2D can be composed using 1D, 3D can be composed using 2D,

  …
- Latency / Bandwidth trade-offs

Recap

- Q1: Which collective primitive maps to the distributed SGD gradient synchronization step?
- Q2: How many messages do we need to transfer over the network for a single iteration of GPT-3 SGD update assuming 8-gpu parallelism?
- Q3: For Q2, assuming 1D mesh, should we use MST or Ring?

Collective Pros

- A set of structured / well-defined communication primitives
- Extremely well-optimized
- Beautiful math, easy to analyze, and easy to understand its performance

Collective Cons

- Lack of Fault Tolerance
  - What if one node (in the ring) is dead?
- Requires Homogeneity
  - What if one node computes slower than all other nodes?
  - What if one link has lower bandwidth than the other node?

Real Cluster:

- Need Fault tolerance
- Heterogeneous hardware setup

Where we are

Motivations, Economics, Ecosystems, Trends

Skip this

Networking

~~Datacenter networking~~

~~Collective communication~~

Storage

(Distributed) File Systems / Database

Cloud storage

Compute

Distributed Computing

Big data processing

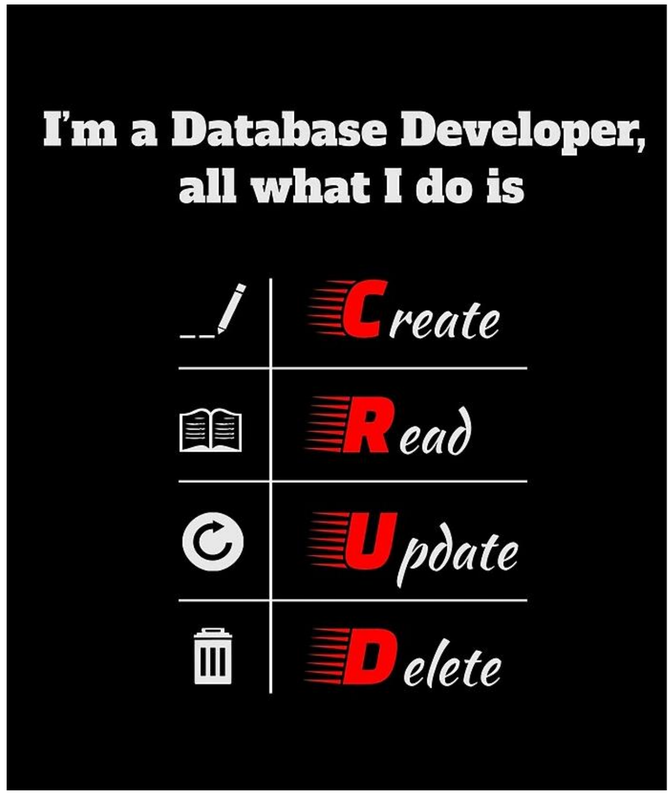
But Some Basic Knowledge Check

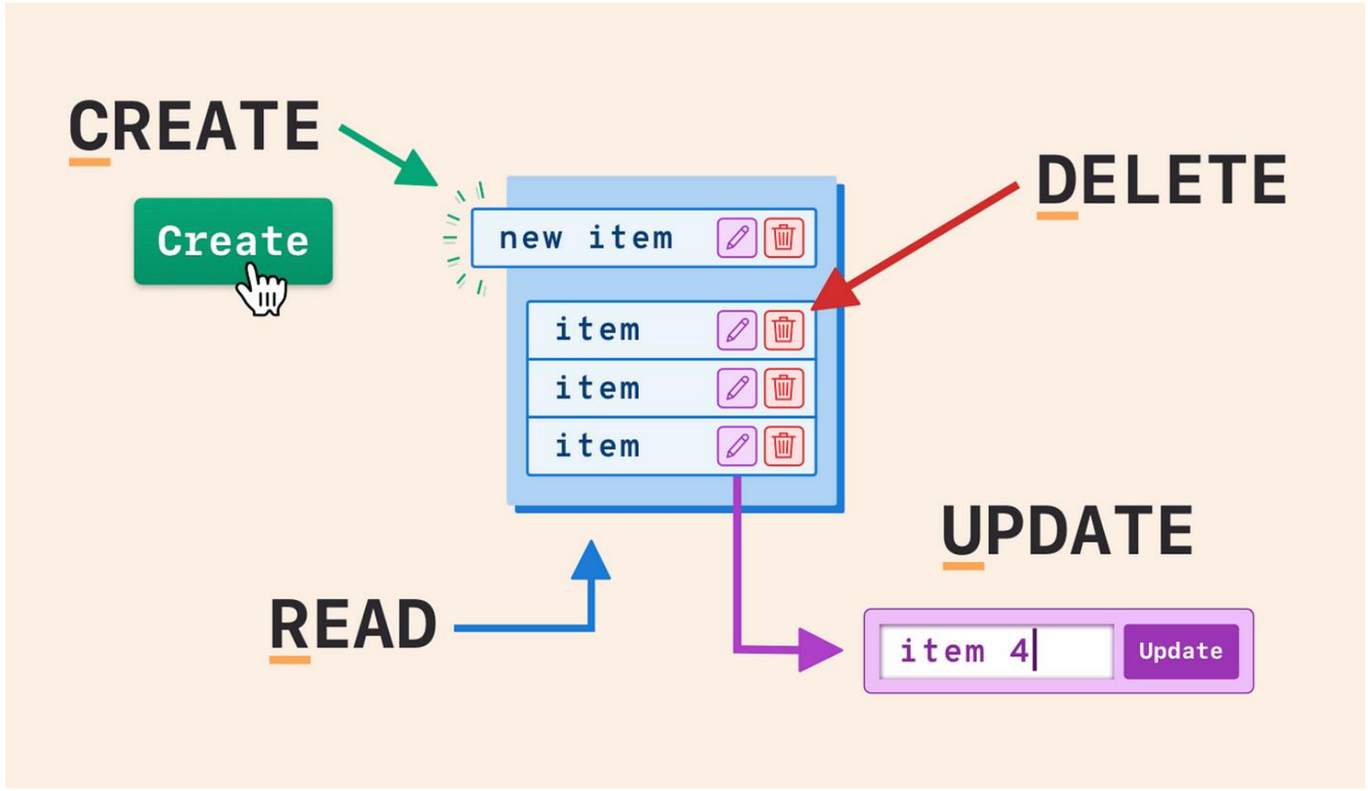
- **What is a Database**
- Have you heard these terms?
  - HashTable
  - SSTable and LSM-Trees
  - BTree?
- Optional readings will cover this – highly recommend to read

But Some Important Concepts

- OLTP v.s. OLAP
- Data warehousing
- Schemas for Analytics
- Column-oriented storage
- Data cubes and materialized views

CRUD


I'm a Database Developer,
all what I do is
Create
Read
Update
Delete

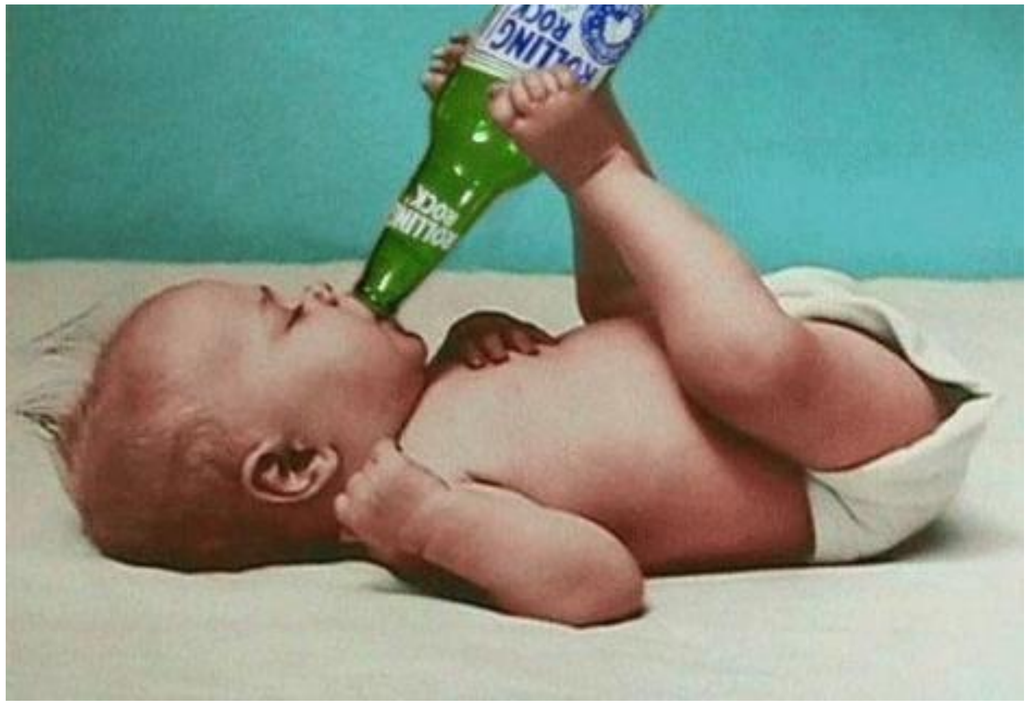

CREATE
Create
new item
item
item
item
DELETE
UPDATE
READ
item 4
Update

Database transactions

- Make sale
- Place an order
- Pay an employee's salary
- Comment a blog post
- Act in games
- Add/remove contract to an address book

Online transaction processing (OLTP)

Walmart Beer and Diaper (1988)



Forbes 1988

- Unexpected correlation:
  - Sales of diapers and beer

https://www.forbes.com/forbes/1998/0406/6107128a.html?sh=2574a9316260

Data analytics

- What was the total revenue of each of our stores in Jan?
- How many more bananas than usual did we sell during our latest data?
- Which brand of baby food is most often purchased together with brand X diapers?

Online analytic processing (OLAP)

OLTP v.s. OLAP

Property	Transaction processing systems (OLTP)	Analytic systems (OLAP)
Main read pattern	Small number of records per query, fetched by key	Aggregate over large number of records

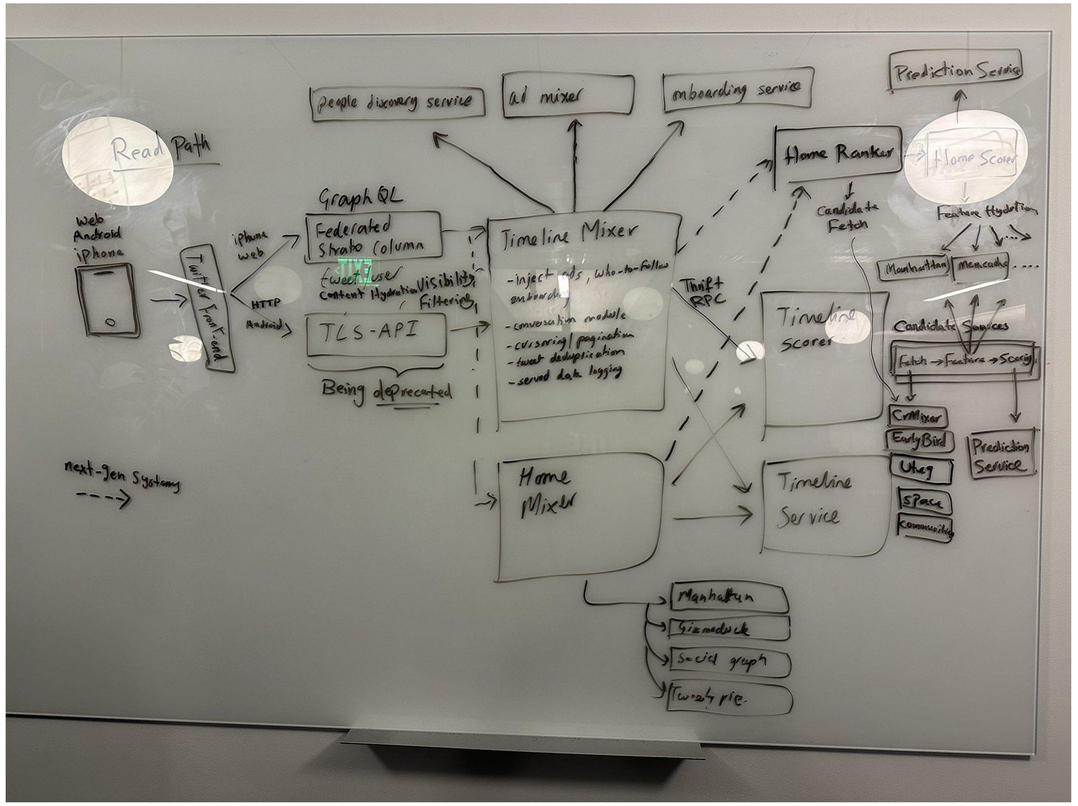
OLTP v.s. OLAP

Property	Transaction processing systems (OLTP)	Analytic systems (OLAP)
Main read pattern	Small number of records per query, fetched by key	Aggregate over large number of records
Main write pattern	Random-access, low-latency writes from user input	Bulk import (ETL) or event stream
Primarily used by	End user/customer, via web application	Internal analyst, for decision support
What data represents	Latest state of data (current point in time)	History of events that happened over time
Dataset size	Gigabytes to terabytes	Terabytes to petabytes

Today's topic

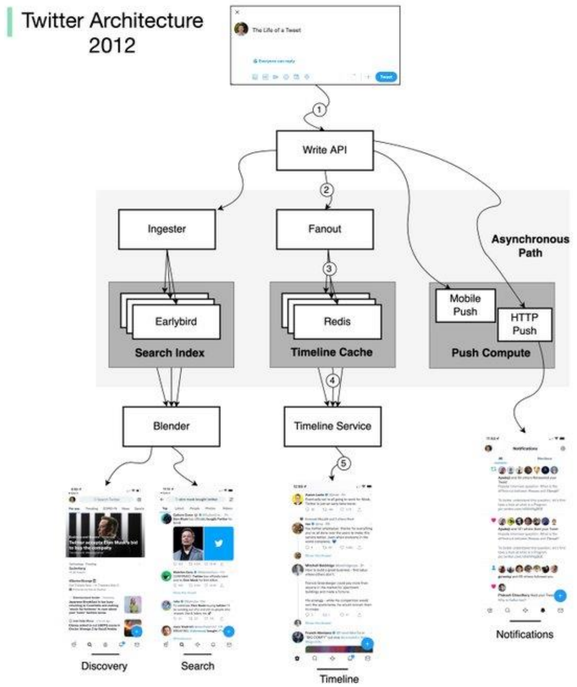
- OLTP v.s. OLAP
- Data warehousing
- Schemas for Analytics
- Column-oriented storage

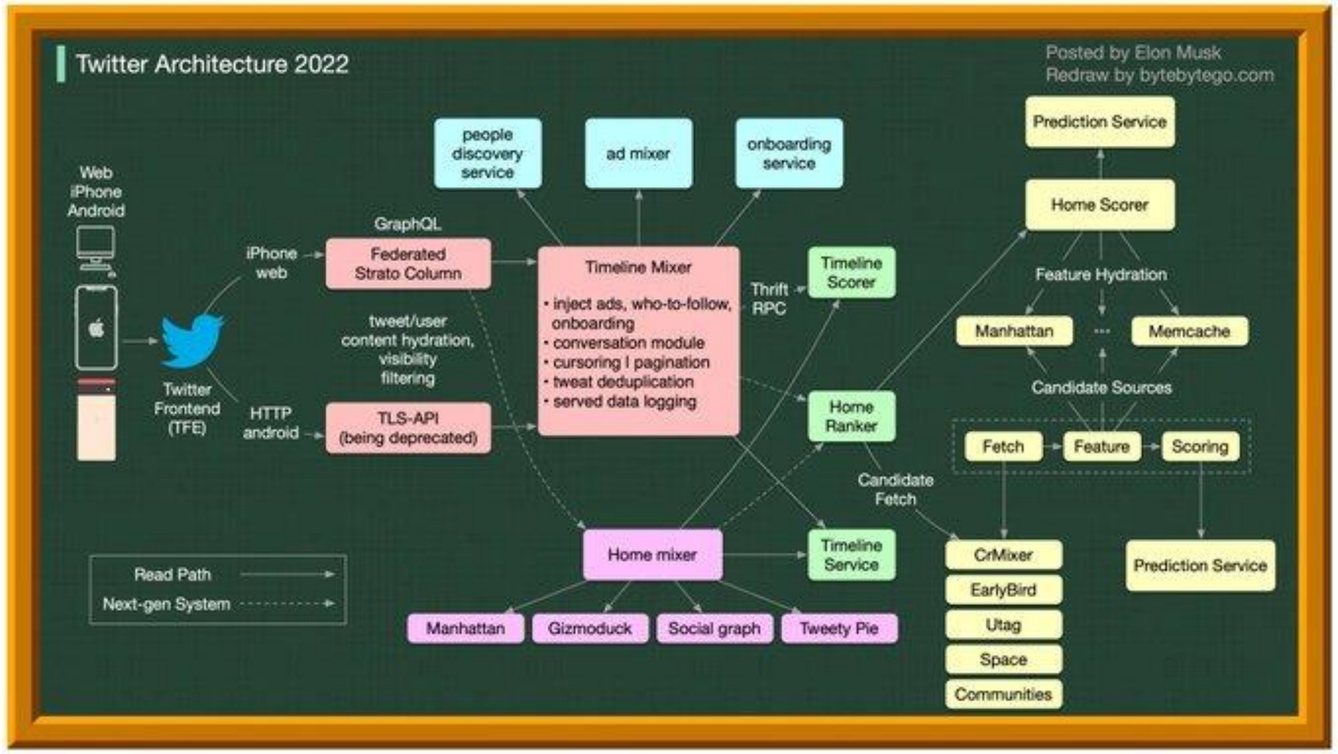
Transaction systems are complex.



Elon Musk's Twitter System Design Diagram Explained
https://www.youtube.com/watch?v=_Y5aGCOkymQ

Transaction systems need to be highly available.





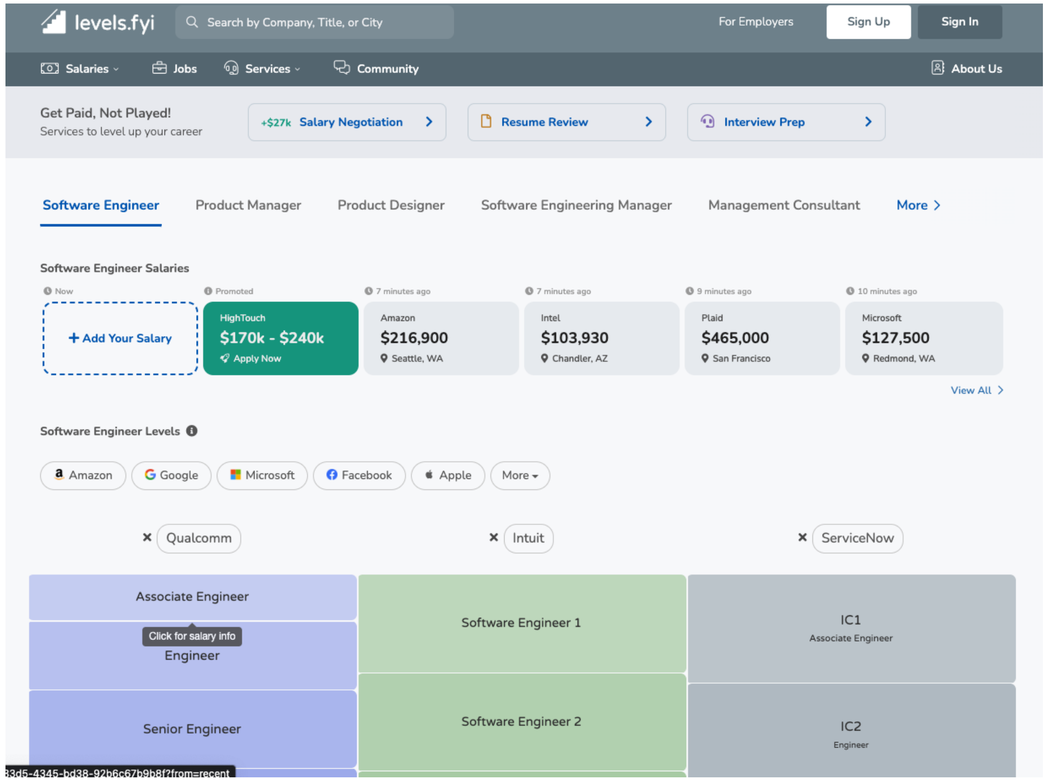
- Low latency.
- Highly available.
- Ad hoc analytic queries are expensive.

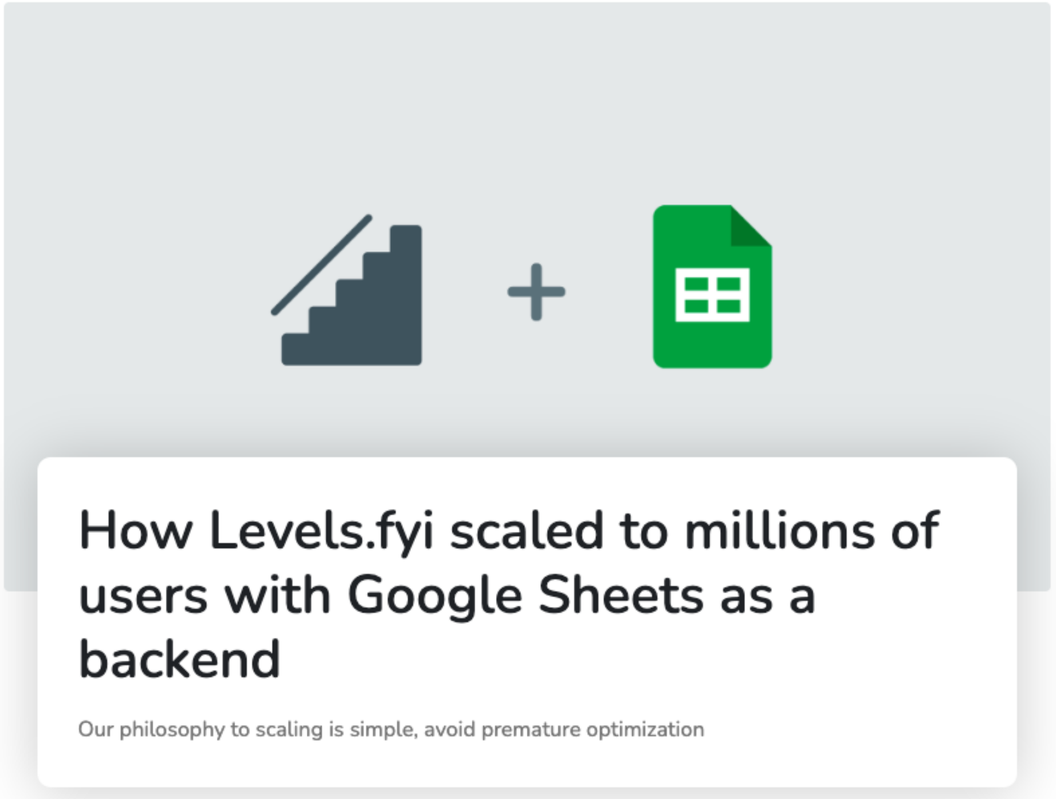
https://twitter.com/alexxubyte/status/1594008281340530688

Data warehouse

- A separate database that analysts can query to their hearts' content, without affecting OLTP operations.
- Maintain a read-only copy for analytic purposes.
- Only exist in almost all large enterprises.

Small companies?

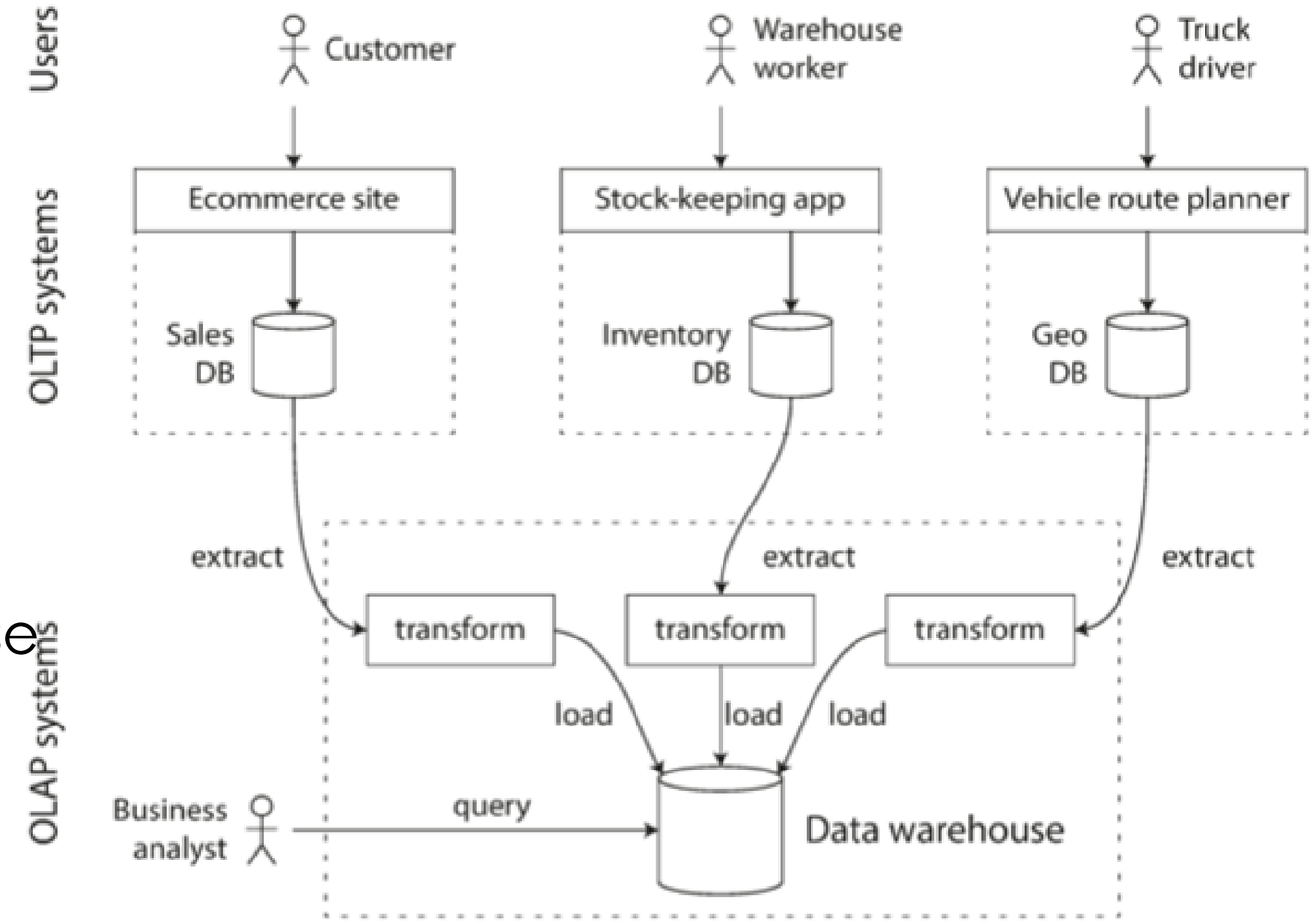




https://www.levels.fyi/blog/scaling-to-millions-with-google-sheets.html

Extract-Transform-Load (ETL)

- Extract
  - Periodica data dump
  - Continuous streaming
- Transform
  - Analysis-friendly schema
  - Data cleaning
- Load into a data warehouse



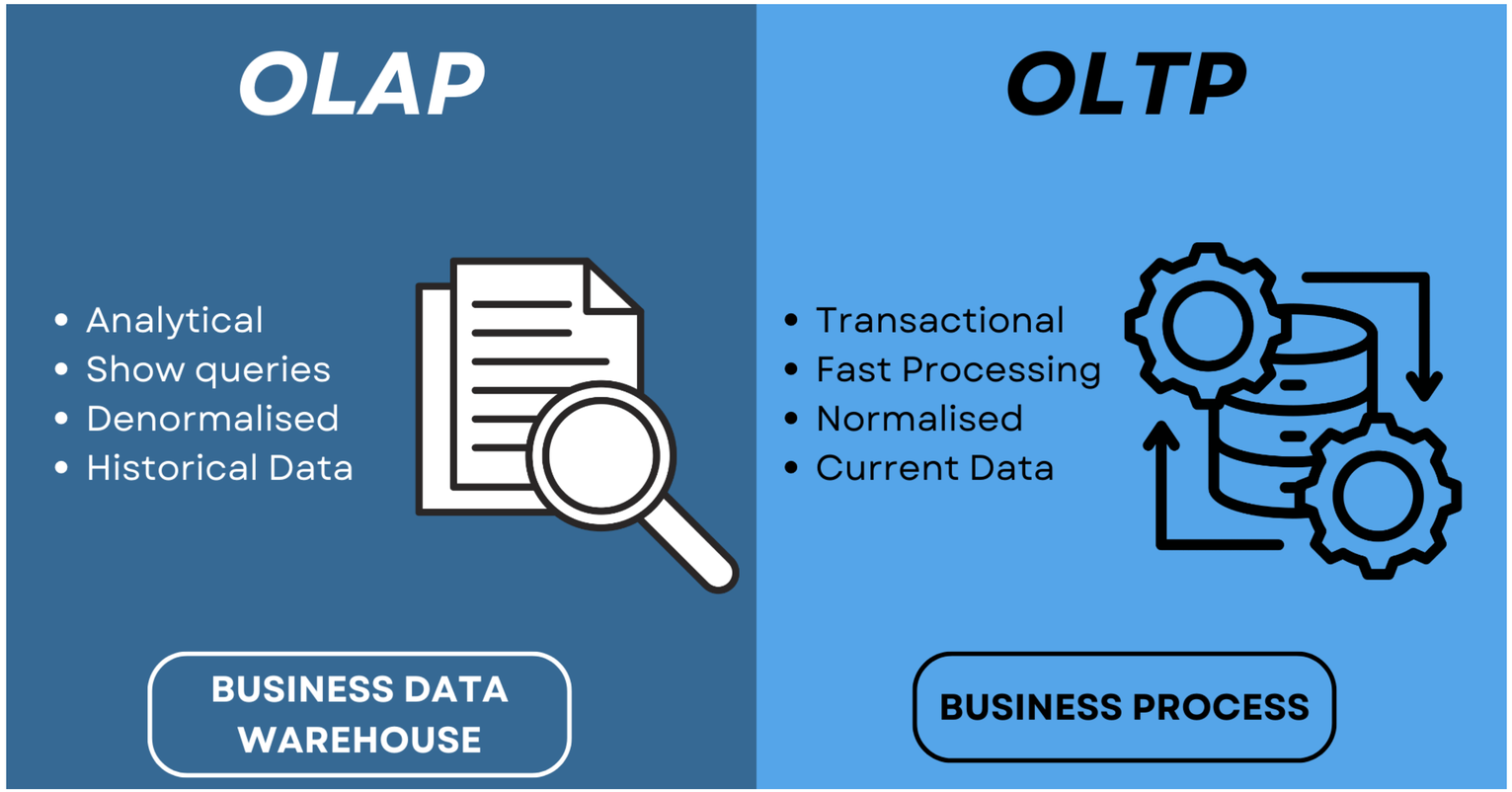
Why data warehouse?

- Separation of concerns
  - Performance (reliability, latency)
  - Expertise requirement, management
- The classic indexes (e.g., SSTable, B-tree) are good for reading and writing a single record.
  - But are not good at answering analytic queries.

How do you interact with OLAP & OLTP

- SQL query interface
  - *Select * from*
  - "A database system can be considered mature when it has an SQL query interface".
  - Both OLAP and OLTP
- OLAP:
  - More and more codeless user interfaces.
  - Text2SQL
  - Note: This is a big market of innovations

Sumary


OLAP
Analytical
Show queries
Denormalised
Historical Data
BUSINESS DATA WAREHOUSE
OLTP
Transactional
Fast Processing
Normalised
Current Data
BUSINESS PROCESS

More Stories?

TRIFACTA

400M

Streamlit

800M / ~30 persons

databricks

100B

83B

Where We Are

Motivations, Economics, Ecosystems, Trends

Networking

Storage

Part3: Compute

~~Datacenter networking~~

~~Collective communication~~

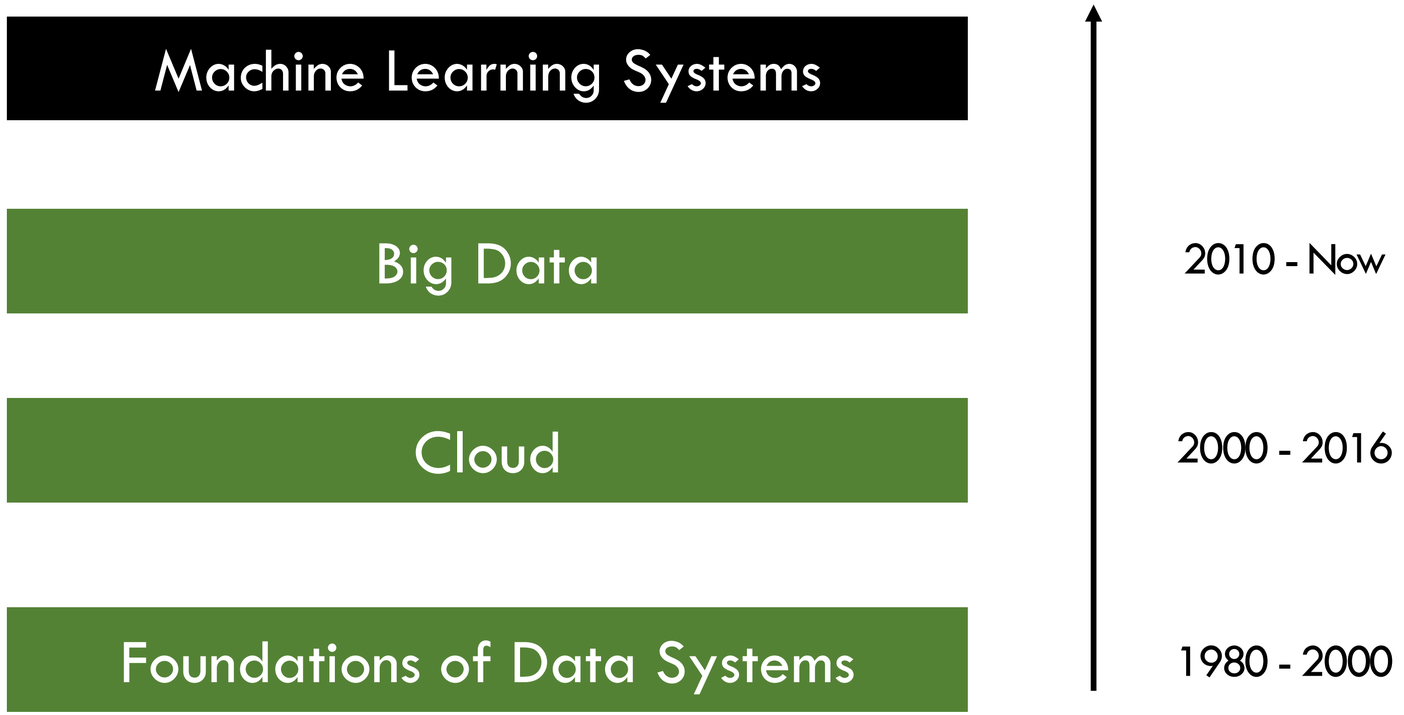
(Distributed) File Systems / Database

Cloud storage

Distributed Computing

Big data processing

Where We Are


Machine Learning Systems
Big Data
Cloud
Foundations of Data Systems
2010 - Now
2000 - 2016
1980 - 2000

Distributed Computing and Big Data

- Parallelism Basics
- Data Replication and partitioning
- Batched Processing
- Streaming Processing

Today's topic: Parallelism

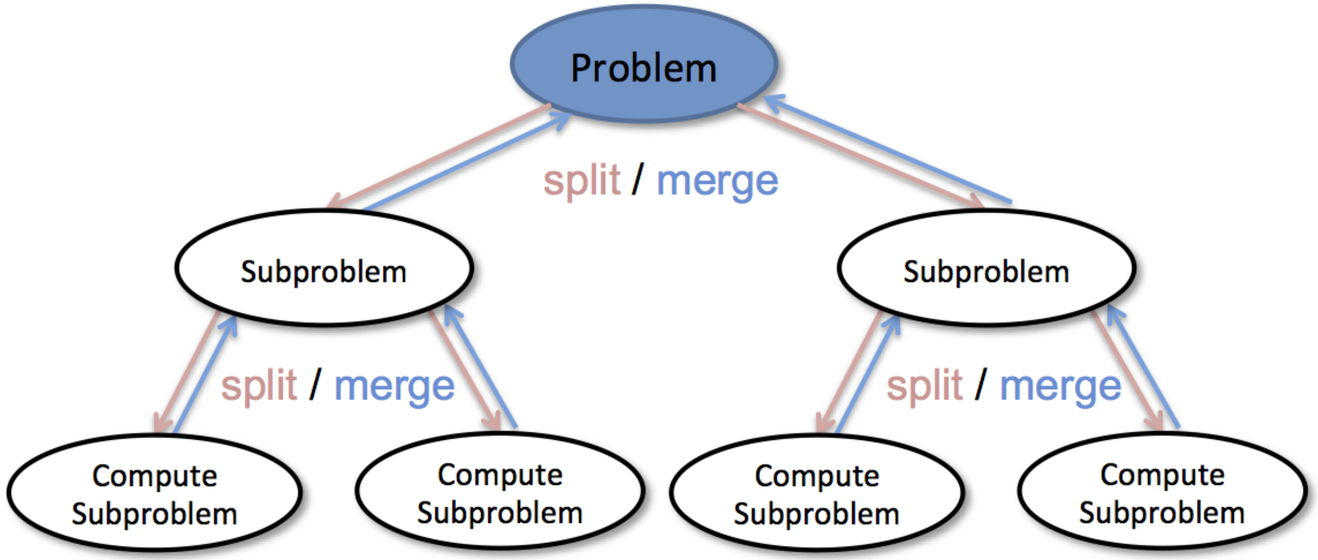
- Express data processing in abstraction
- Parallelisms

Parallel Data Processing

Central Issue: Workload takes too long for one processor!

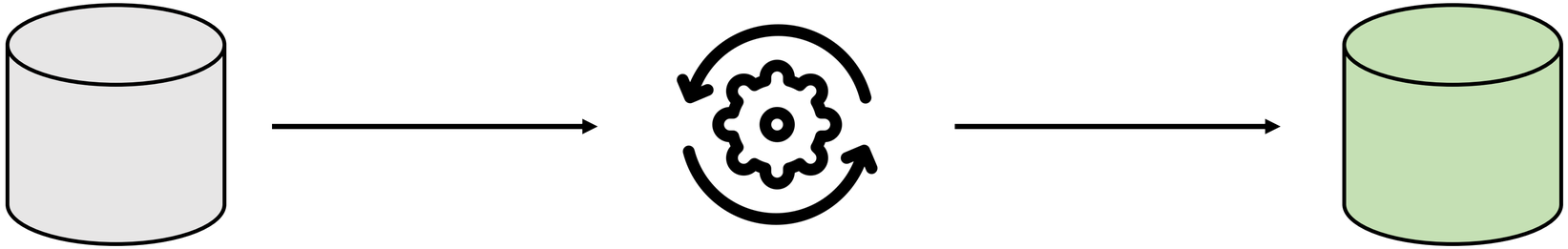
Basic Idea: Split up workload across processors and perhaps also across machines/workers (aka "Divide and Conquer")

Remind you of PA1 (hope you've enjoyed it)



https://medium.com/cracking-the-data-science-interview/divide-and-conquer-algorithms-b135681d08fc

Data Processing: Abstraction



Original data

Processing functions

- sum, mean
- Page rank
- Supervised Learning
- Clustering
- Model inference

Result data

- data
- ML models

Q: How to represent various processing functions?

How to Express Arbitrarily Complex Processing Functions?

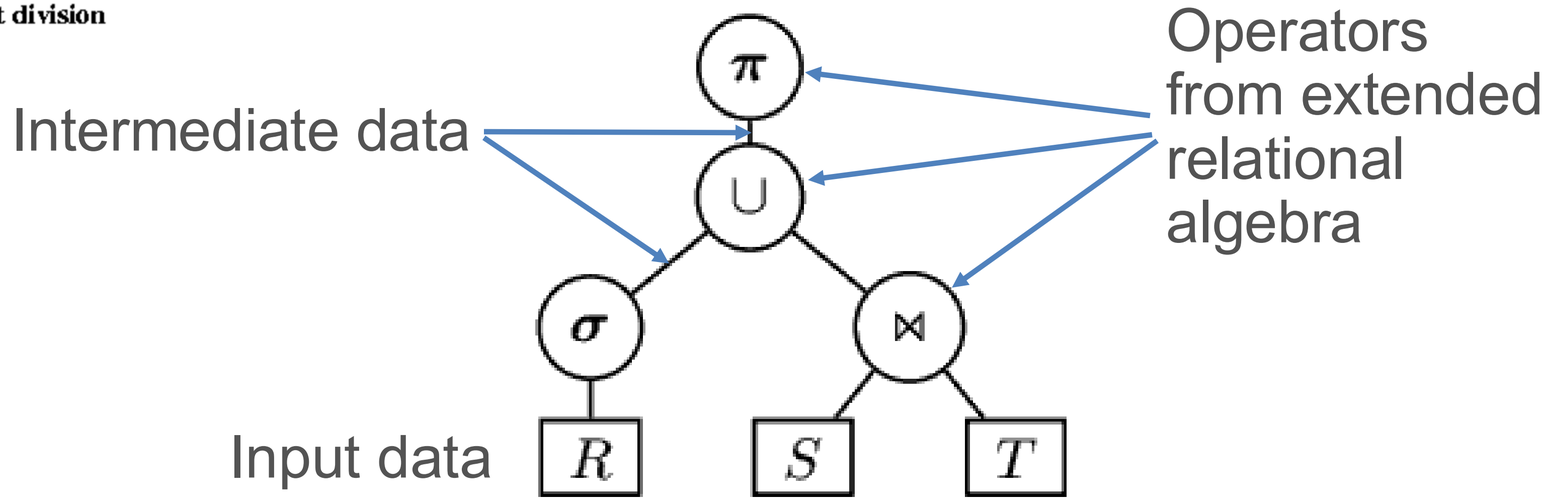
***Dataflow Graph*:** common in parallel data processing

- A ***directed*** graph representation of a program
  - **Vertices:** abstract operations from a restricted set of computational primitives:
  - **Edges:** data flowing directions (hence data dependency)
- Examples
  - Relational dataflows: RDBMS, Pandas, Modin
  - Matrix/tensor dataflows: NumPy, PyTorch, TensorFlow
- Enables us to reason about data-intensive programs at a higher level

Example: Relational Dataflow Graph

$\cup$	set union	σ	selection
$\cap$	set intersection	π	projection
$-$	set difference	$\bowtie$	join
$\times$	cartesian product	$\div$	set division

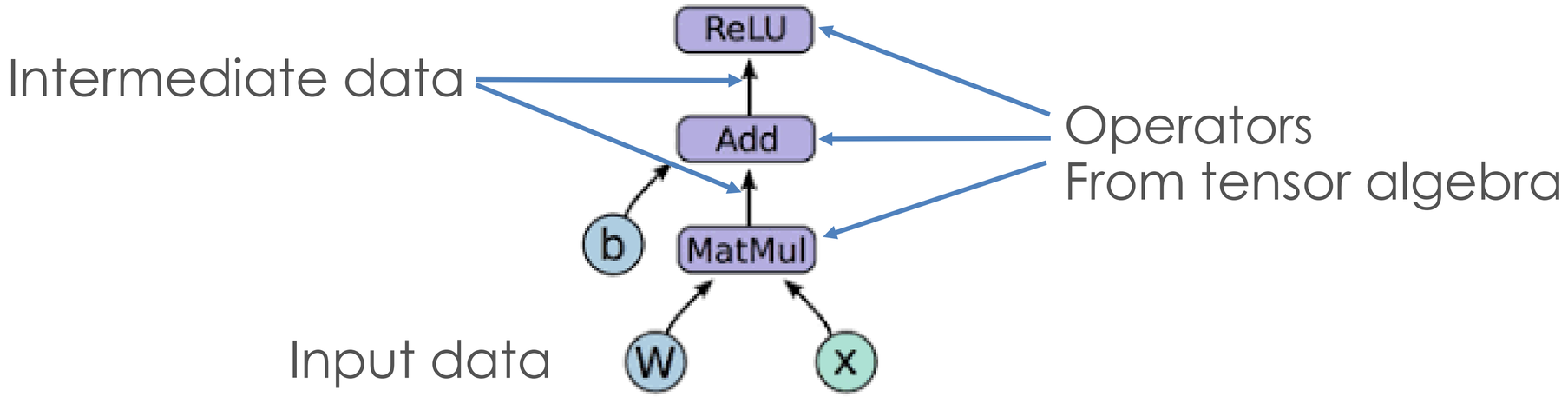
$$\pi(\sigma(R) \cup S \bowtie T)$$



Aka **Logical Query Plan** in the DB systems world

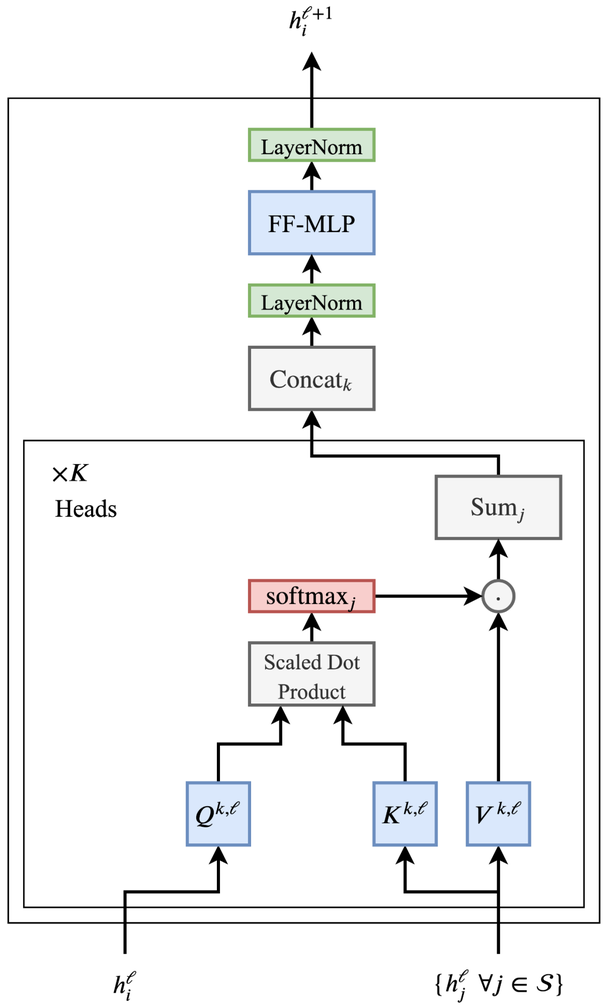
Example: Machine Learning Dataflow Graph

$$ReLU(WX + b)$$



Aka **Neural network computational graph** in ML systems

What is ChatGPT's dataflow graph Looking like?



Parallelism

Central Issue: Workload takes too long for one processor!

Basic Idea: Split up workload across processors and perhaps also across machines/workers (aka "Divide and Conquer")

Key parallelism paradigms in data systems

- **assuming there will be coordination:**

func \ data	**Shared**	**Replicated**	**Partitioned**
Replicated	N/A (rare cases)		Data parallelism
Partitioned	Task parallelism		Hybrid parallelism

Terms are confusing

- Different domains term them differently in different contexts
- Architecture/parallel computing: single-node multi-cores
  - SIMD, MIMD, SIMT
- Distributed system: multiple-node multi-cores
  - SPMD vs. MPMD
- Machine learning community
  - Data parallelism vs. Model parallelism
  - Inter-operator parallelism vs. Intra-operator parallelism

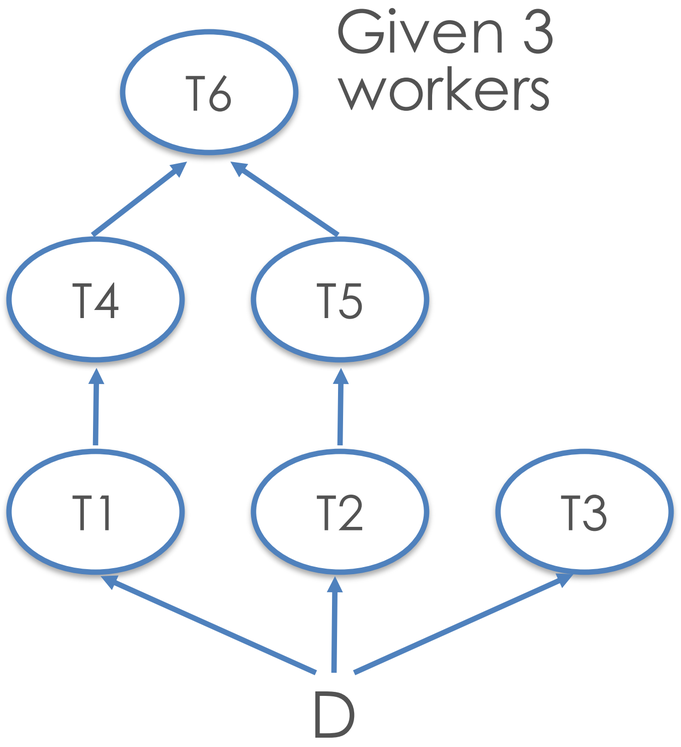
Today's topic: Parallelism

- Express data processing in abstraction
- Parallelisms
  - **Task parallelism**
  - Data parallelism
  - Terms: SIMD, SIMT, SPMD, MPMD

Task Parallelism

Basic Idea: Split up *tasks* across workers; if there is a common dataset that they read, just make copies of it (aka *replication*)

Example:



4) After T4 & T5 end, run T6 on W1; W2 is *idle*

3) After T1 ends, run T4 on W1; after T2 ends, run T5 on W2; after T3 ends, W3 is *idle*

2) Put T1 on worker 1 (W1), T2 on W2, T3 on W3; run all 3 in parallel

1) Copy whole D to all workers

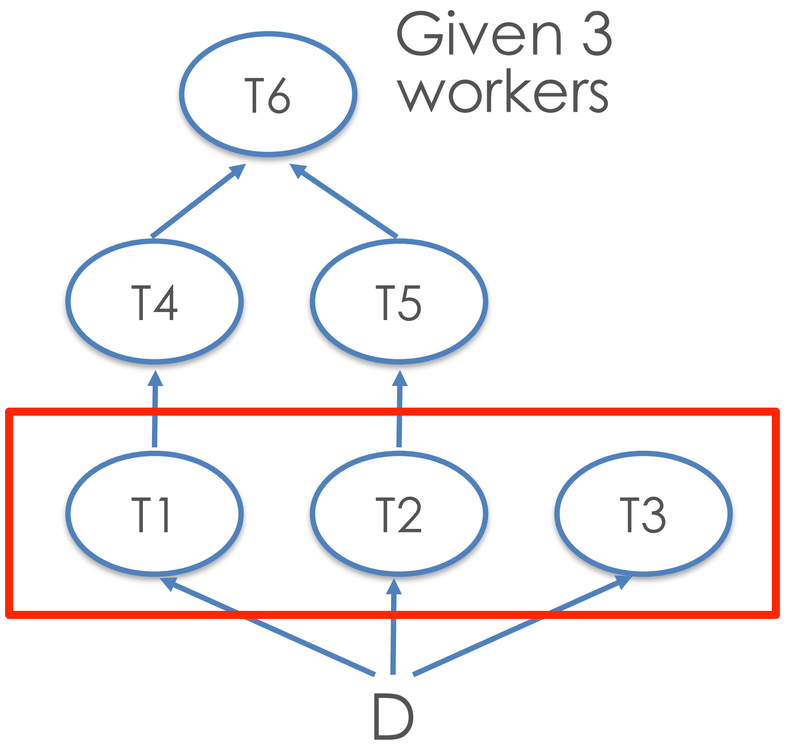
Task Parallelism

- Topological sort of tasks in task graph for scheduling
- Notion of a "worker" can be at processor/core level, not just at node/server level
  - Thread-level parallelism possible instead of process-level
  - E.g., Ray: 4 worker nodes x 4 cores = 16 workers total
- Main pros of task parallelism:
  - Simple to understand
  - Independence of workers => low software complexity
- Main cons of task parallelism:
  - Can be difficult to implement
  - Idle times possible on workers

Degree of Parallelism

- The largest amount of *concurrency* possible in the task graph, i.e., how many task can be run simultaneously

Example:



Q: *How do we quantify the runtime performance benefits of task parallelism?*

But over time, degree of parallelism keeps dropping in this example

Degree of parallelism is only 3

So, more than 3 workers is not useful for this workload!

Quantifying Benefit of Parallelism: Speedup

$$\textbf{Speedup} = \frac{\text{Completion time given only 1 worker}}{\text{Completion time given n (>1) workers}}$$

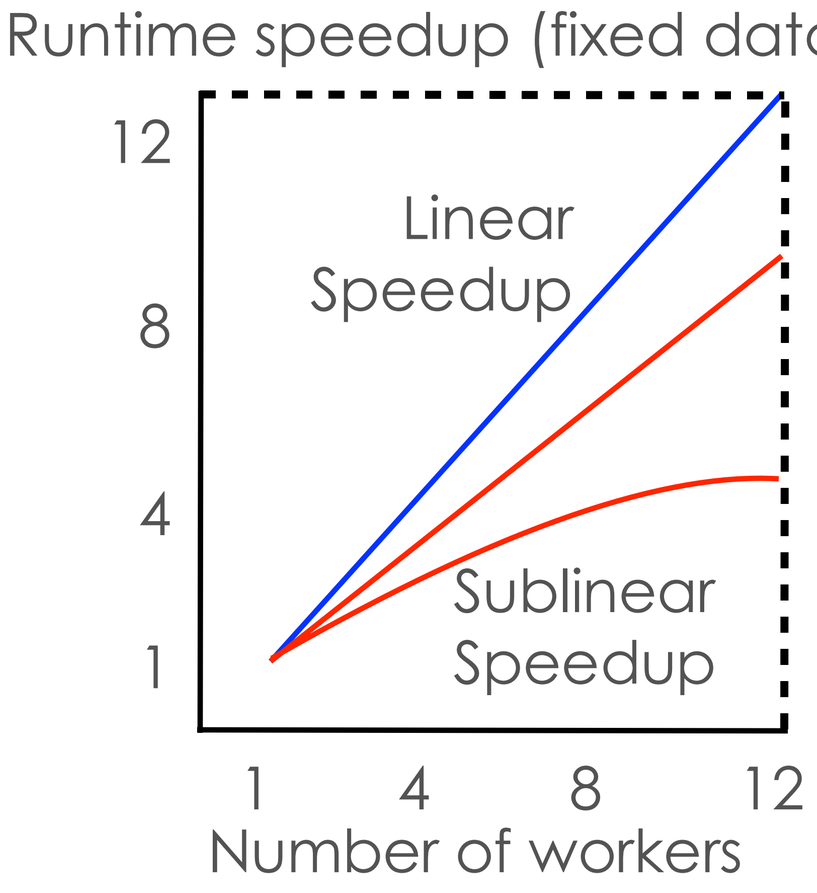
Q: *But given n workers, can we get a speedup of n?*

It depends!

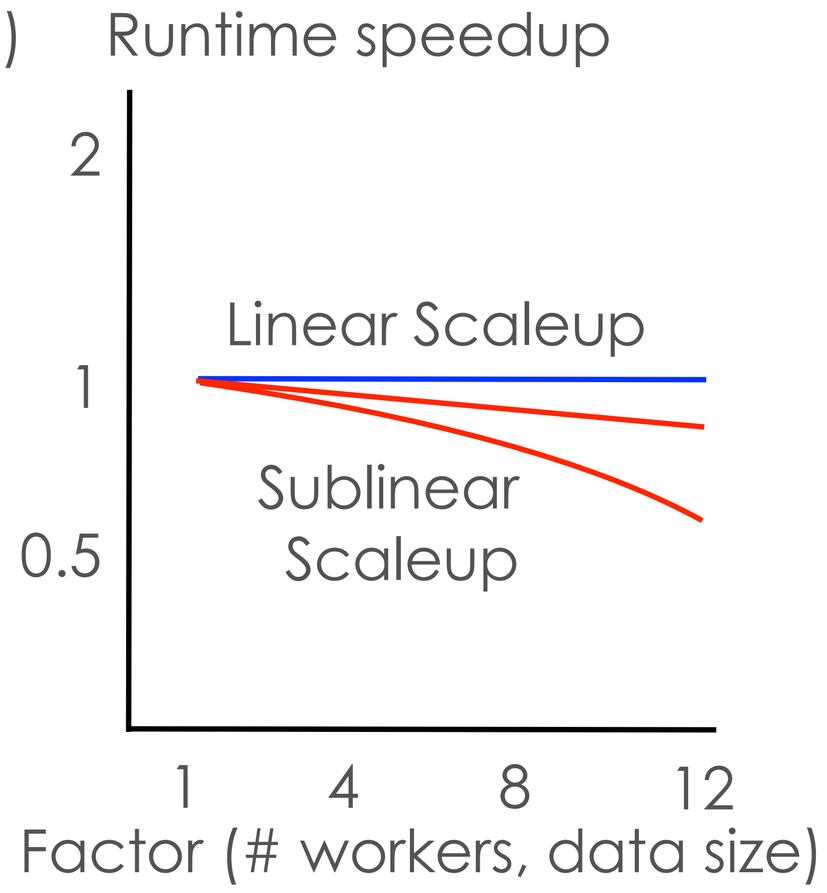
(On degree of parallelism, task dependency graph structure, intermediate data sizes, etc.)

Q: what kind of graphs can give a speedup of n?

Weak and Strong Scaling



Speedup plot / Strong scaling



Scaleup plot / Weak scaling

Q: *Is superlinear speedup/scaleup ever possible?*