Analyzing log data with Apache Spark

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Red Hat Emerging Technology

BACKGROUND

Challenges of log data

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```
SELECT hostname, DATEPART(HH, timestamp) AS hour, COUNT(msg)
   FROM LOGS WHERE level='CRIT' AND msg LIKE '%failure%'
   GROUP BY hostname, hour
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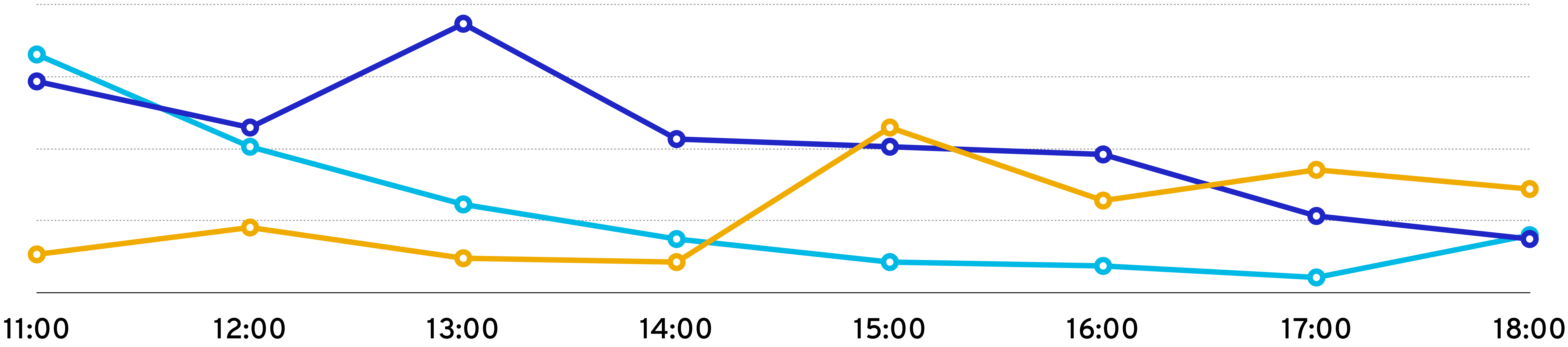
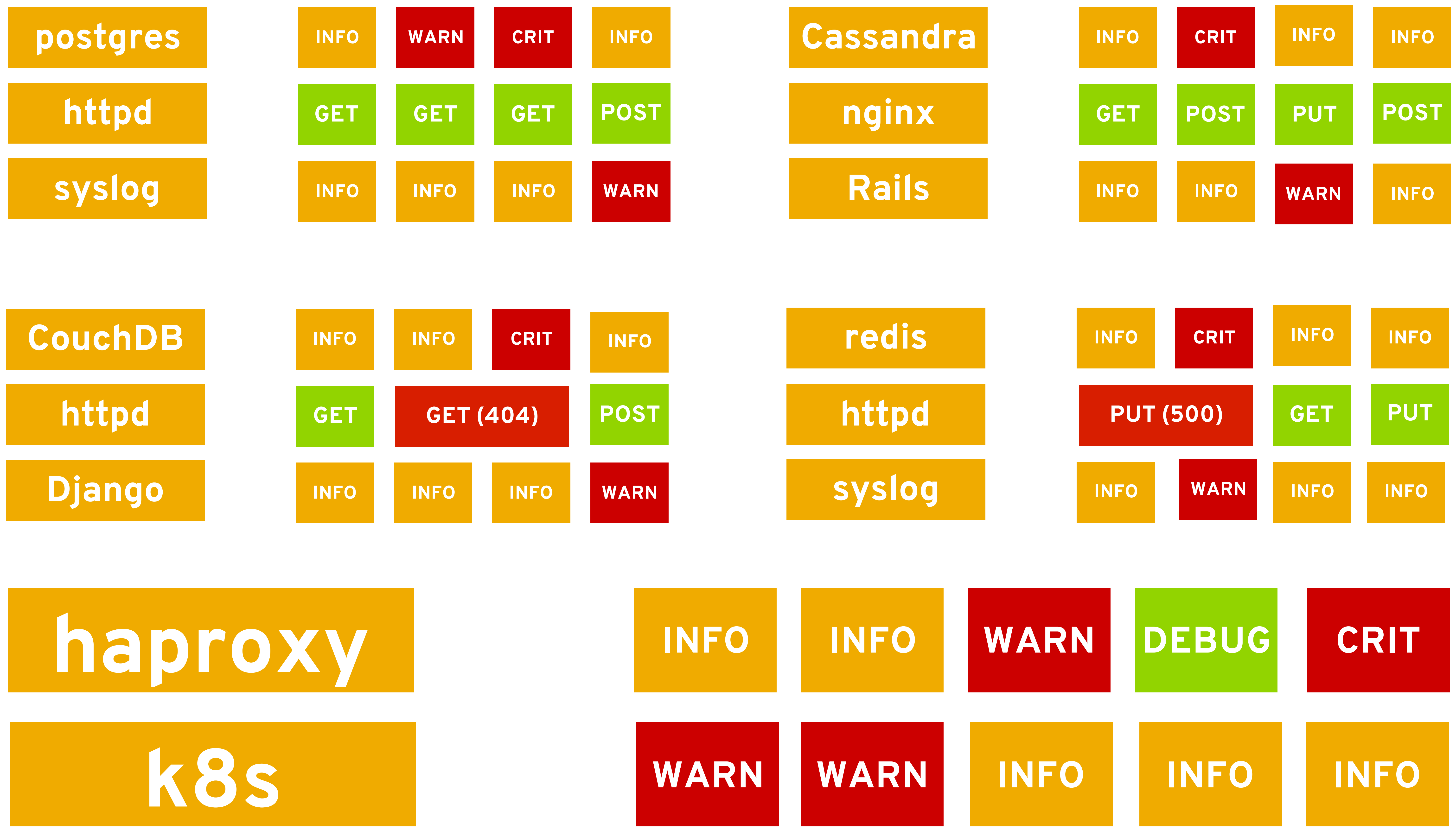


Challenges of log data

postgres	INFO	INFO	WARN	CRIT	DEBUG	INFO
httpd	GET	GET	GET	POST	GET (404)	
syslog	WARN	INFO	WARN	INFO	INFO	INFO

(ca. 2000)

Challenges of log data



(ca. 2016)

Challenges of log data

How many **services** are generating logs in your datacenter **today?**

DATA INGEST

Collecting log data

collecting

Ingesting live log data via rsyslog, logstash, fluentd

normalizing

Reconciling log record metadata across sources

analysis

cache warehoused data as Parquet files on Gluster volume local to Spark cluster

Collecting log data

warehousing

Storing normalized records in ES indices

analysis

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Schema mediation

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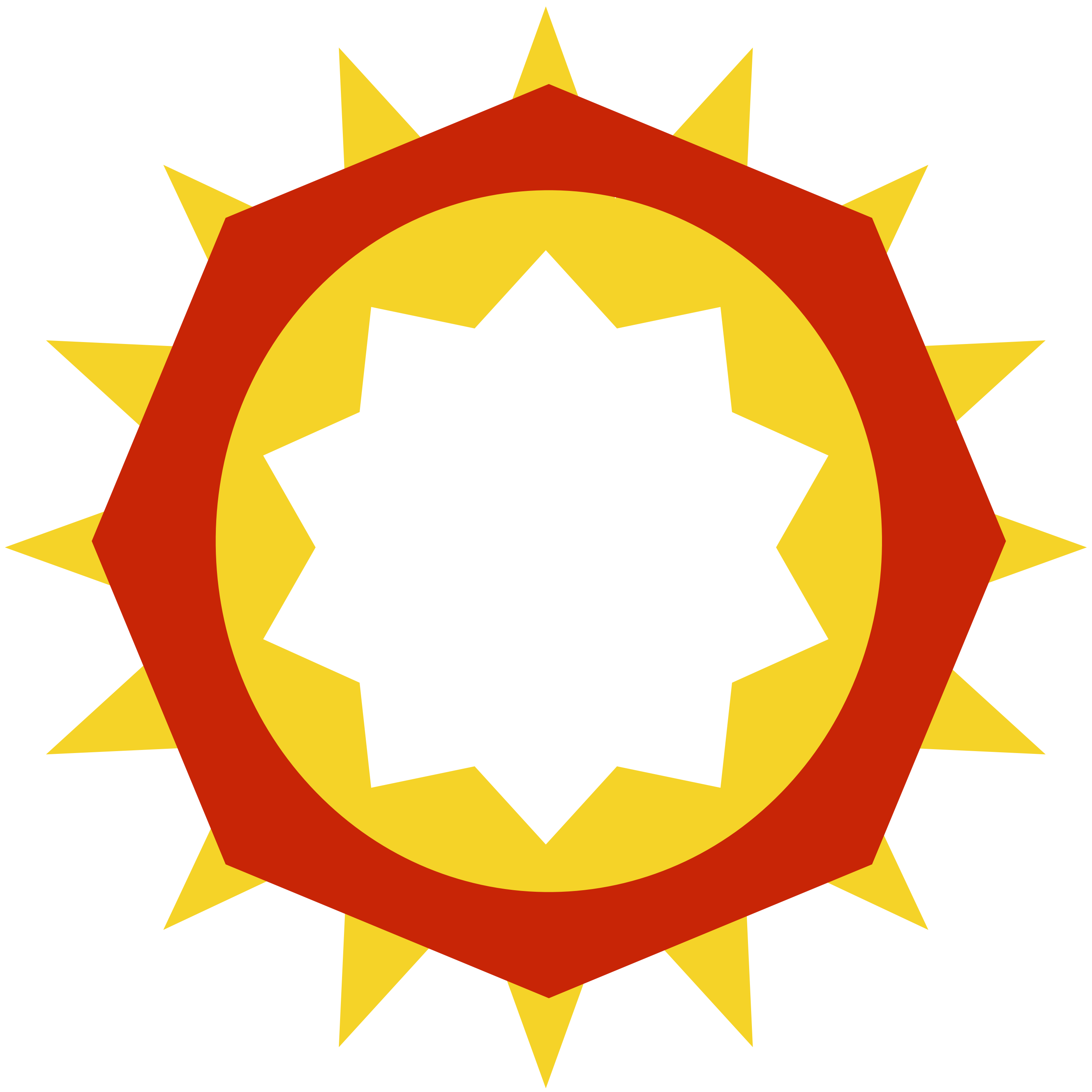

Schema mediation

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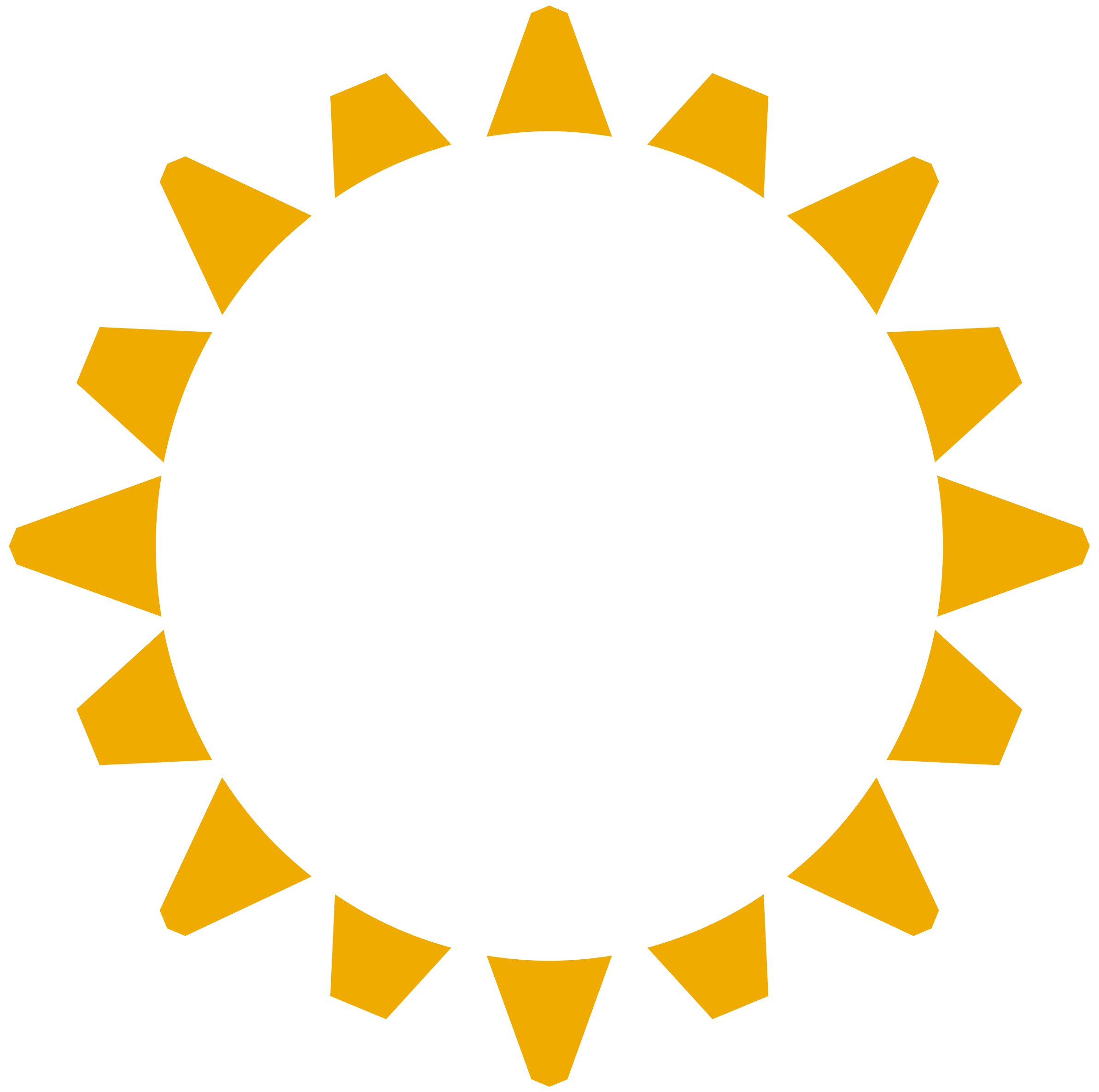

timestamp, level, host, IP addresses, message, &c.

rsyslog-style metadata, like app name, facility, &c.

Exploring structured data

```
logs
  .select("level").distinct
  .map { case Row(s: String) => s }
  .collect
```

```
debug, notice, emerg,
err, warning, crit, info,
severe, alert
```

```
logs
  .groupBy($"level", $"rsyslog.app_name")
  .agg(count("level").as("total"))
  .orderBy($"total".desc)
  .show
```

info	kubelet	17933574
info	kube-proxy	10961117
err	journal	6867921
info	systemd	5184475

...

Exploring structured data

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This class must be declared outside the REPL!

```
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FEATURE ENGINEERING

From log records to vectors

What does it mean for two sets of categorical features to be similar?

```
red      -> 000
green    -> 010
blue     -> 100
orange   -> 001
```

```
pancakes      -> 10000
waffles       -> 01000
aebliskiver   -> 00100
omelets       -> 00001
bacon         -> 00000
hash browns   -> 00010
```

From log records to vectors

What does it mean for two sets of categorical features to be similar?

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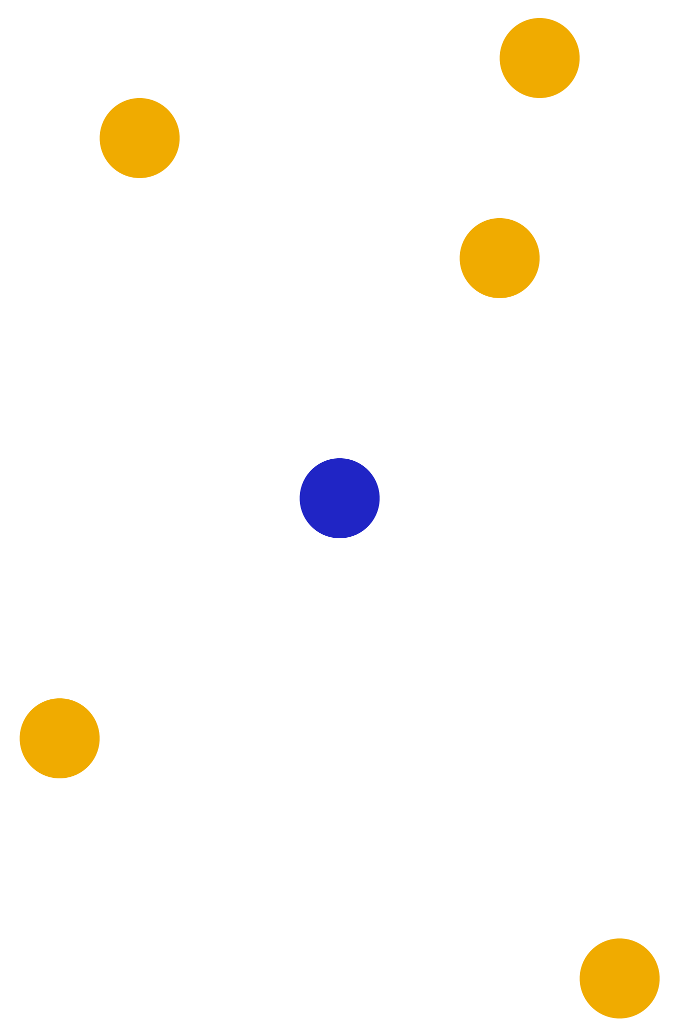
```
red pancakes     -> 00010000
orange waffles   -> 00101000
```

Similarity and distance



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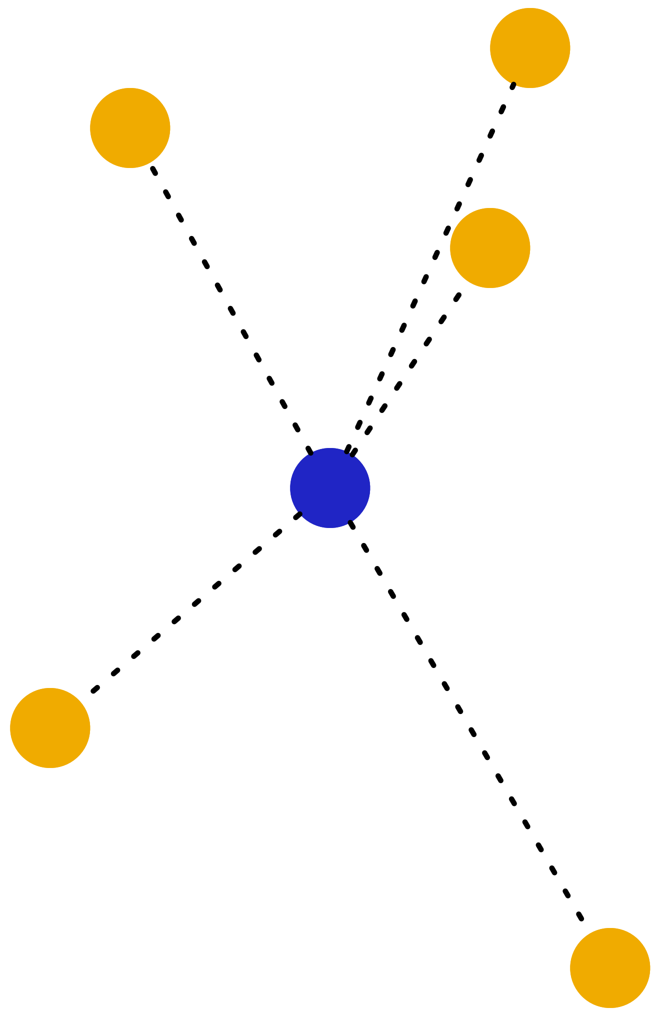

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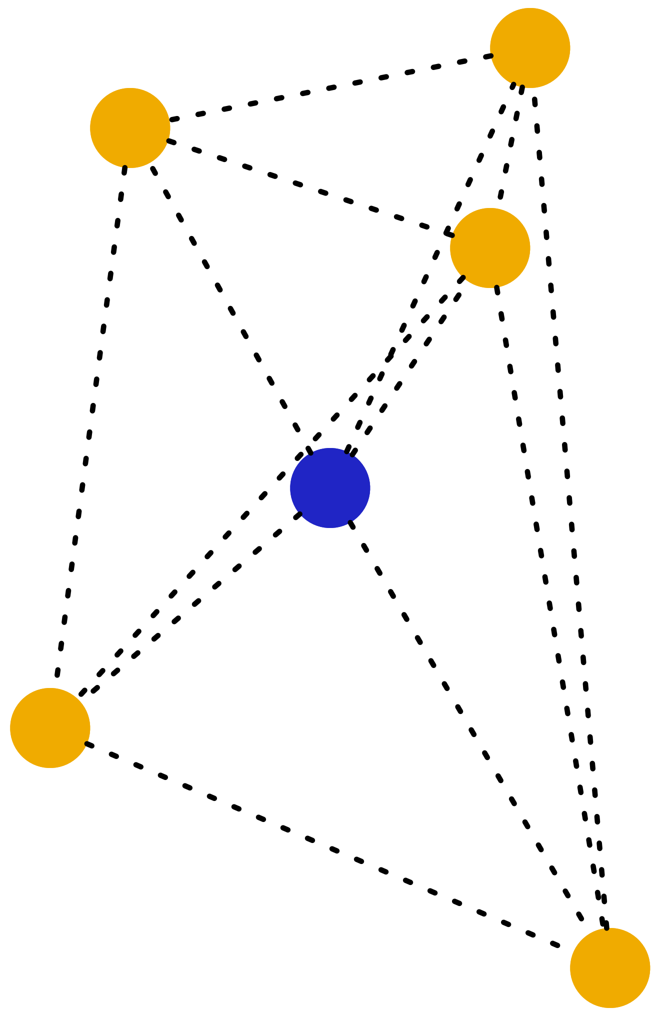
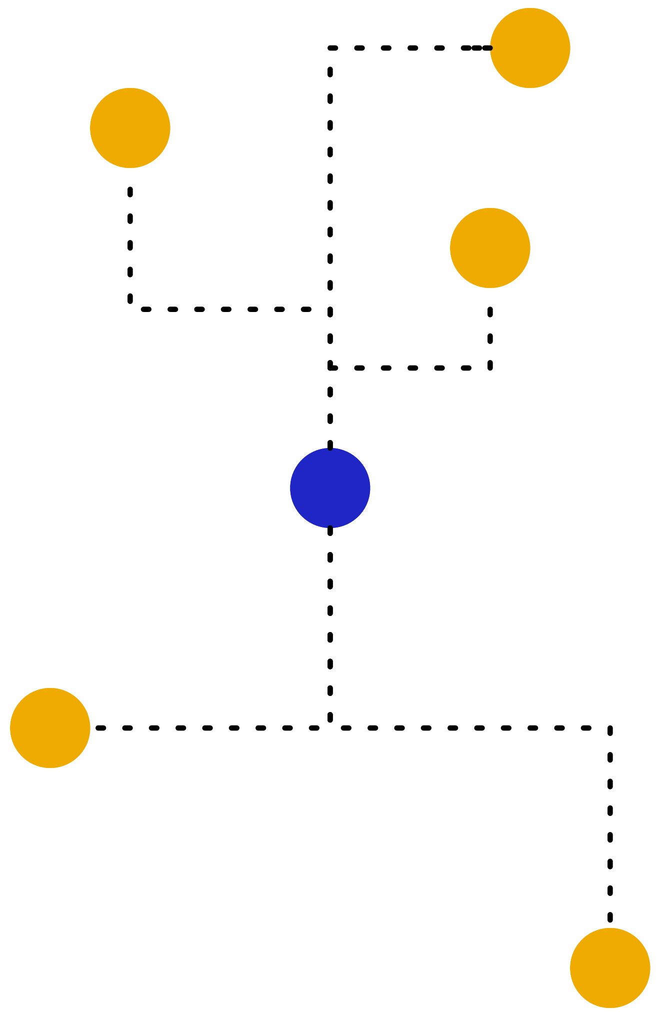


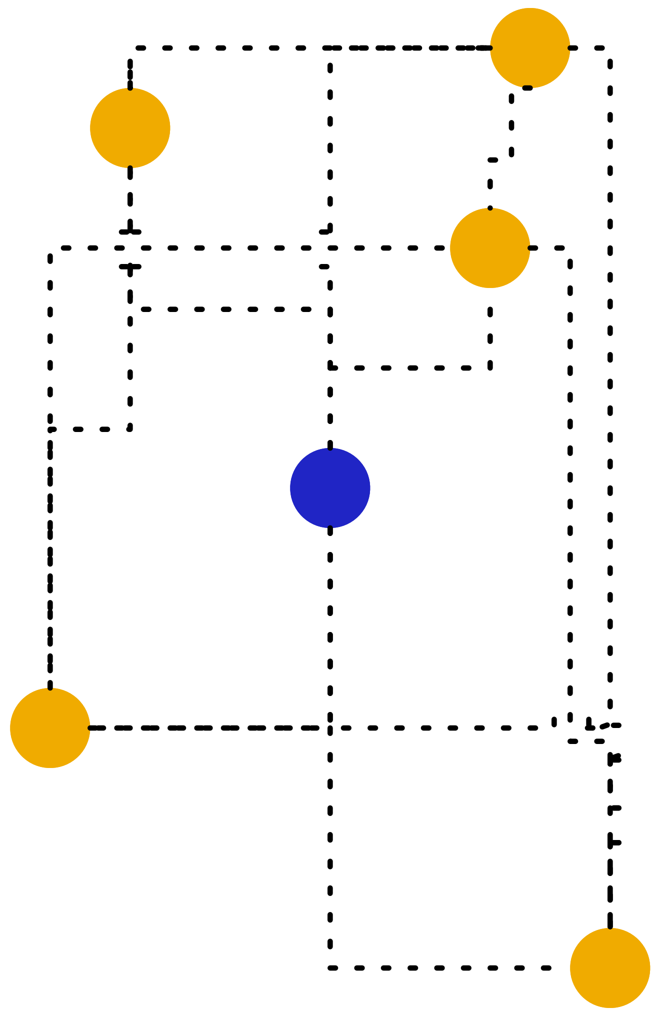
$$\sqrt{(q - p) \cdot (q - p)}$$

Similarity and distance



$$\sum_{i=1}^{n} |p_i - q_i|$$

Similarity and distance



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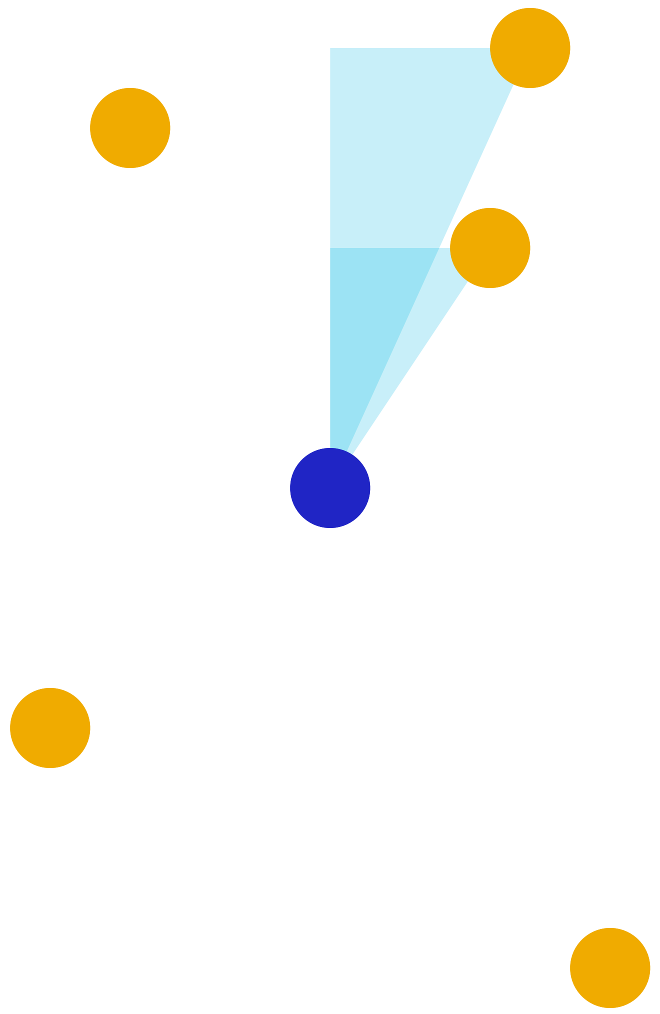
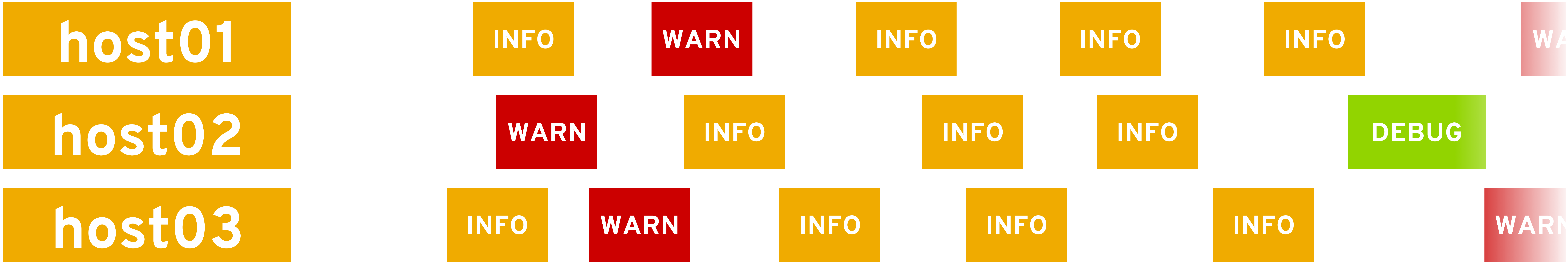


$$\frac{p \cdot q}{\|p\| \, \|q\|}$$

Other interesting features



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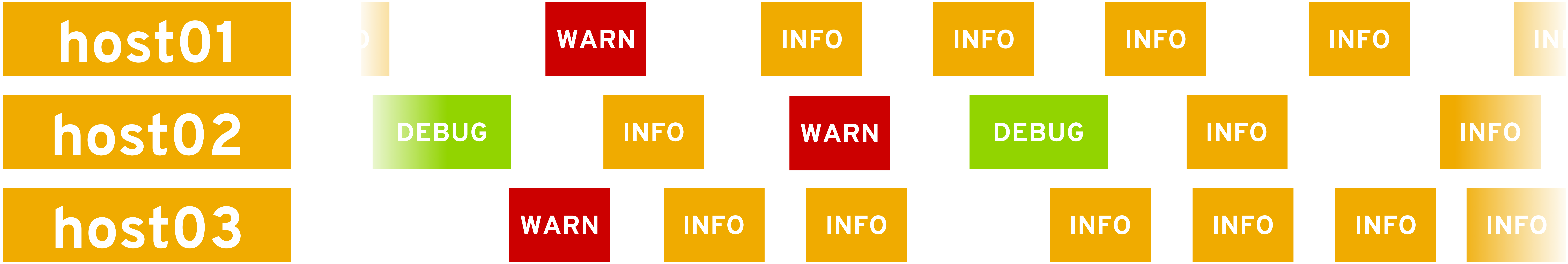

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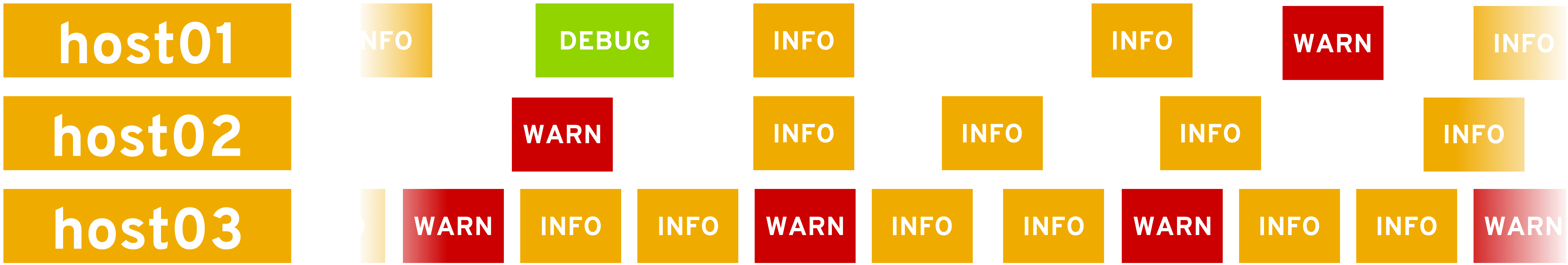

Other interesting features

★★★:	Great food, great service, a must-visit!
★★★★:	Our whole table got gastroenteritis.
★:	This place is so wonderful that it has ruined all other tacos for me and my family.

Other interesting features

```
INFO:  Everything is great!  Just checking in to let you know I'm OK.
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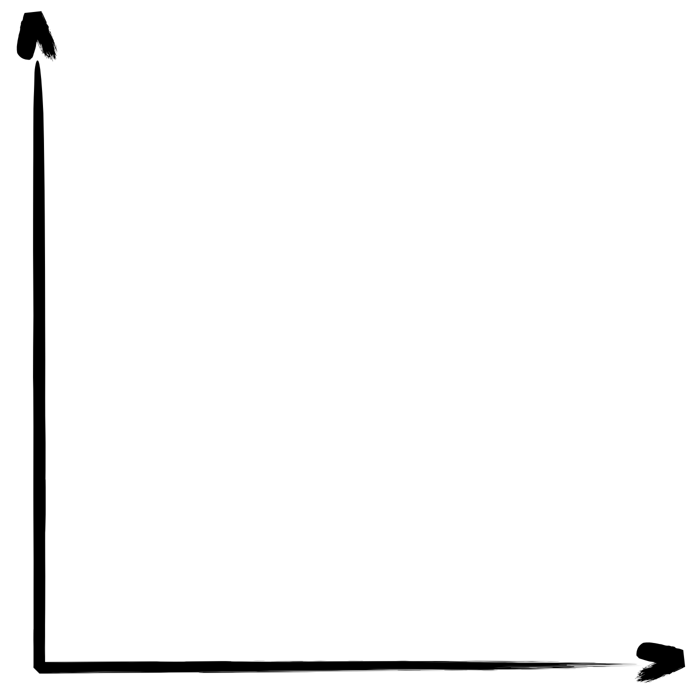
See https://links.freevariable.com/nlp-logs/ for more!

VISUALIZING STRUCTURE and FINDING OUTLIERS

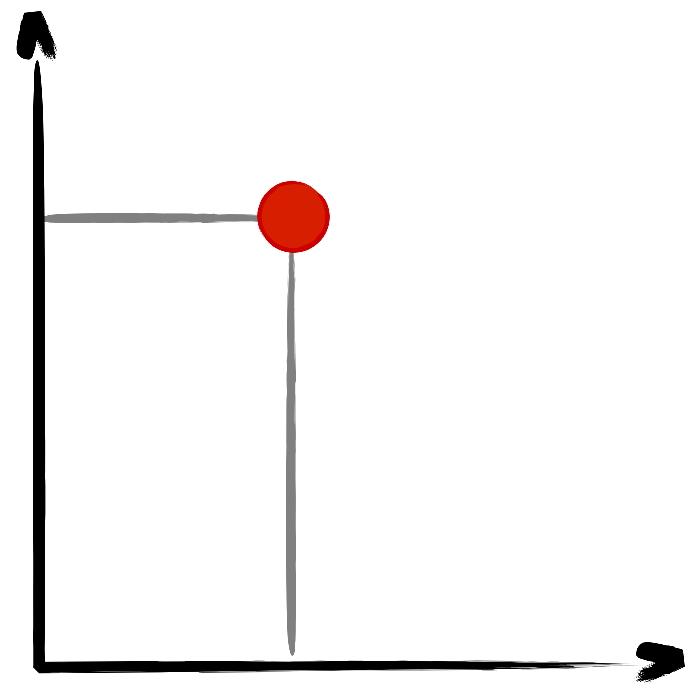
Multidimensional data

Multidimensional data



[4,7]

Multidimensional data



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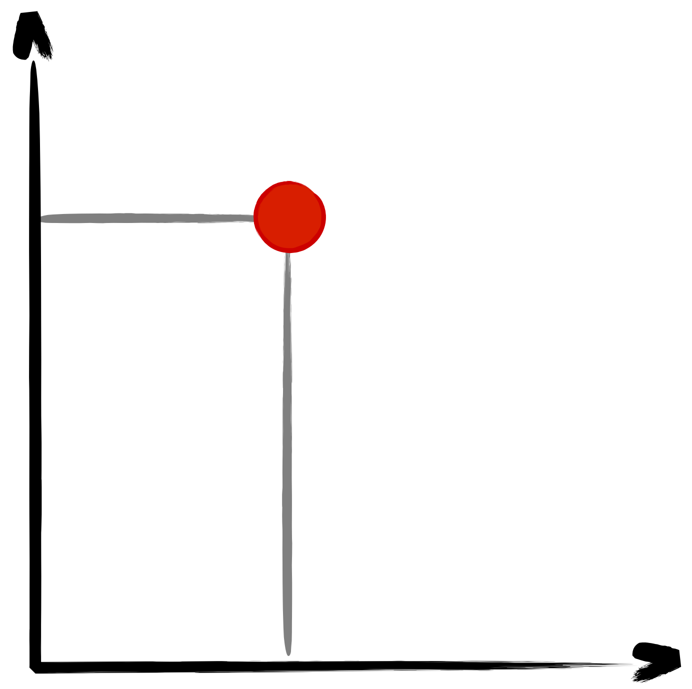

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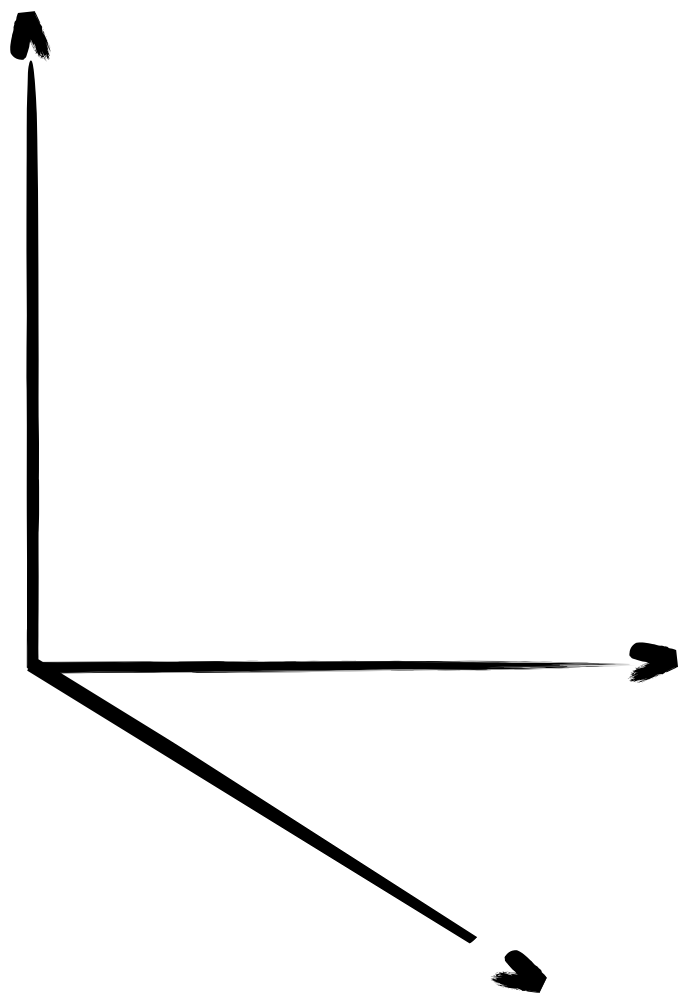

[2,3,5]

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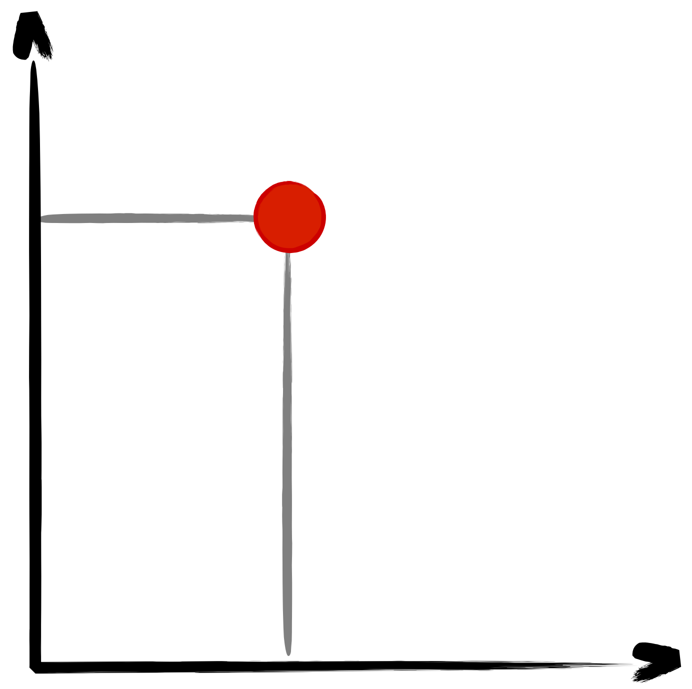

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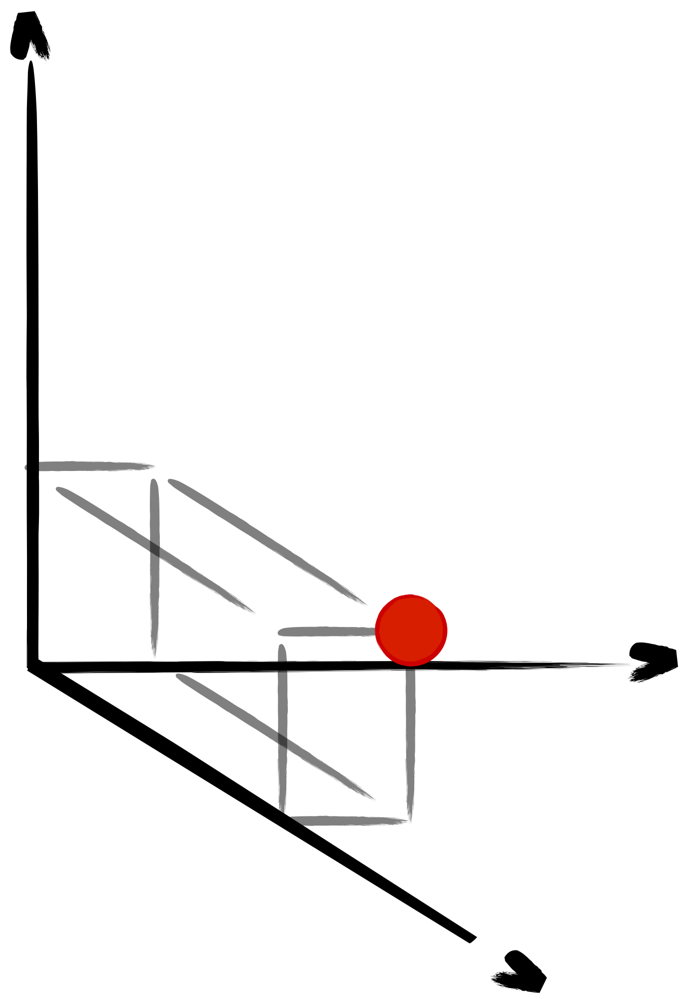

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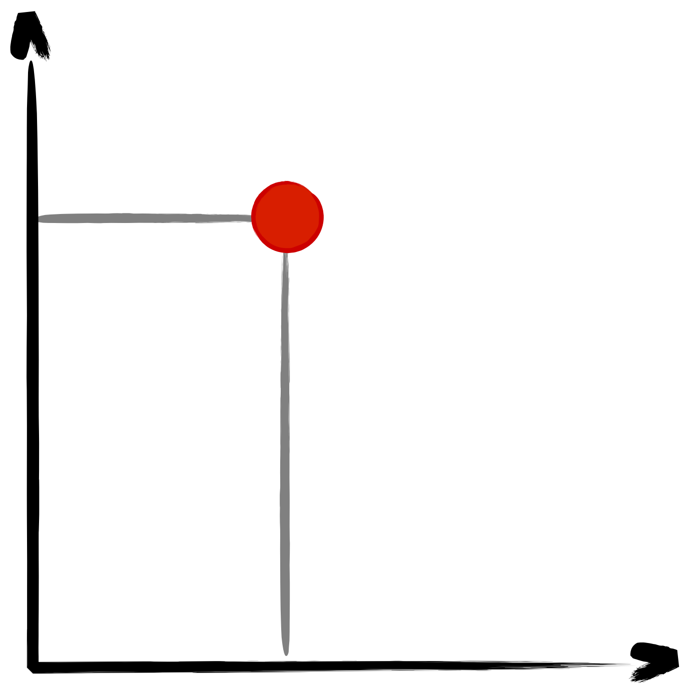

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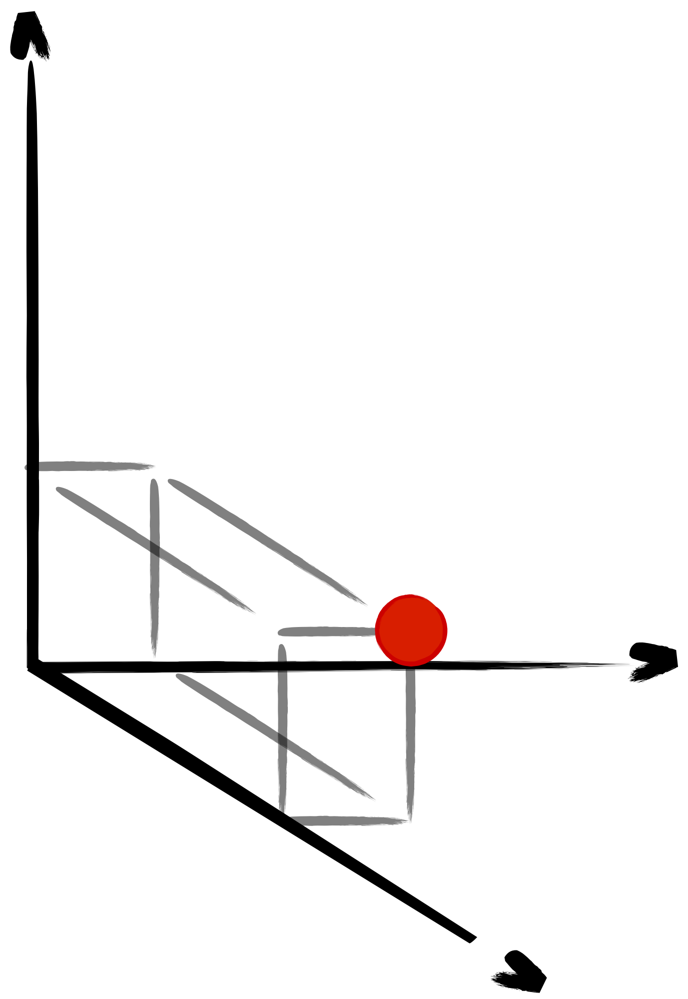

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[7,1,6,5,12,
8,9,2,2,4,
7,11,6,1,5]

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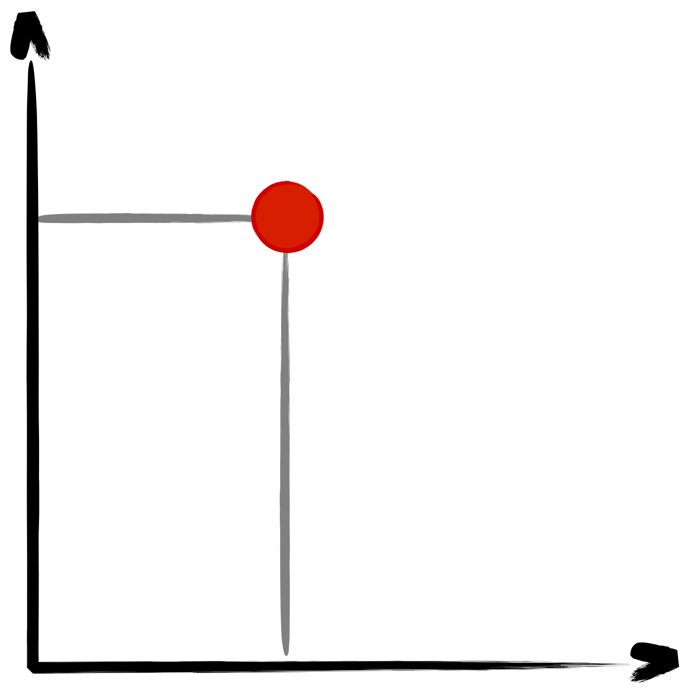

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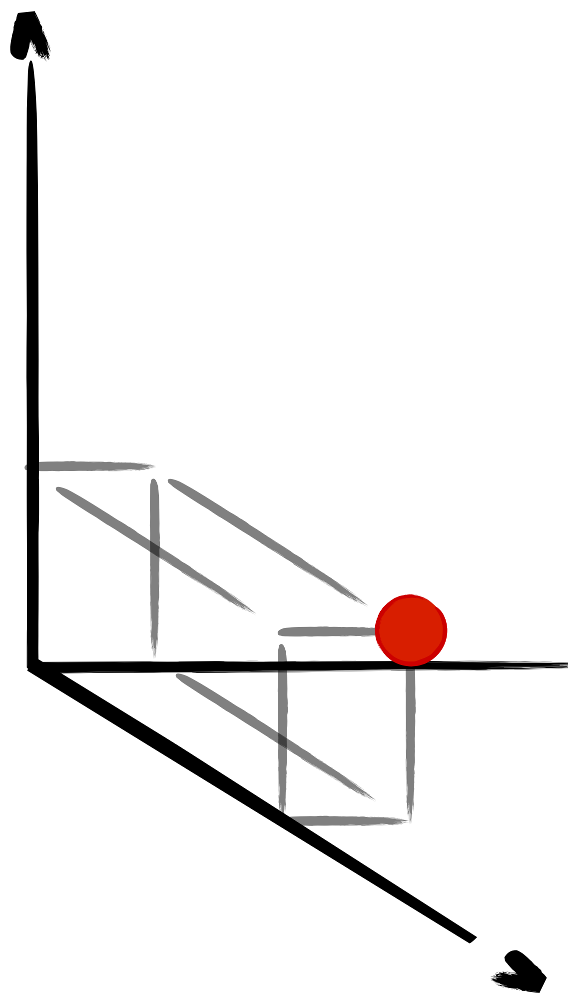

[2,3,5]

[7,1,6,5,12,
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A linear approach: PCA

$$
\begin{bmatrix}
0 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\
1 & 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 \\
0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\
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1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
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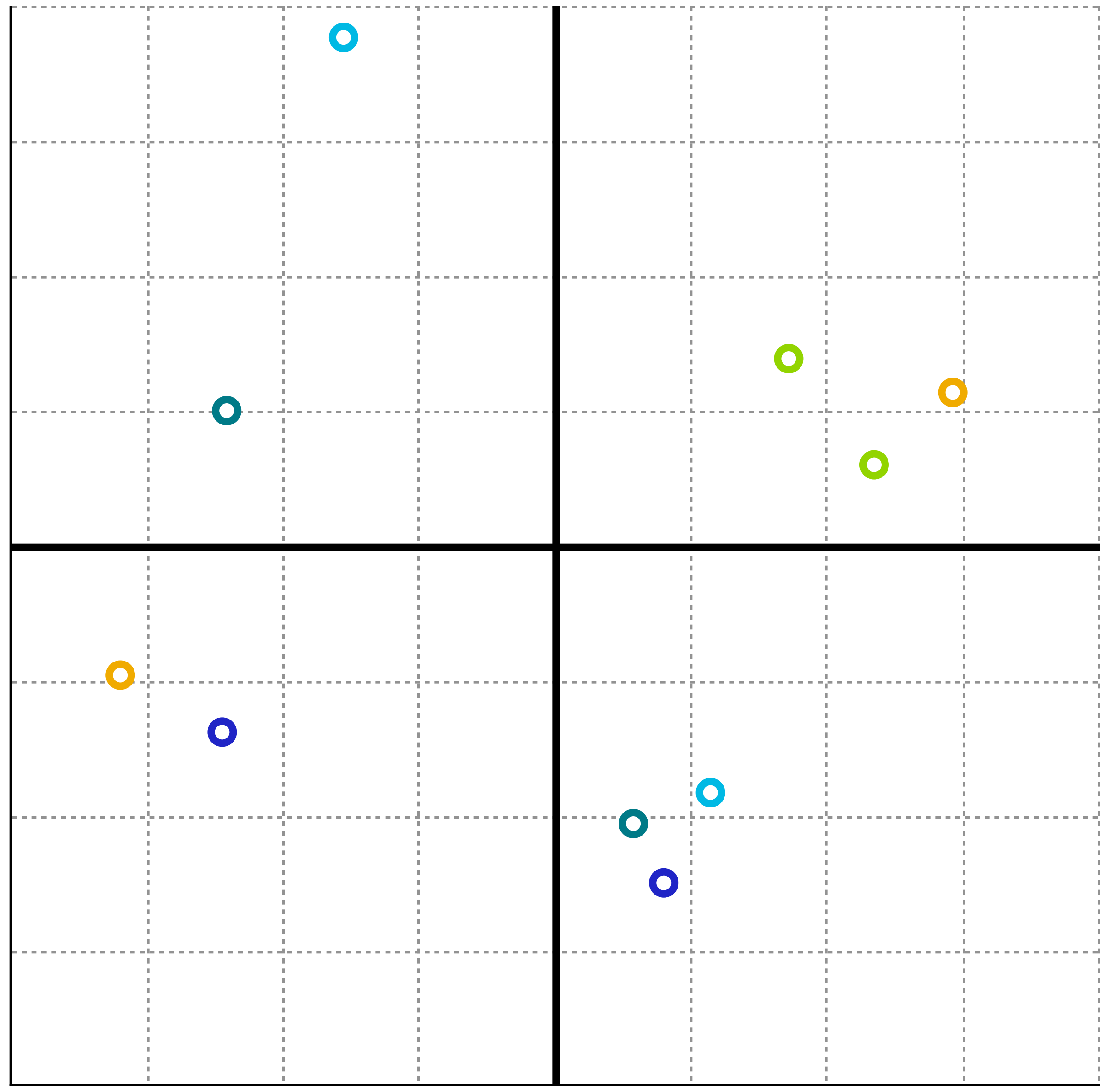
$$



1.5
1
0.5
0
−0.5
−2
−1.5
−1
−0.5
0
0.5

Tree-based approaches

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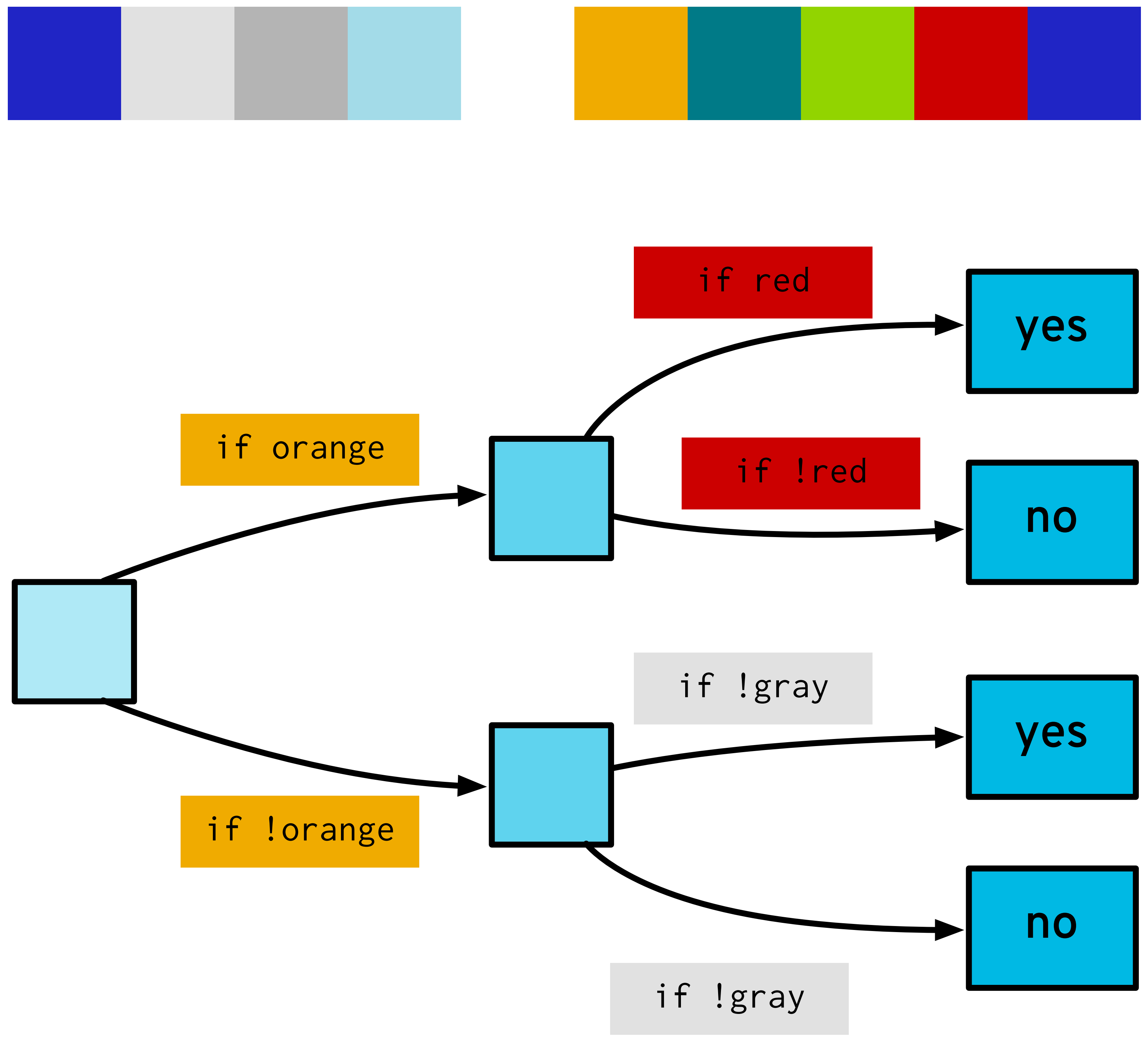

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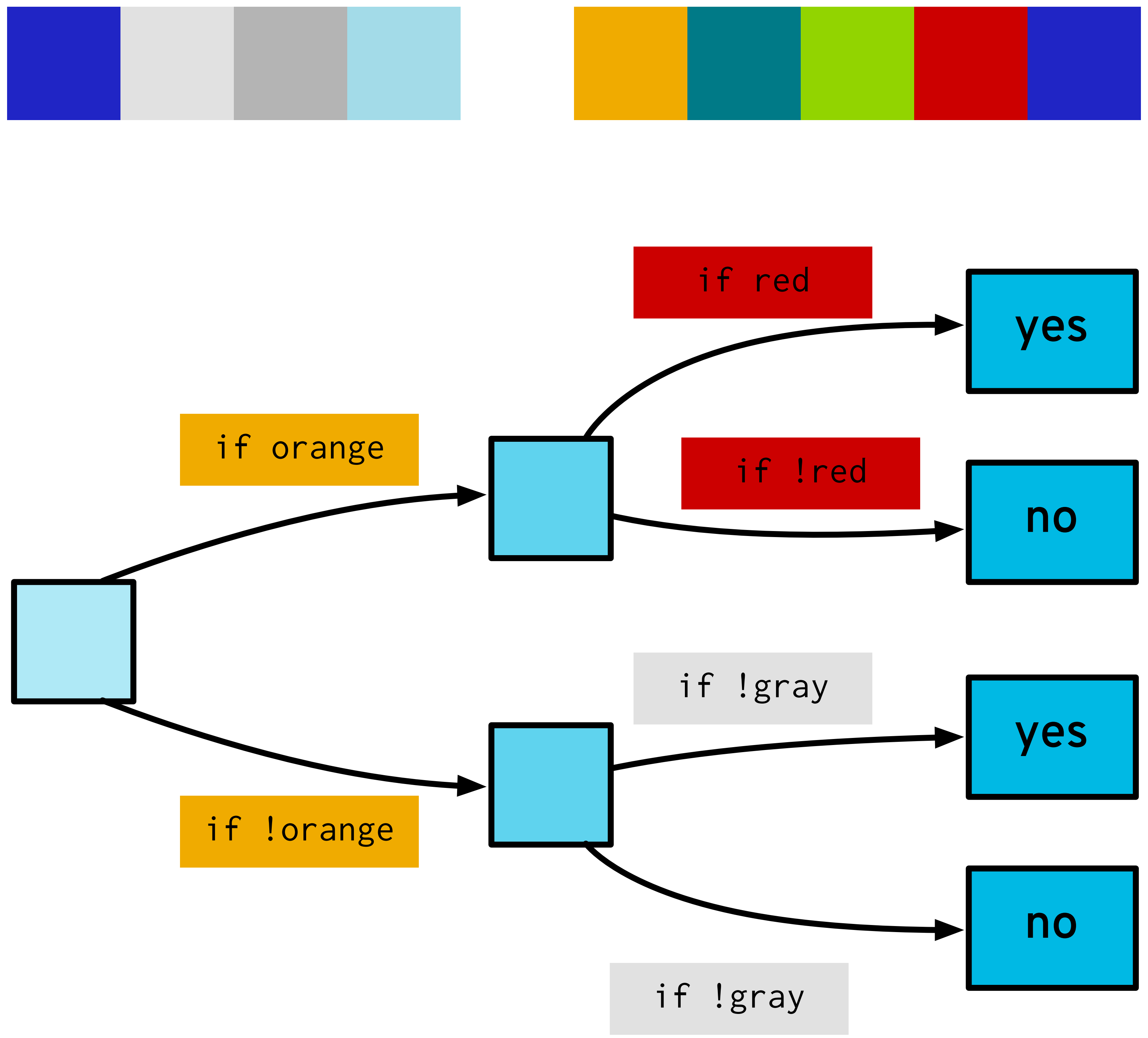

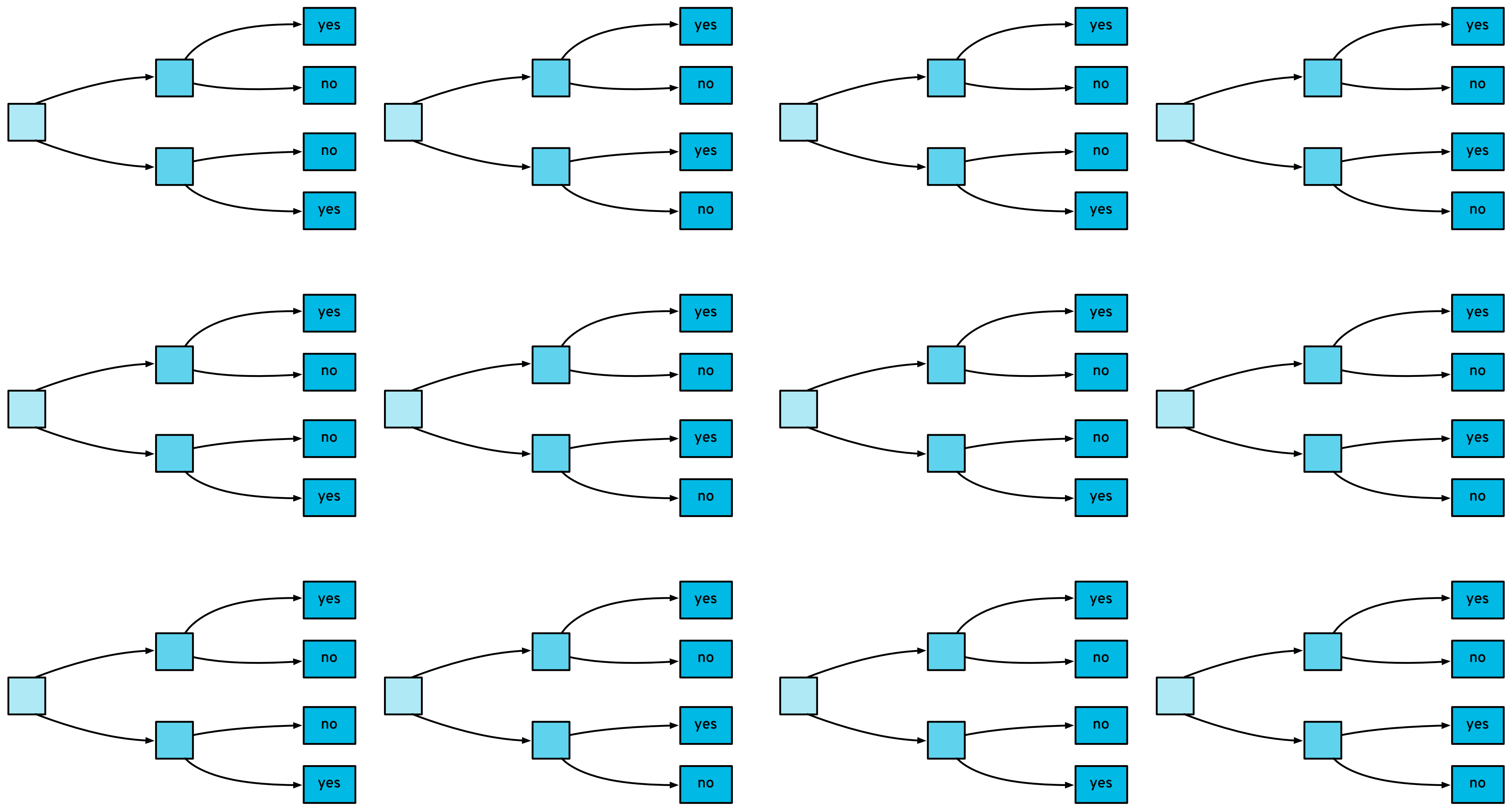

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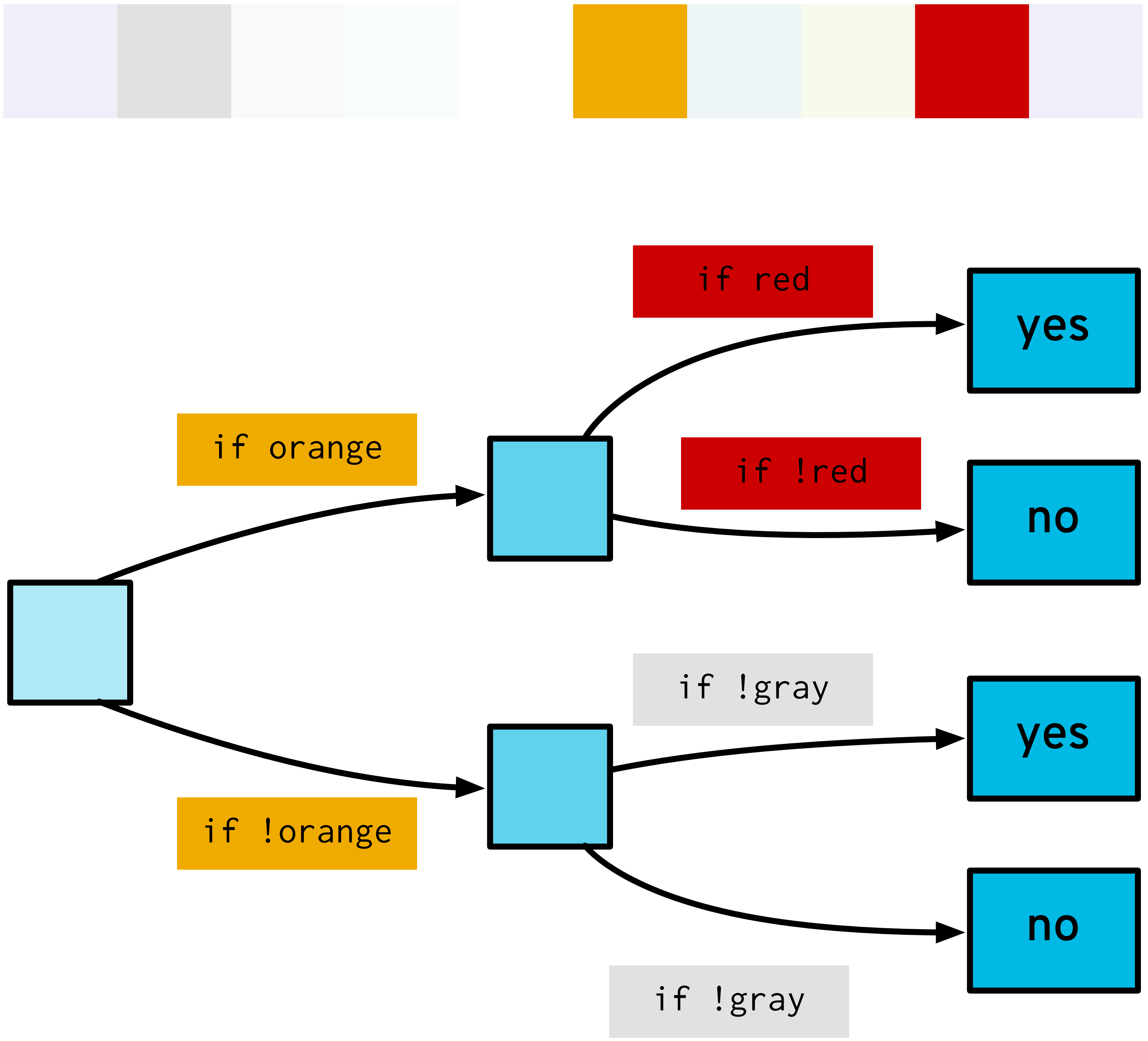
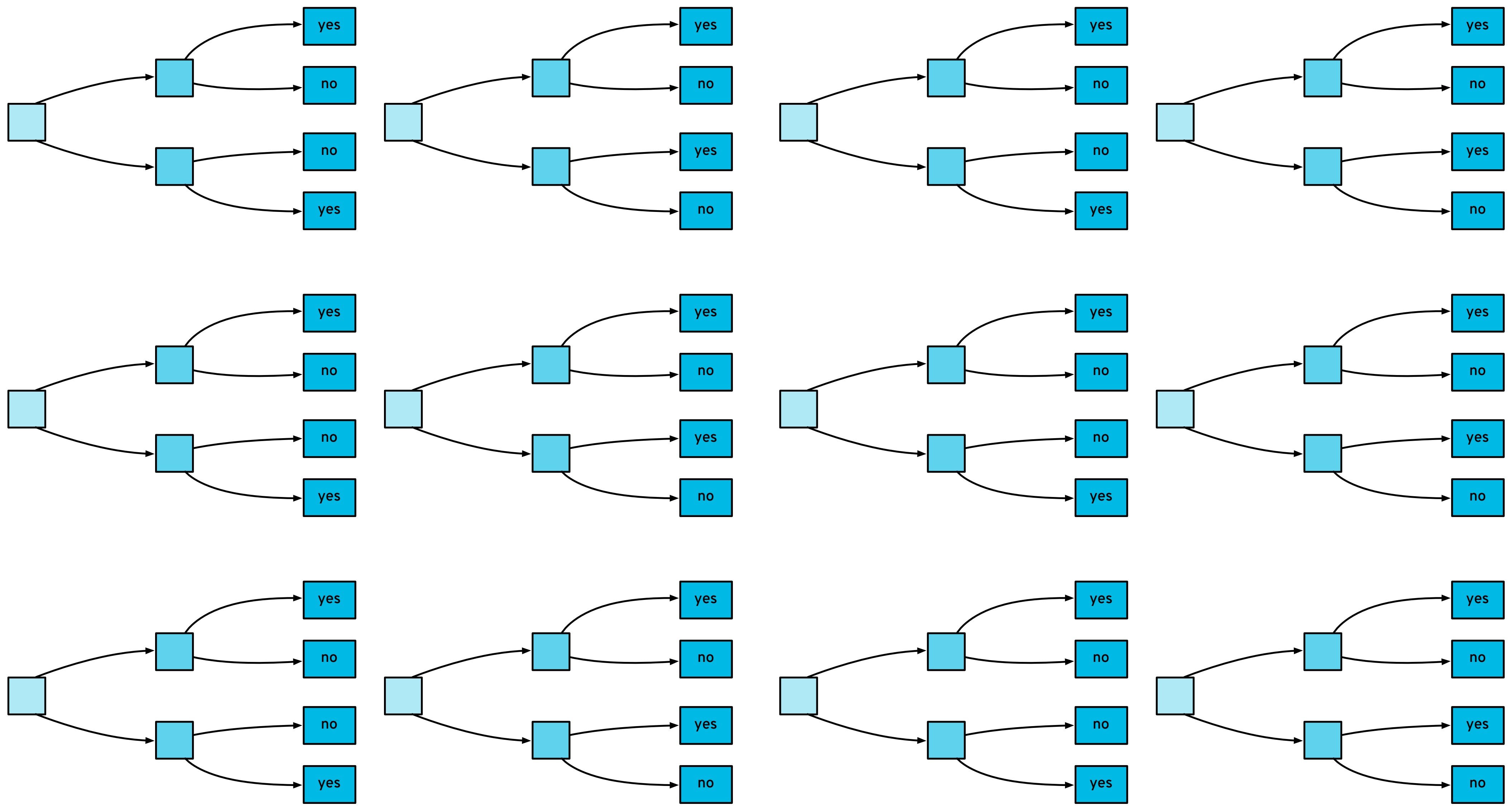
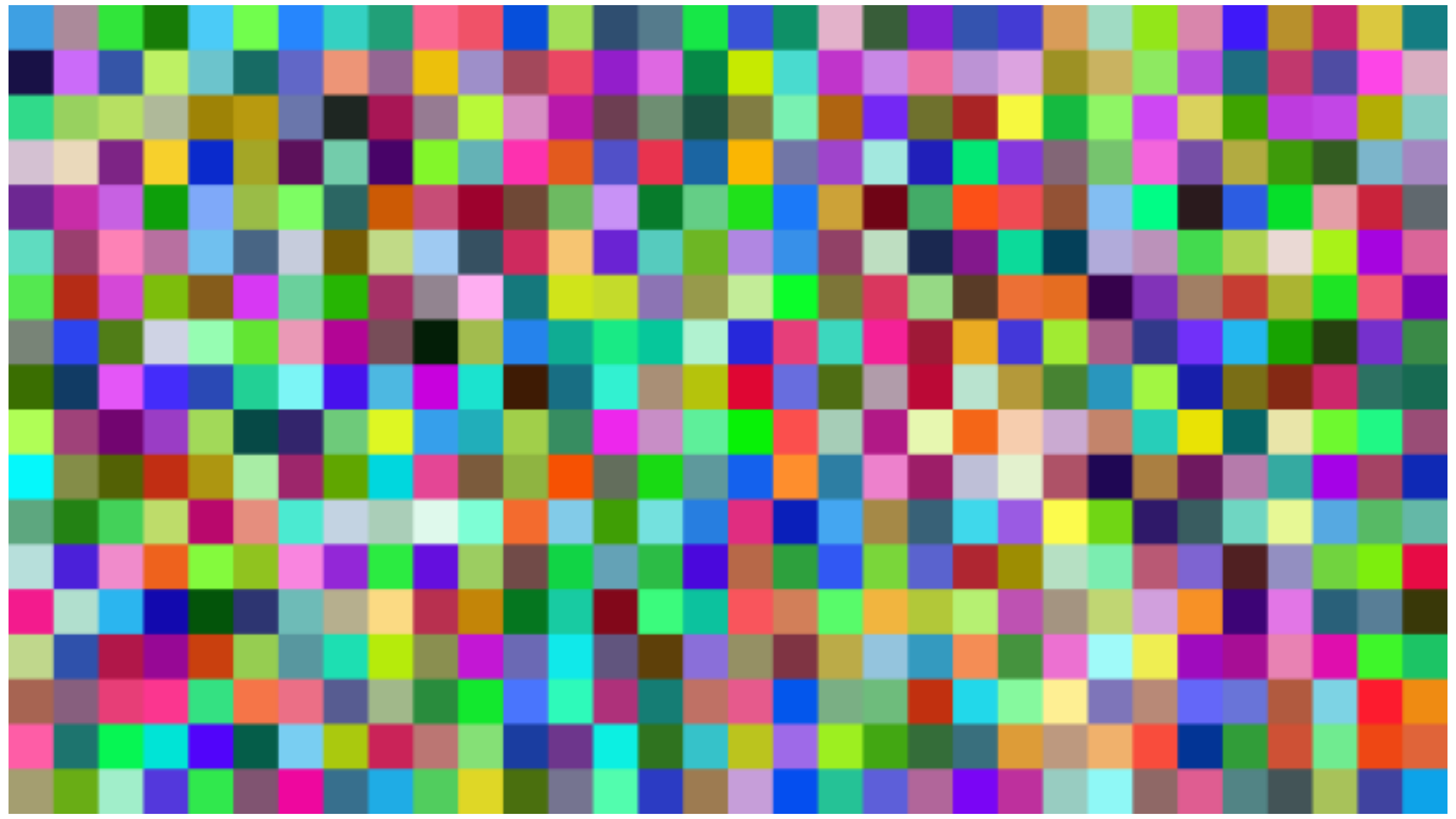
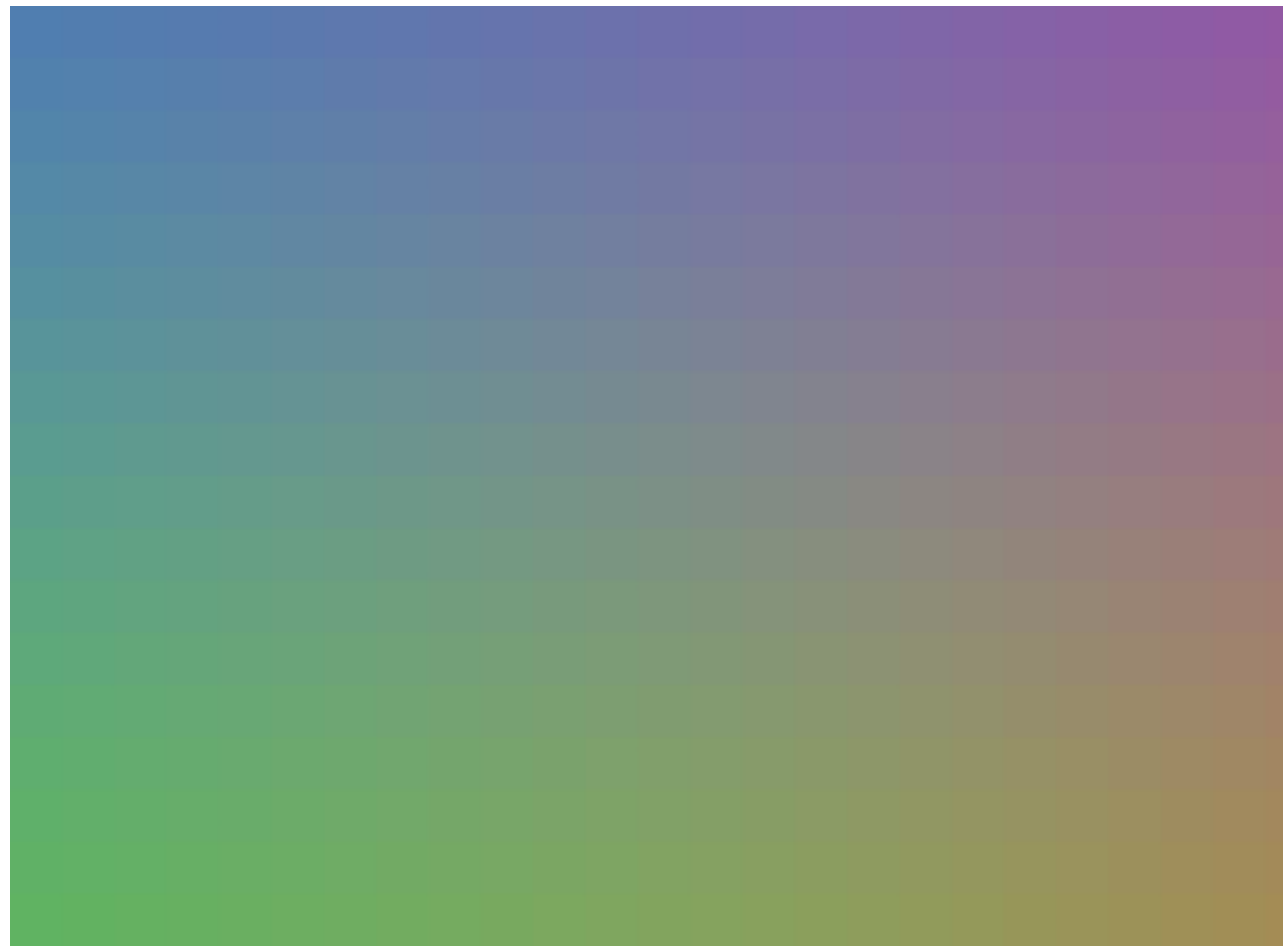




Self-organizing maps





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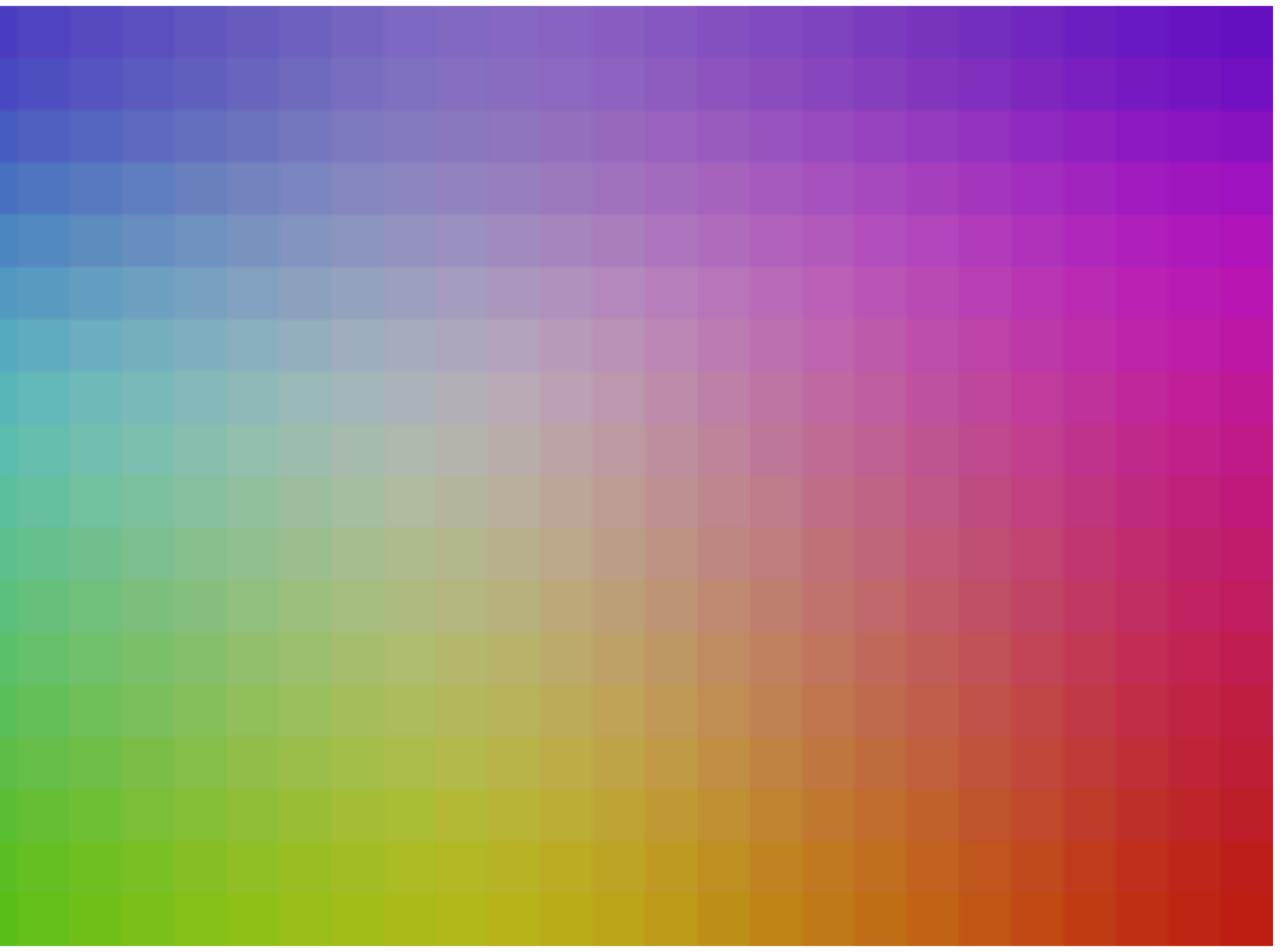
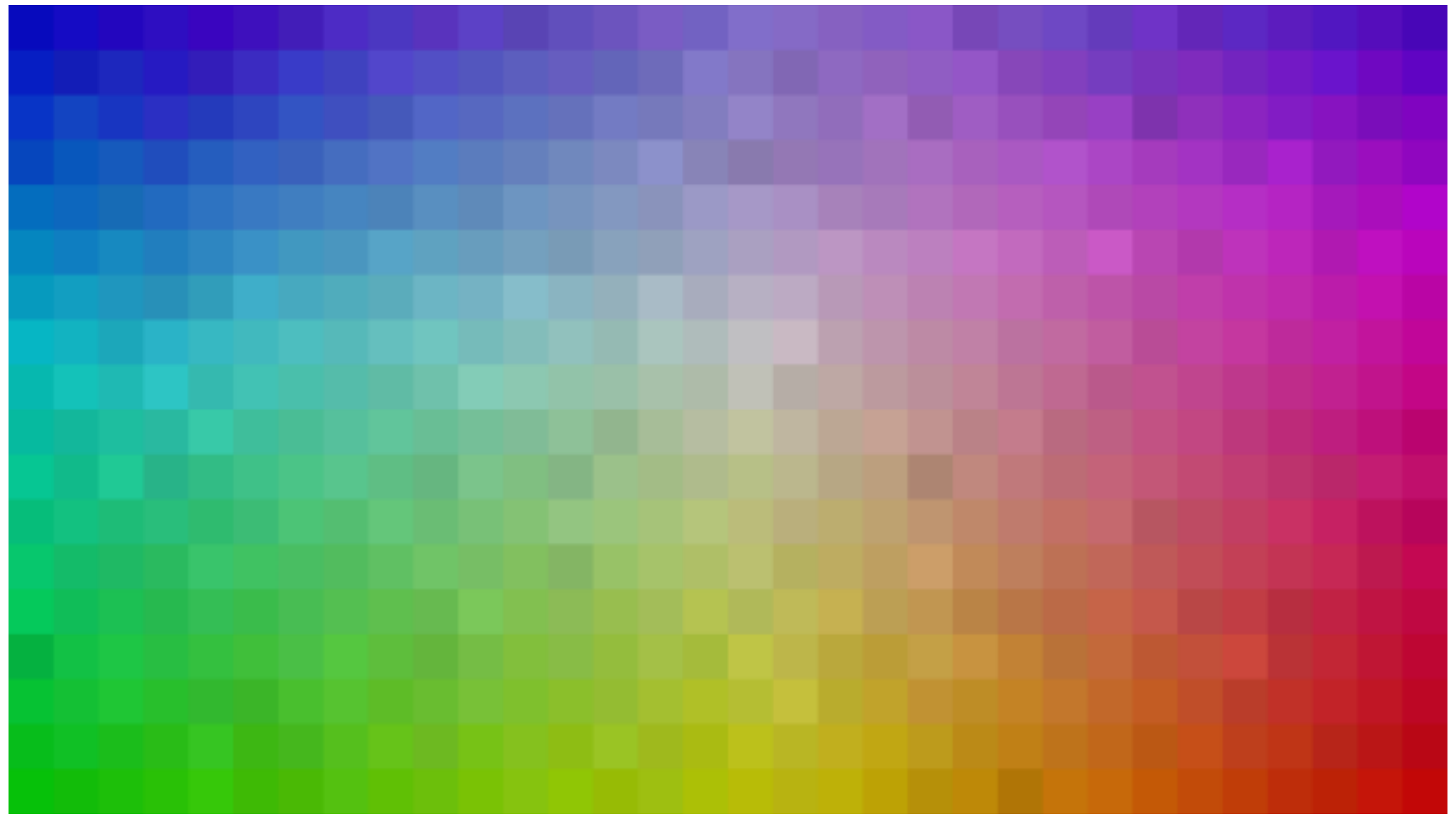
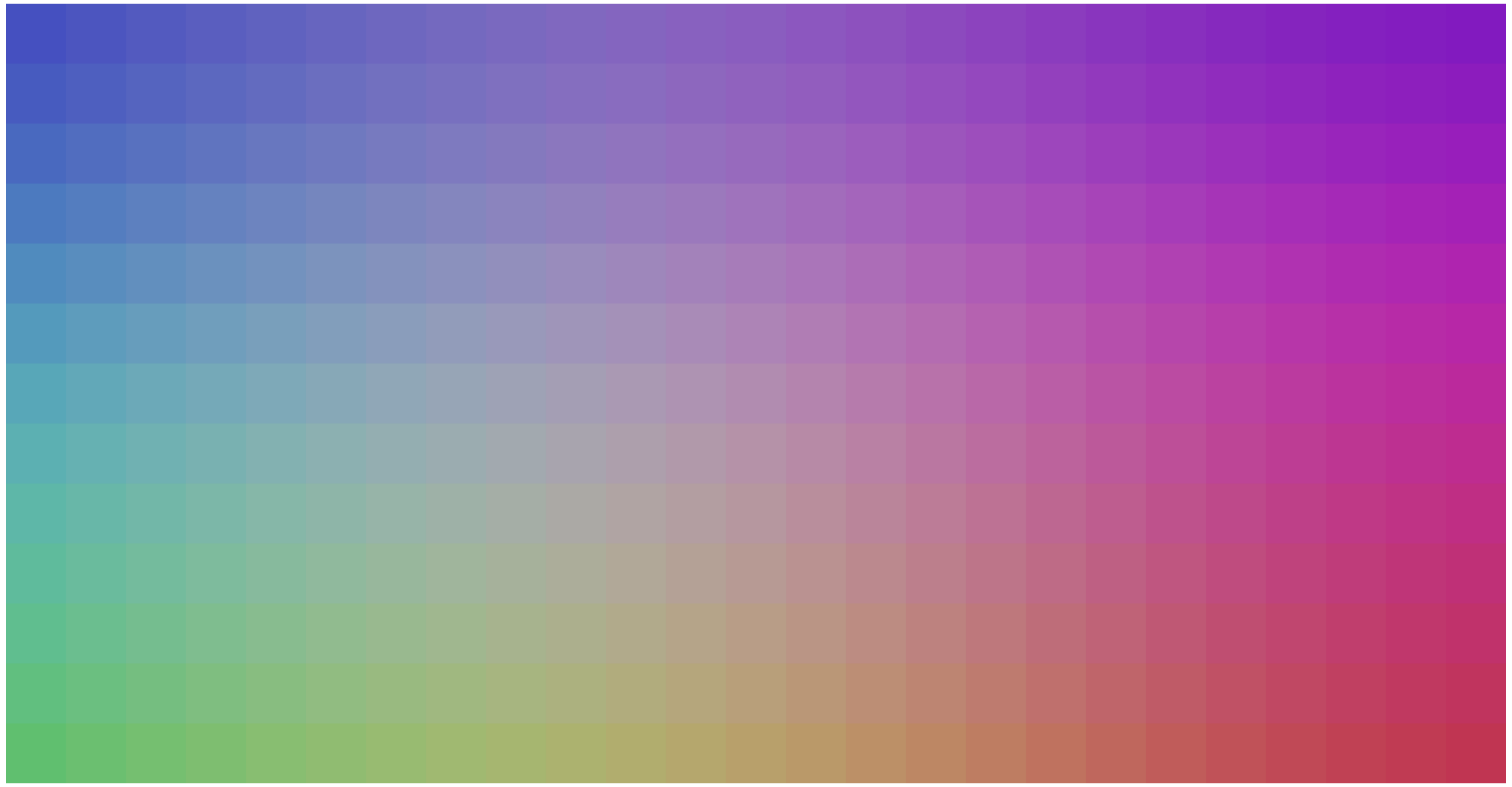




Finding outliers with SOMs



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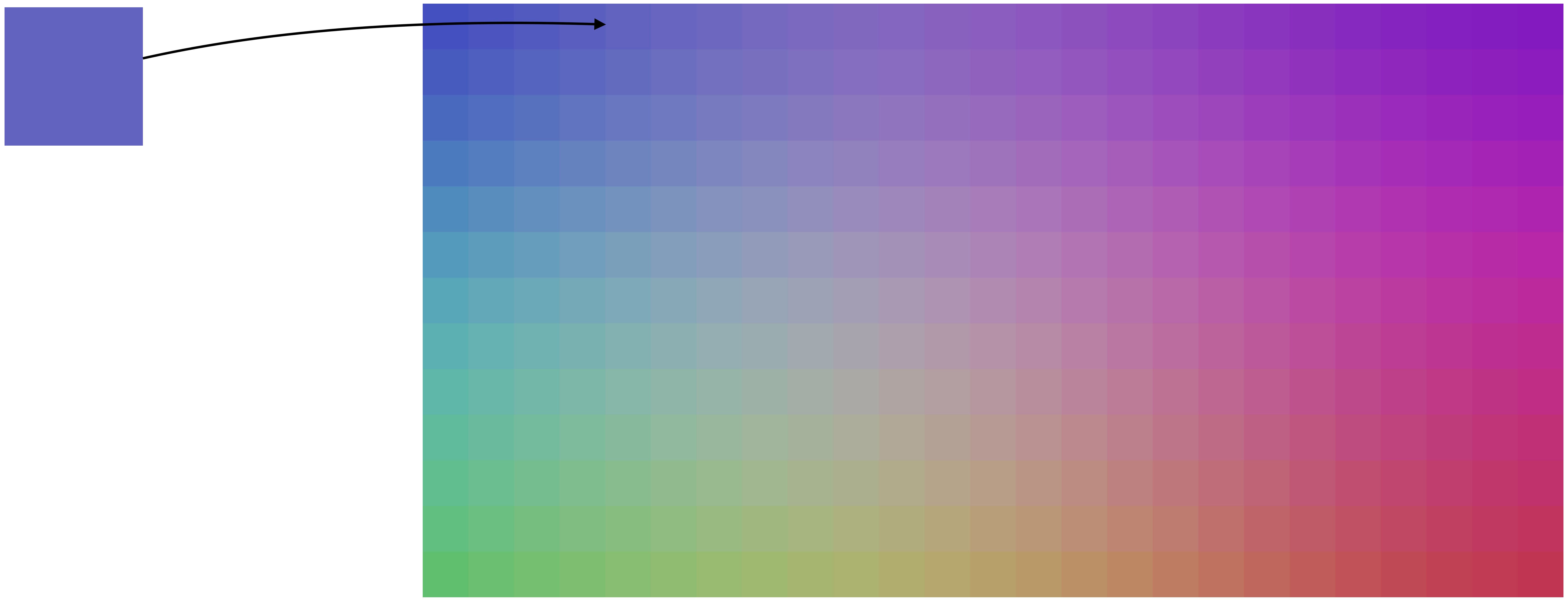

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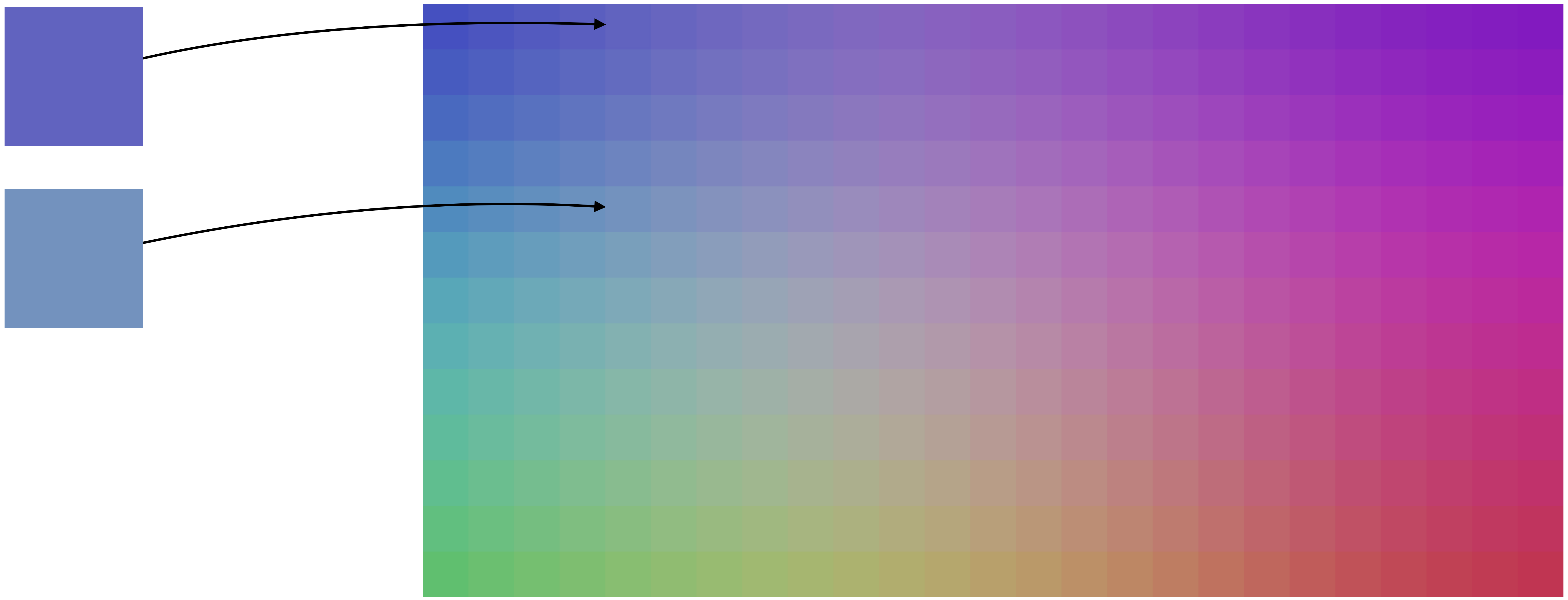

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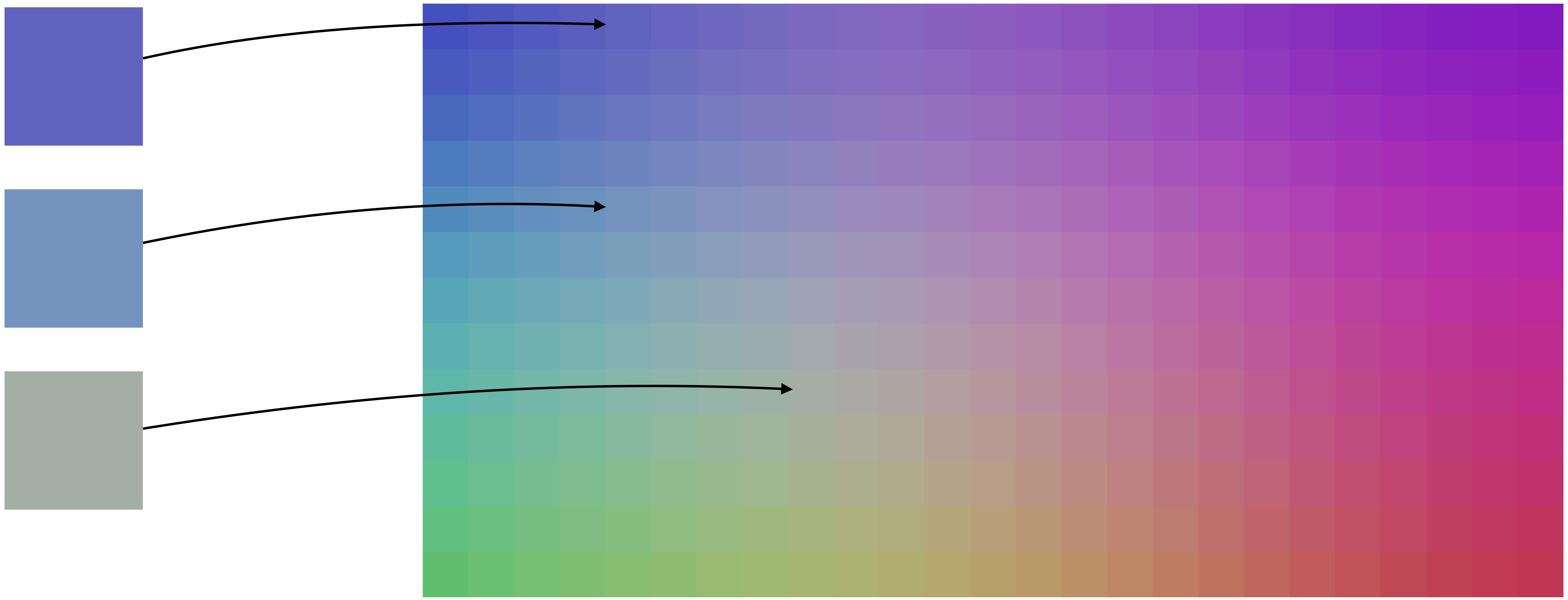

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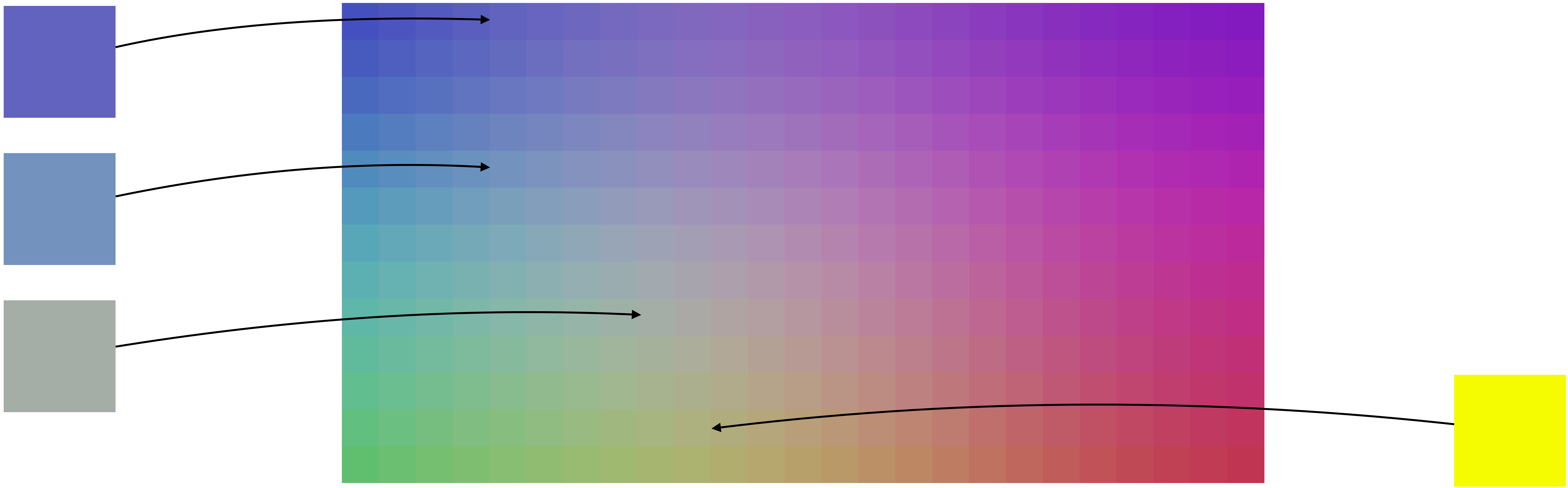
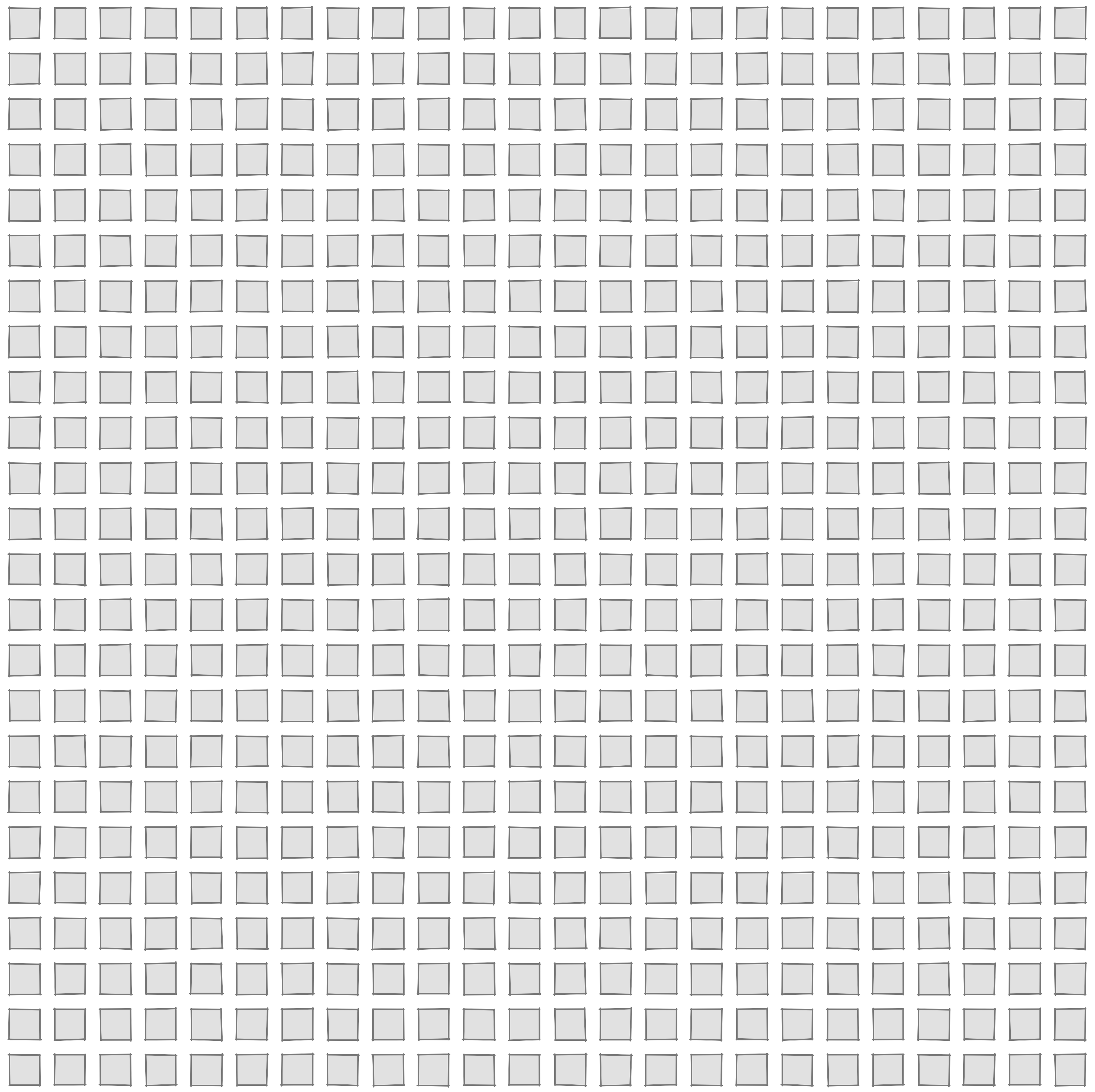


Outliers in log data



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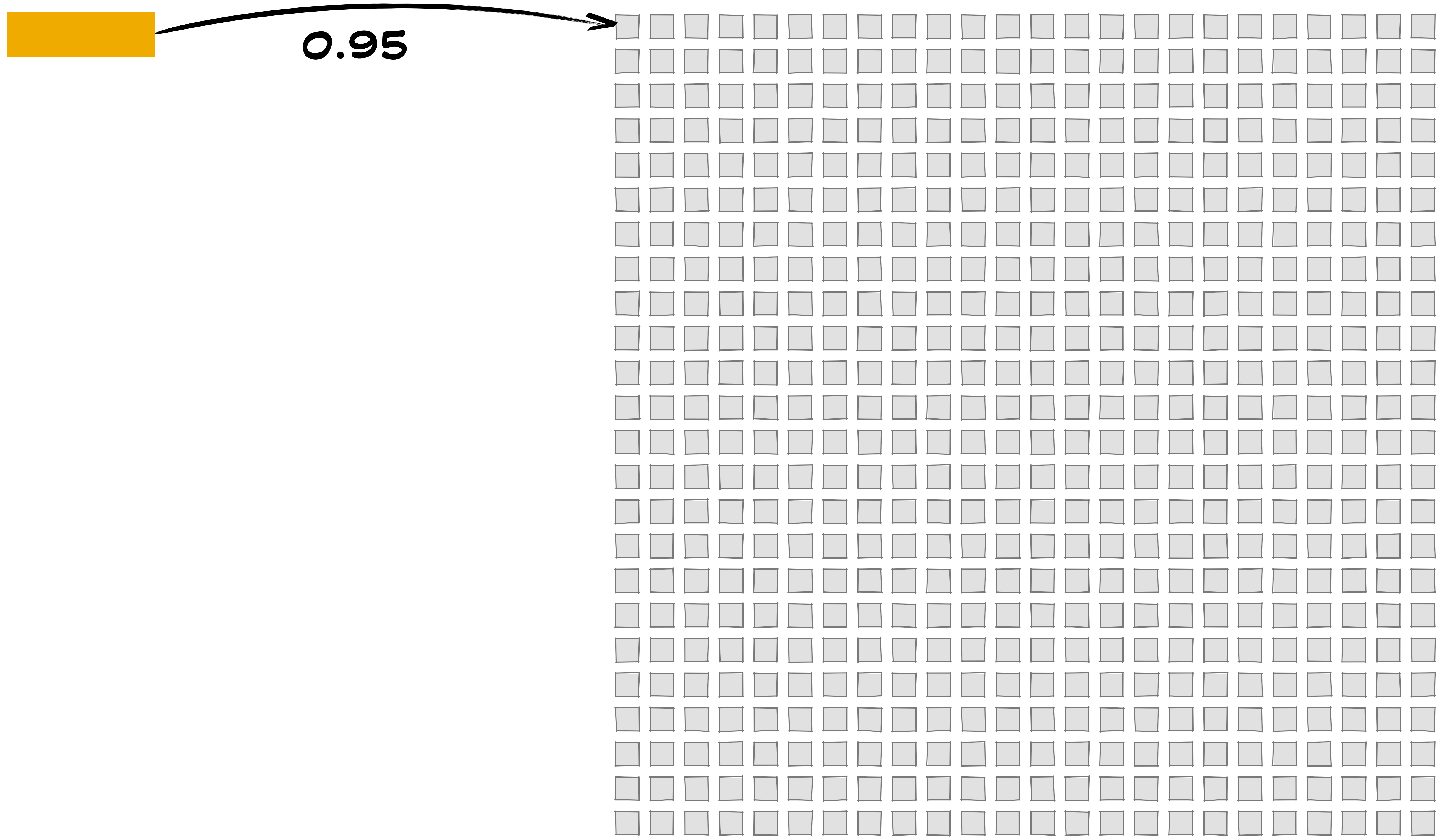

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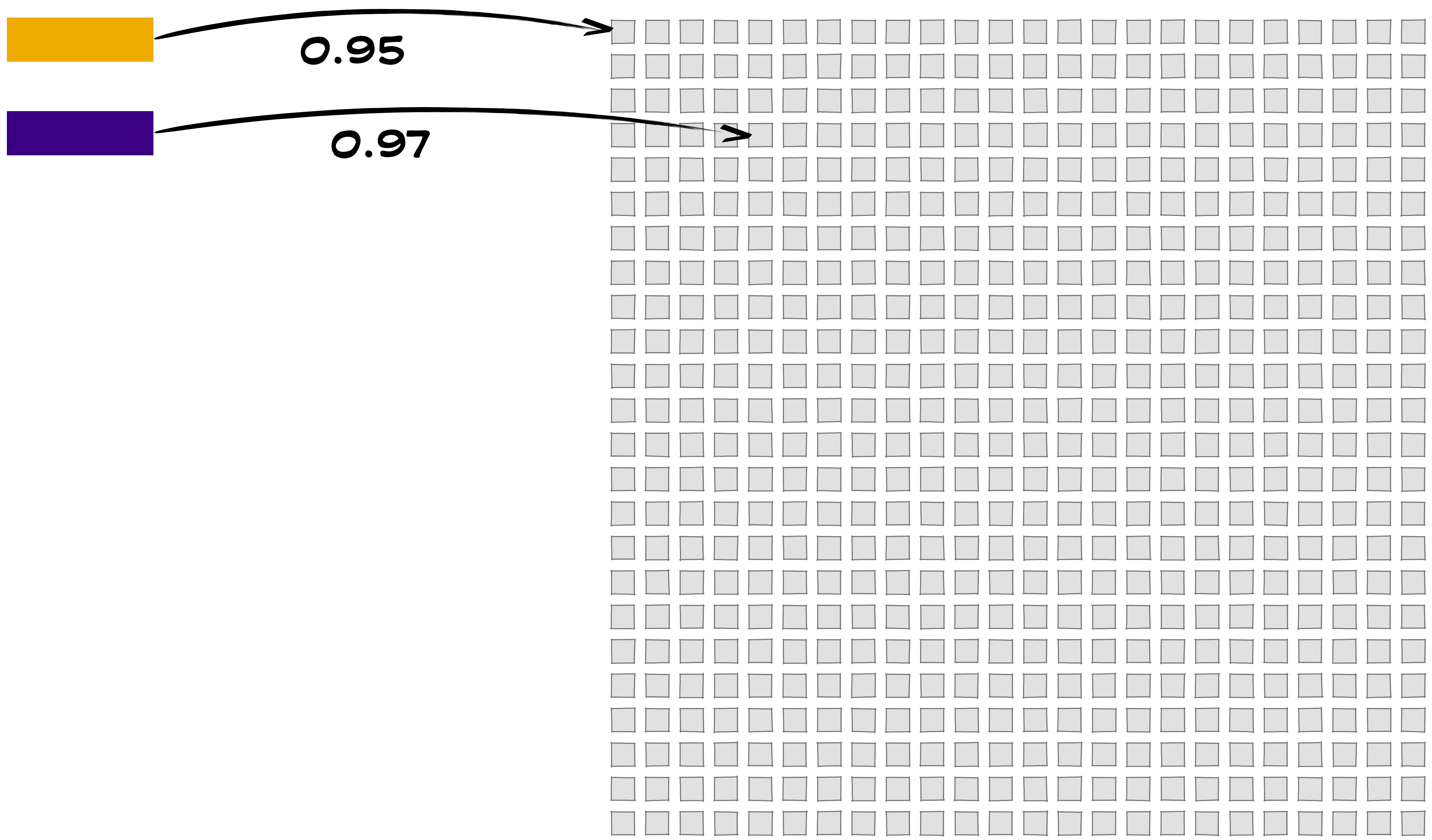

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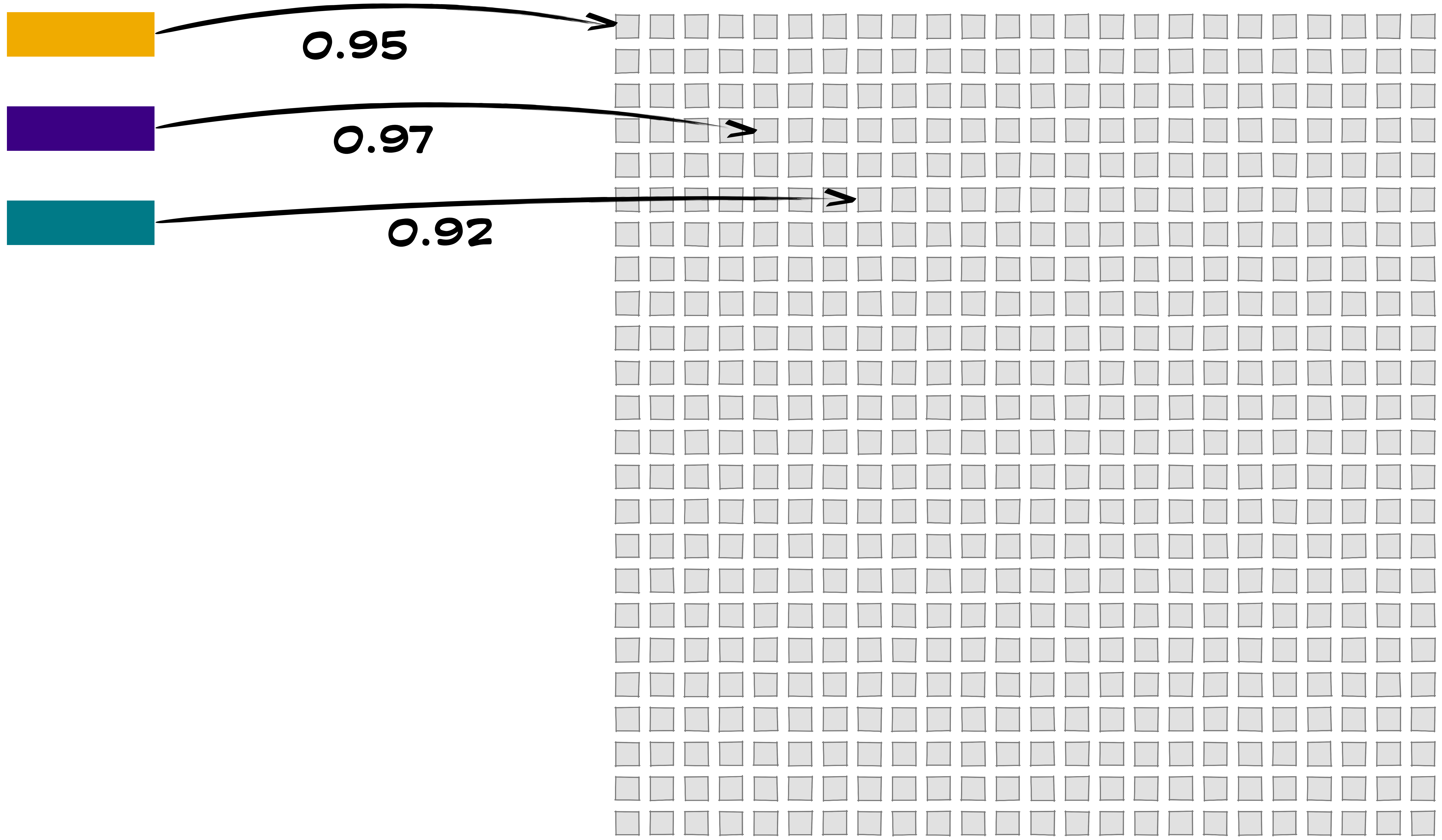

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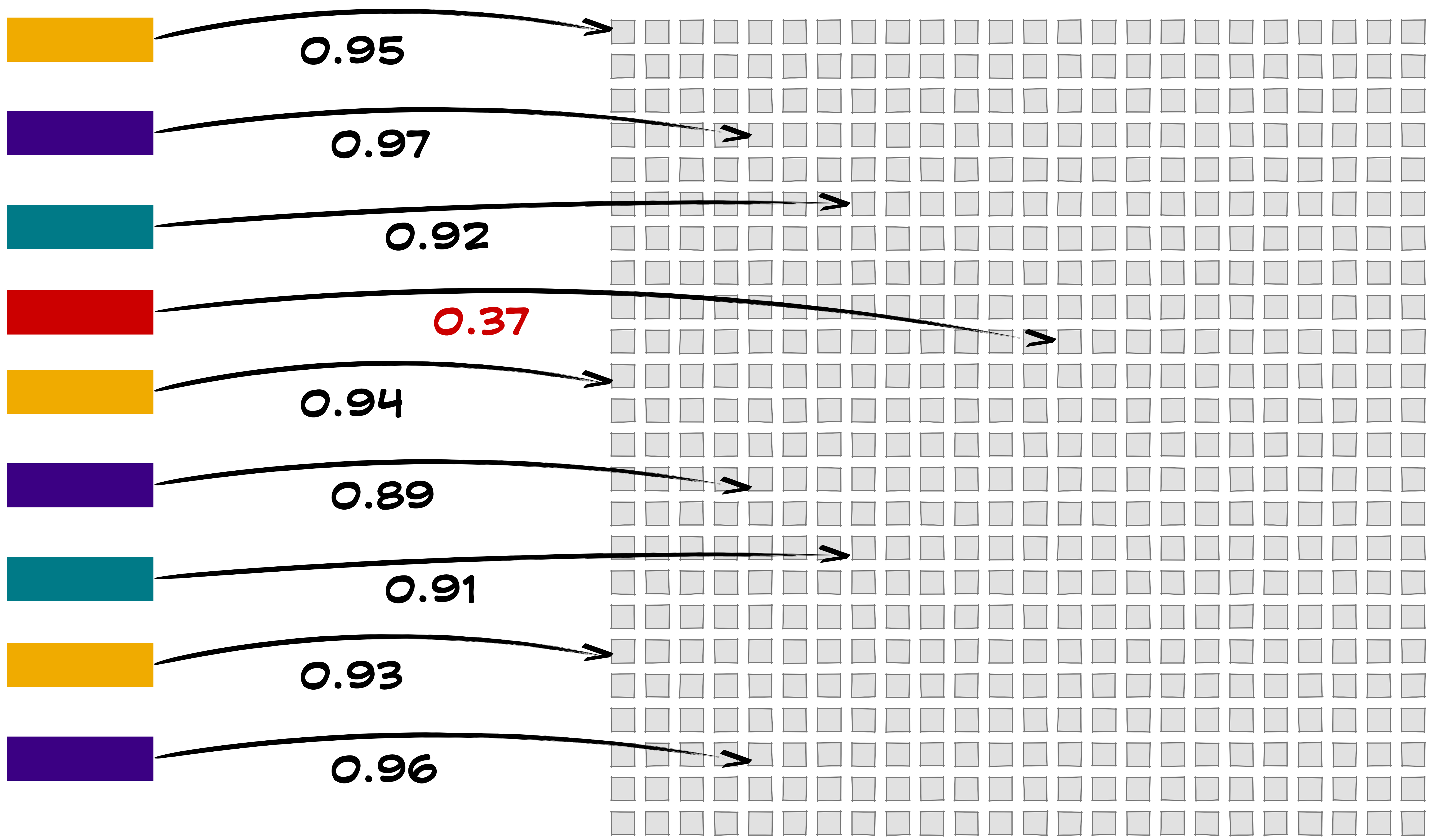
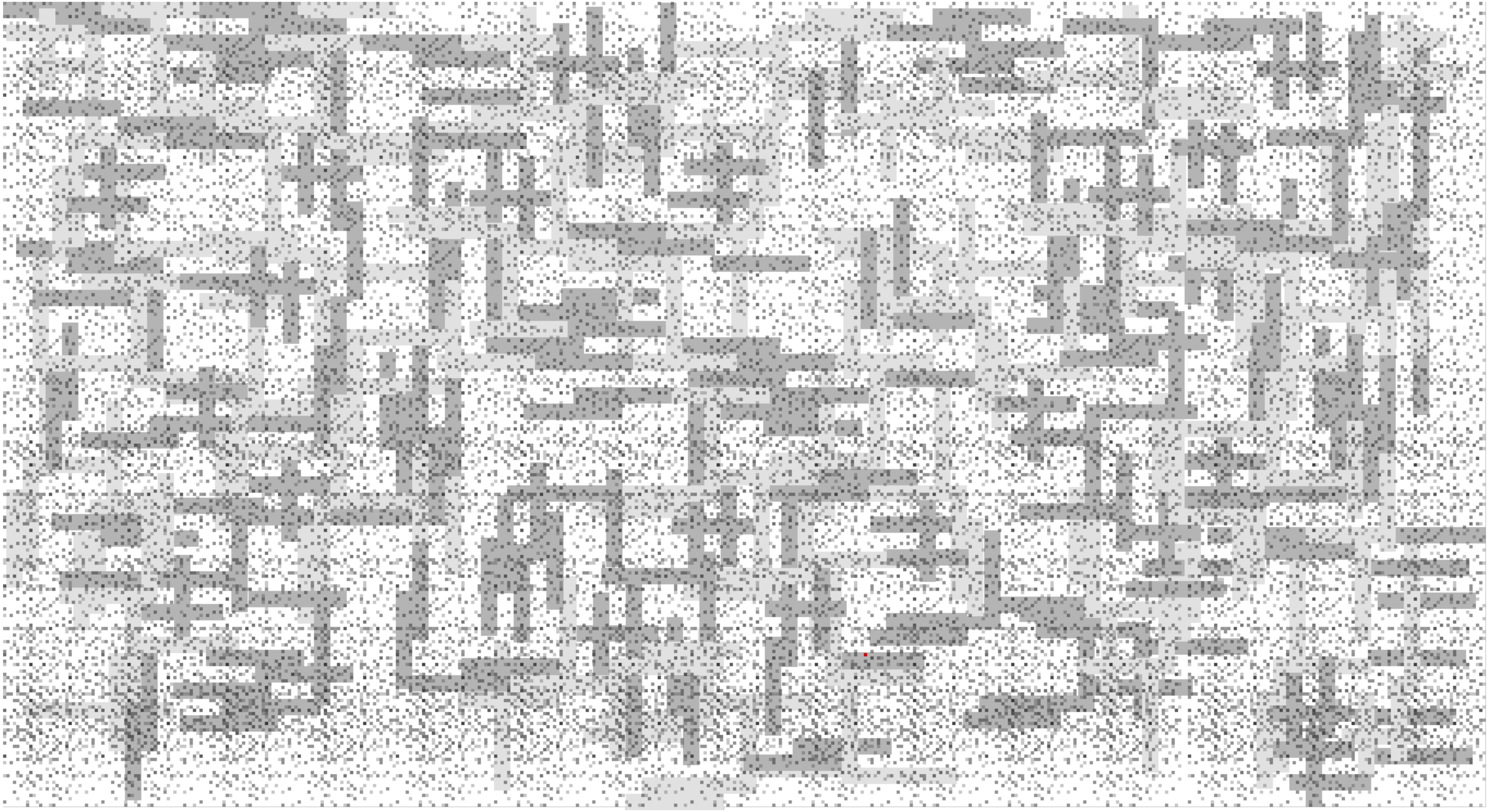
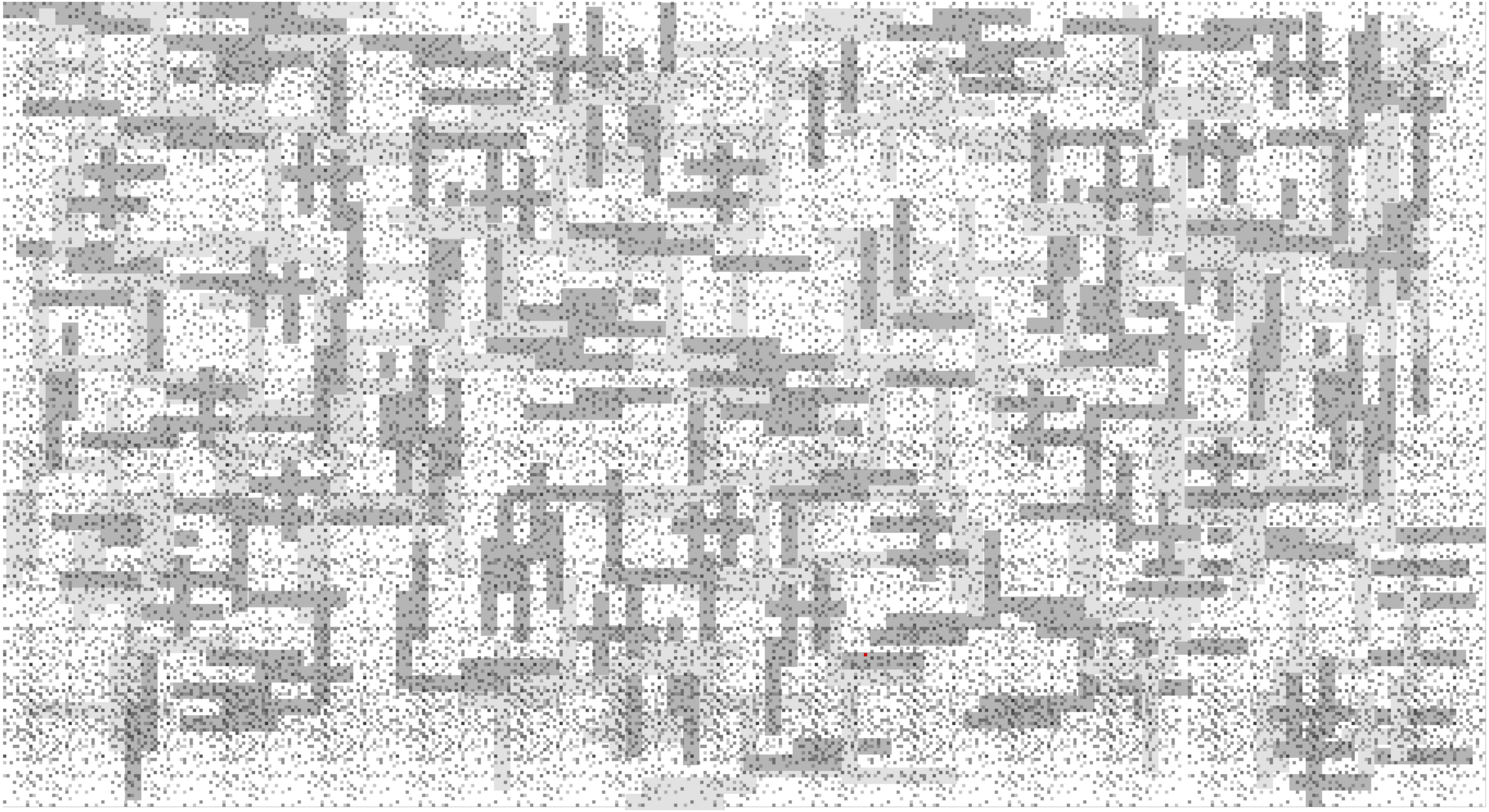


An **outlier** is any record whose best match was **at least** 4σ below the mean.



Out of 310 million log records, we identified 0.0012% as outliers.

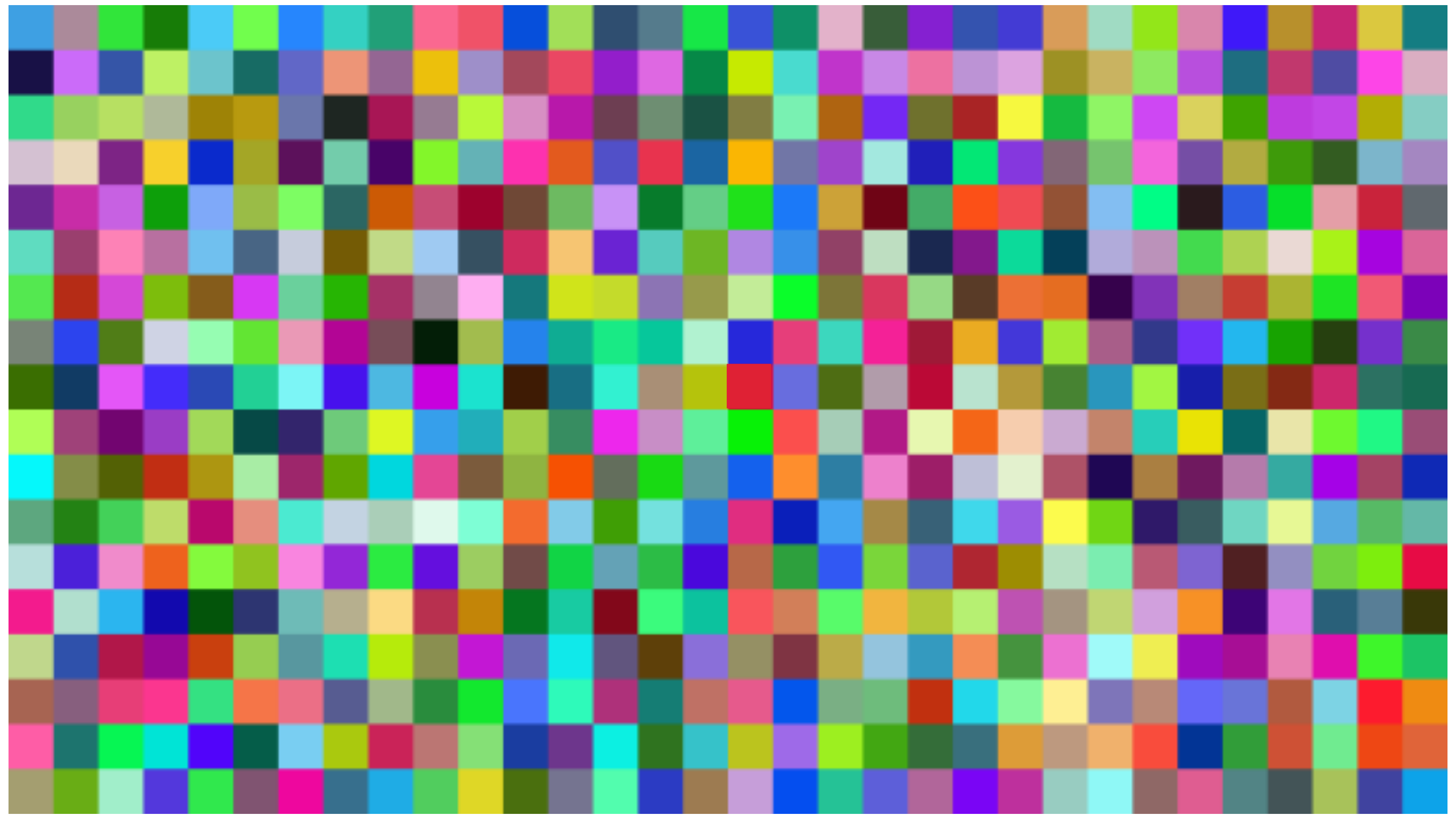


Thirty most extreme outliers

10	`Can not communicate with power supply 2.`
9	`Power supply 2 failed.`
8	`Power supply redundancy is lost.`
1	`Drive A is removed.`
1	`Can not communicate with power supply 1.`
1	`Power supply 1 failed.`

SOM TRAINING in SPARK

On-line SOM training



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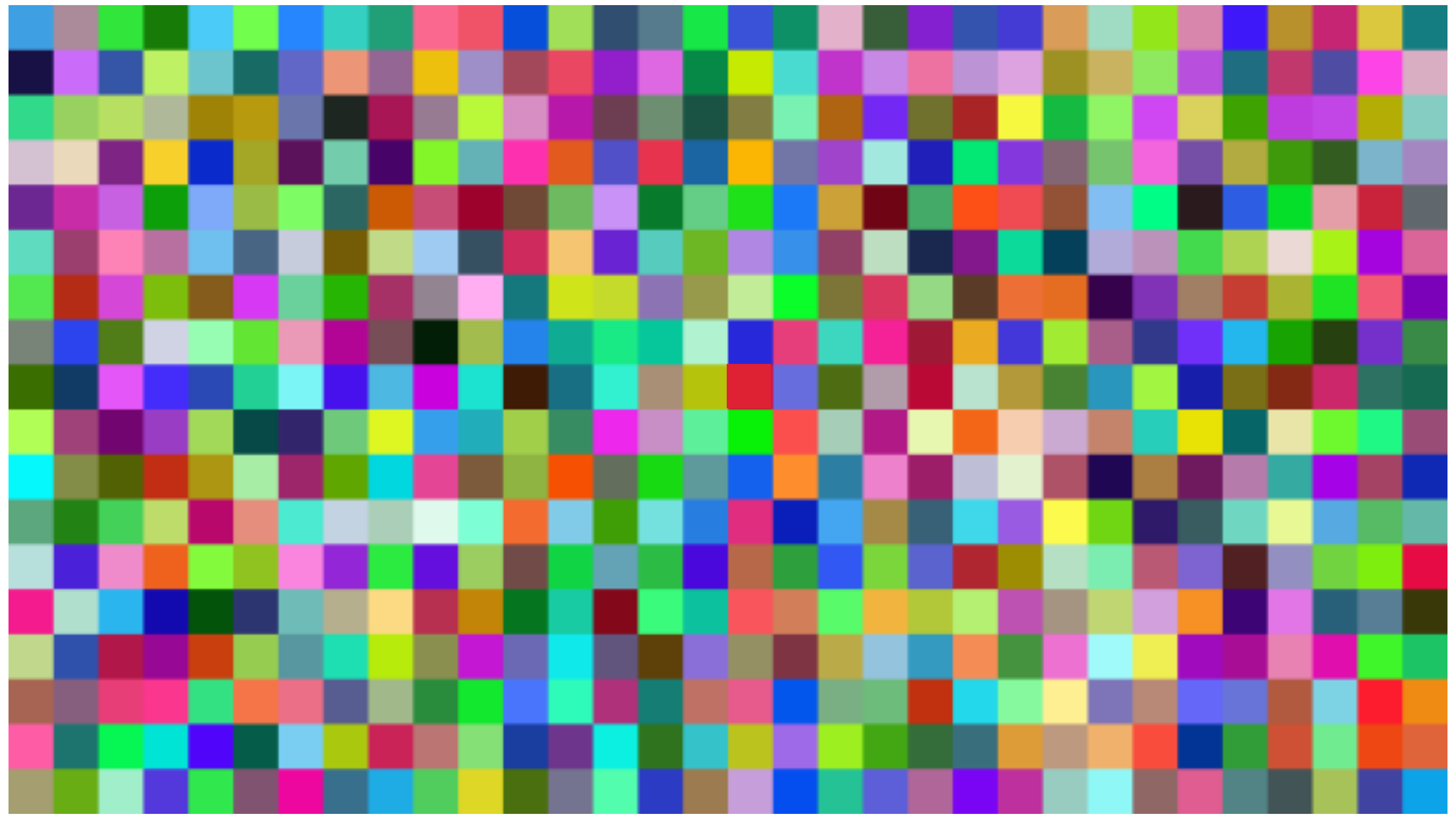

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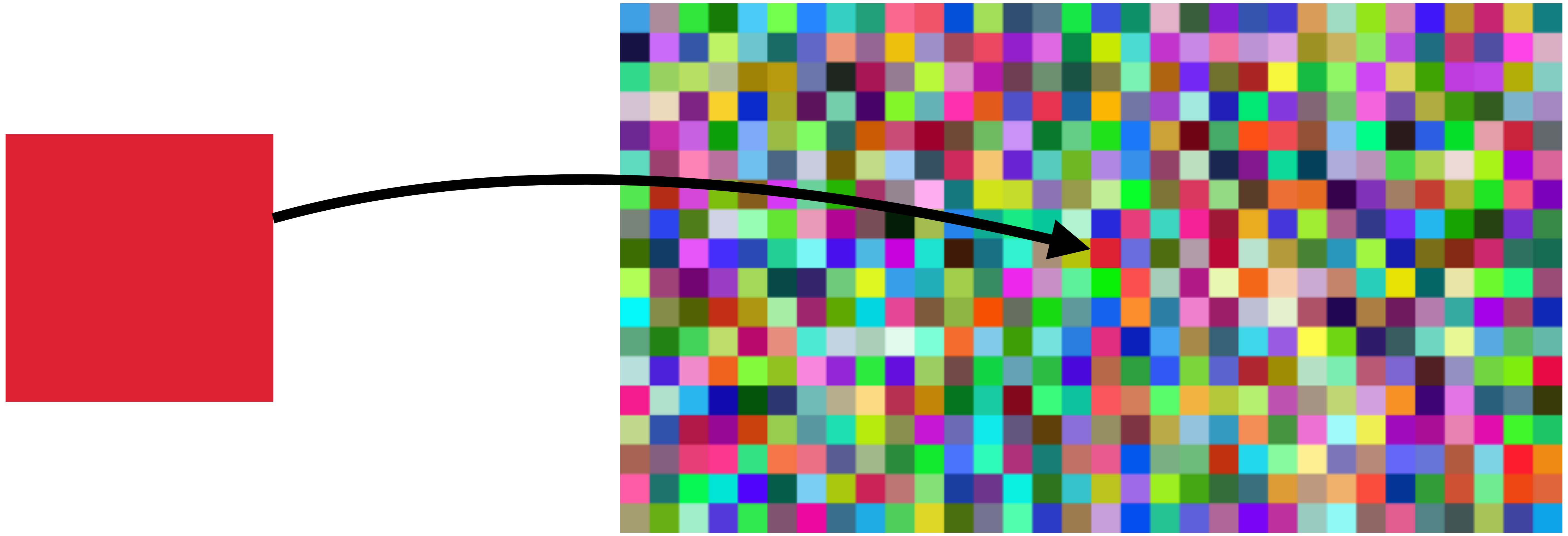

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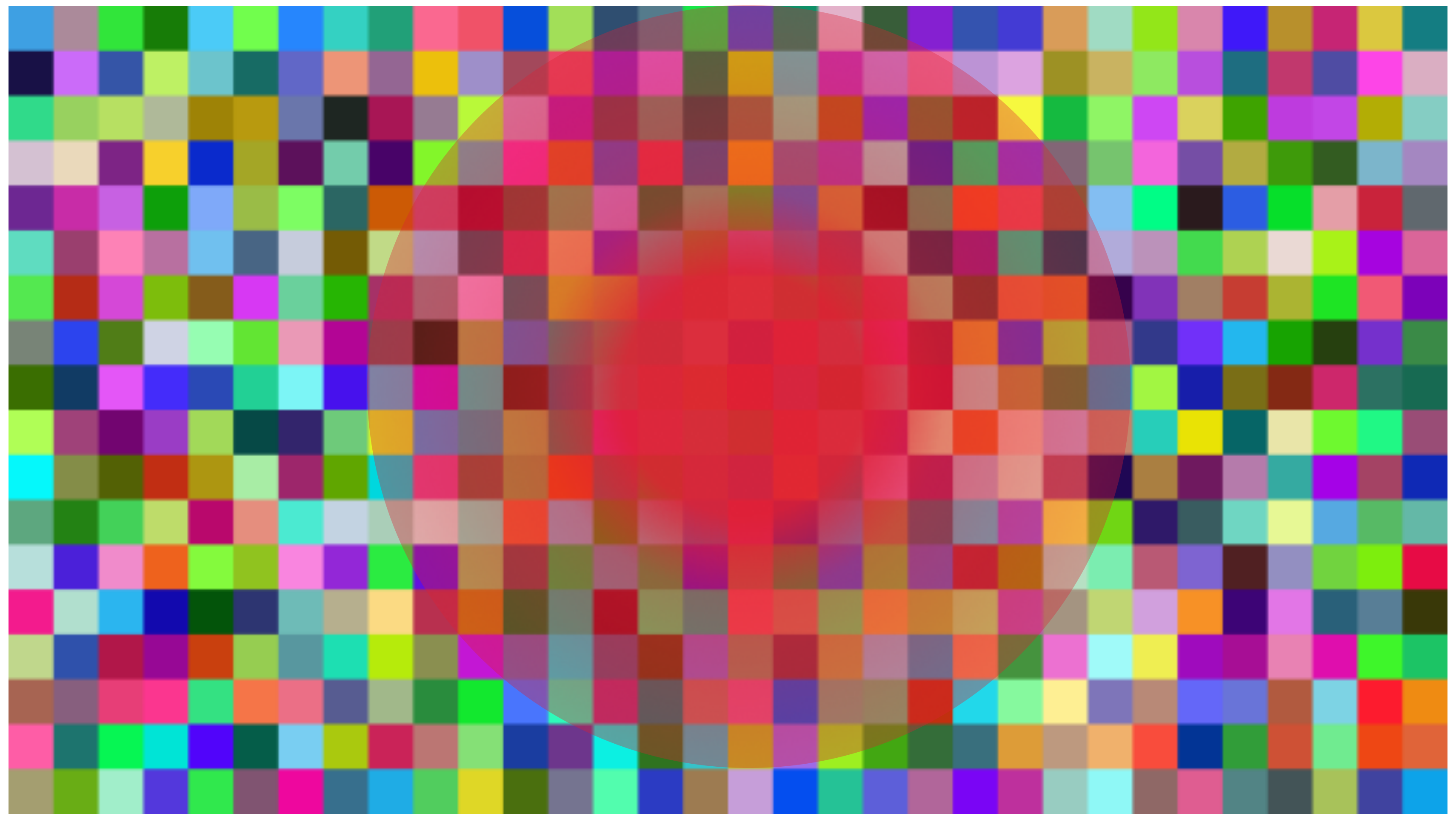

On-line SOM training

```
while t < iterations:
 for ex in examples:
    t = t + 1
    if t == iterations:
      break
    bestMatch = closest(som_t, ex)
    for (unit, wt) in neighborhood(bestMatch, sigma(t)):
      som_t+1[unit] = som_t[unit] + ex * alpha(t) * wt
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at each step, we update each unit by
adding its value from the previous step...

On-line SOM training

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to the example that we considered...

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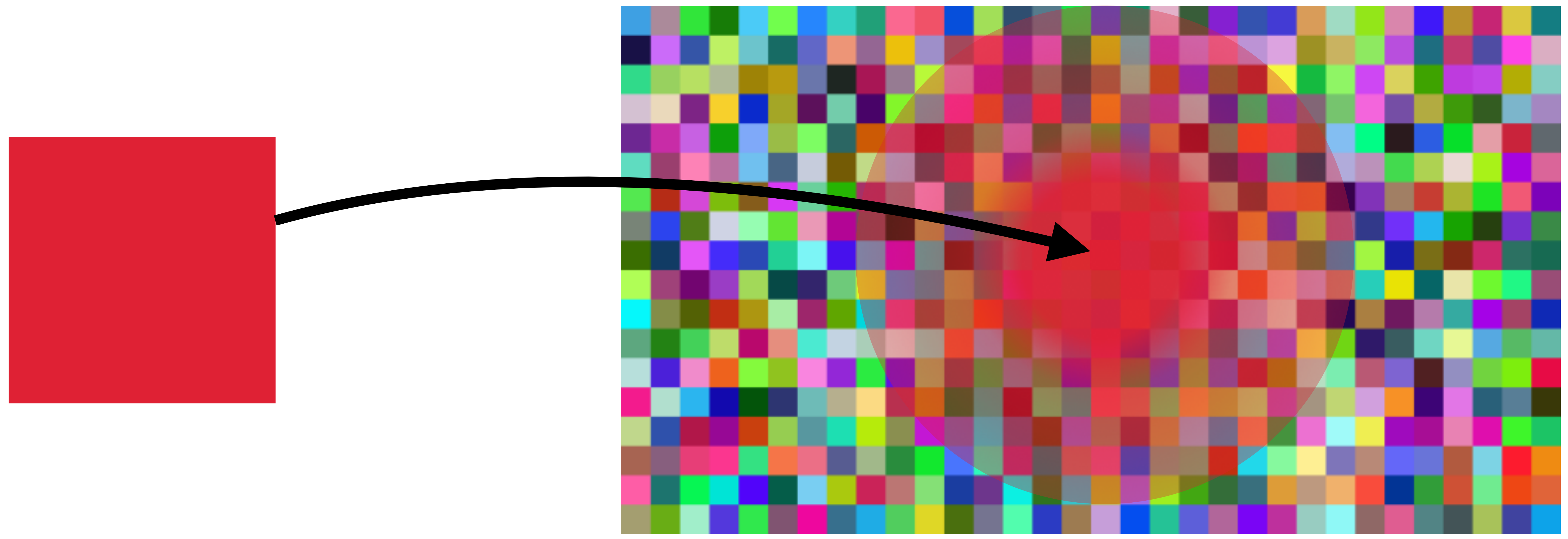
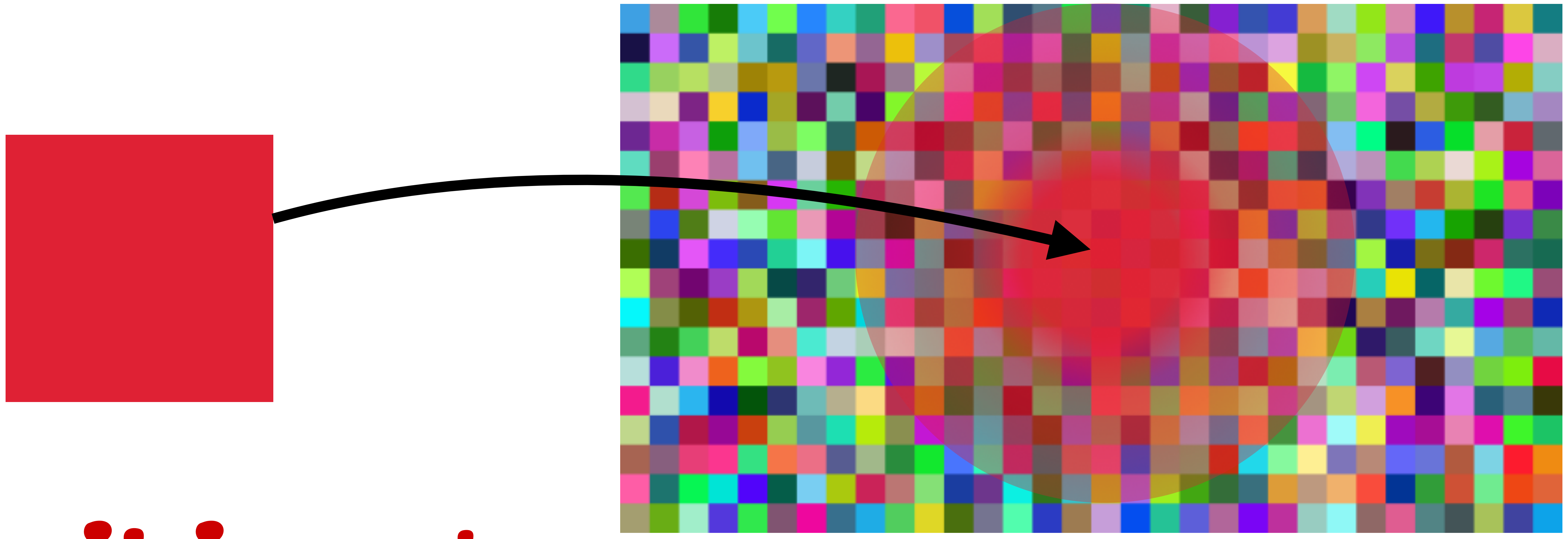
 for ex in examples:
    t = t + 1
    if t == iterations:
      break
    bestMatch = closest(som_t, ex)
    for (unit, wt) in neighborhood(bestMatch, sigma(t)):
      som_t+1[unit] = som_t[unit] + ex * alpha(t) * wt
```

scaled by a learning factor and the distance from this unit to its best match

On-line SOM training



On-line SOM training



not parallel

sensitive to example order

sensitive to learning rate

Batch SOM training

```
for t in (1 to iterations):
  state = newState()
  for ex in examples:
    bestMatch = closest(som_{t-1}, ex)
    hood = neighborhood(bestMatch, sigma(t))
    state.matches += ex * hood
    state.hoods += hood
  som_t = newSOM(state.matches / state.hoods)
```

Batch SOM training

```
for t in (1 to iterations):
  state = newState()
  for ex in examples:
    bestMatch = closest(som_{t-1}, ex)
    hood = neighborhood(bestMatch, sigma(t))
    state.matches += ex * hood
    state.hoods += hood
  som_t = newSOM(state.matches / state.hoods)
```

update the state of every cell in the neighborhood of the best matching unit, weighting by distance

Batch SOM training

```
for t in (1 to iterations):
  state = newState()
  for ex in examples:
    bestMatch = closest(som_{t-1}, ex)
    hood = neighborhood(bestMatch, sigma(t))
    state.matches += ex * hood
    state.hoods += hood
  som_t = newSOM(state.matches / state.hoods)
```

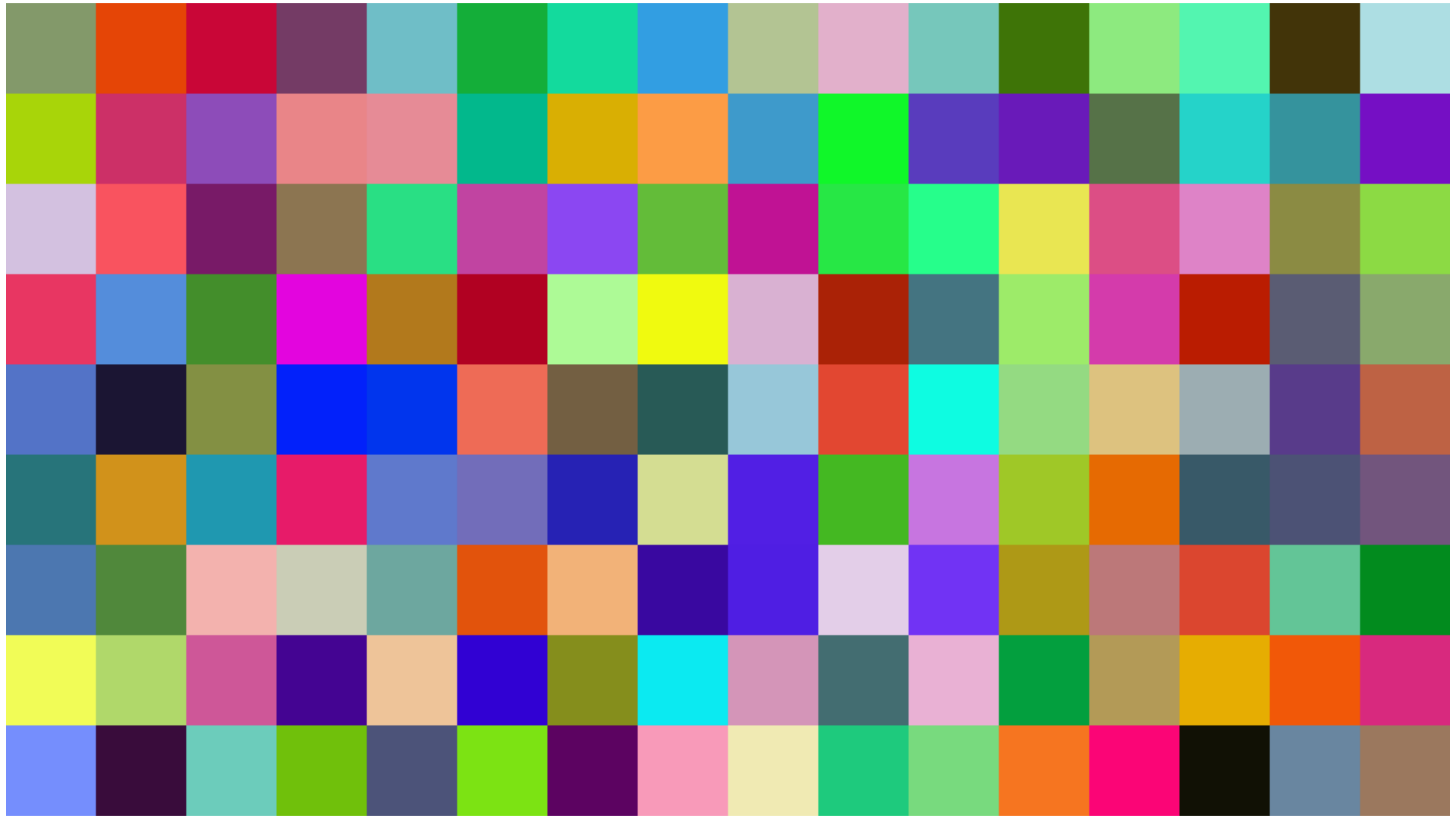
keep track of the distance weights
we've seen for a weighted average

Batch SOM training

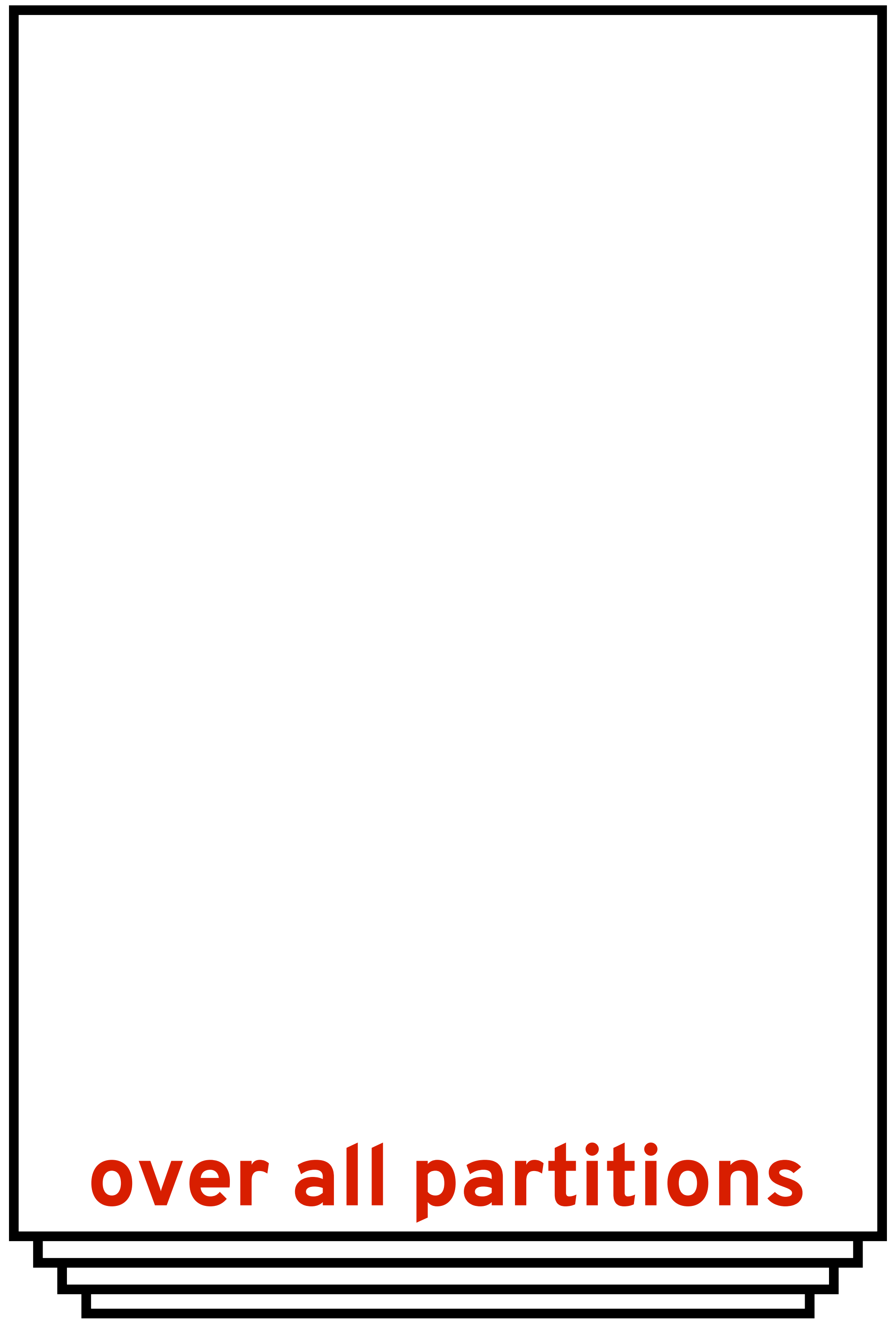
```
for t in (1 to iterations):
  state = newState()
  for ex in examples:
    bestMatch = closest(som_{t-1}, ex)
    hood = neighborhood(bestMatch, sigma(t))
    state.matches += ex * hood
    state.hoods += hood
  som_t = newSOM(state.matches / state.hoods)
```

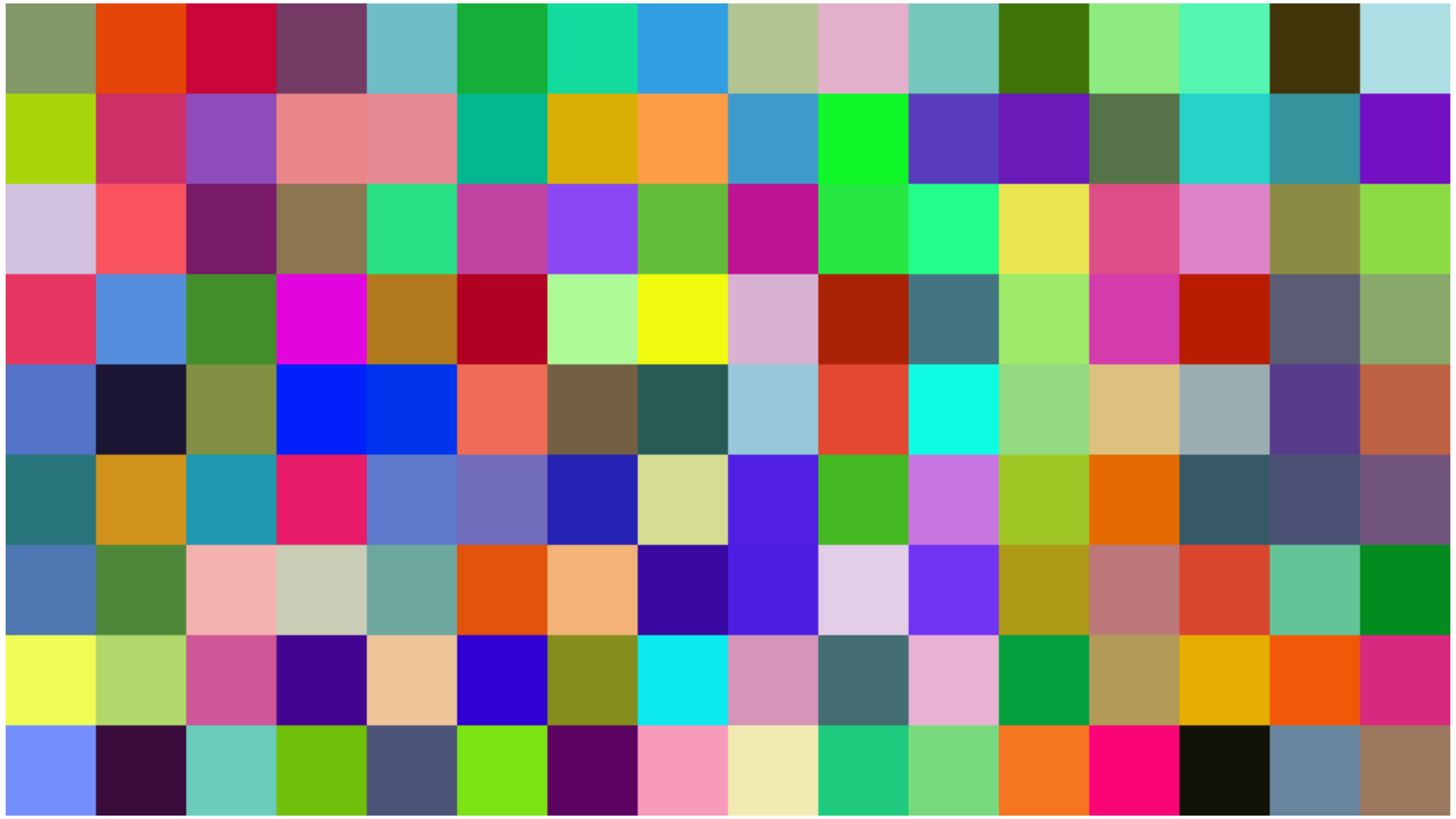
since we can easily **merge multiple states**, we can **train in parallel** across many examples

Batch SOM training



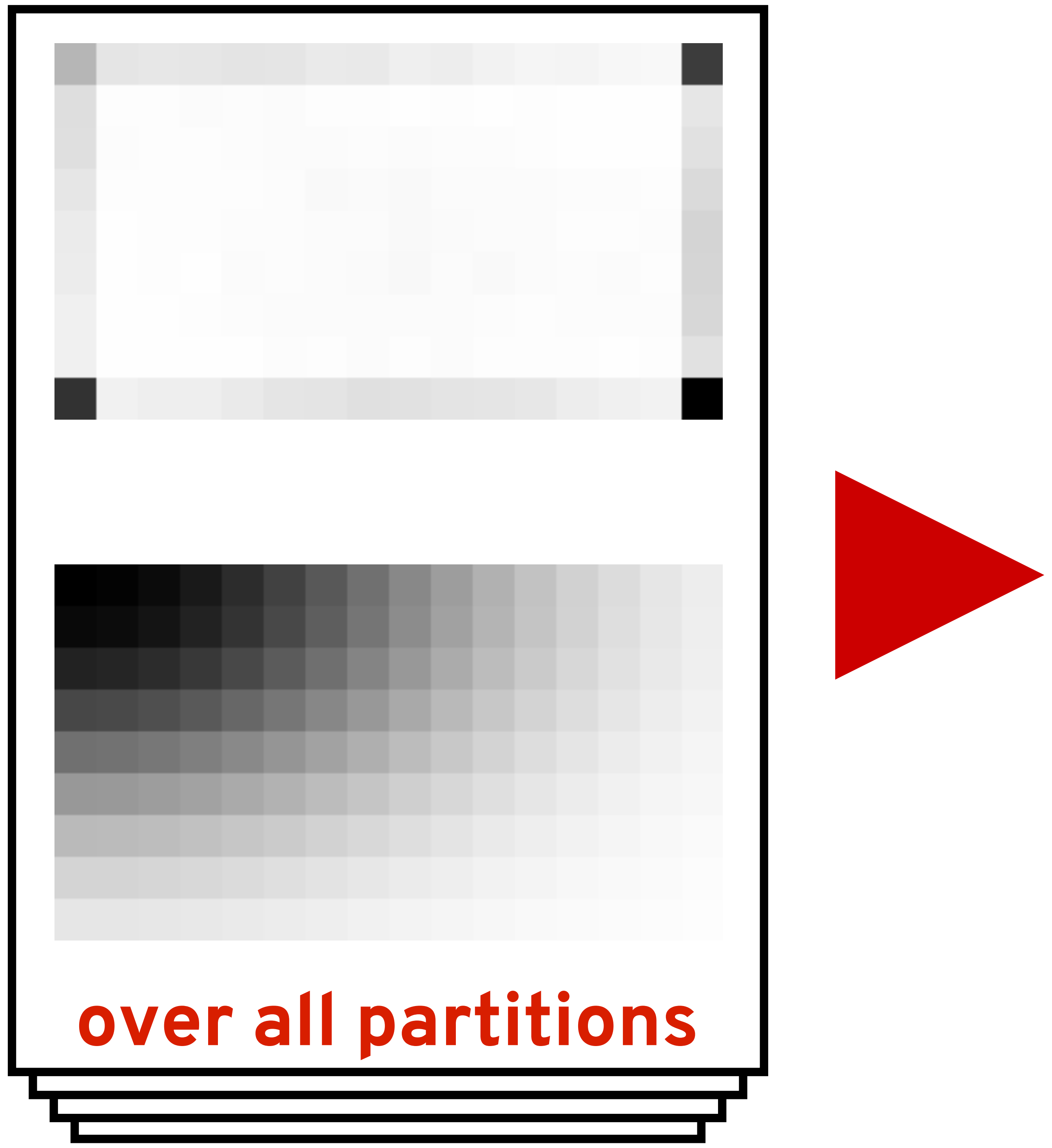
Batch SOM training

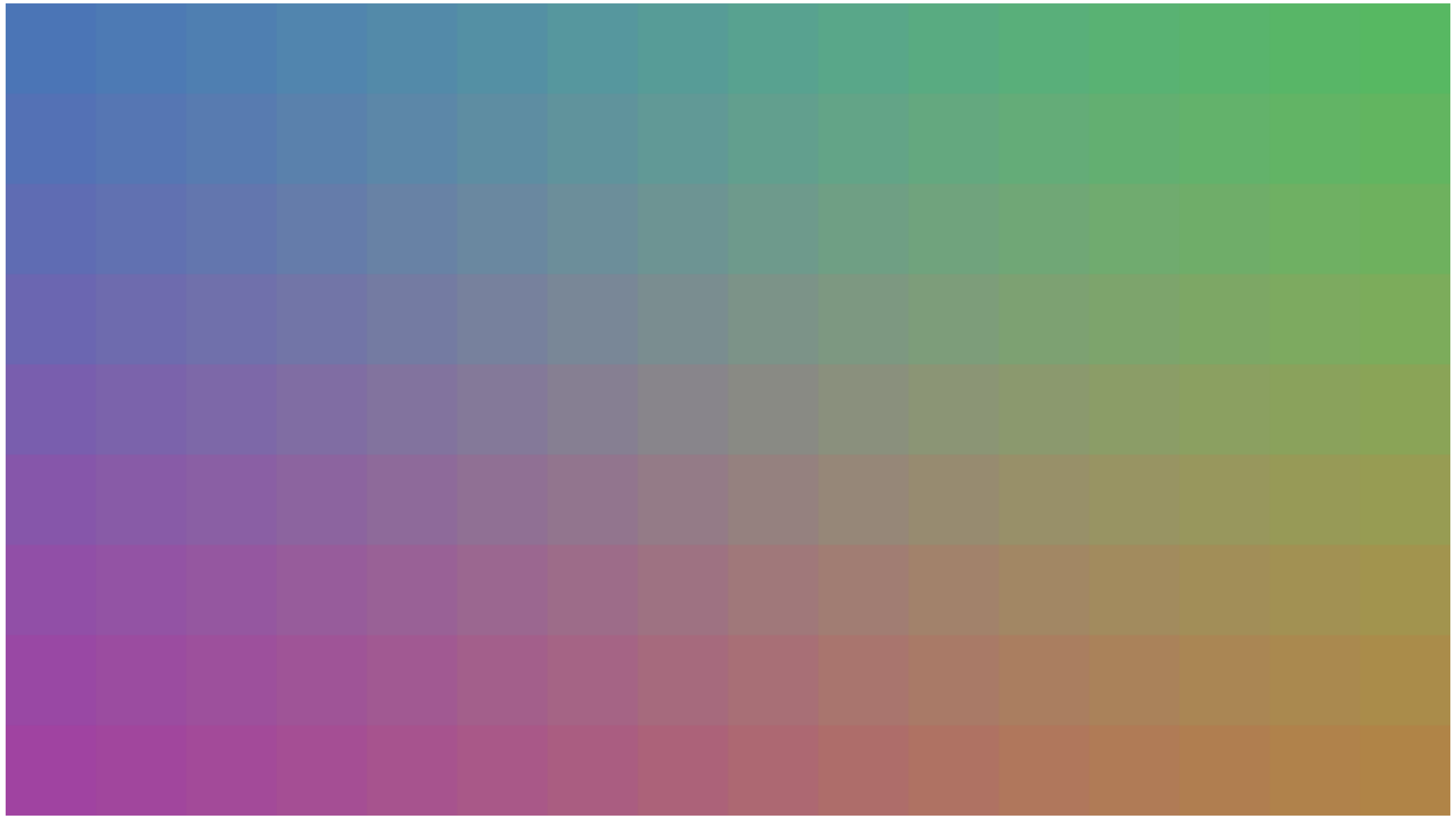




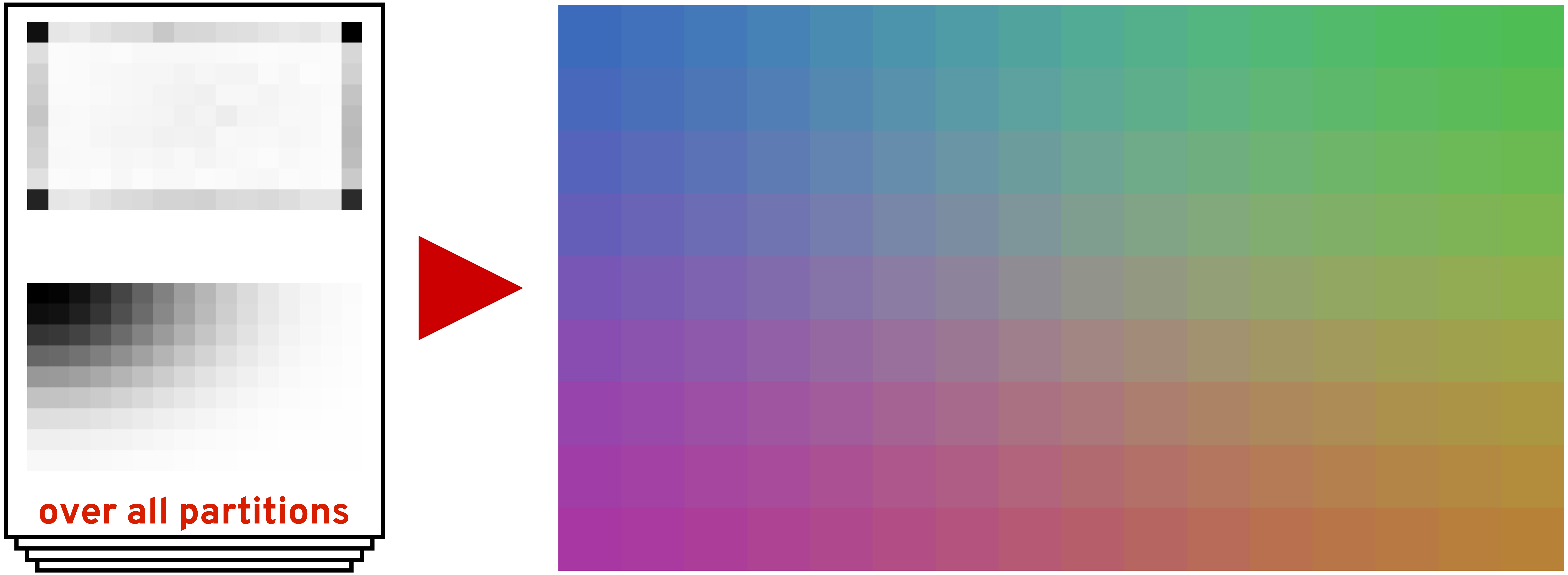
Batch SOM training

Batch SOM training

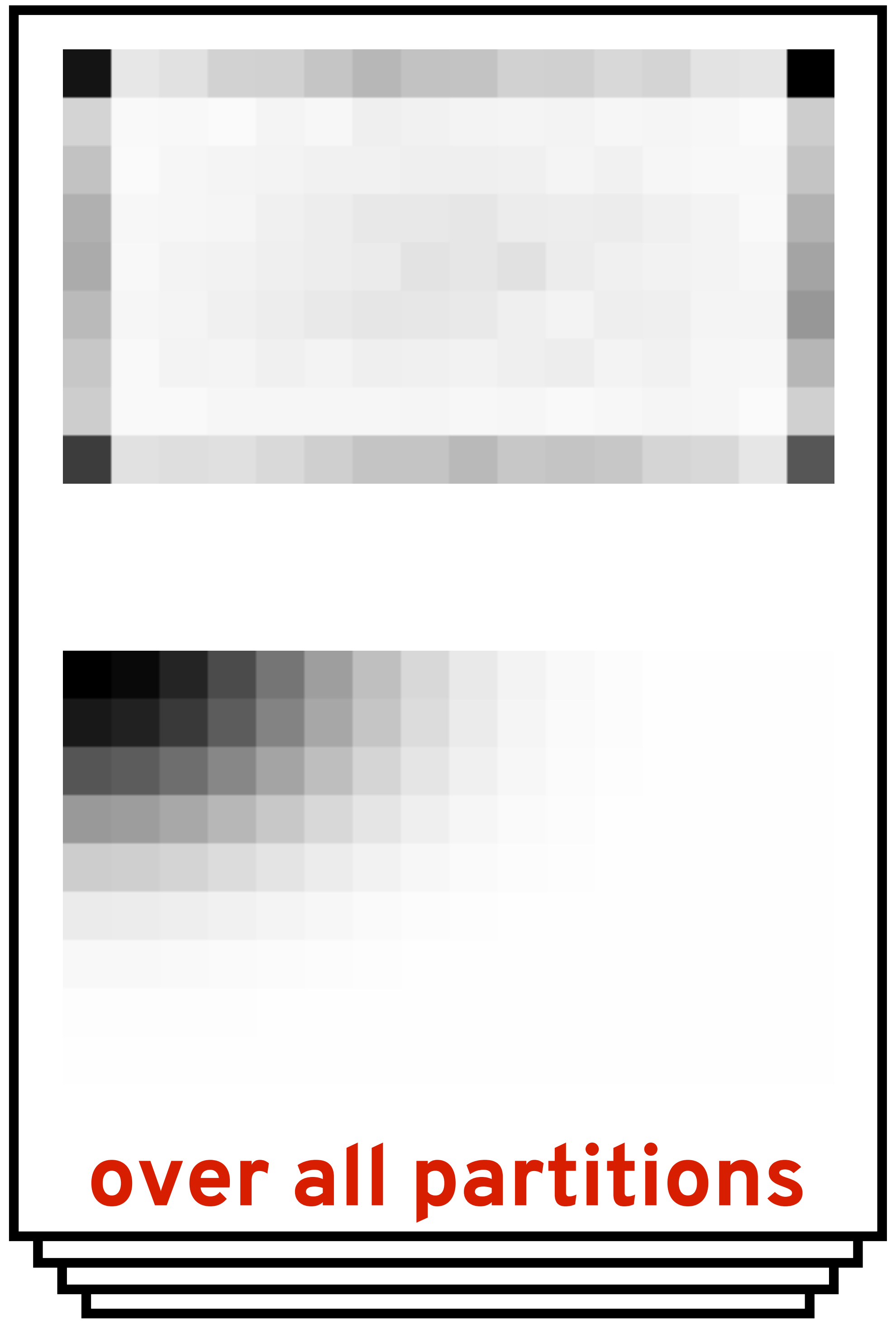


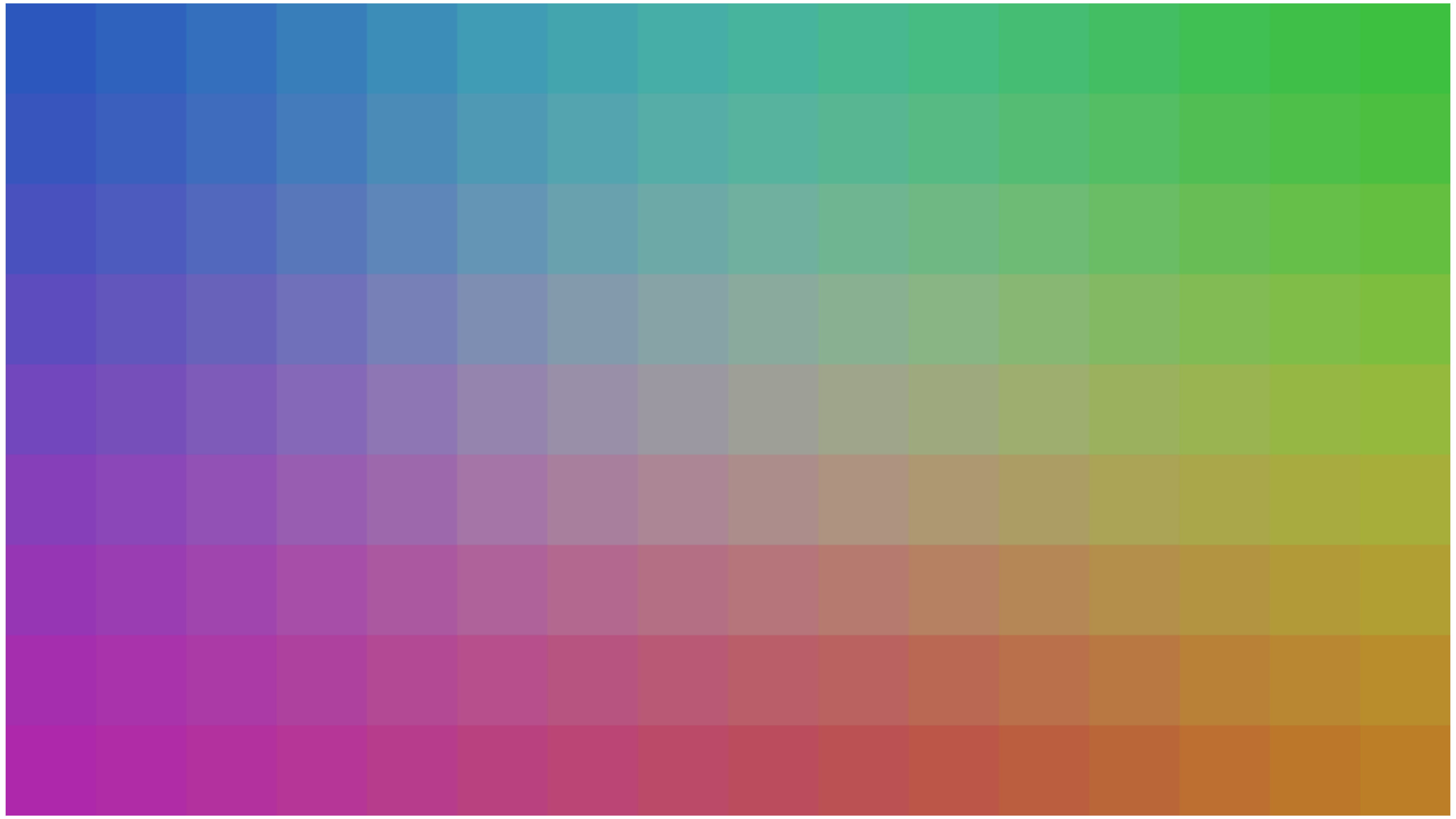


Batch SOM training

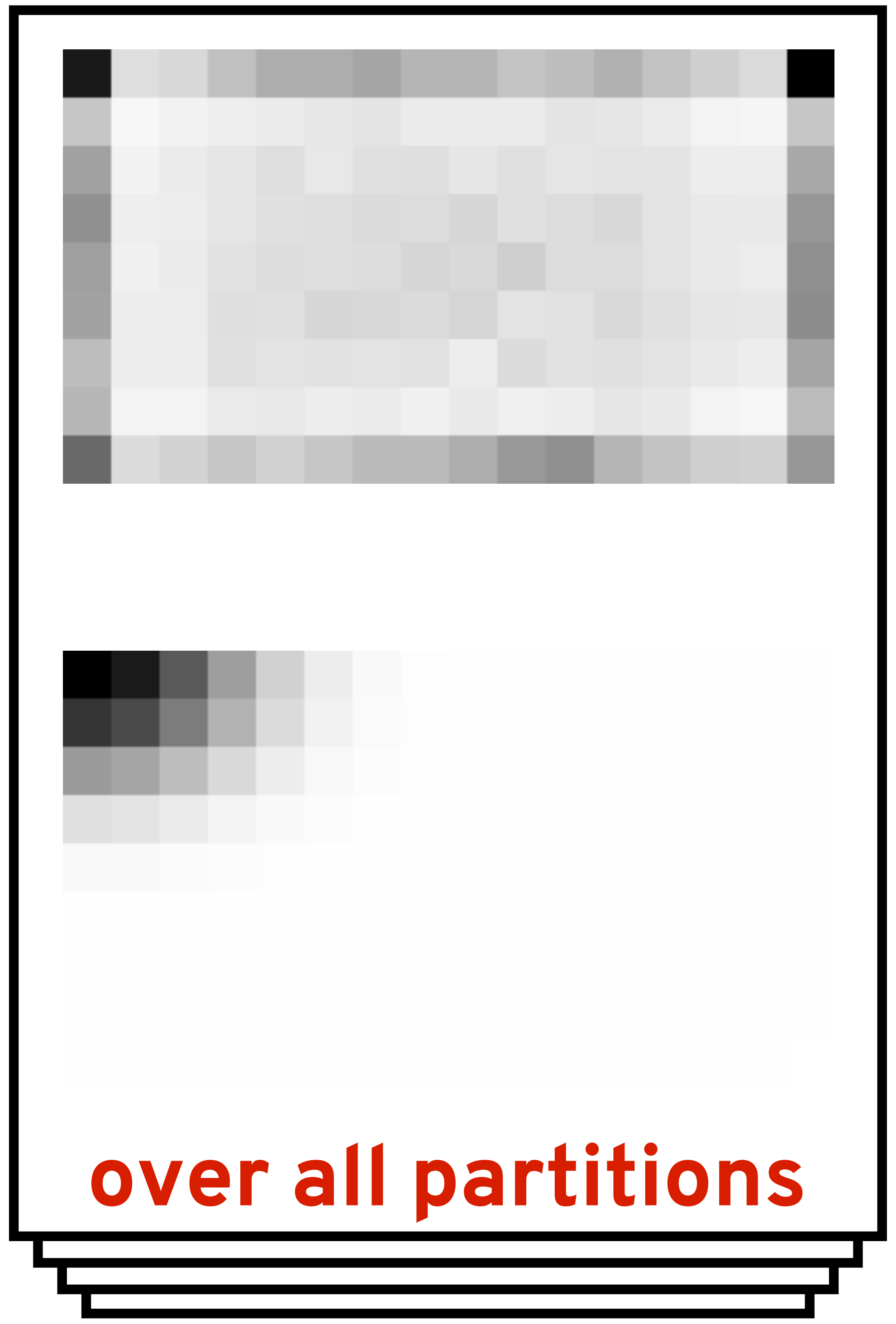


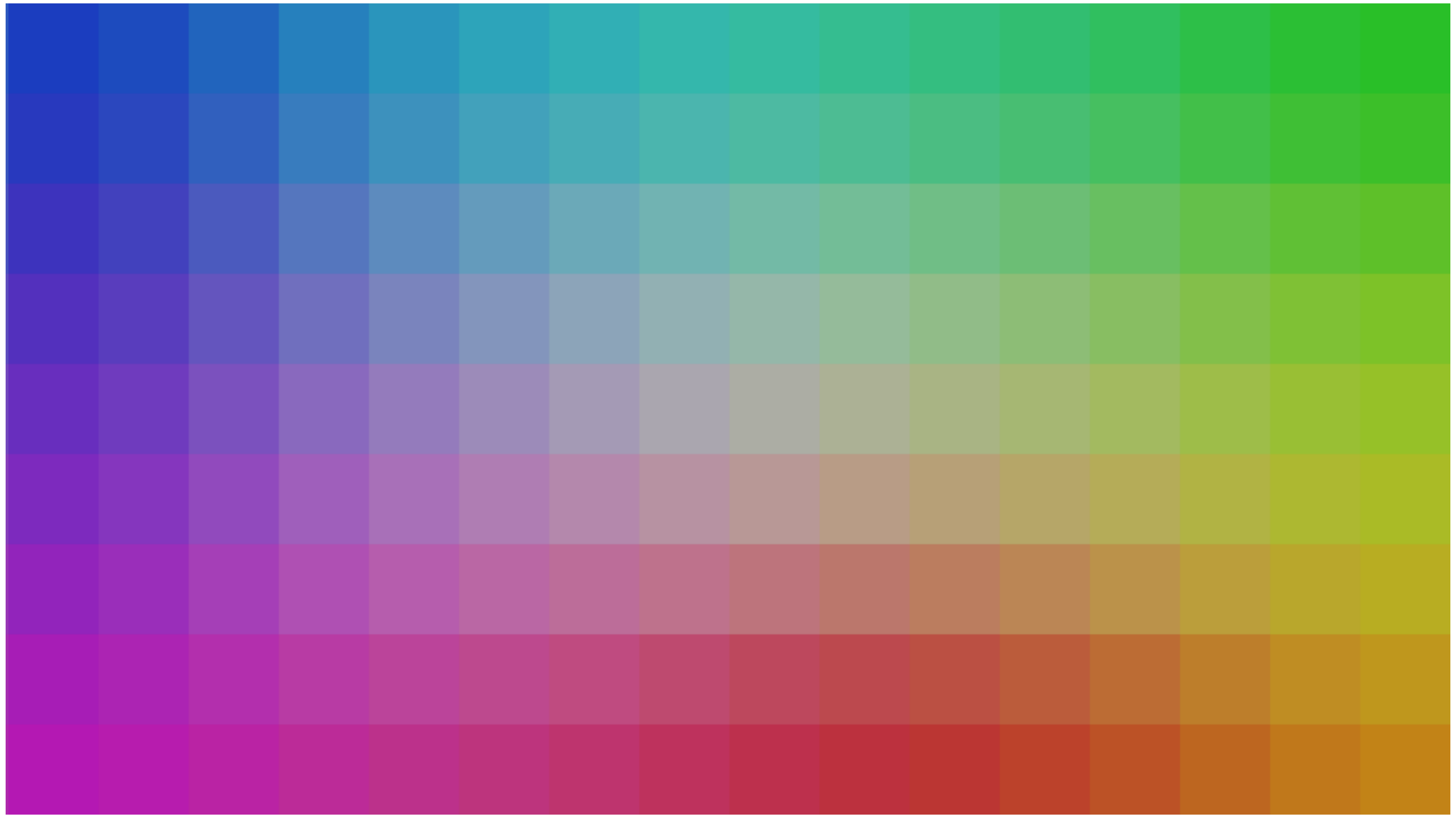
Batch SOM training

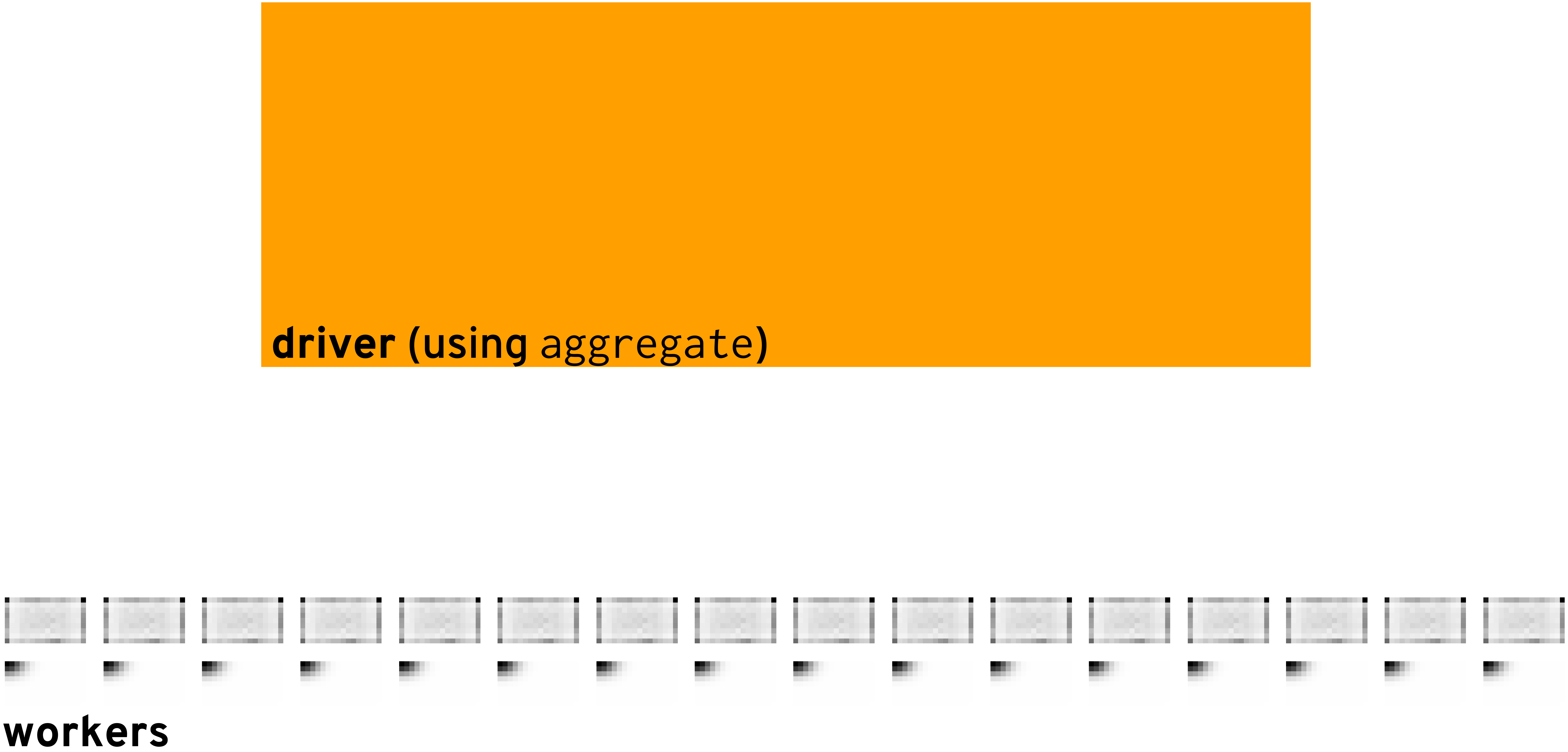


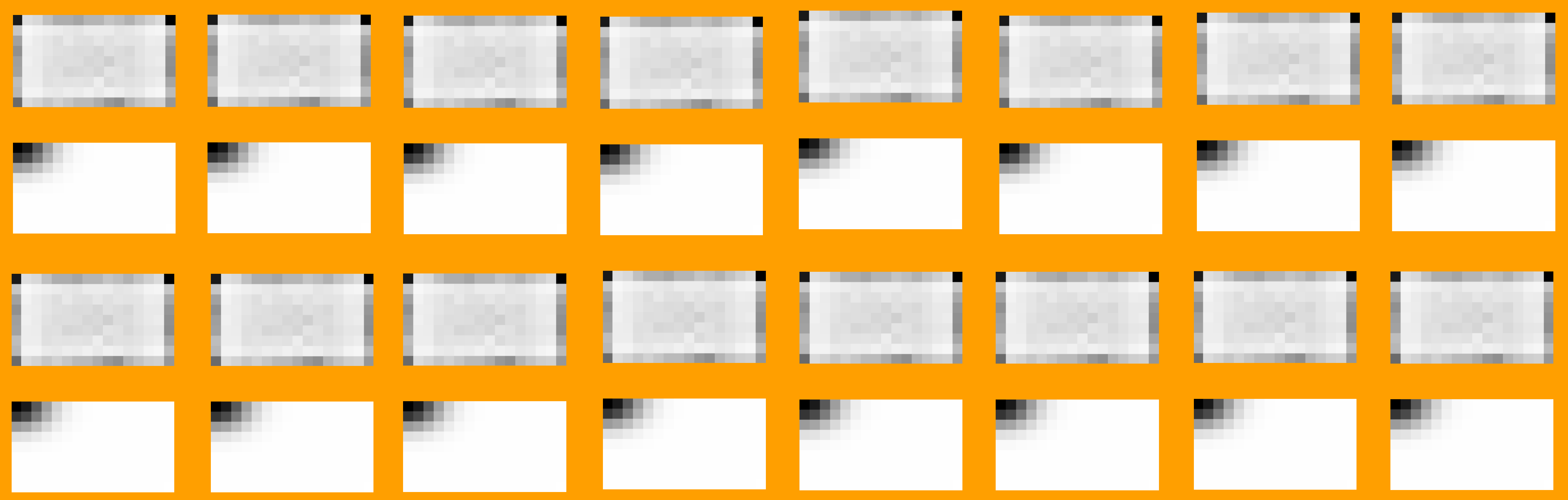


Batch SOM training



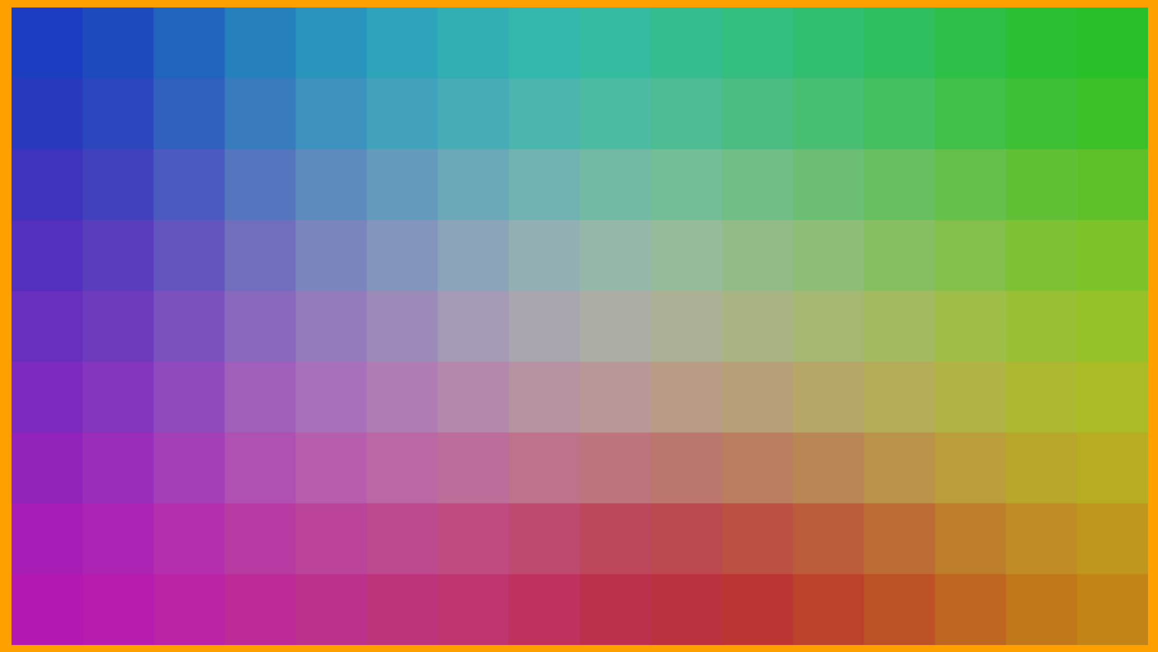



driver (using aggregate)
workers



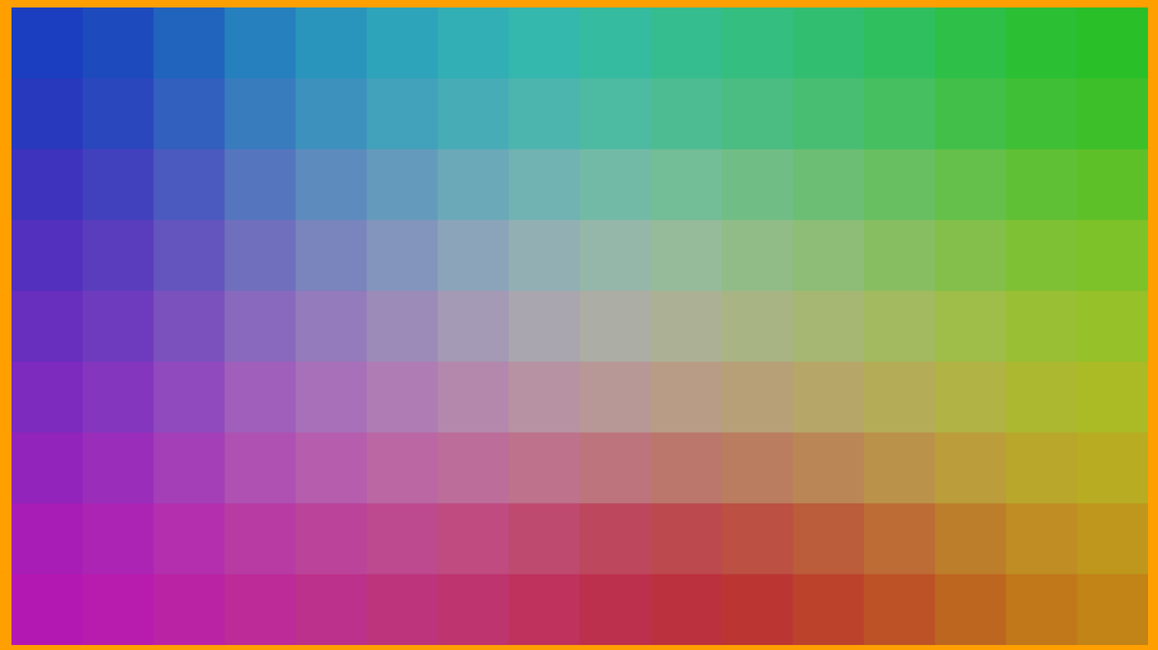
driver **(using** aggregate**)**

workers



driver (using `aggregate`)

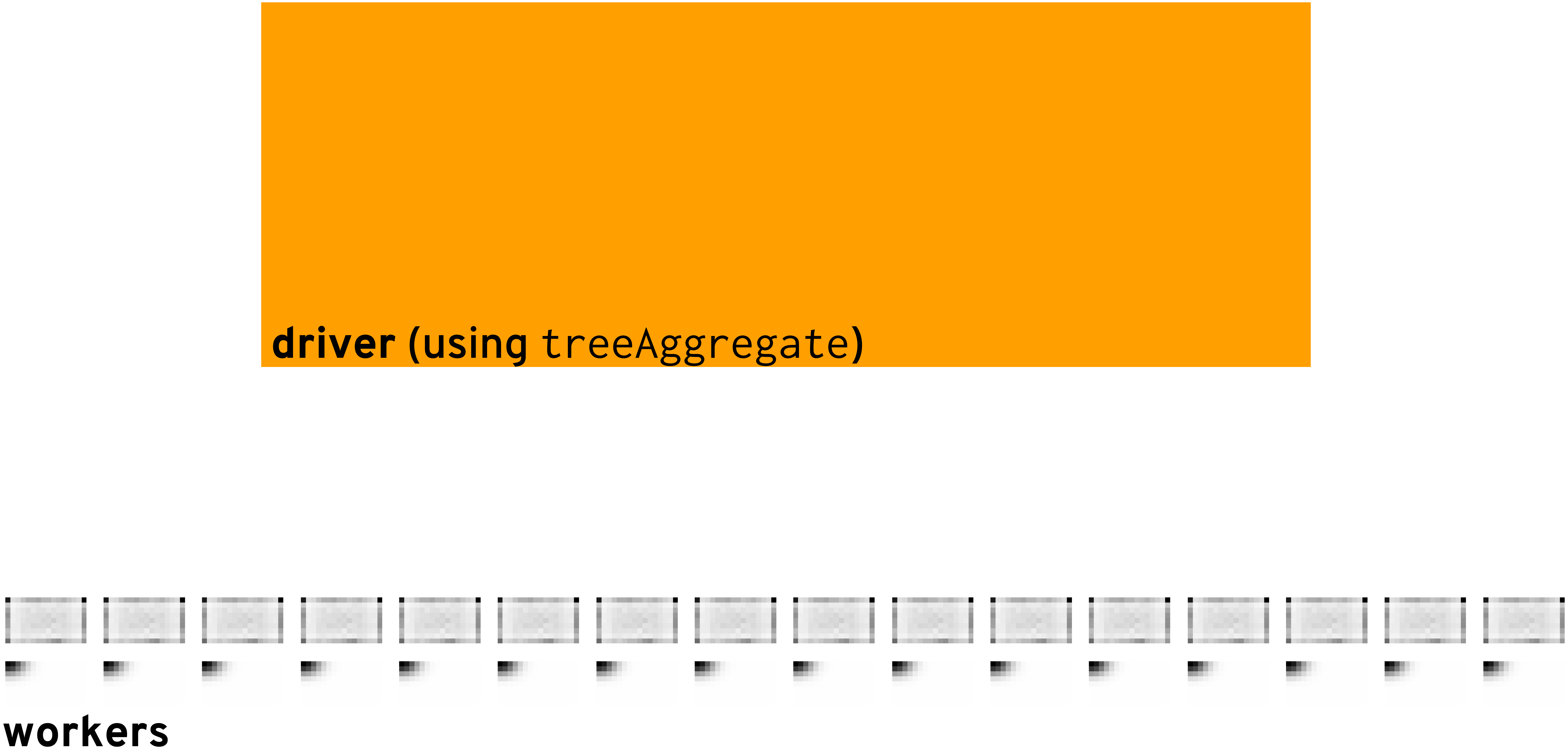
workers

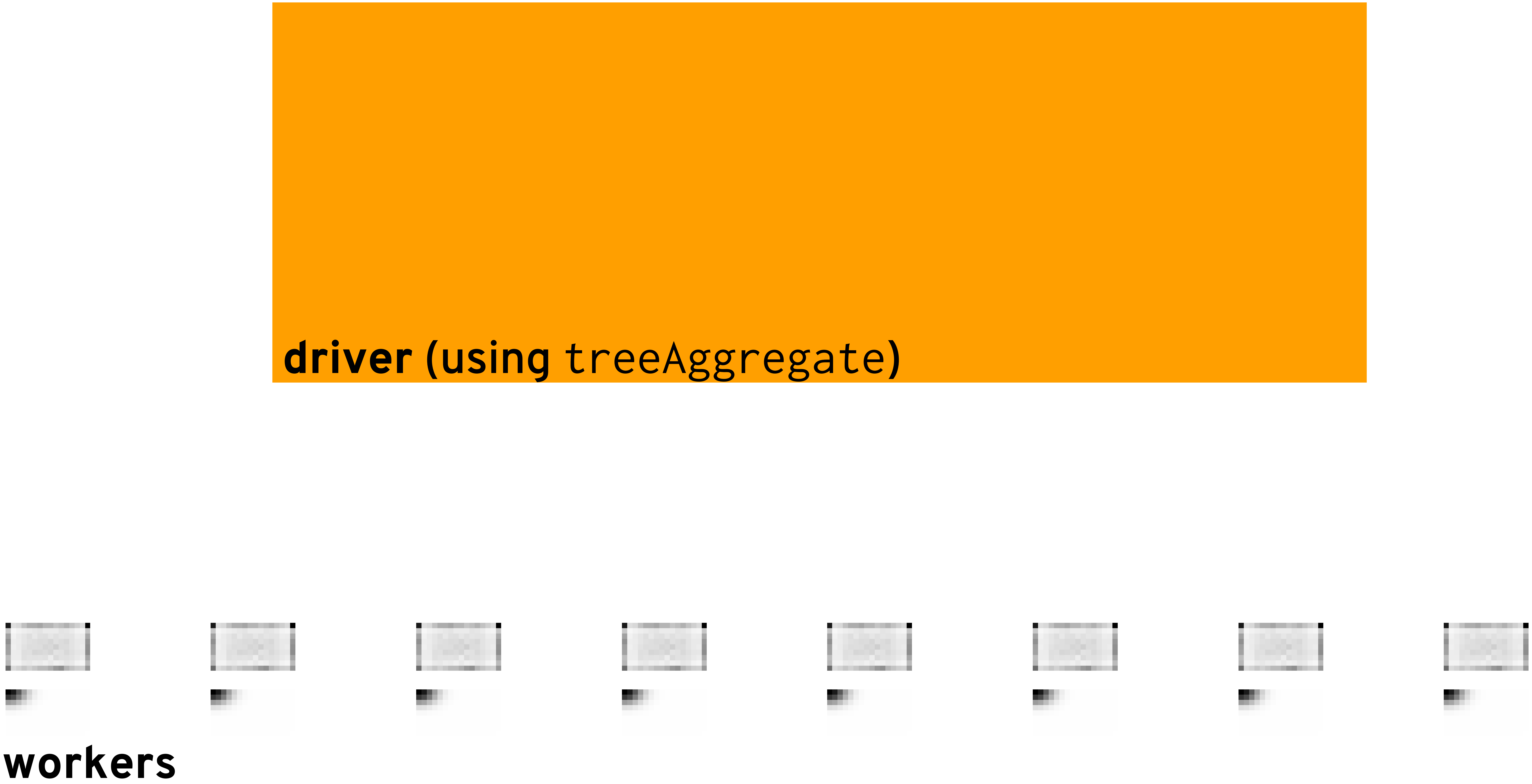


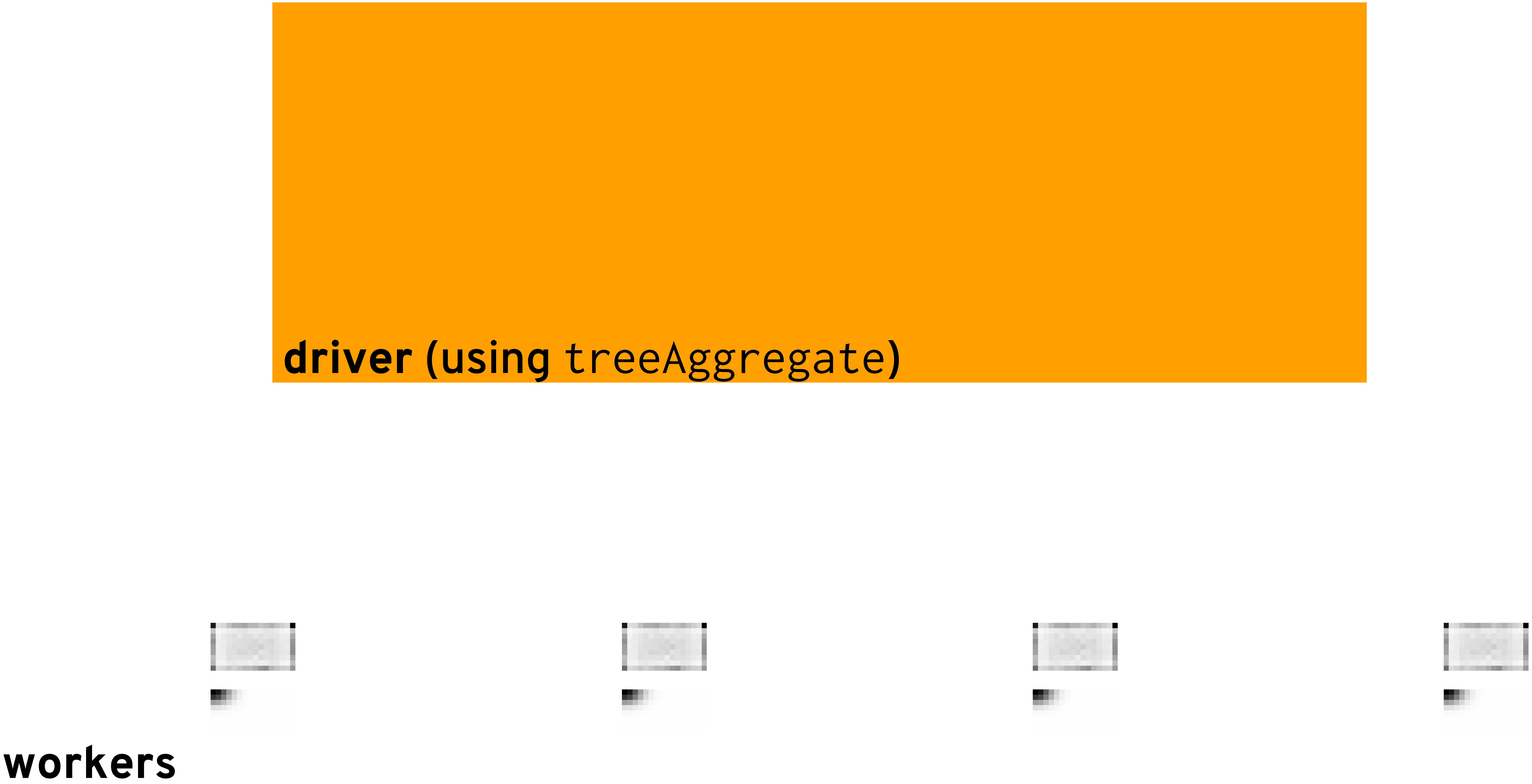
driver (using `aggregate`)

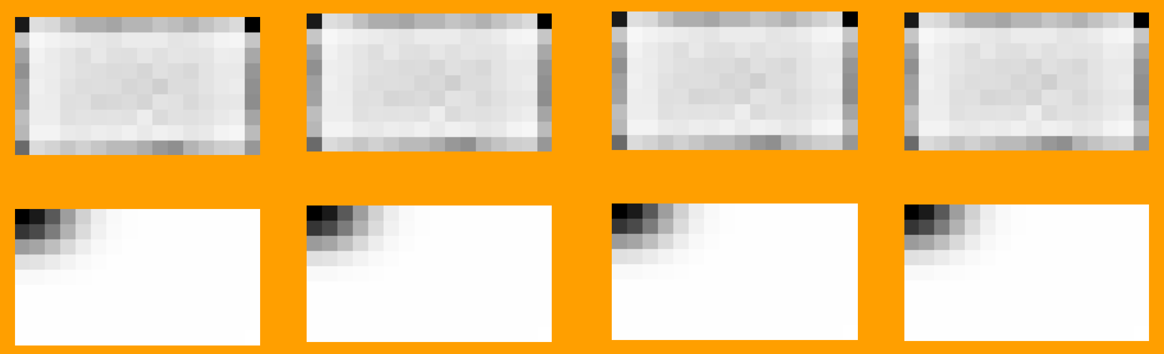
What if you have a 3 mb model and 2,048 partitions?

workers


driver (using treeAggregate)
workers

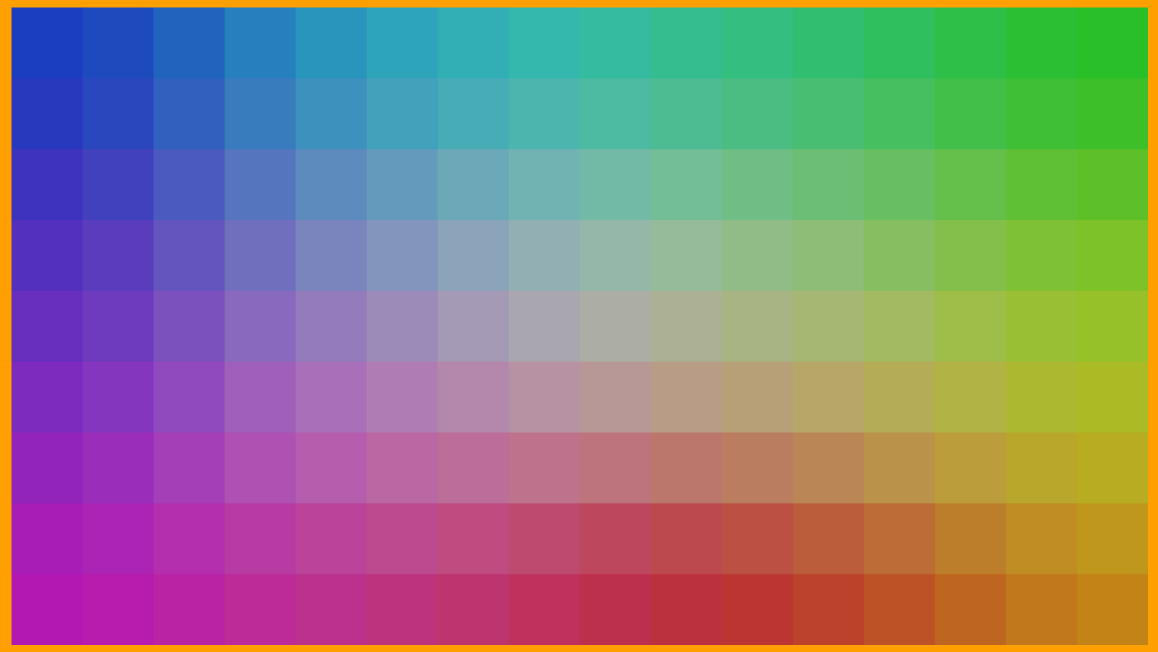

driver (using treeAggregate)
workers


driver (using treeAggregate)
workers



driver (using `treeAggregate`)

workers



driver (using `treeAggregate`)

workers

SHARING MODELS BEYOND SPARK

Sharing models

```
class Model(private var entries: breeze.linalg.DenseVector[Double],
            /* ... lots of (possibly) mutable state ... */ )
    implements java.io.Serializable {

  // lots of implementation details here

}
```

Sharing models

```
case class FrozenModel(entries: Array[Double], /* ... */ ) { }

class Model(private var entries: breeze.linalg.DenseVector[Double],
            /* ... lots of (possibly) mutable state ... */ )
    implements java.io.Serializable {

  // lots of implementation details here

}
```

Sharing models

```
case class FrozenModel(entries: Array[Double], /* ... */ ) { }

class Model(private var entries: breeze.linalg.DenseVector[Double],
            /* ... lots of (possibly) mutable state ... */ )
    implements java.io.Serializable {

  // lots of implementation details here

  def freeze: FrozenModel = // ...
}

object Model {
  def thaw(im: FrozenModel): Model = // ...
}
```

Sharing models

```
import org.json4s.jackson.Serialization
import org.json4s.jackson.Serialization.{read=>jread, write=>jwrite}
implicit val formats = Serialization.formats(NoTypeHints)

def toJson(m: Model): String = {
  jwrite(som.freeze)
}

def fromJson(json: String): Try[Model] = {
  Try({
    Model.thaw(jread[FrozenModel](json))
  })
}
```

Sharing models

```
import org.json4s.jackson.Serialization
import org.json4s.jackson.Serialization.{read=>jread, write=>jwrite}
implicit val formats = Serialization.formats(NoTypeHints)

def toJson(m: Model): String = {
  jwrite(som.freeze)
}

def fromJson(json: String): Try[Model] = {
  Try({
    Model.thaw(jread[FrozenModel](json))
  })
}
```

Also consider how you'll share feature encoders and other parts of your learning pipeline!

PRACTICAL MATTERS

Spark and ElasticSearch

Data locality is an issue and **caching** is even more important than when running from local storage.

If your data are **write-once**, consider **exporting ES indices to Parquet files** and **analyzing those instead.**

Structured queries in Spark

Always program defensively: mediate schemas, explicitly convert `null` values, etc.

Use the `Dataset` **API whenever possible** to **minimize boilerplate** and benefit from **query planning** without (entirely) forsaking **type safety**.

Memory and partitioning

Large JVM heaps can lead to **appalling GC pauses** and **executor timeouts.**

Use **multiple JVMs** or **off-heap storage** (in Spark 2.0!)

Tree aggregation can save you **both memory and execution time** by partially aggregating at worker nodes.

Interoperability

Avoid **brittle** or **language-specific** model serializers when **sharing models** with non-Spark environments.

JSON is imperfect but **ubiquitous.** However, `json4s` will **serialize case classes for free**!

See also **SPARK-13944**, merged recently into 2.0.

Feature engineering

Favor **feature engineering effort** over **complex or novel learning algorithms.**

Prefer approaches that train **interpretable models.**

Design your feature engineering pipeline so you can **translate feature vectors back to factor values.**

THANKS!

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