Learning

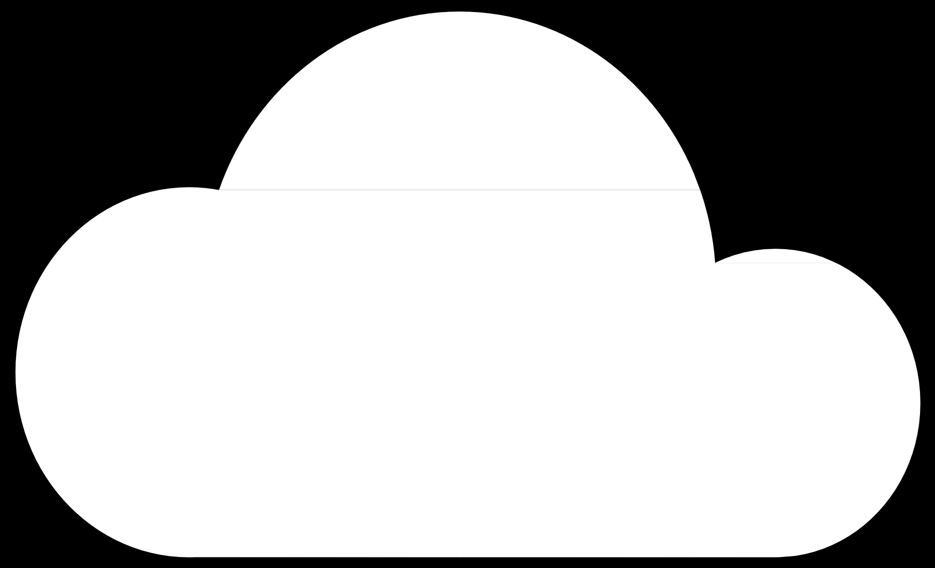
Supervised Learning

supervised learning

given a data set of input-output pairs, learn a function to map inputs to outputs

classification

supervised learning task of learning a function mapping an input point to a discrete category



Date	Humidity (relative humidity)	Pressure (sea level, mb)	Rain

Date	Humidity (relative humidity)	Pressure (sea level, mb)	Rain
January 1	93%	999.7	Rain
January 2	49%	1015.5	No Rain
January 3	79%	1031.1	No Rain
January 4	65%	984.9	Rain
January 5	90%	975.2	Rain

$$f(humidity, pressure)$$

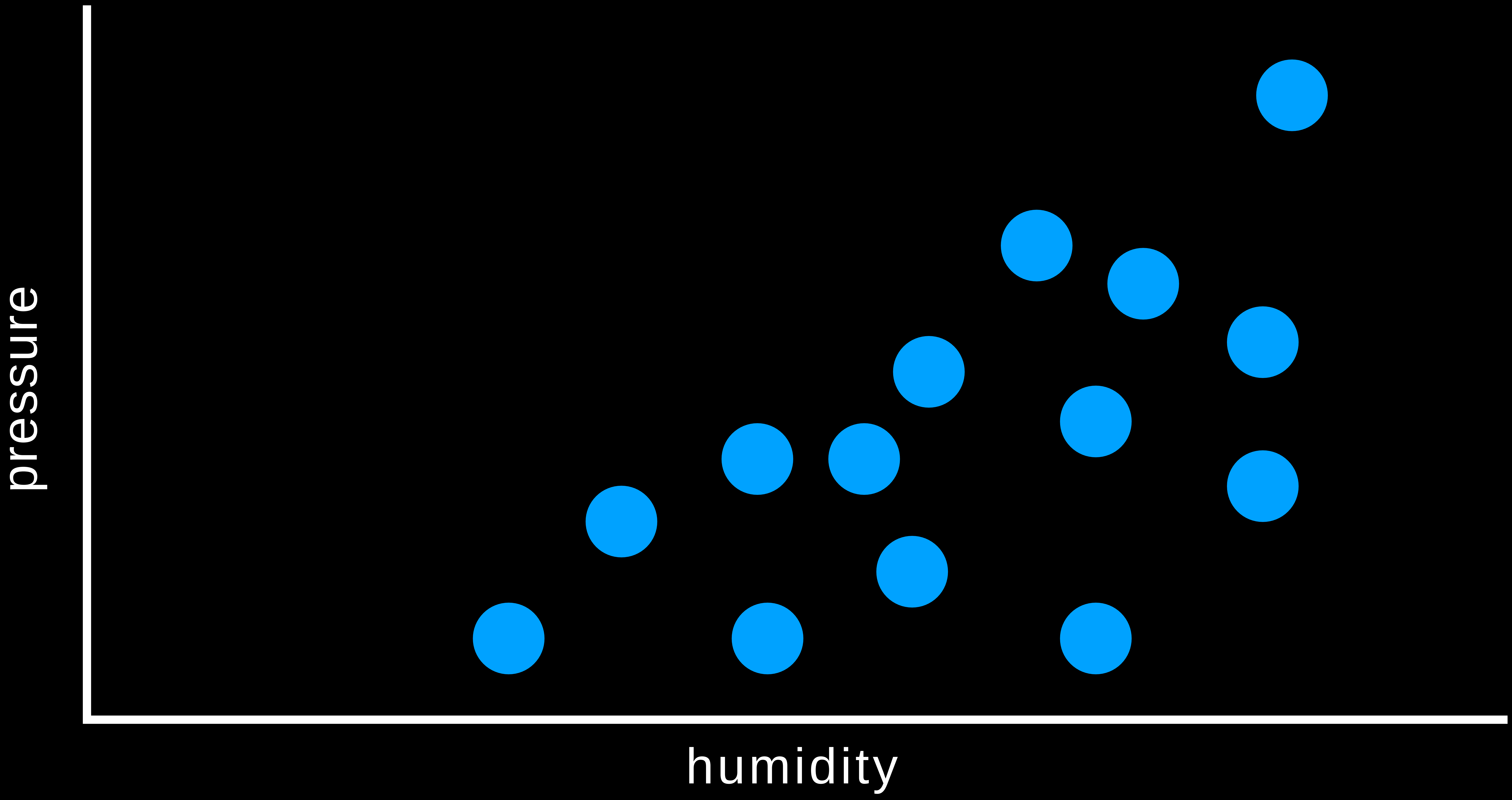
$$f(93, 999.7) = \text{Rain}$$

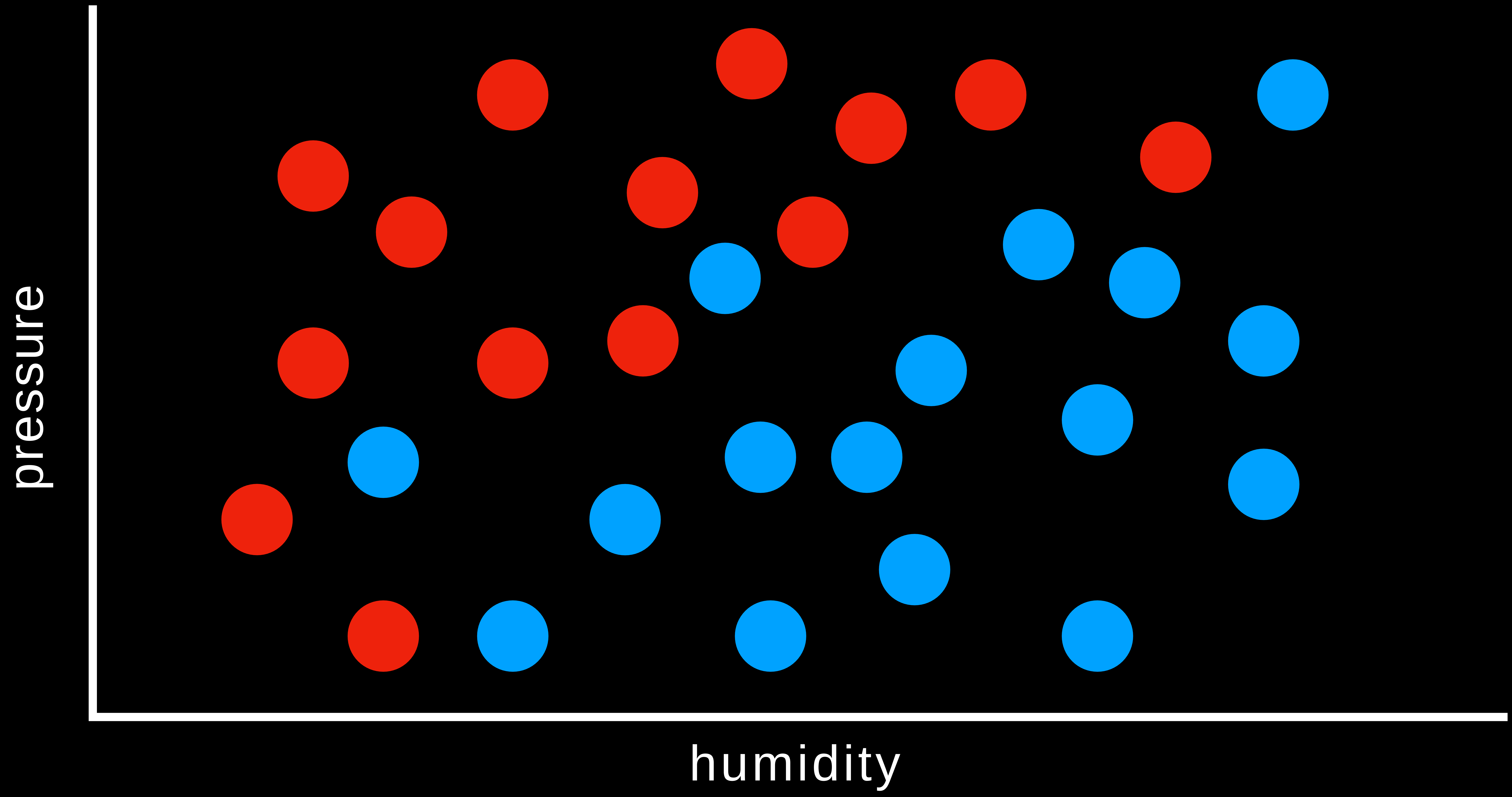
$$f(49, 1015.5) = \text{No Rain}$$

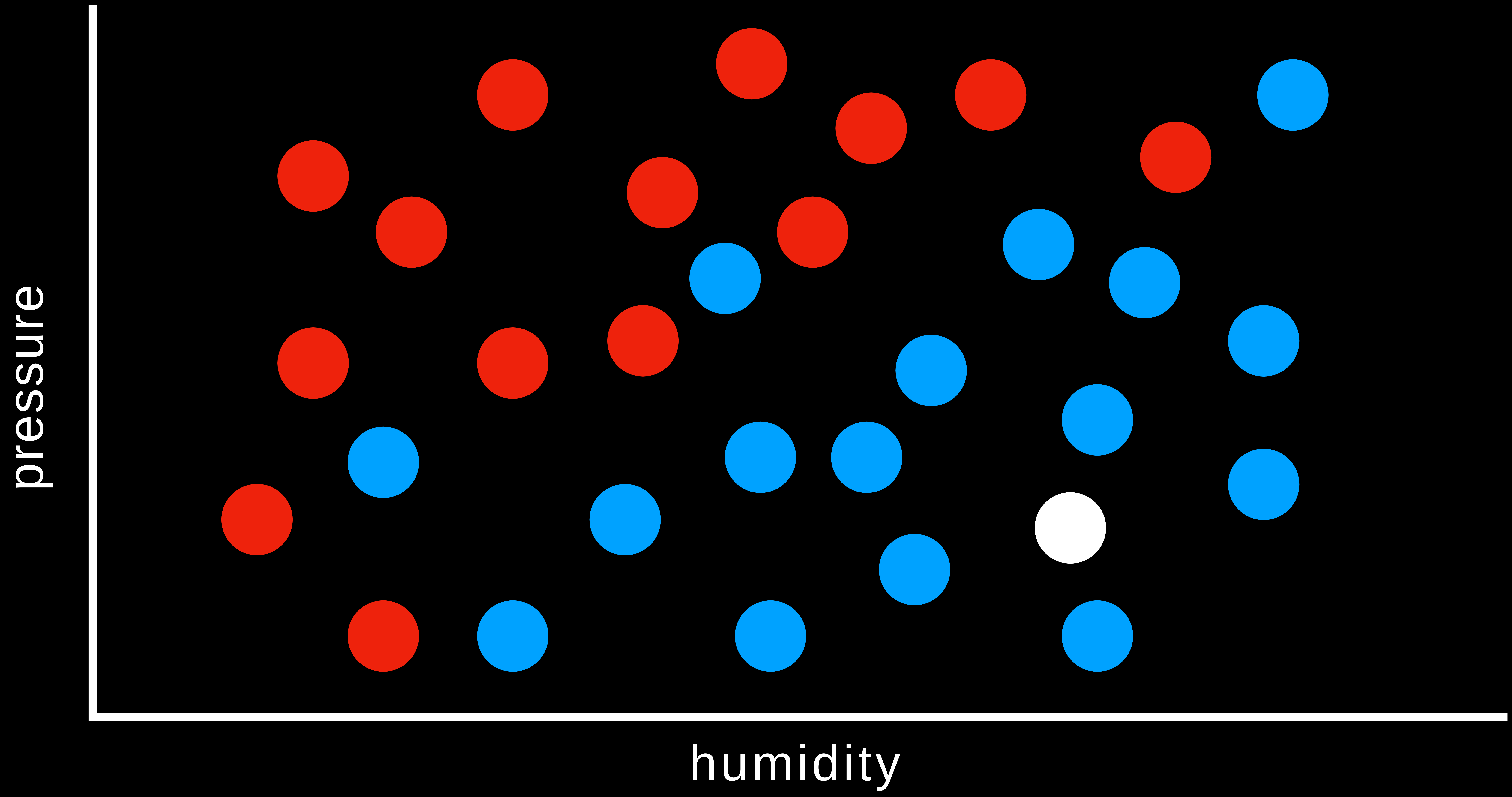
$$f(79, 1031.1) = \text{No Rain}$$

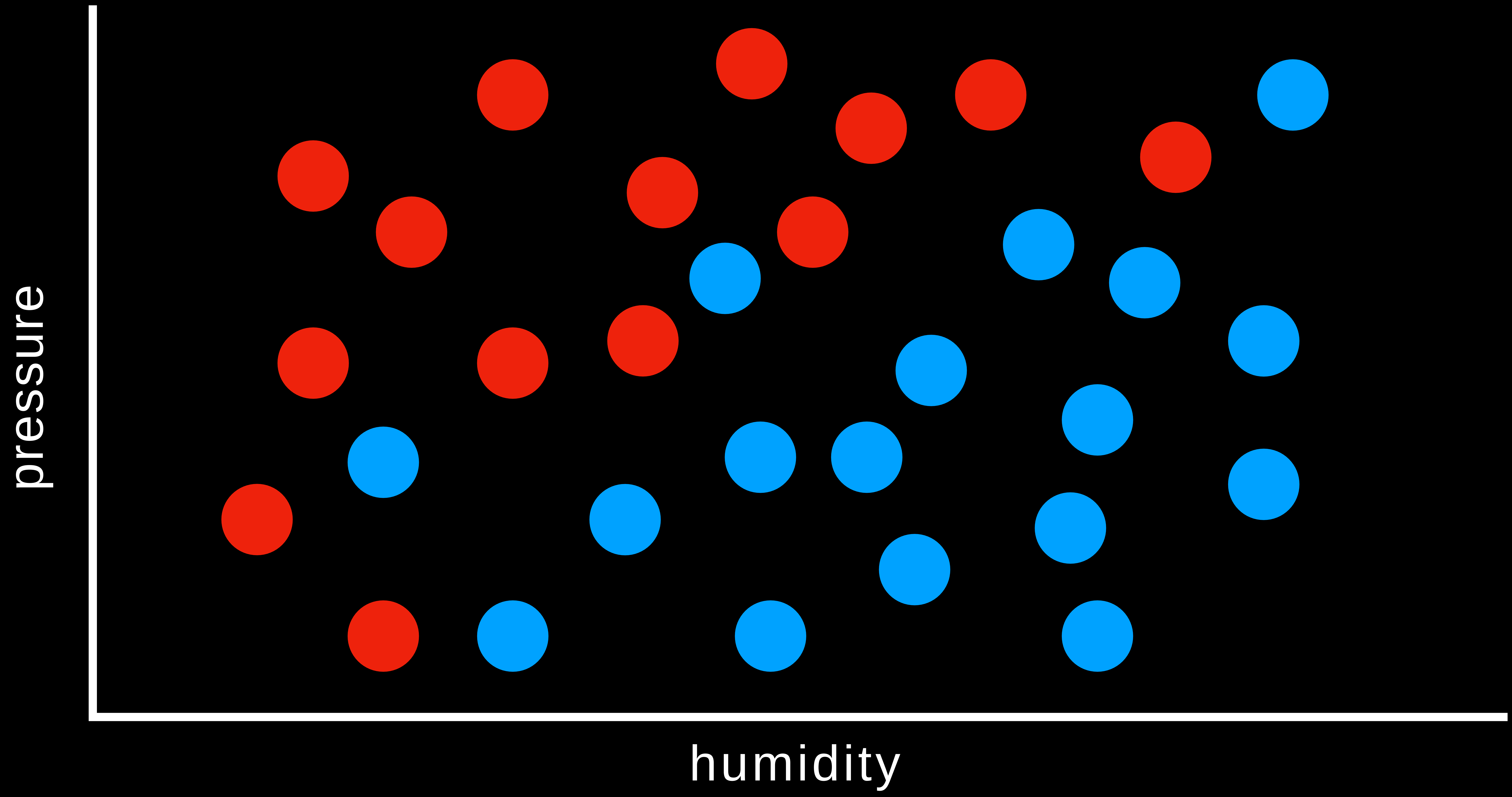
$$h(humidity, pressure)$$


pressure
humidity


pressure
humidity

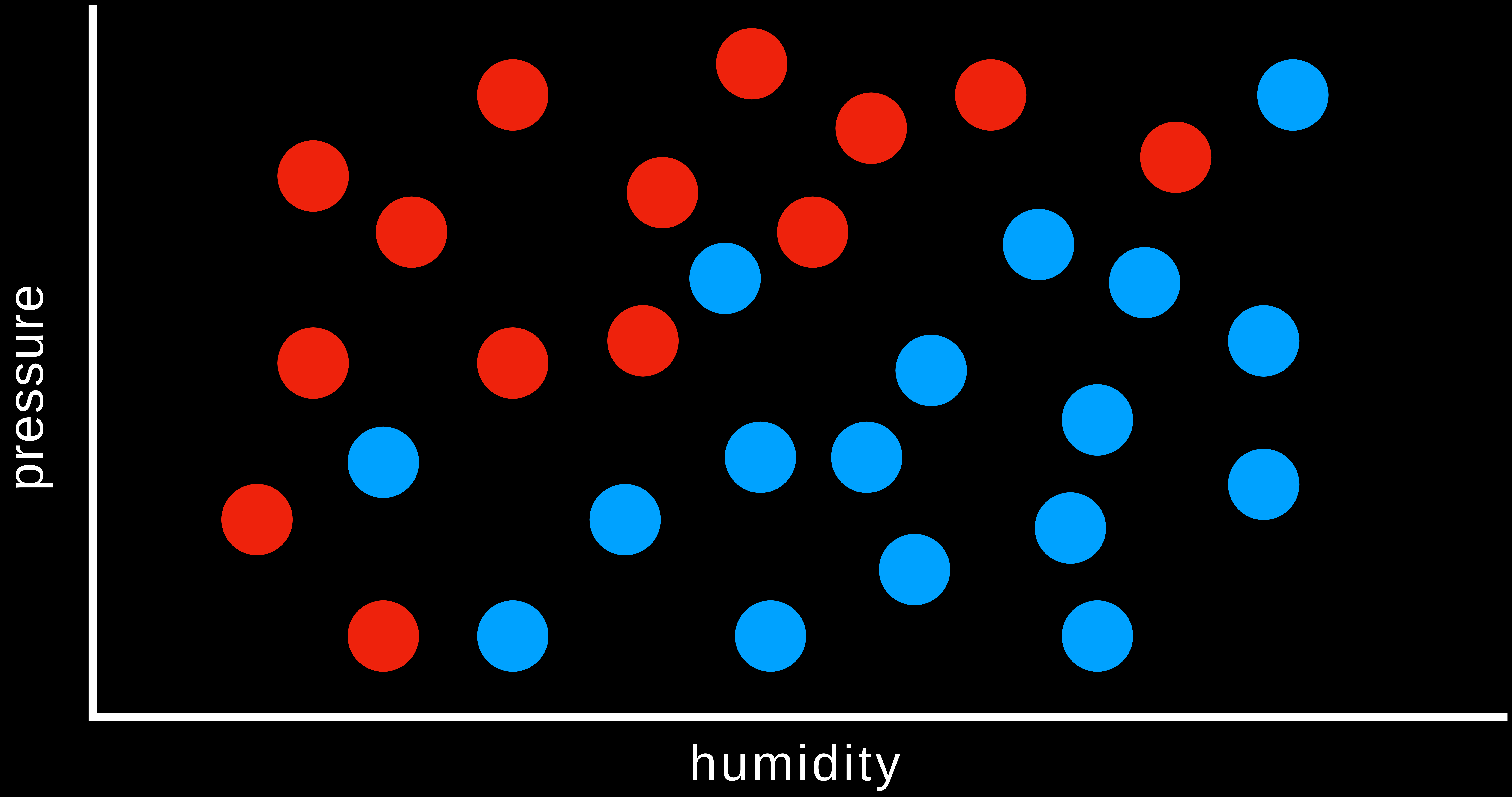

pressure
humidity

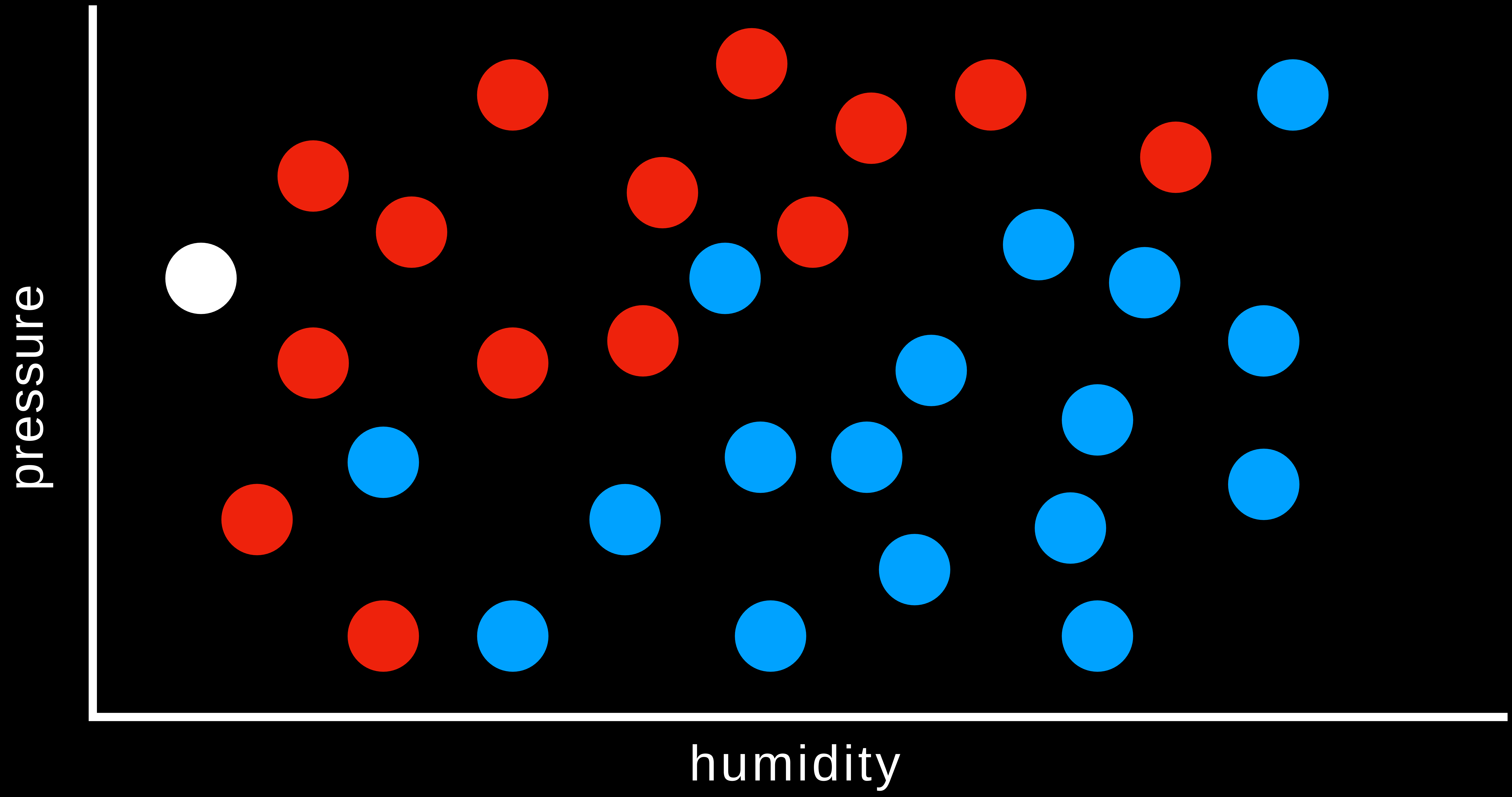

pressure
humidity

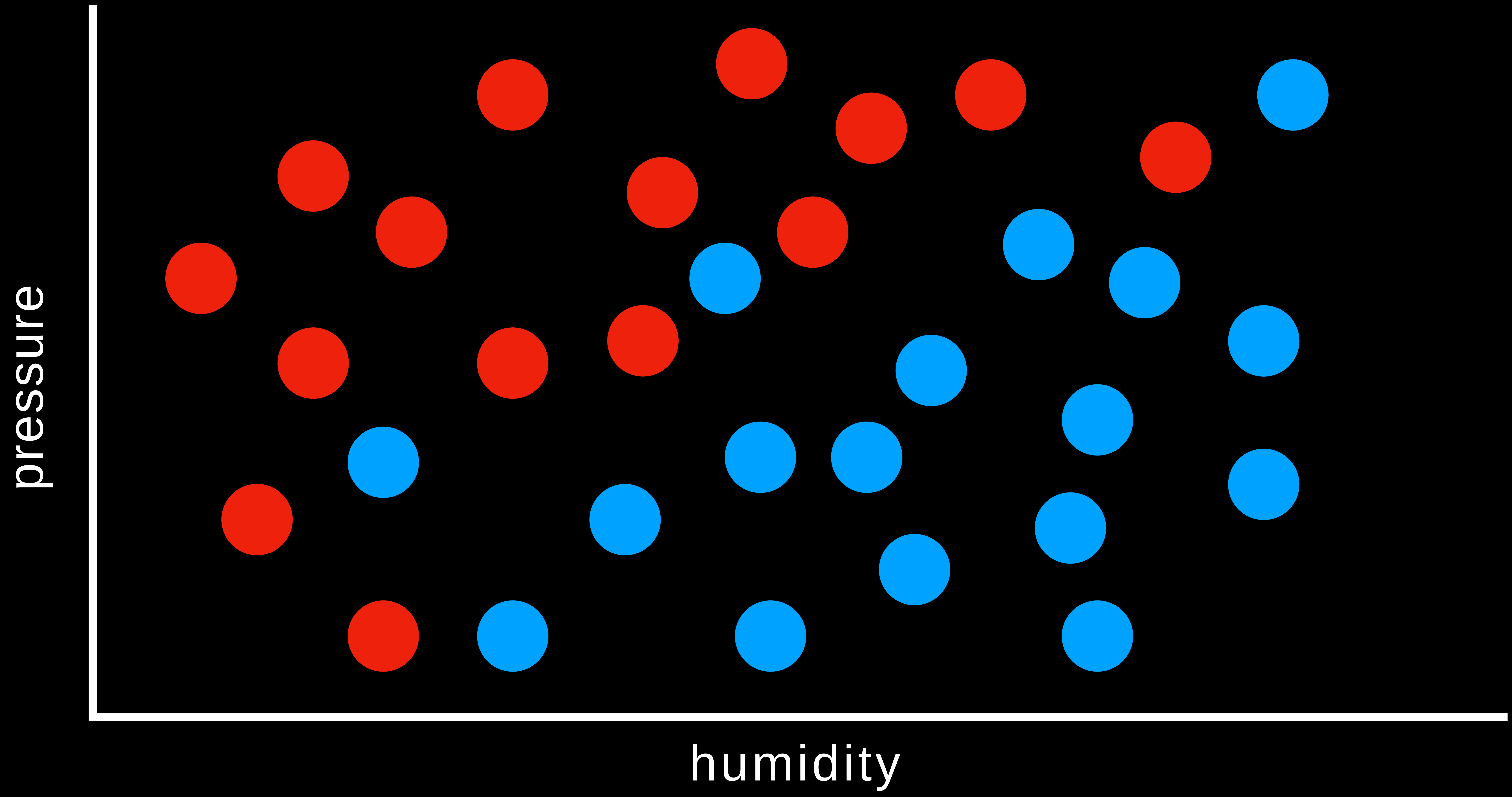

pressure
humidity

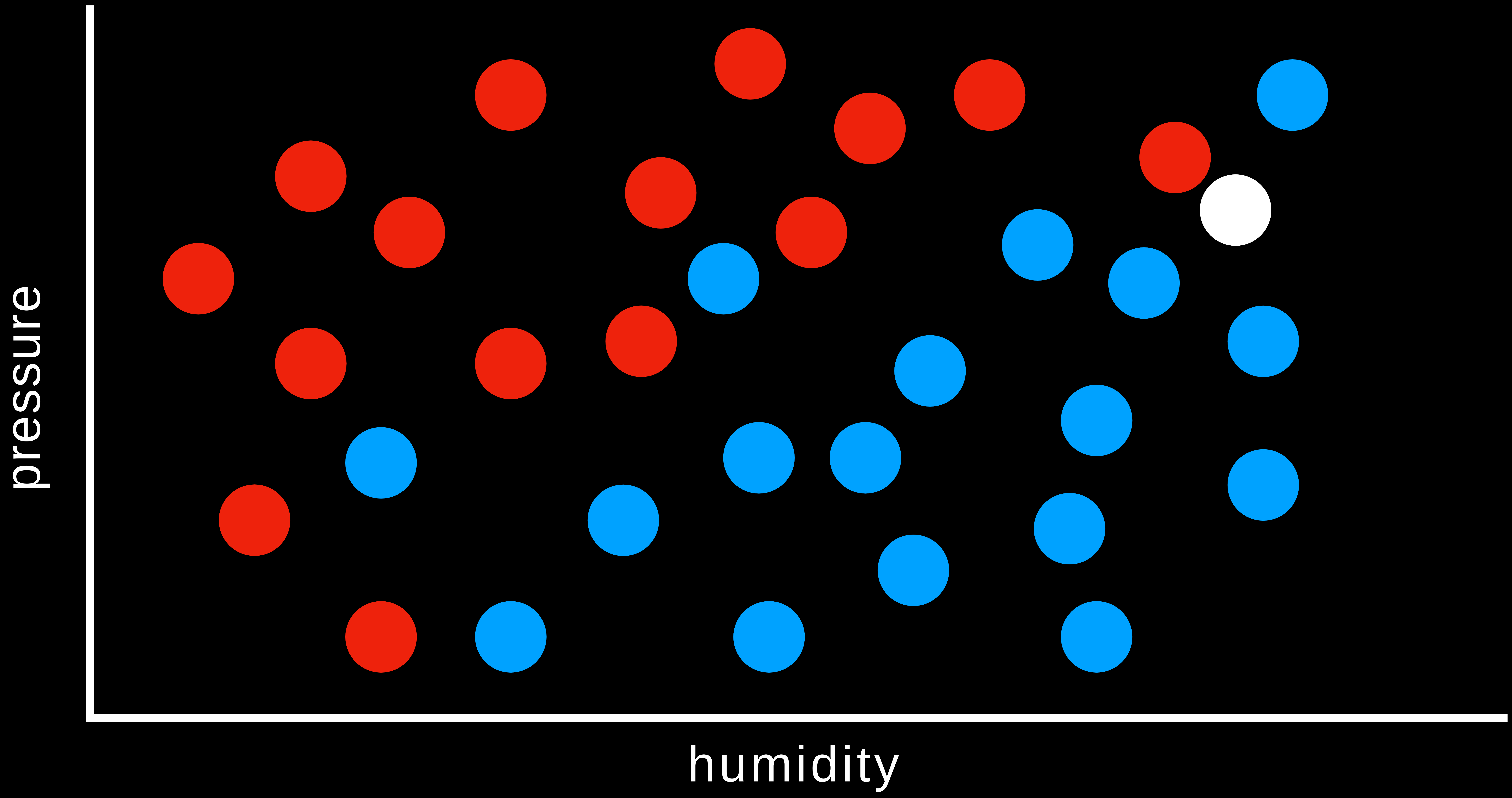
nearest-neighbor classification

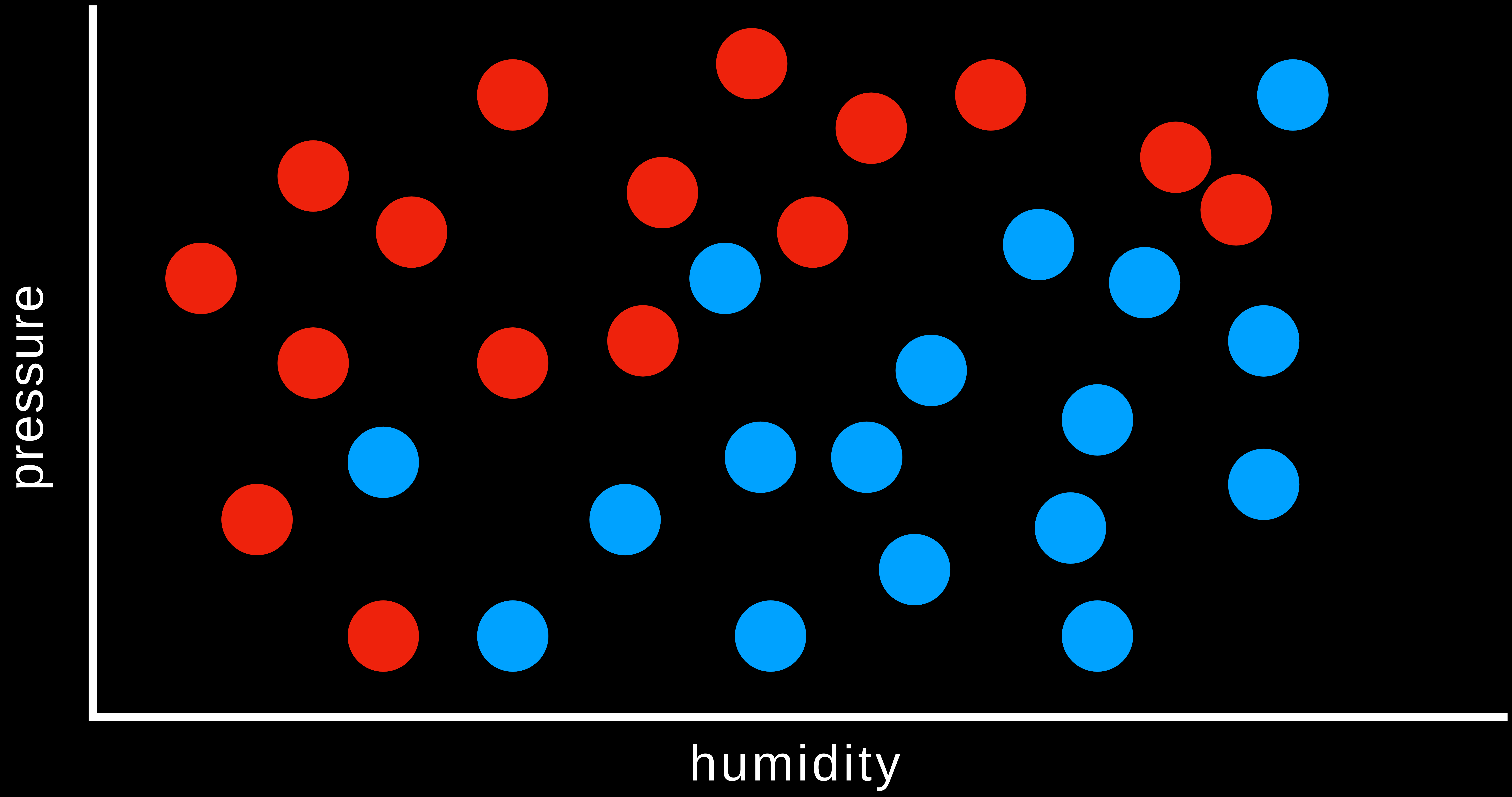
algorithm that, given an input, chooses the class of the nearest data point to that input

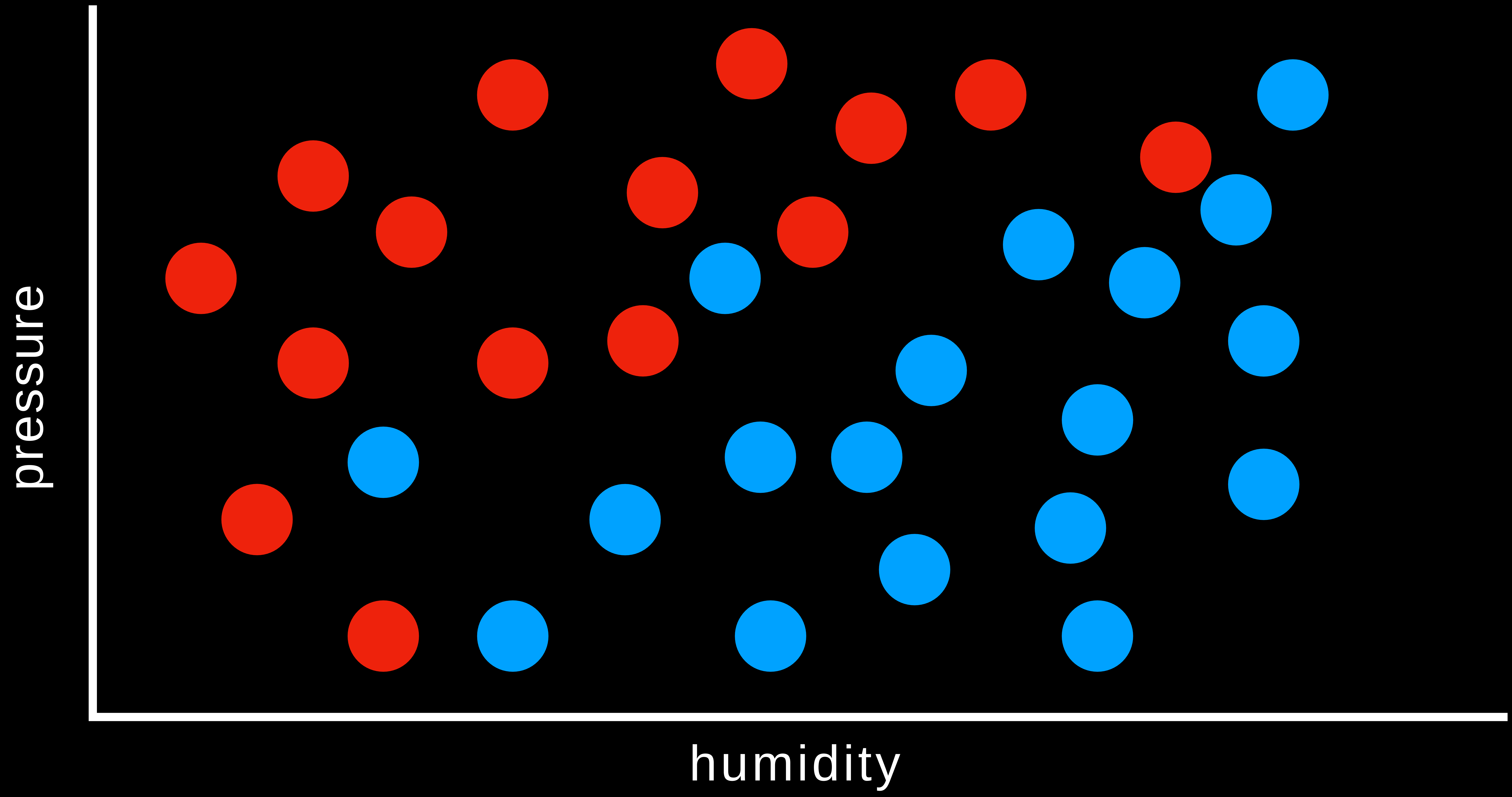

pressure
humidity


pressure
humidity


pressure
humidity

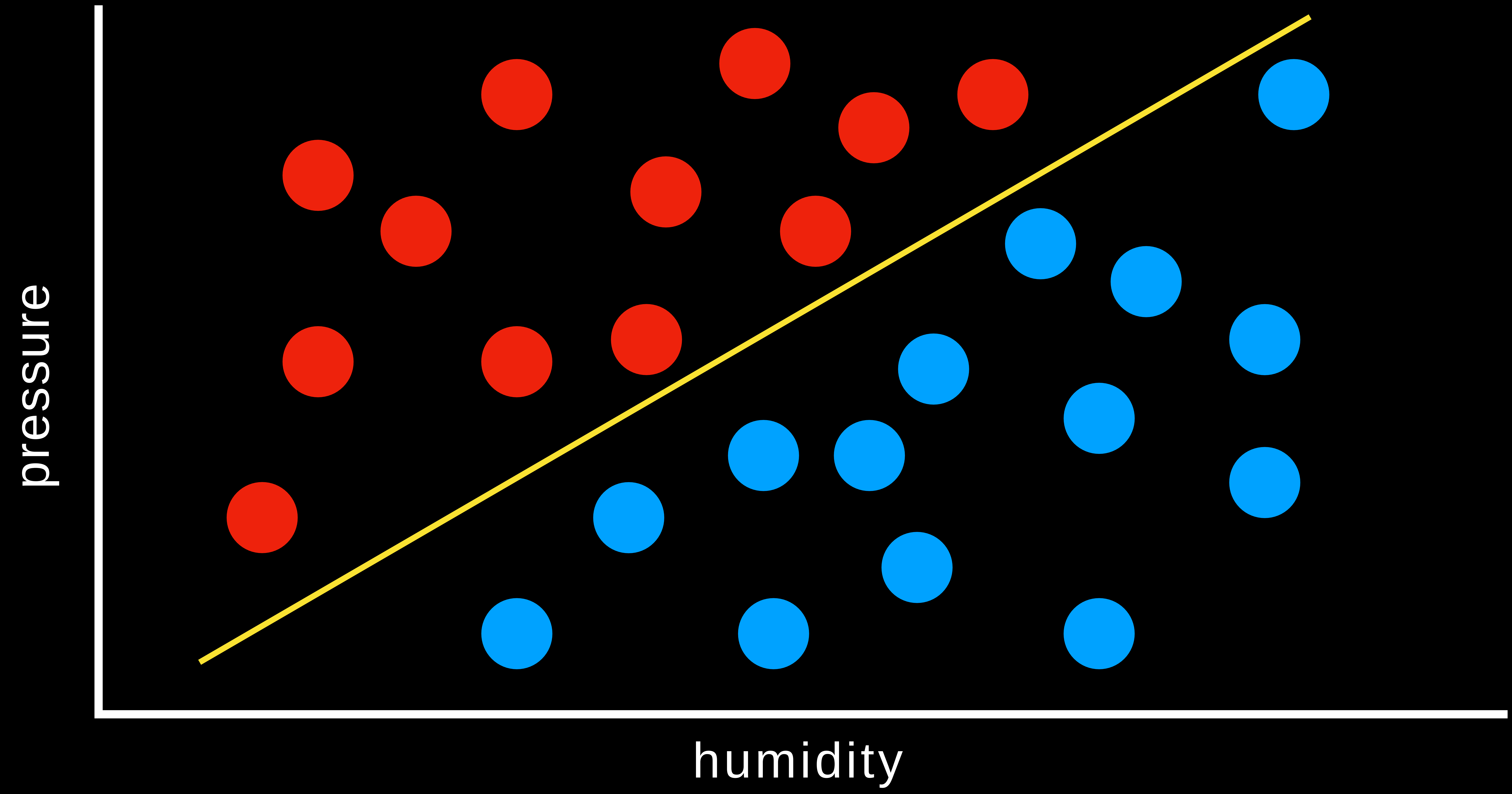

pressure
humidity

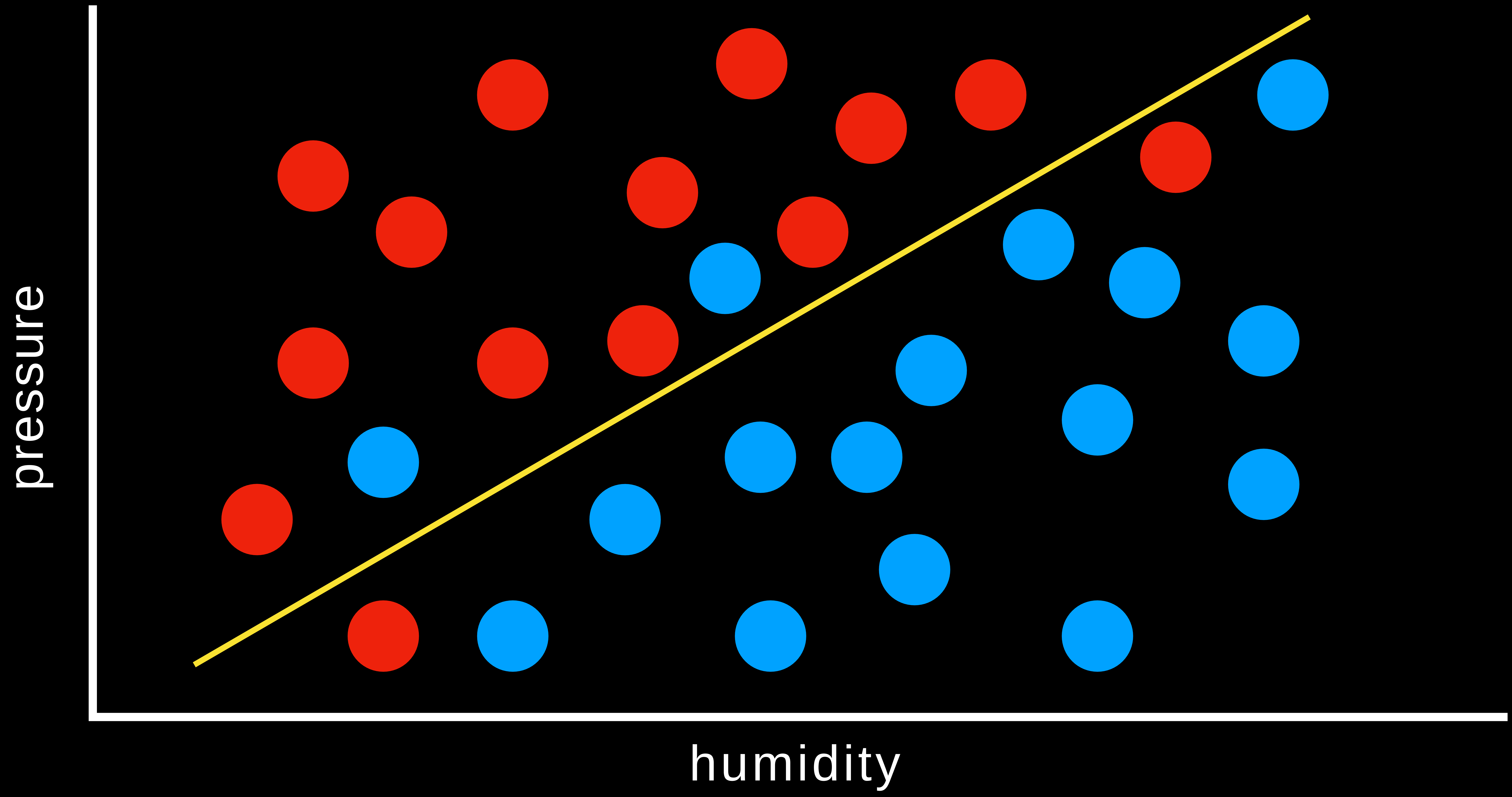

pressure
humidity


pressure
humidity

k-nearest-neighbor classification

algorithm that, given an input, chooses the most common class out of the k nearest data points to that input


pressure
humidity


pressure
humidity

x_1 = Humidity

x_2 = Pressure

$$h(x_1, x_2) = \begin{cases} \text{Rain if } w_0 + w_1 x_1 + w_2 x_2 \geq 0 \\ \text{No Rain otherwise} \end{cases}$$

Weight Vector $\mathbf{w}$: (w_0, w_1, w_2)

Input Vector $\mathbf{x}$: $(1, x_1, x_2)$

$\mathbf{w} \cdot \mathbf{x}$: $w_0 + w_1x_1 + w_2x_2$

$$h(x_1, x_2) = \begin{cases} 1 \text{ if } \; w_0 + w_1x_1 + w_2x_2 \geq 0 \\ 0 \text{ otherwise} \end{cases}$$

Weight Vector $\mathbf{w}$: (w_0, w_1, w_2)

Input Vector $\mathbf{x}$: $(1, x_1, x_2)$

$\mathbf{w} \cdot \mathbf{x}$: $w_0 + w_1x_1 + w_2x_2$

$$h_{\mathbf{w}}(\mathbf{x}) = \begin{cases} 1 \text{ if } \mathbf{w} \cdot \mathbf{x} \geq 0 \\ 0 \text{ otherwise} \end{cases}$$

perceptron learning rule

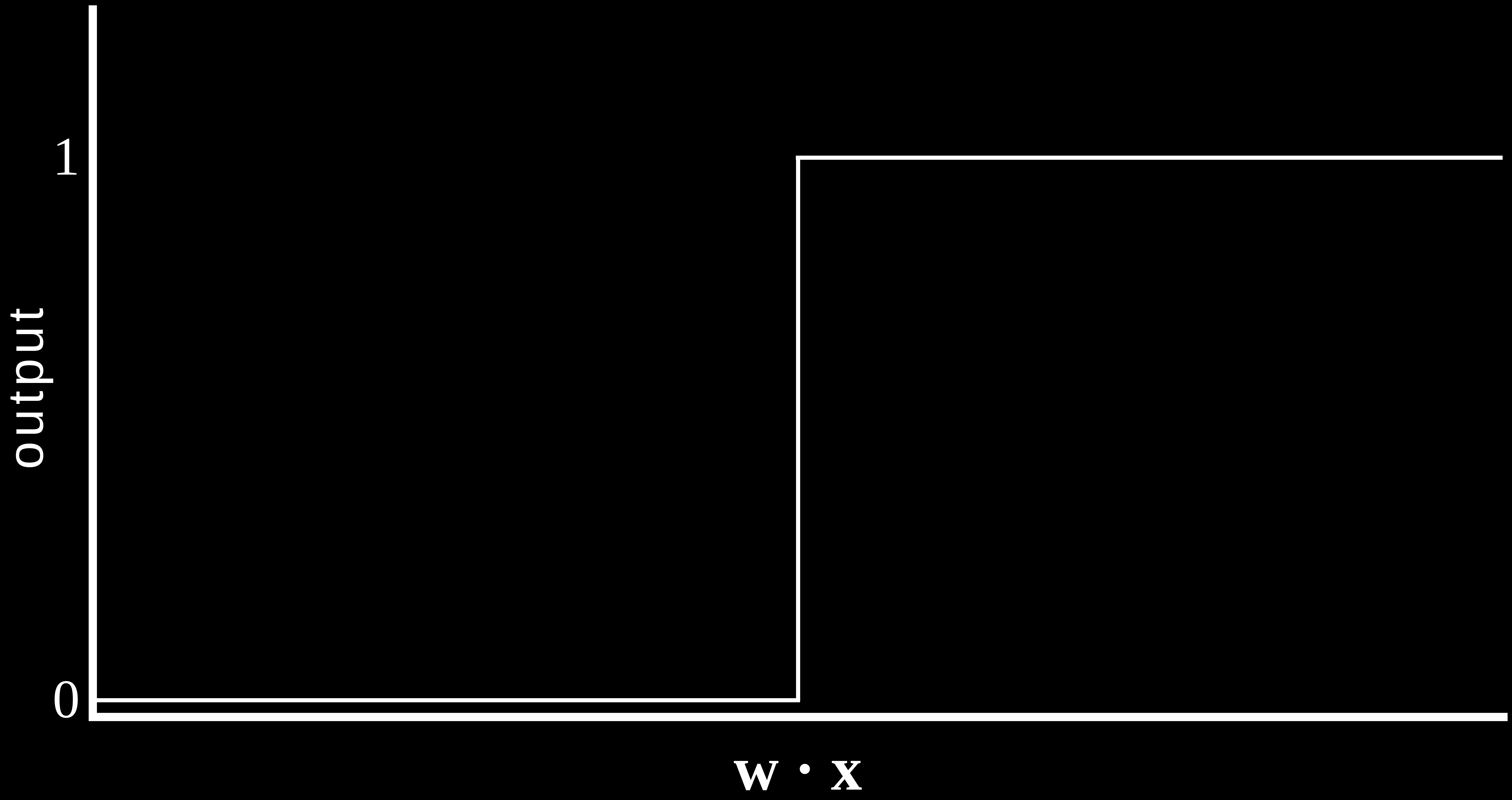
Given data point $(\mathbf{x}, \mathrm{y})$, update each weight according to:

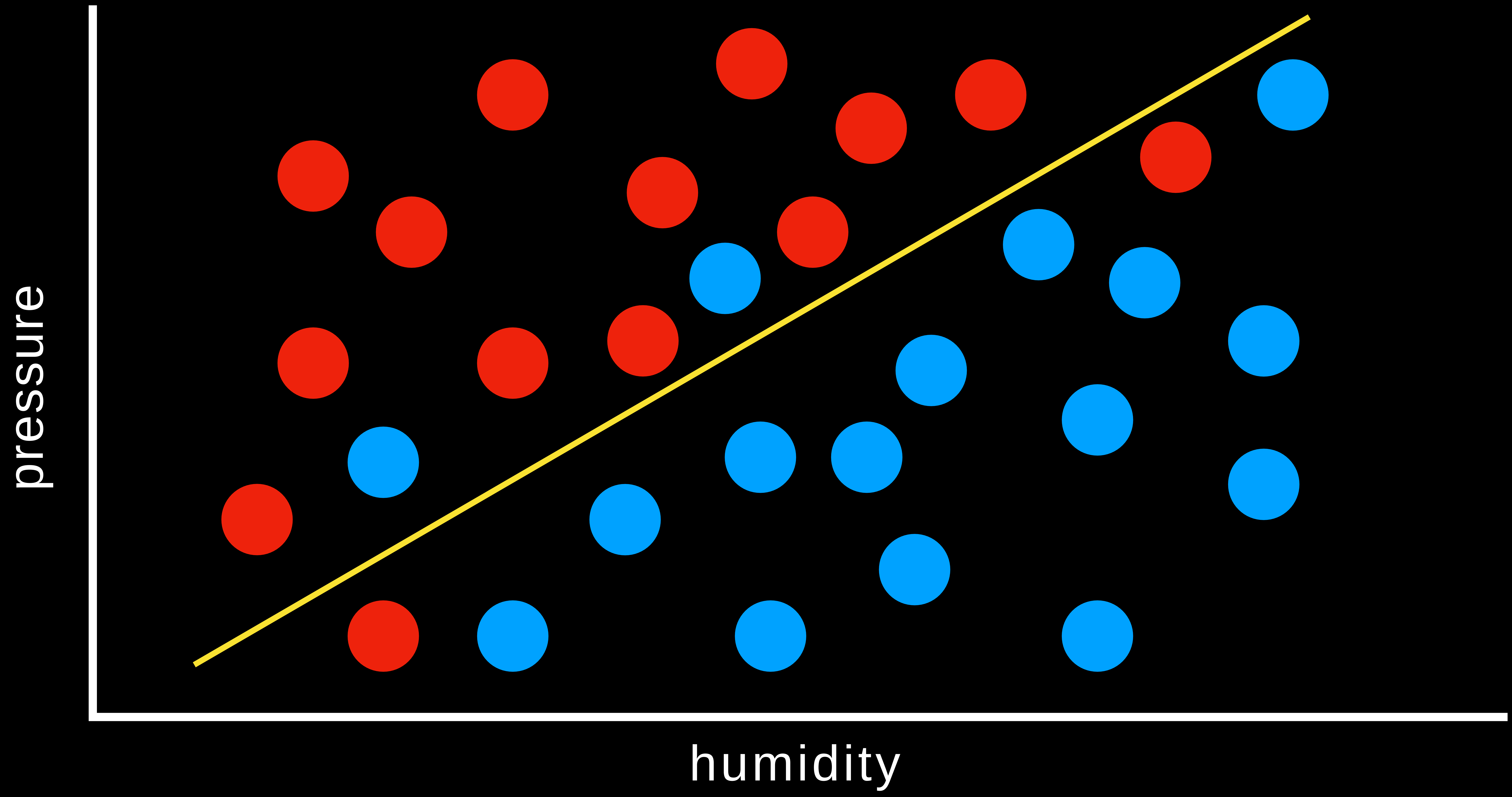
$$w_{\mathrm{i}} = w_{\mathrm{i}} + \alpha(\mathrm{y} - h_{\mathbf{w}}(\mathbf{x})) \times x_{\mathrm{i}}$$

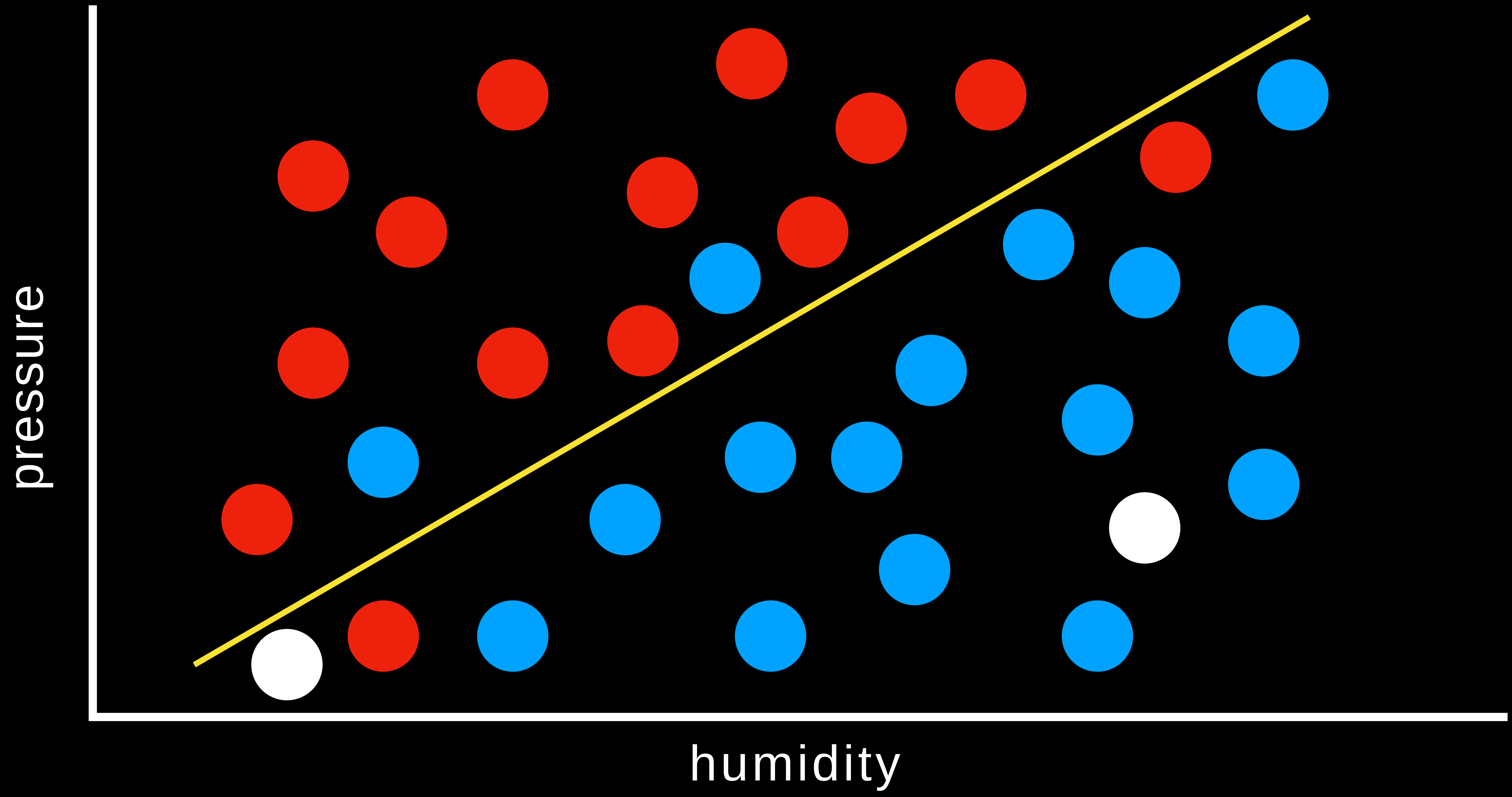
perceptron learning rule

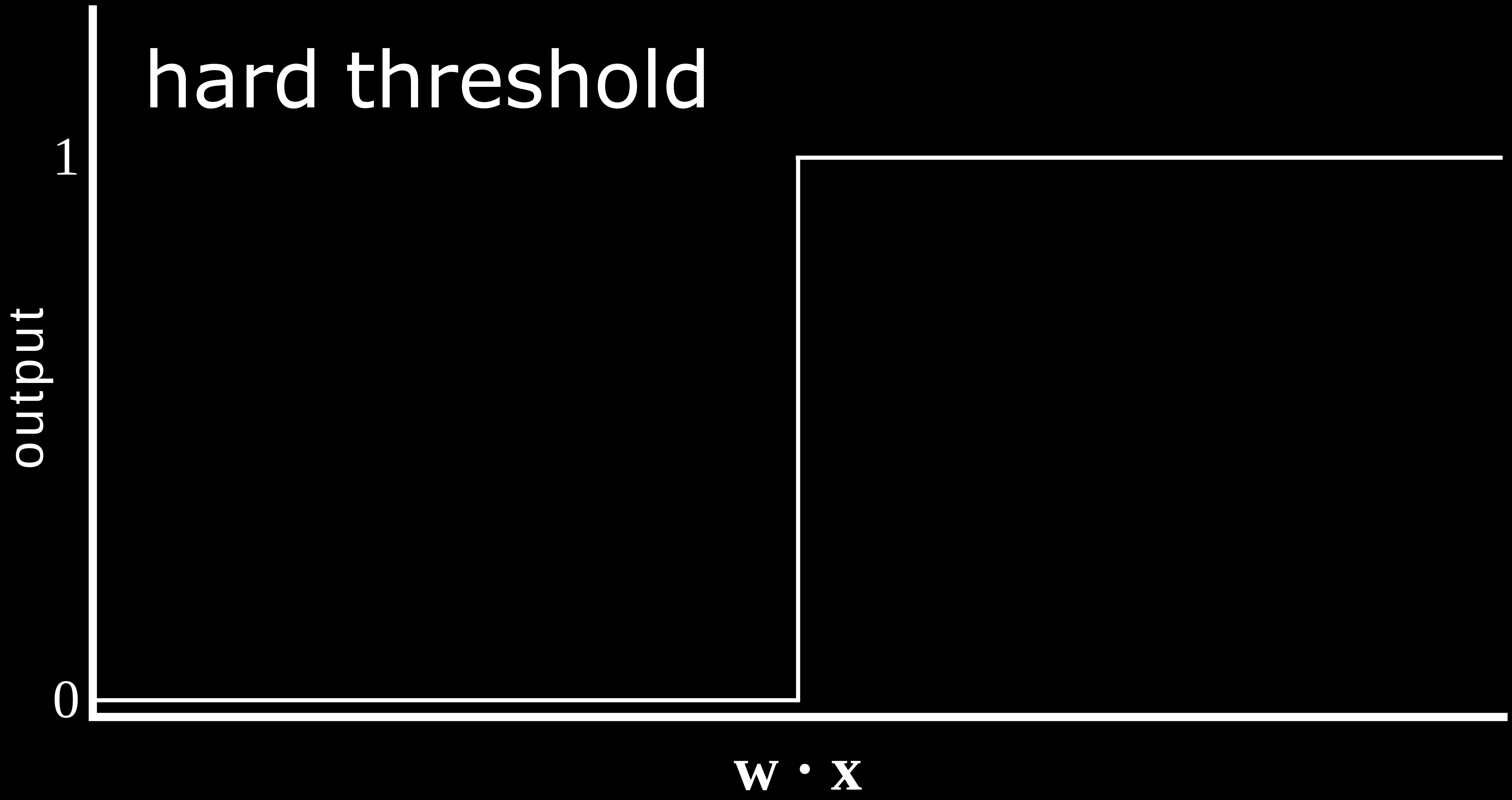
Given data point $(\mathbf{x}, \mathrm{y})$, update each weight according to:

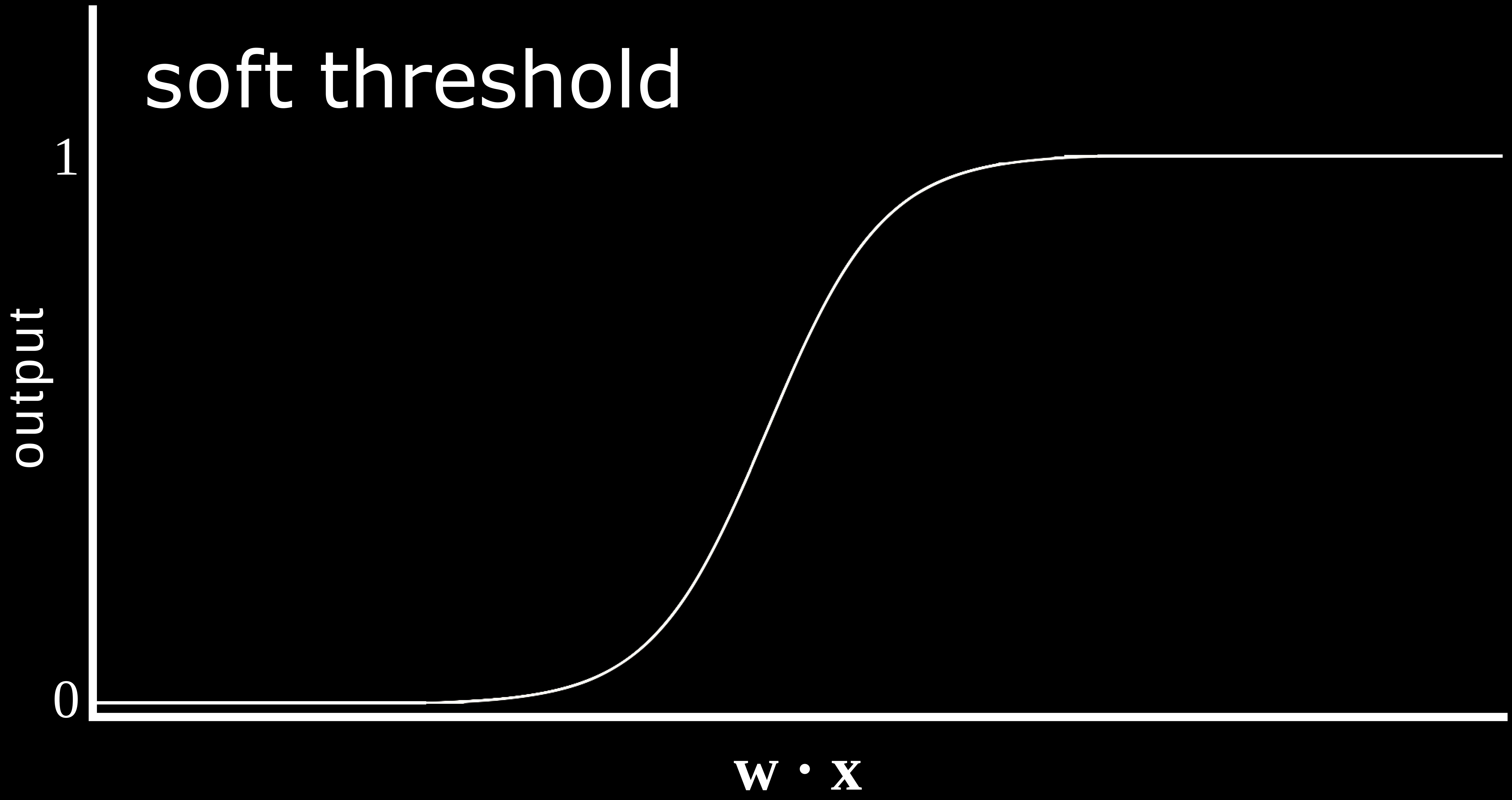
$$w_i = w_i + \alpha(\text{actual value - estimate}) \times x_i$$


1
0
output
w · x

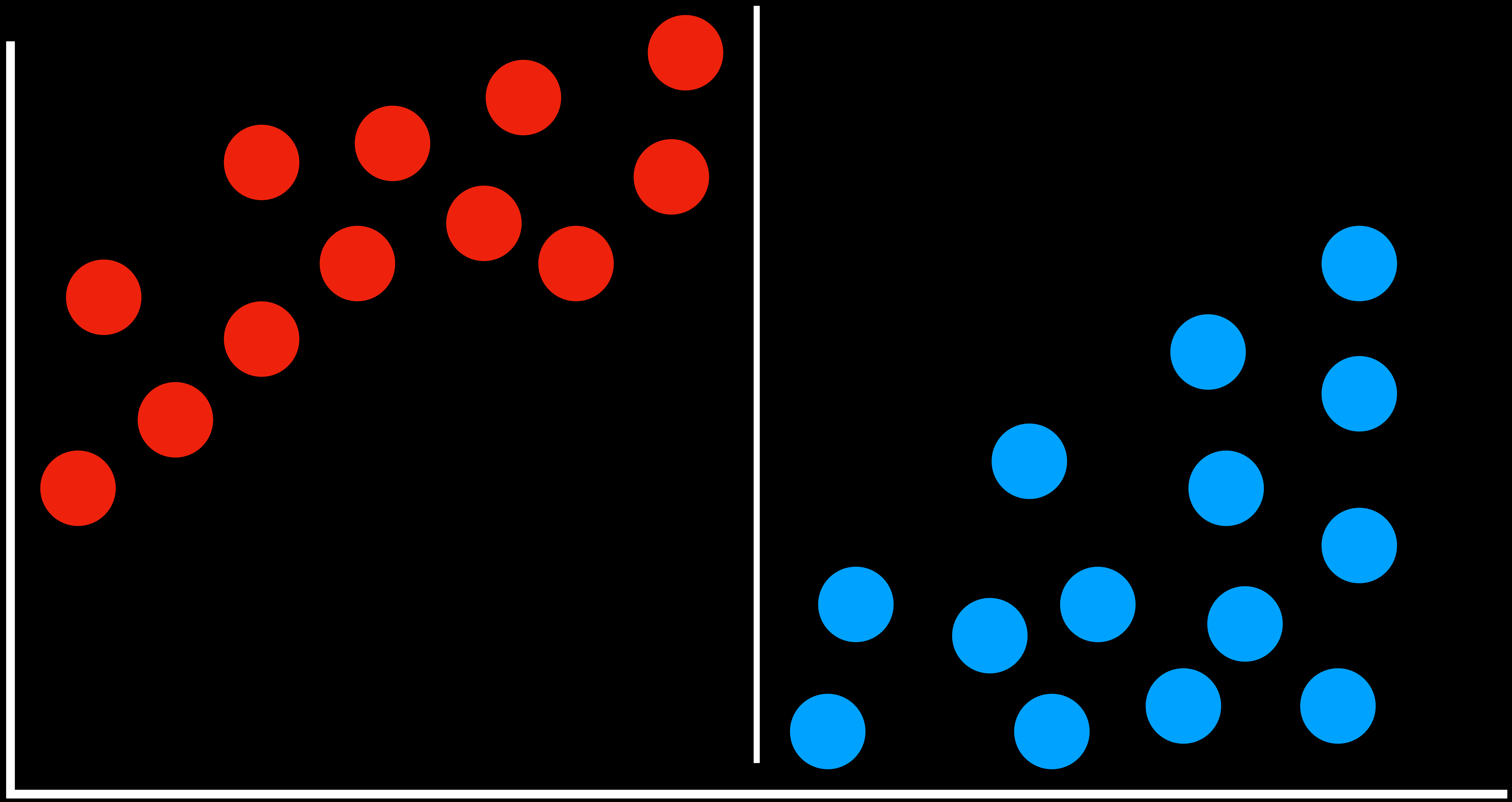

pressure
humidity

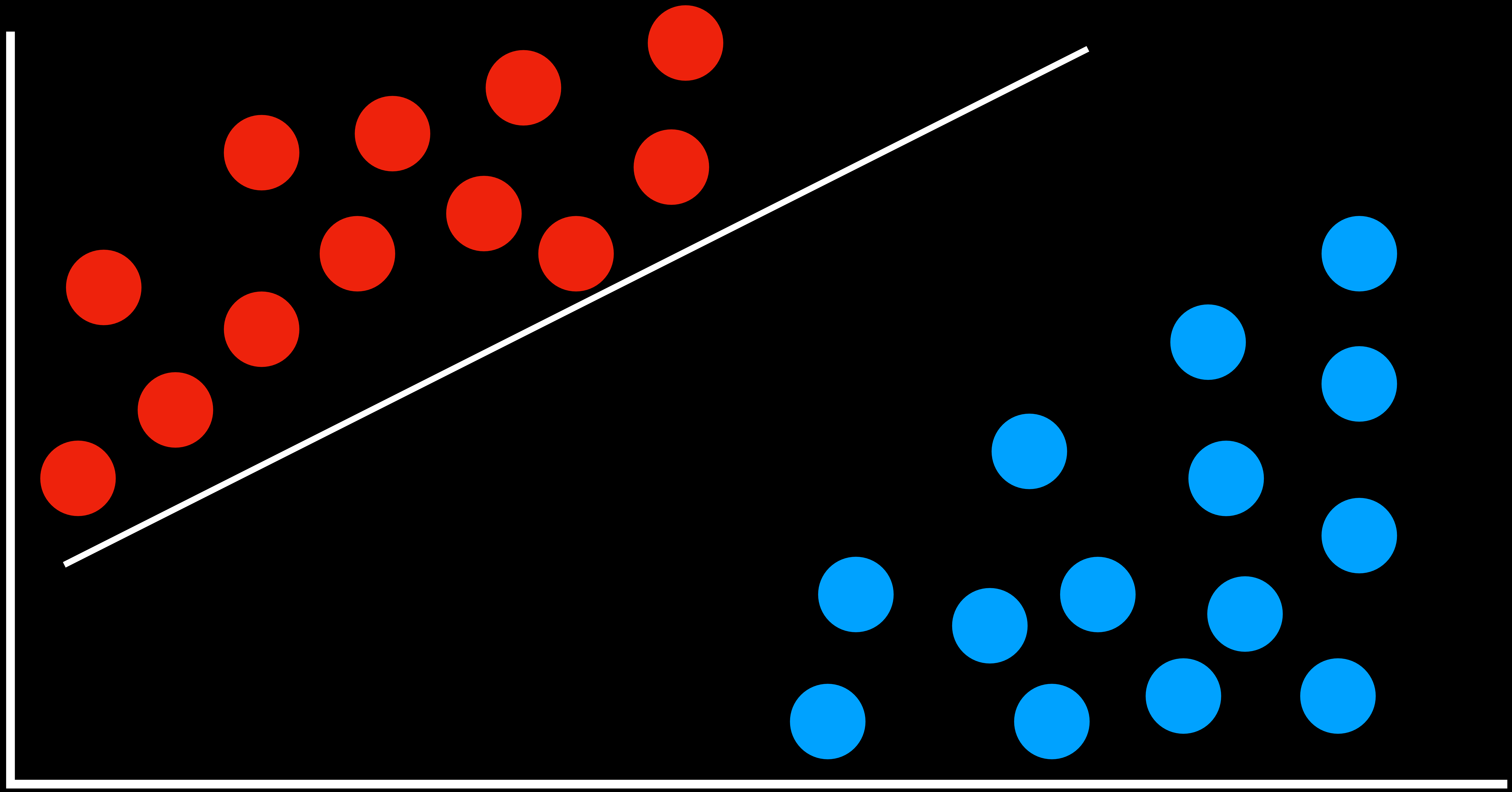

pressure
humidity

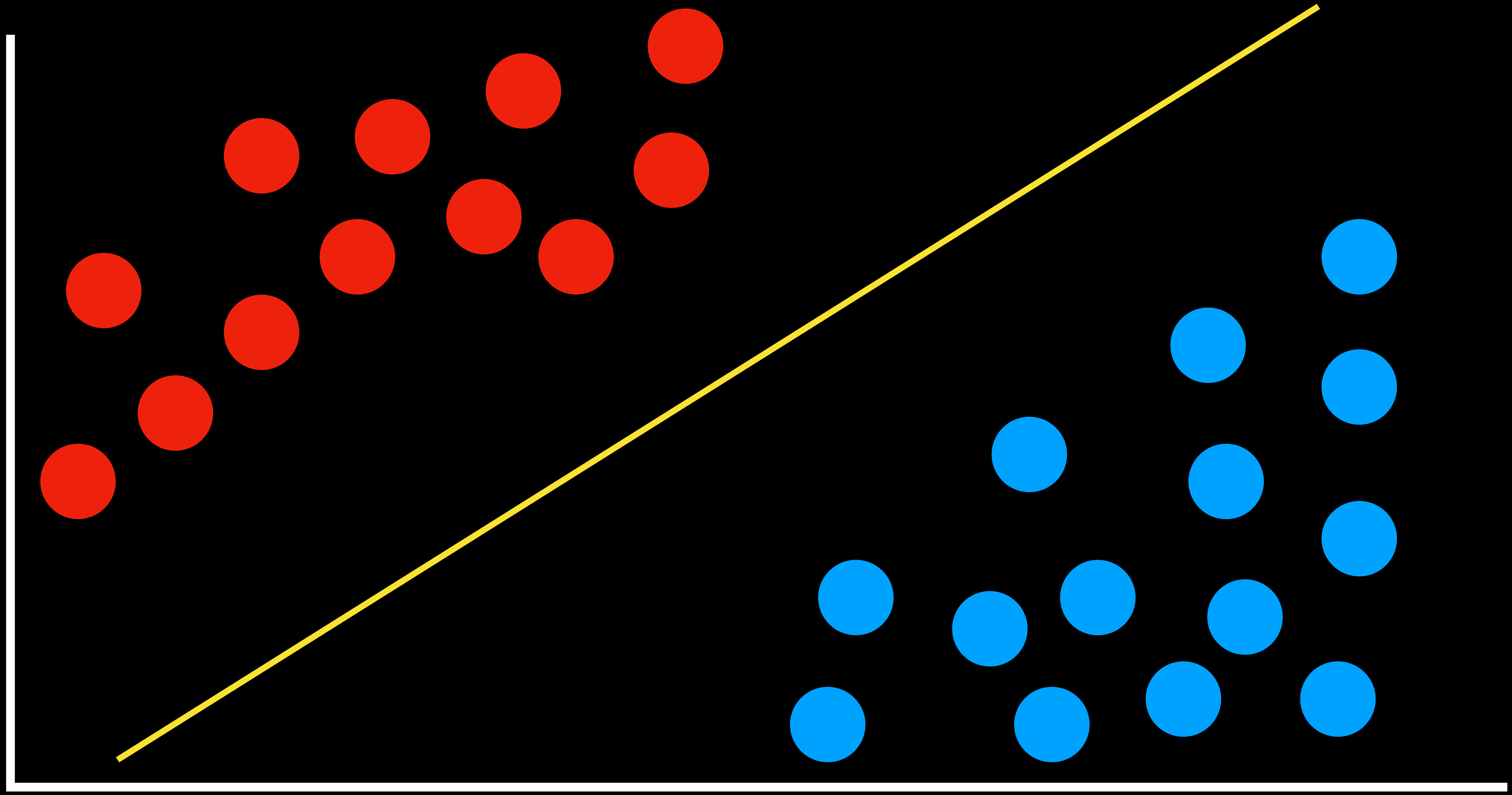

hard threshold
1
0
output
w · x


soft threshold
1
0
output
w · x

Support Vector Machines

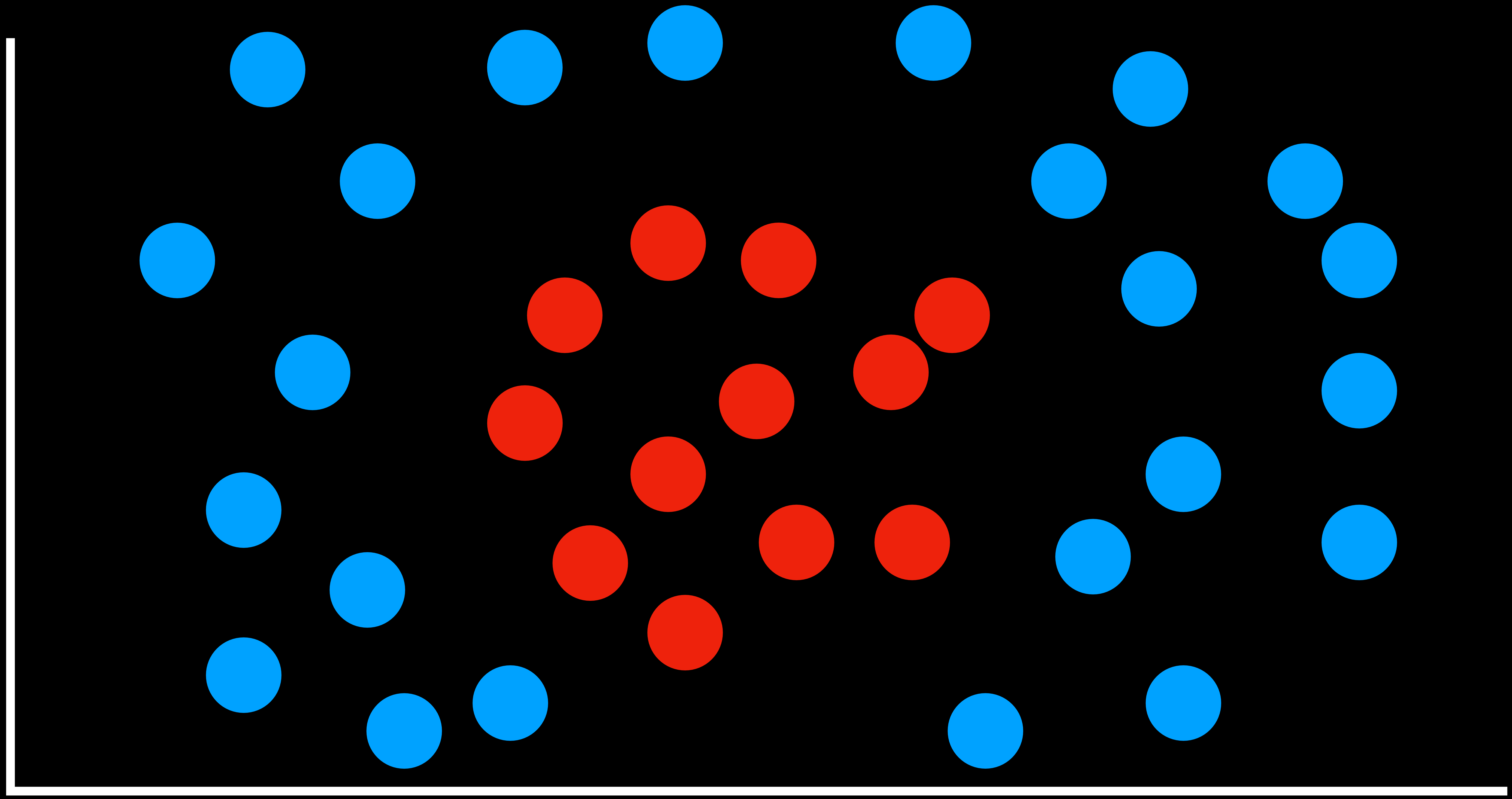


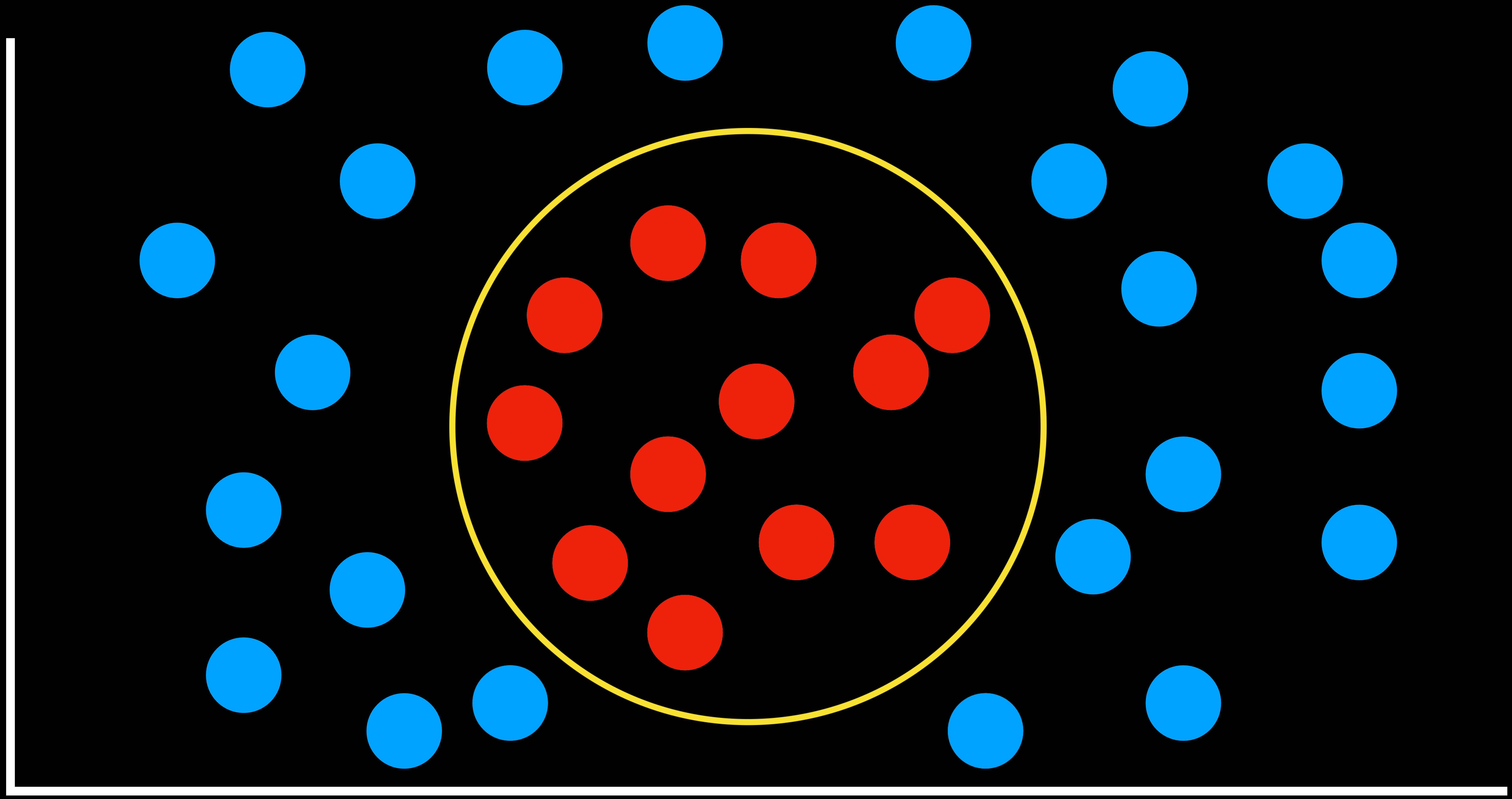




maximum margin separator

boundary that maximizes the distance between any of the data points





regression

supervised learning task of learning a function mapping an input point to a continuous value

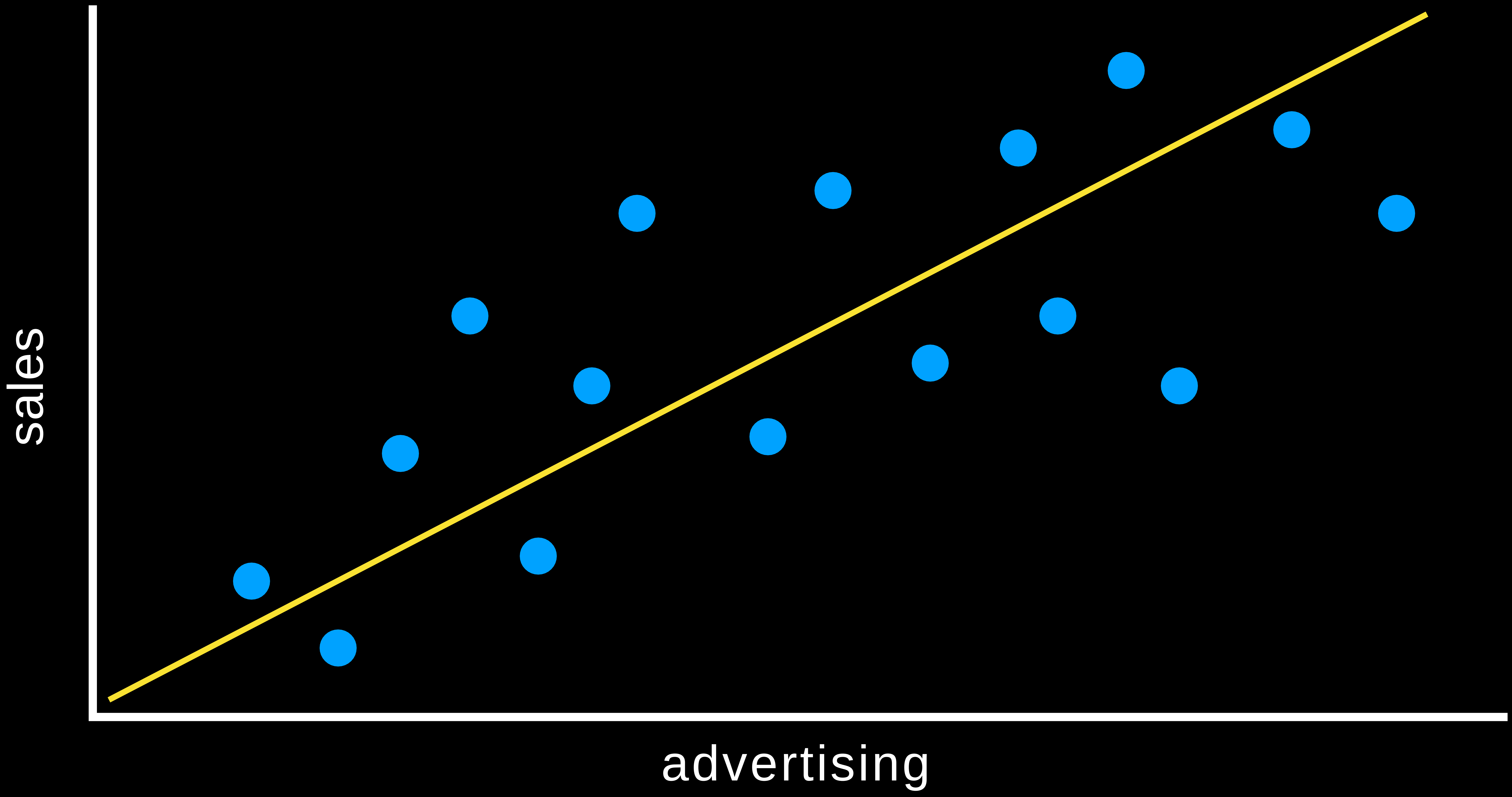
$$f(advertising)$$

$$f(1200) = 5800$$

$$f(2800) = 13400$$

$$f(1800) = 8400$$

$$h(advertising)$$


sales
advertising

Evaluating Hypotheses

loss function

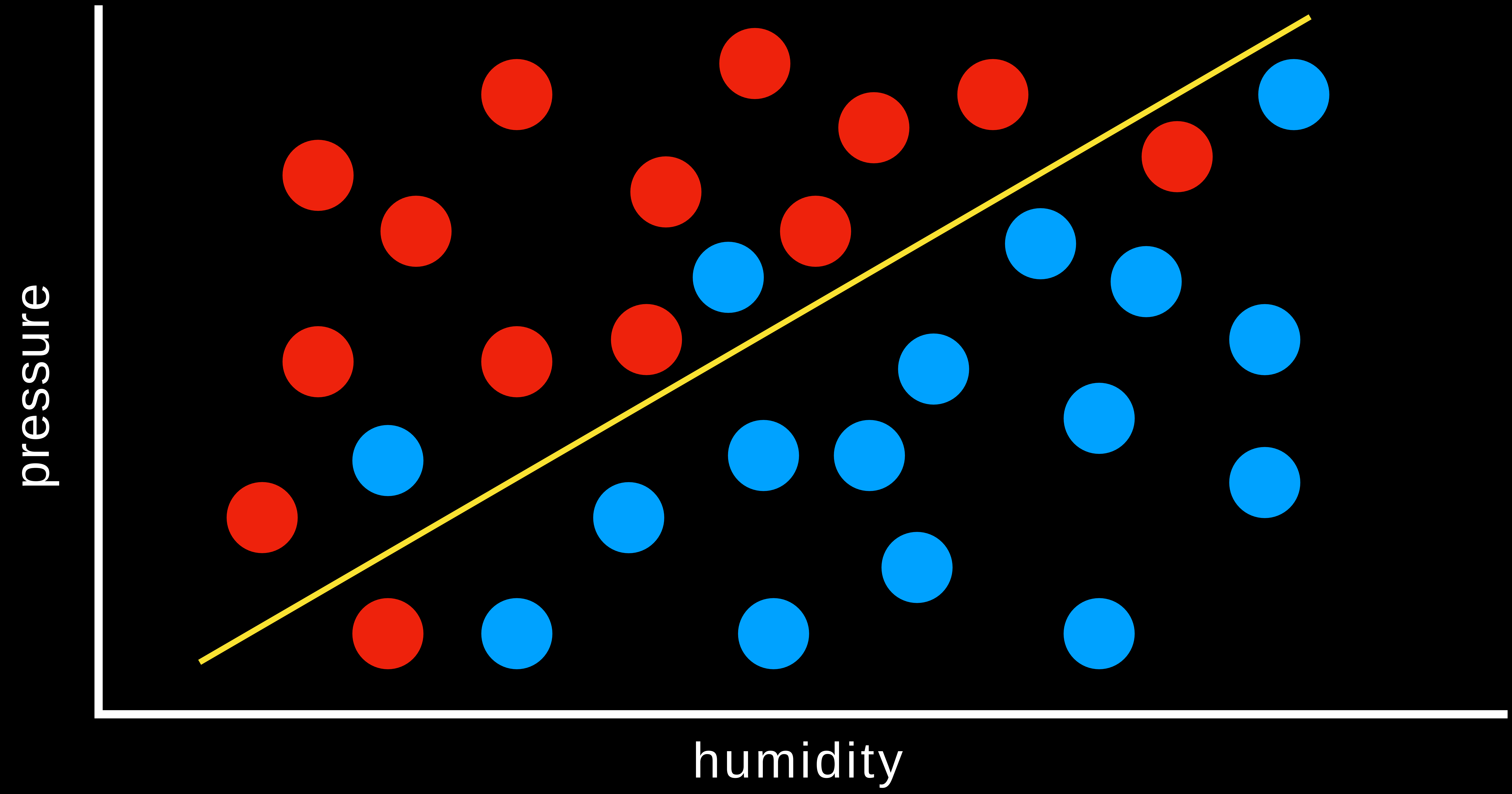
function that expresses how poorly our hypothesis performs

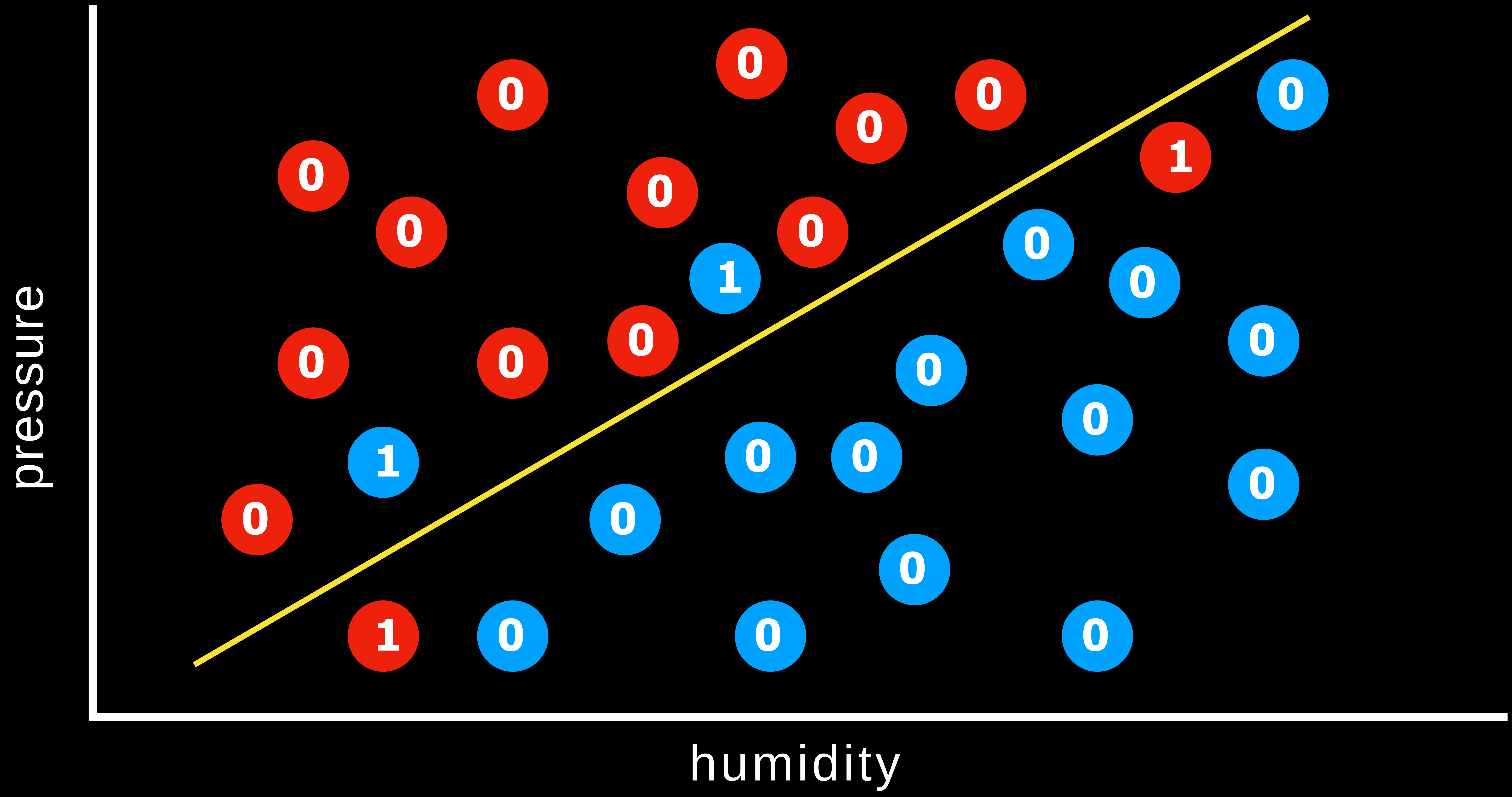
0-1 loss function

$L(\text{actual}, \text{predicted}) =$

$\quad\quad 1 \text{ if actual} = \text{predicted},$

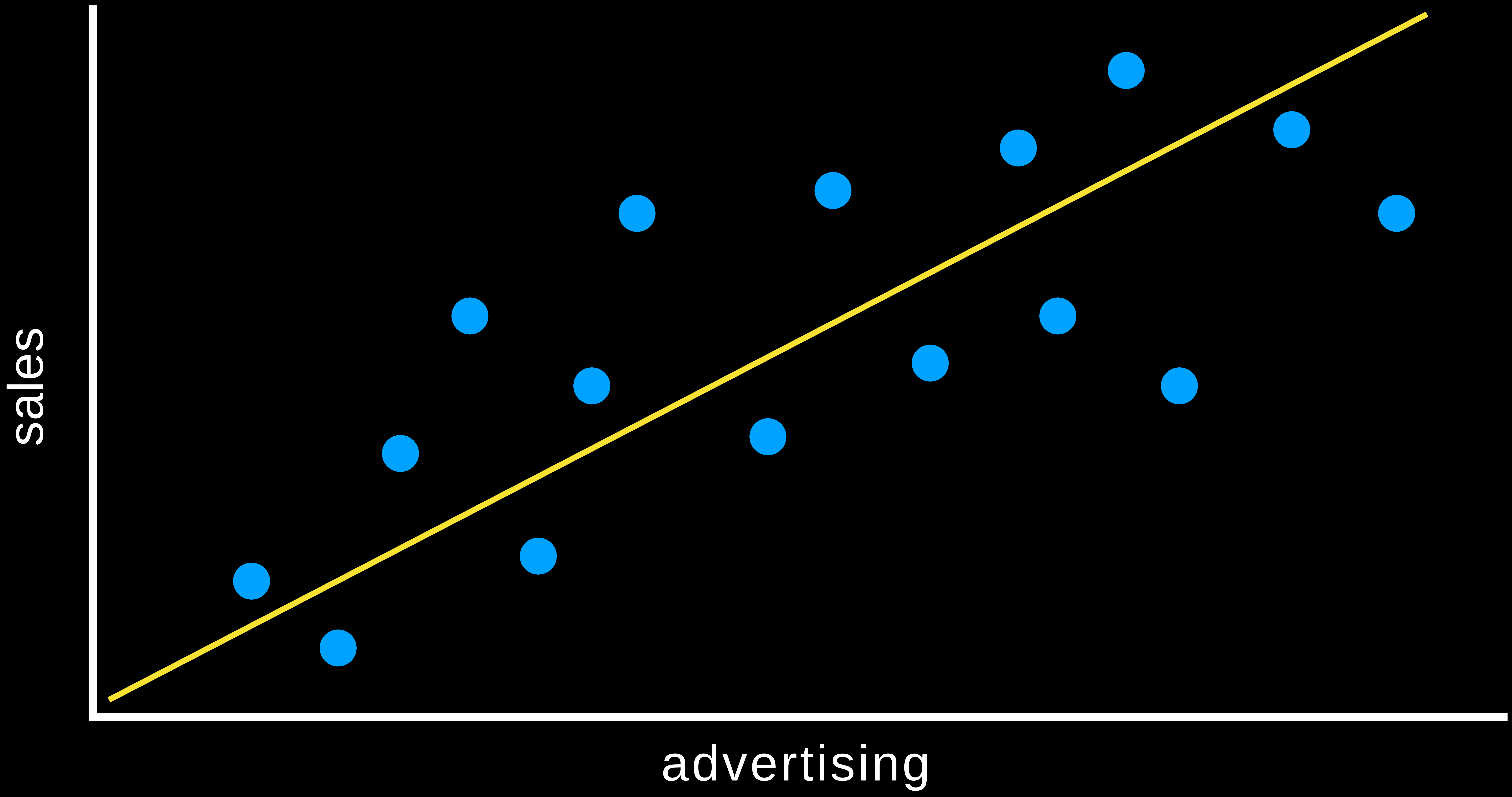
$\quad\quad 2 \text{ otherwise}$

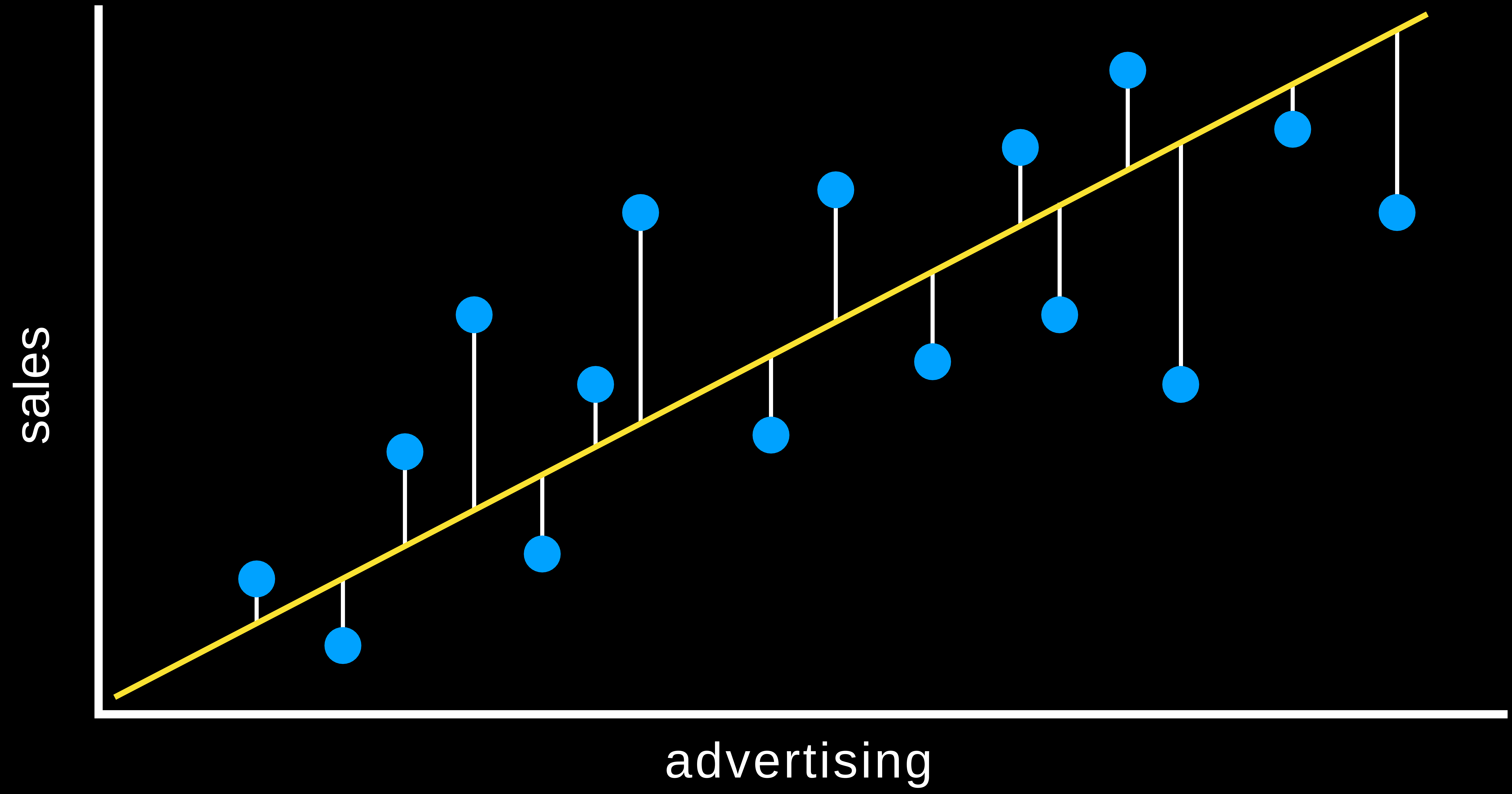

pressure
humidity


pressure
humidity
0
0
0
0
0
0
0
0
1
0
0
1
0
0
0
0
0
0
0
1
0
0
0
0
0
0
1
0
0
0
0

L_1 loss function

$$L(\text{actual}, \text{predicted}) = |\,\text{actual - predicted}\,|$$


sales
advertising

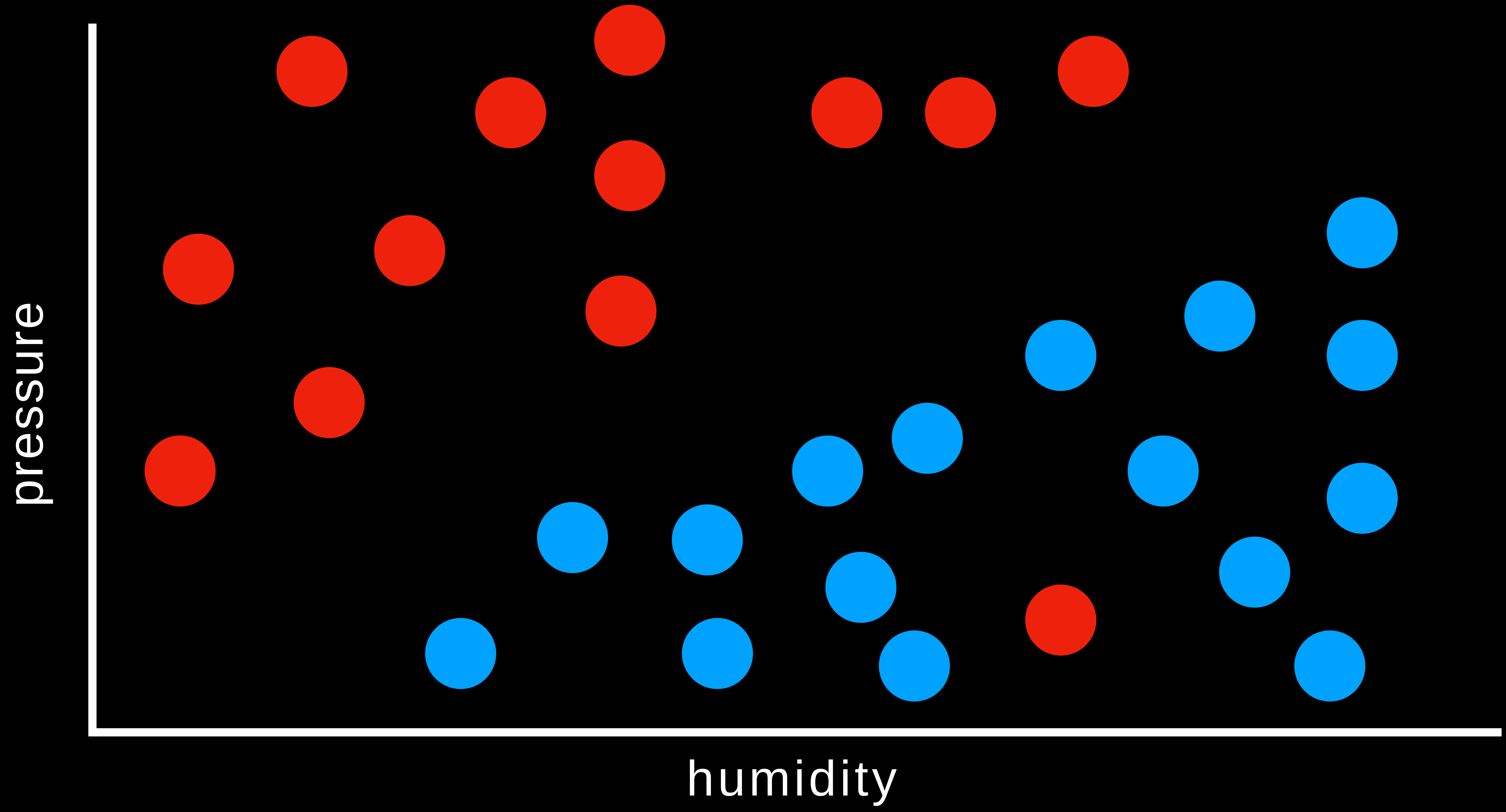

sales
advertising

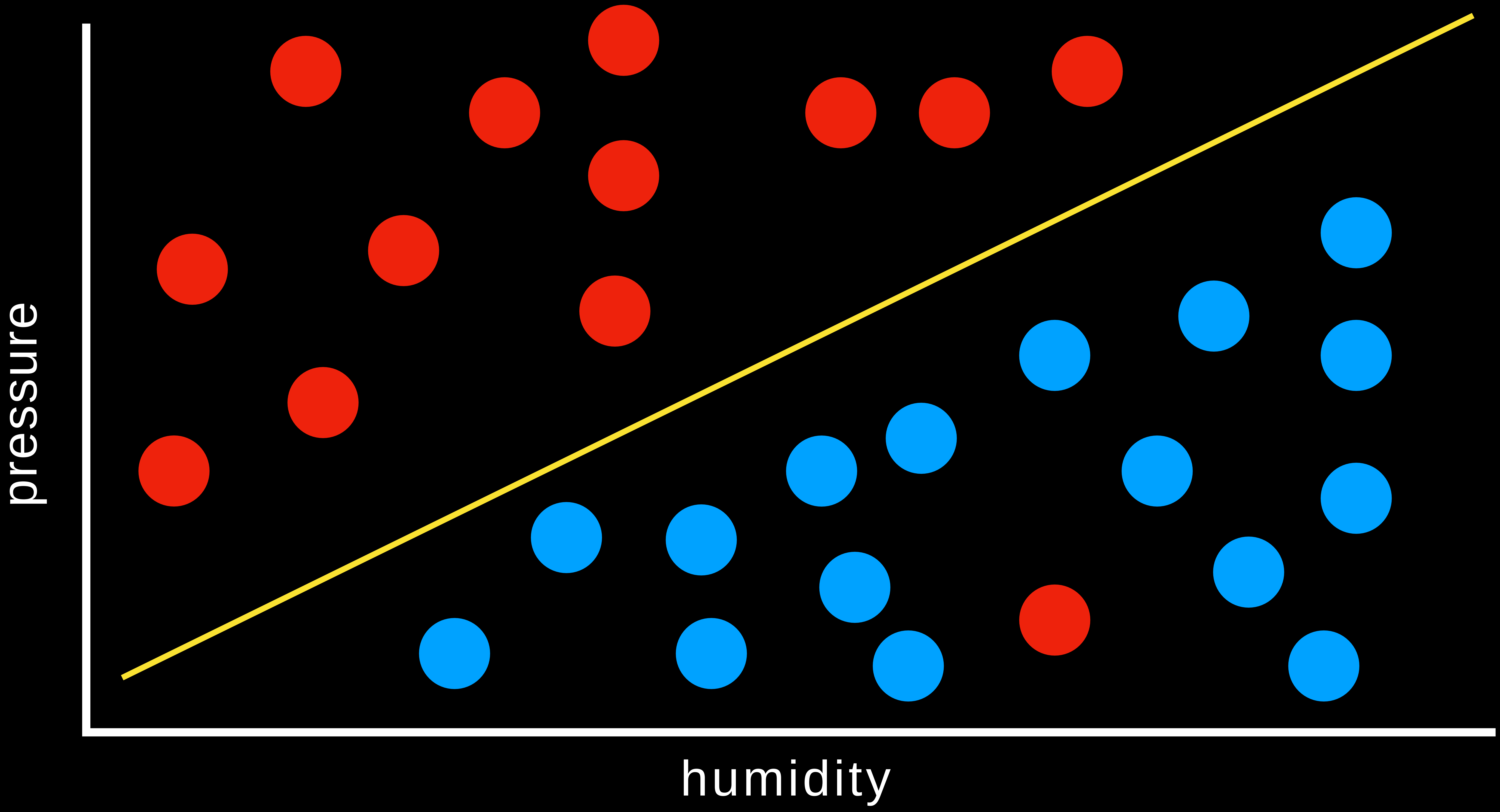
L_2 loss function

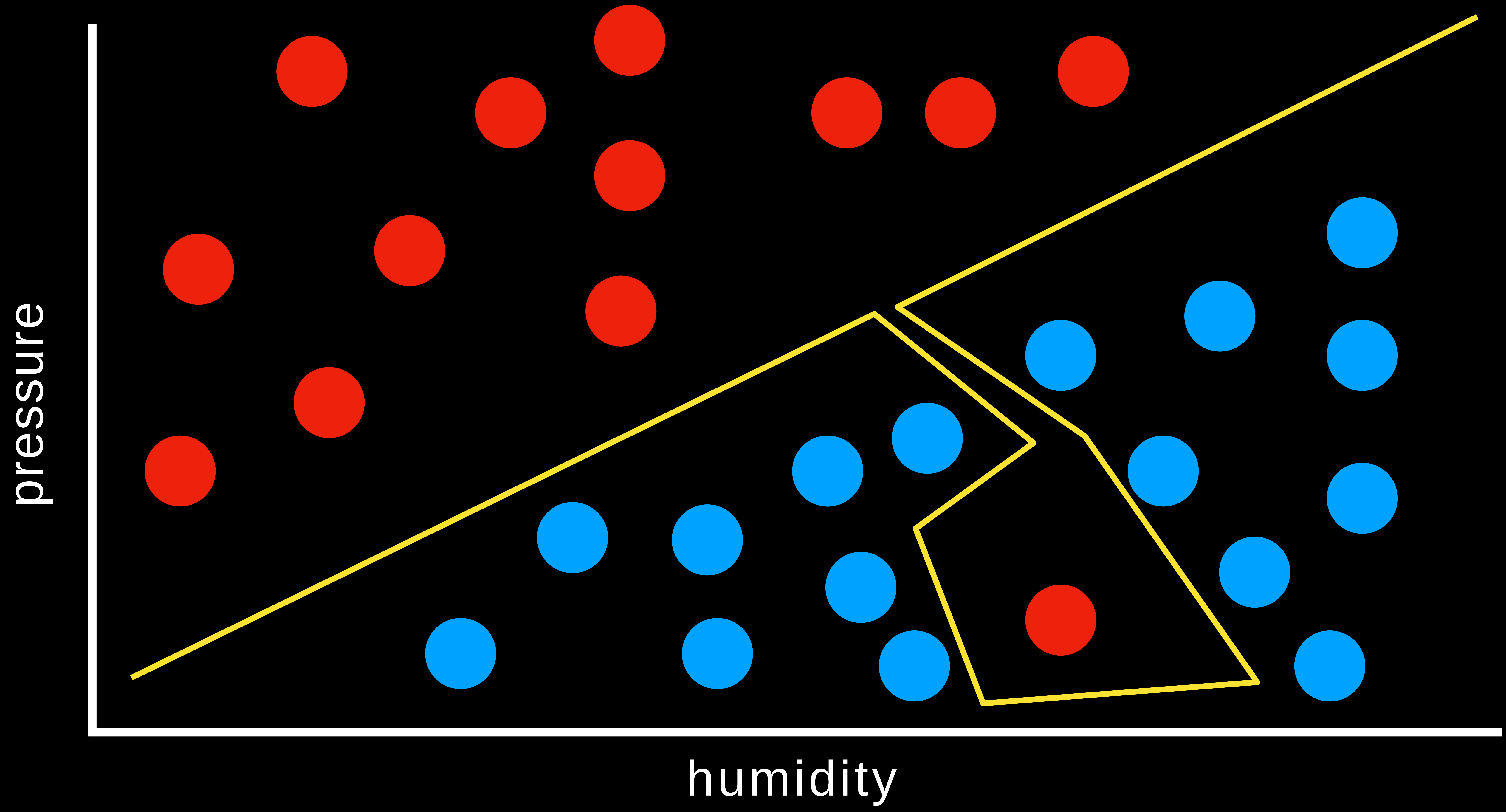
$$L(\text{actual}, \text{predicted}) = (\text{actual} - \text{predicted})^2$$

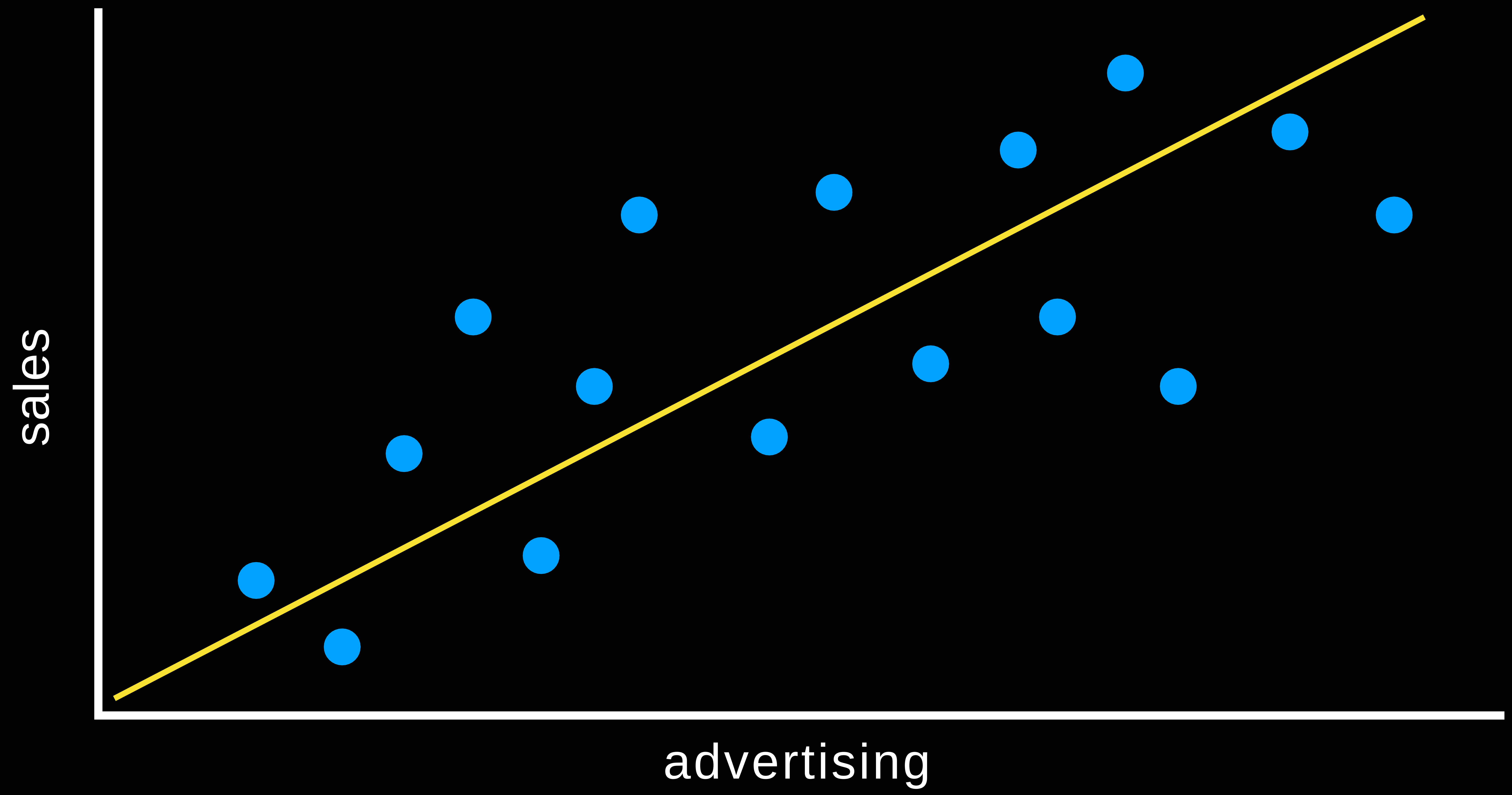
overfitting

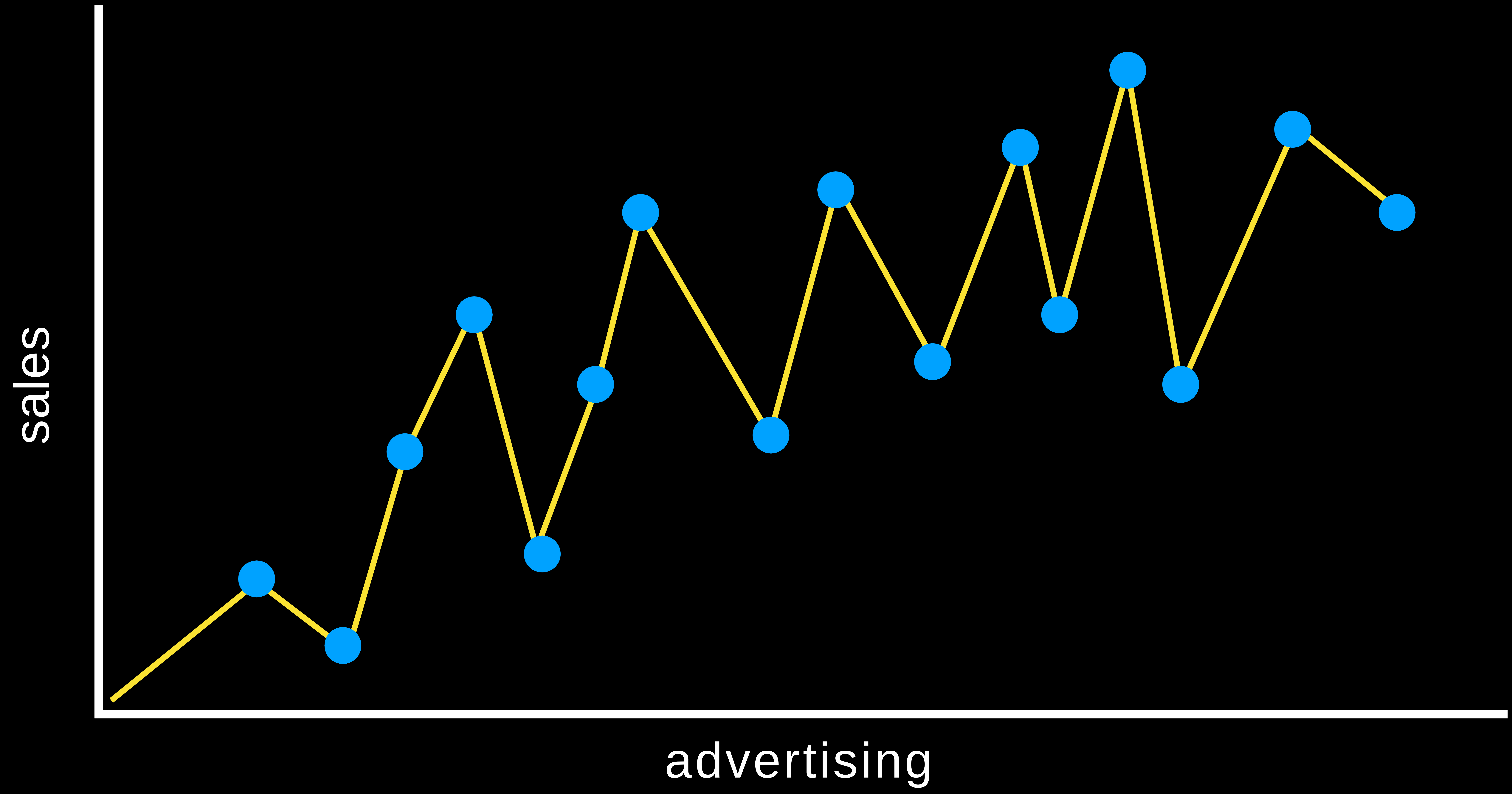
a model that fits too closely to a particular data set and therefore may fail to generalize to future data


pressure
humidity


pressure
humidity


pressure
humidity


sales
advertising


sales
advertising

$$cost(\mathrm{h}) = loss(\mathrm{h})$$

$$\mathit{cost}(\mathrm{h}) = \mathit{loss}(\mathrm{h}) + \quad \mathit{complexity}(\mathrm{h})$$

$$cost(\mathrm{h}) = loss(\mathrm{h}) + \lambda complexity(\mathrm{h})$$

regularization

penalizing hypotheses that are more complex to favor simpler, more general hypotheses

$$\mathit{cost}(\mathrm{h}) = \mathit{loss}(\mathrm{h}) + \lambda \mathit{complexity}(\mathrm{h})$$

holdout cross-validation

splitting data into a **training set** and a **test set**, such that learning happens on the training set and is evaluated on the test set

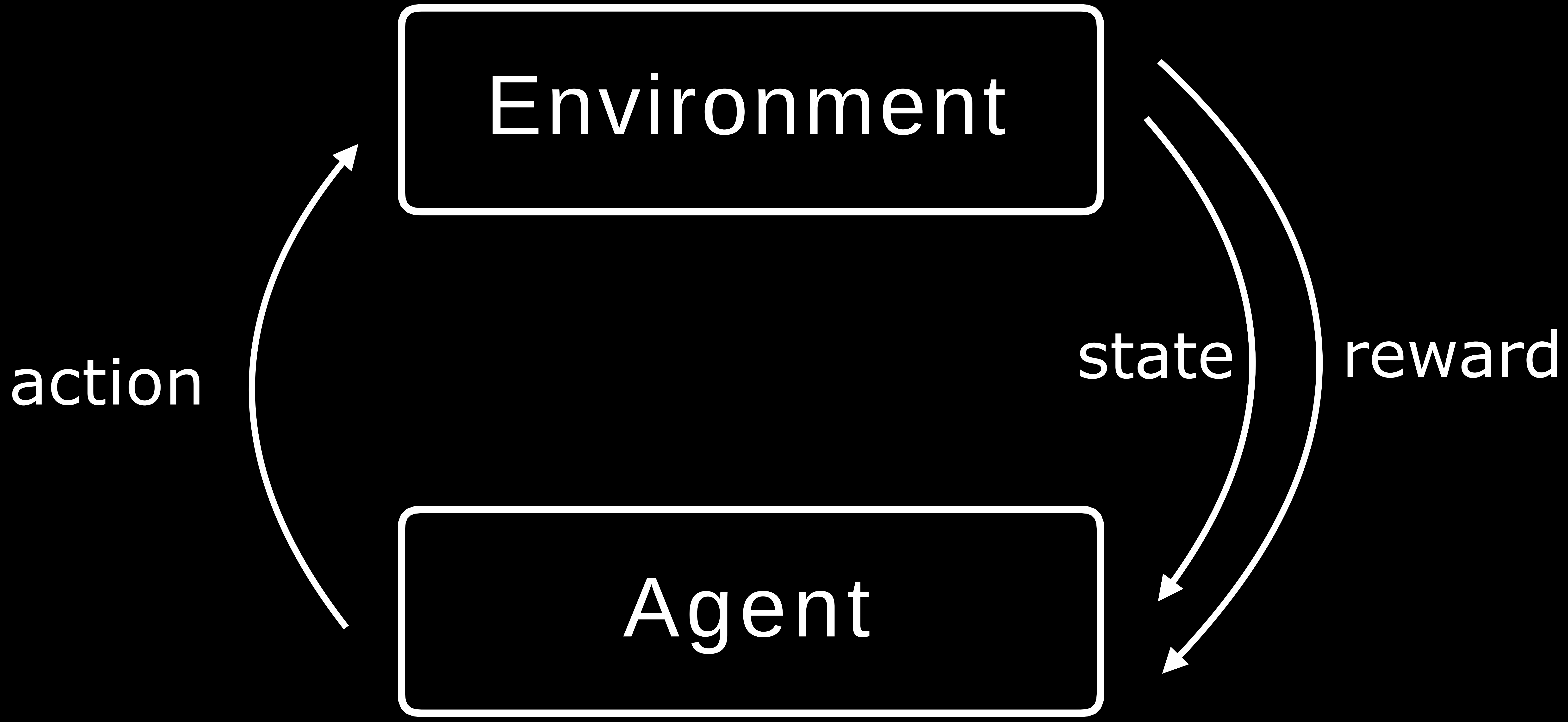
k-fold cross-validation

splitting data into k sets, and experimenting k times, using each set as a test set once, and using remaining data as training set scikit-learn

Reinforcement Learning

reinforcement learning

given a set of rewards or punishments, learn what actions to take in the future


Environment
state
reward
action
Agent

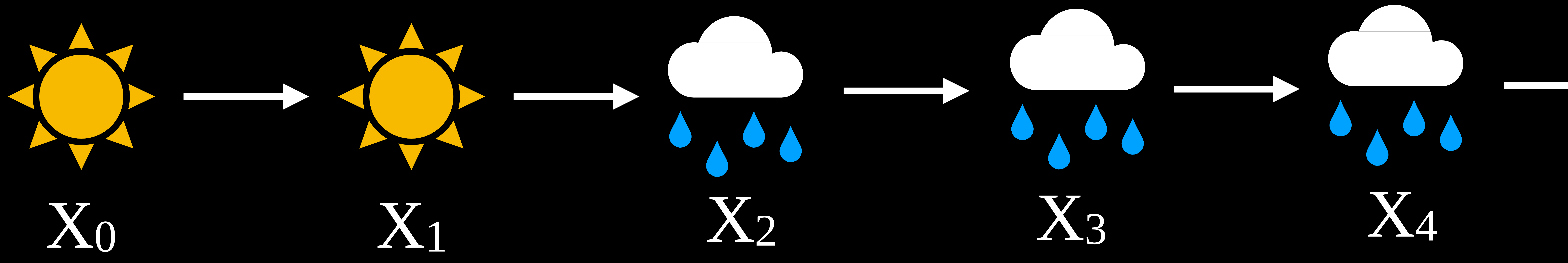
Markov Decision Process

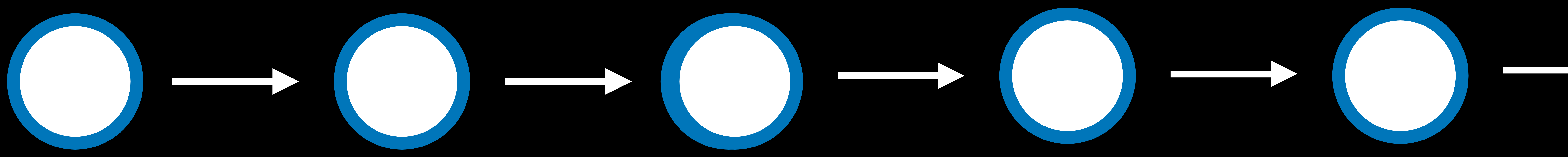
model for decision-making, representing states, actions, and their rewards

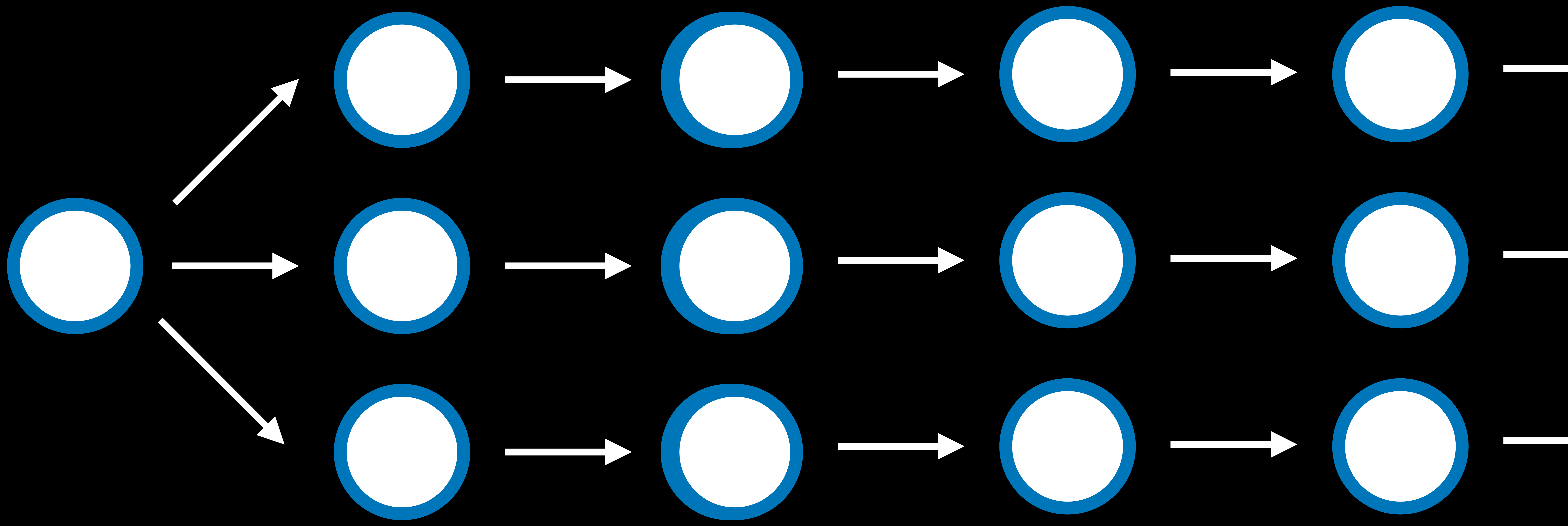
Markov Decision Process

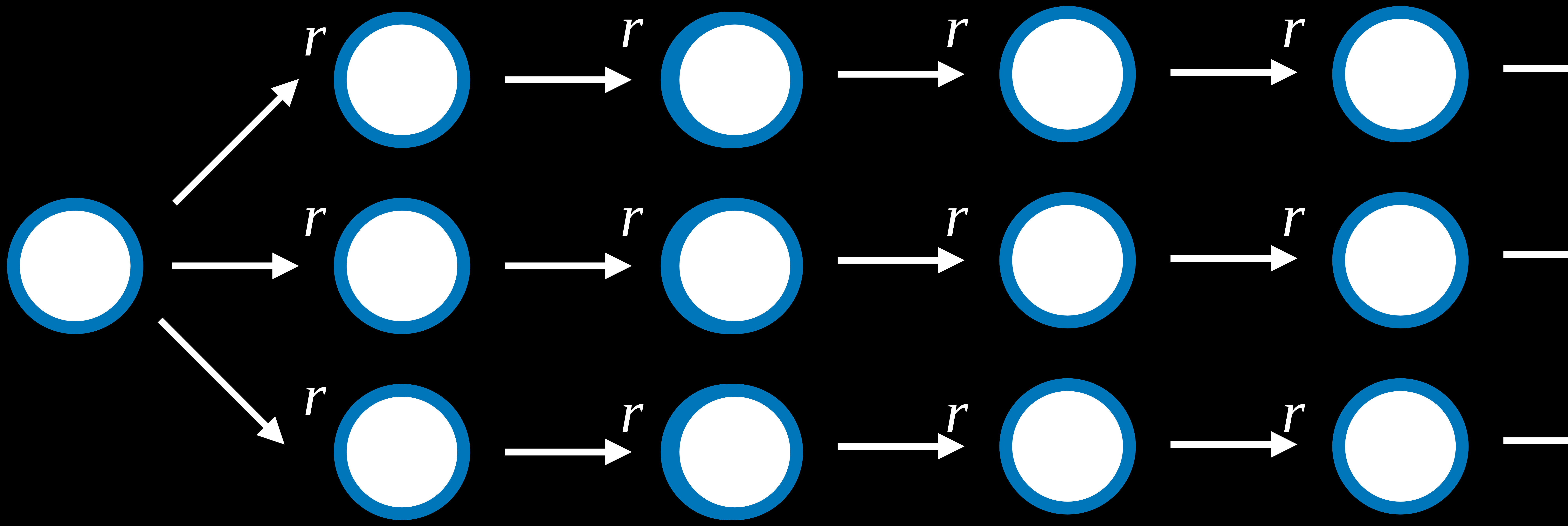
model for decision-making, representing states, actions, and their rewards

Markov Chain



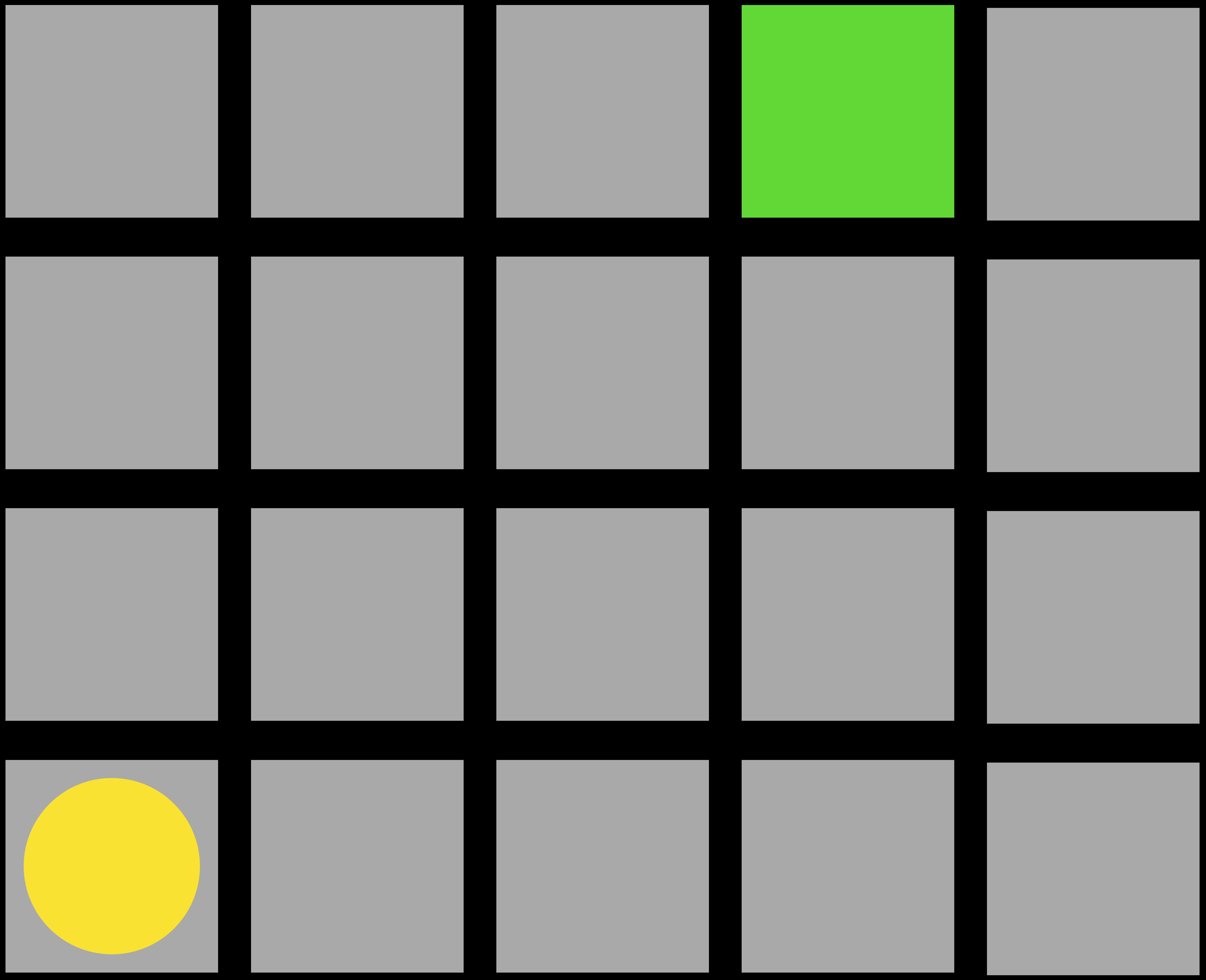


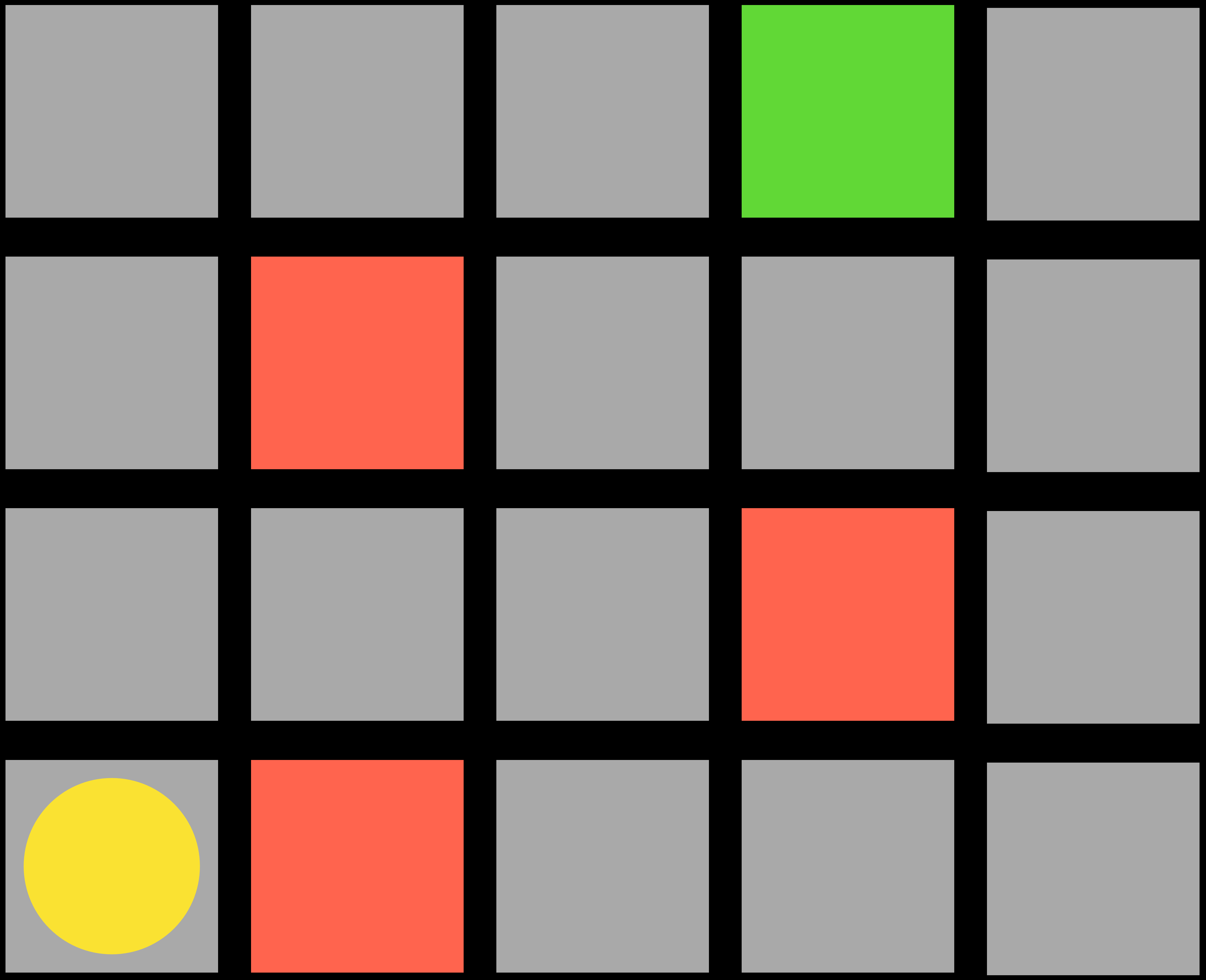


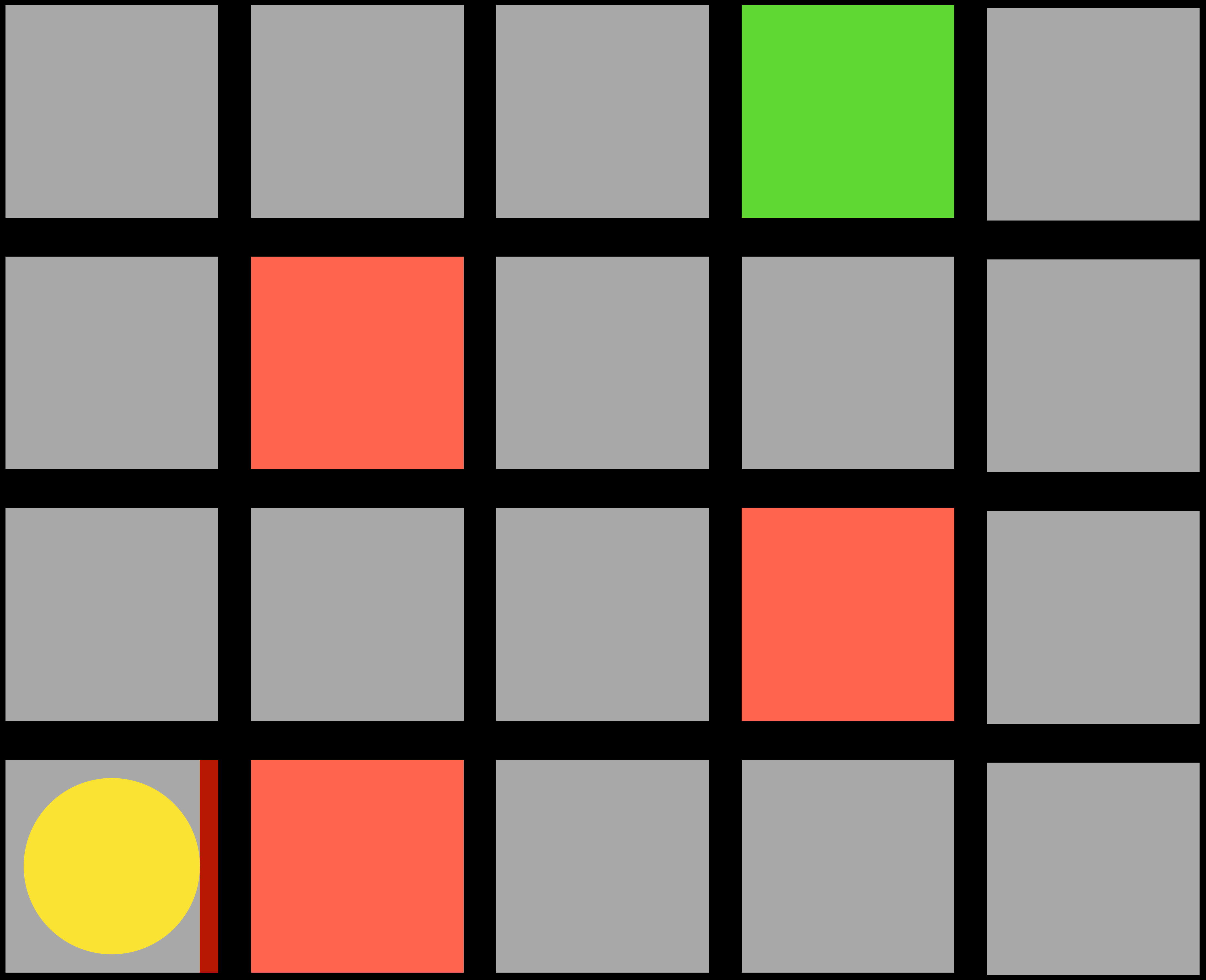

r
r
r
r
r
r
r
r
r
r
r
r

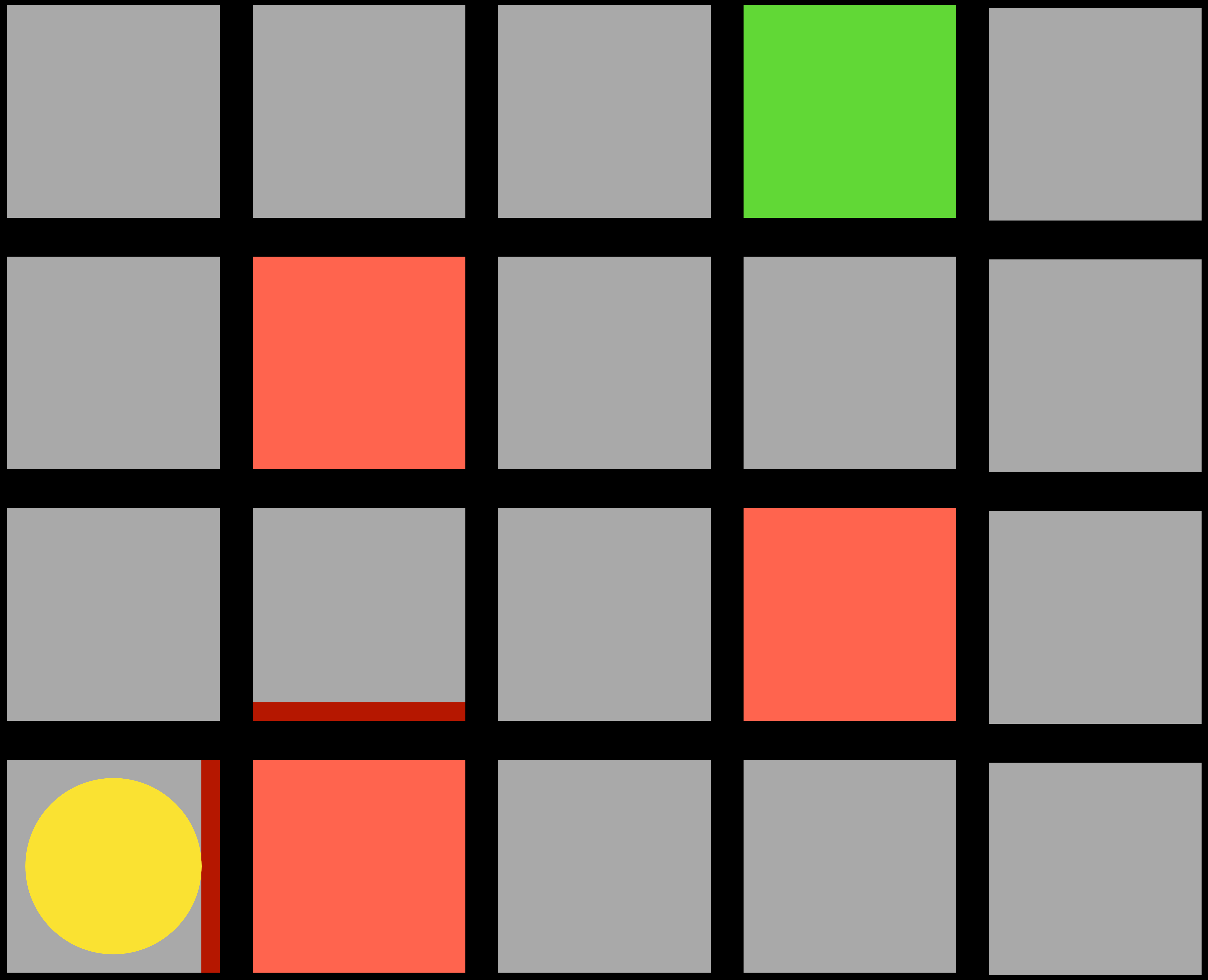
Markov Decision Process

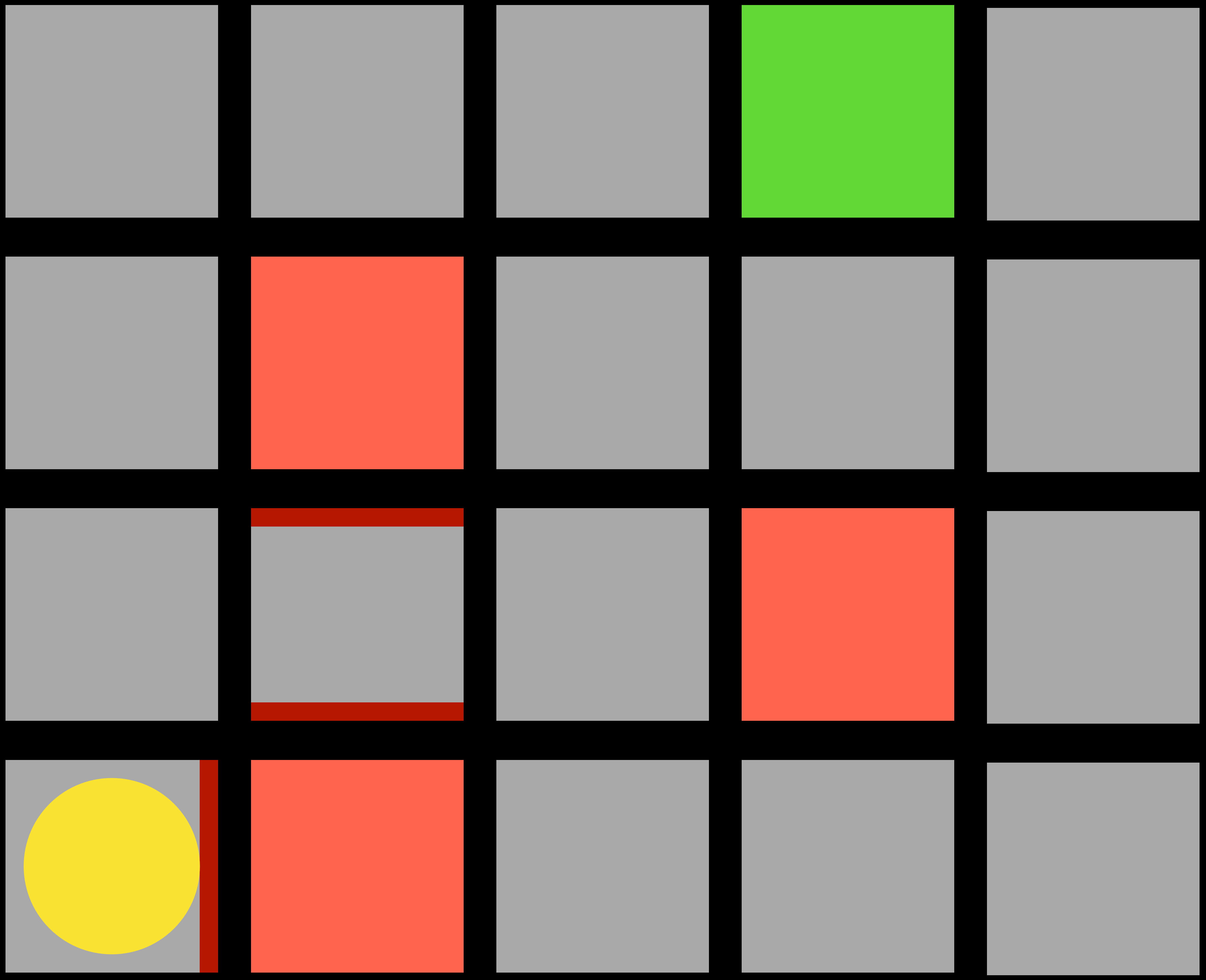
- Set of states S
- Set of actions $\textsc{Actions}(s)$
- Transition model $P(s' \mid s, a)$
- Reward function $R(s, a, s')$

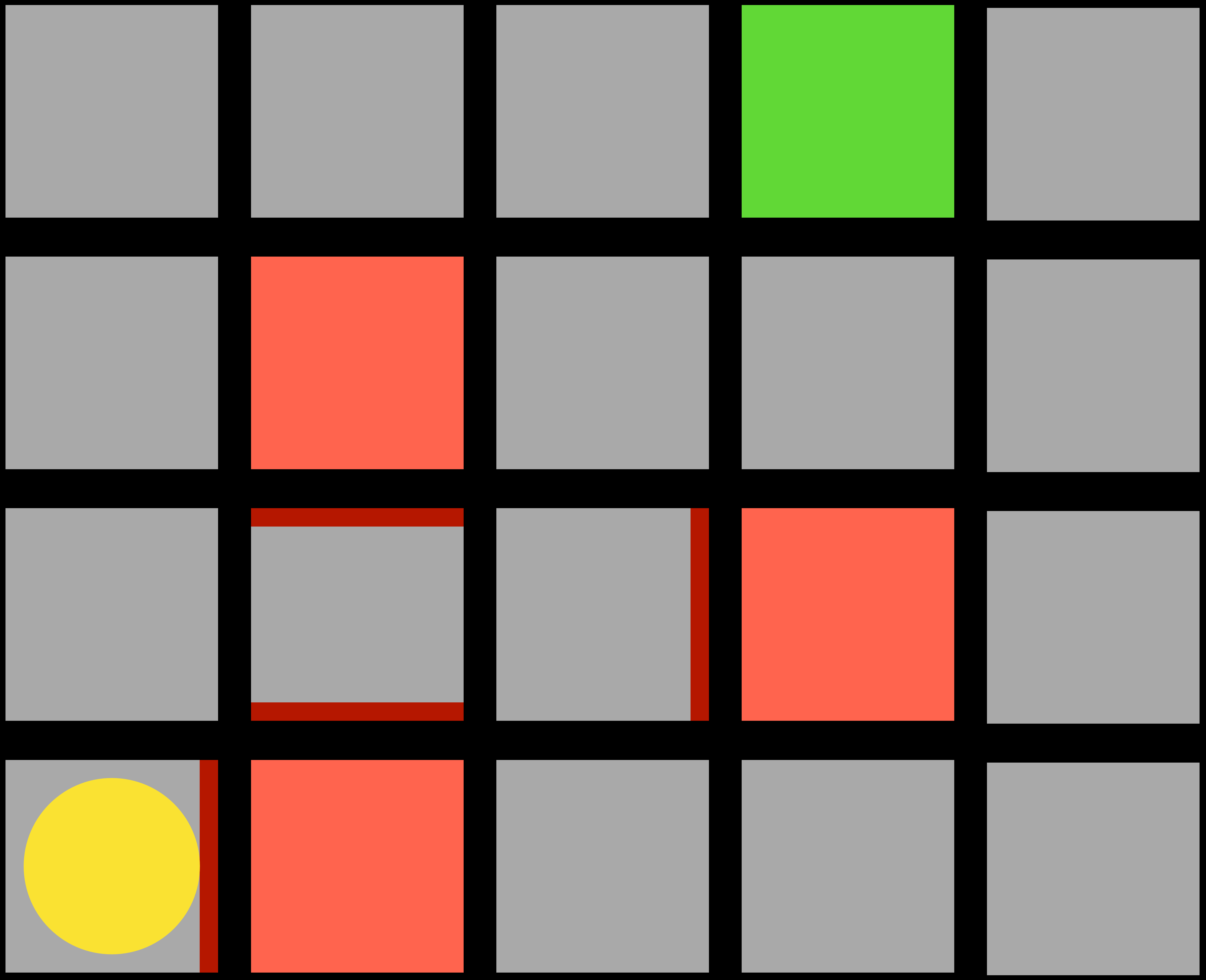


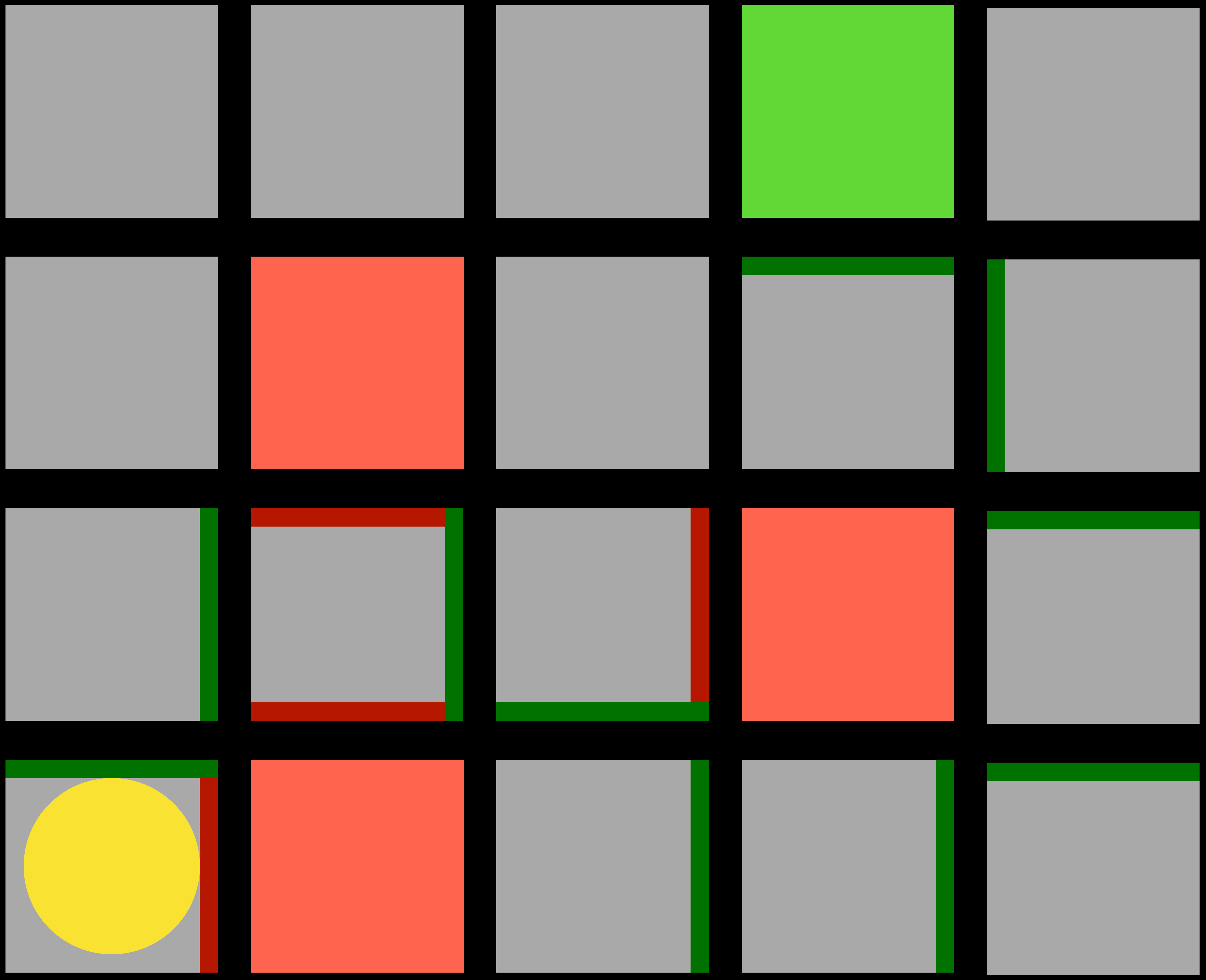


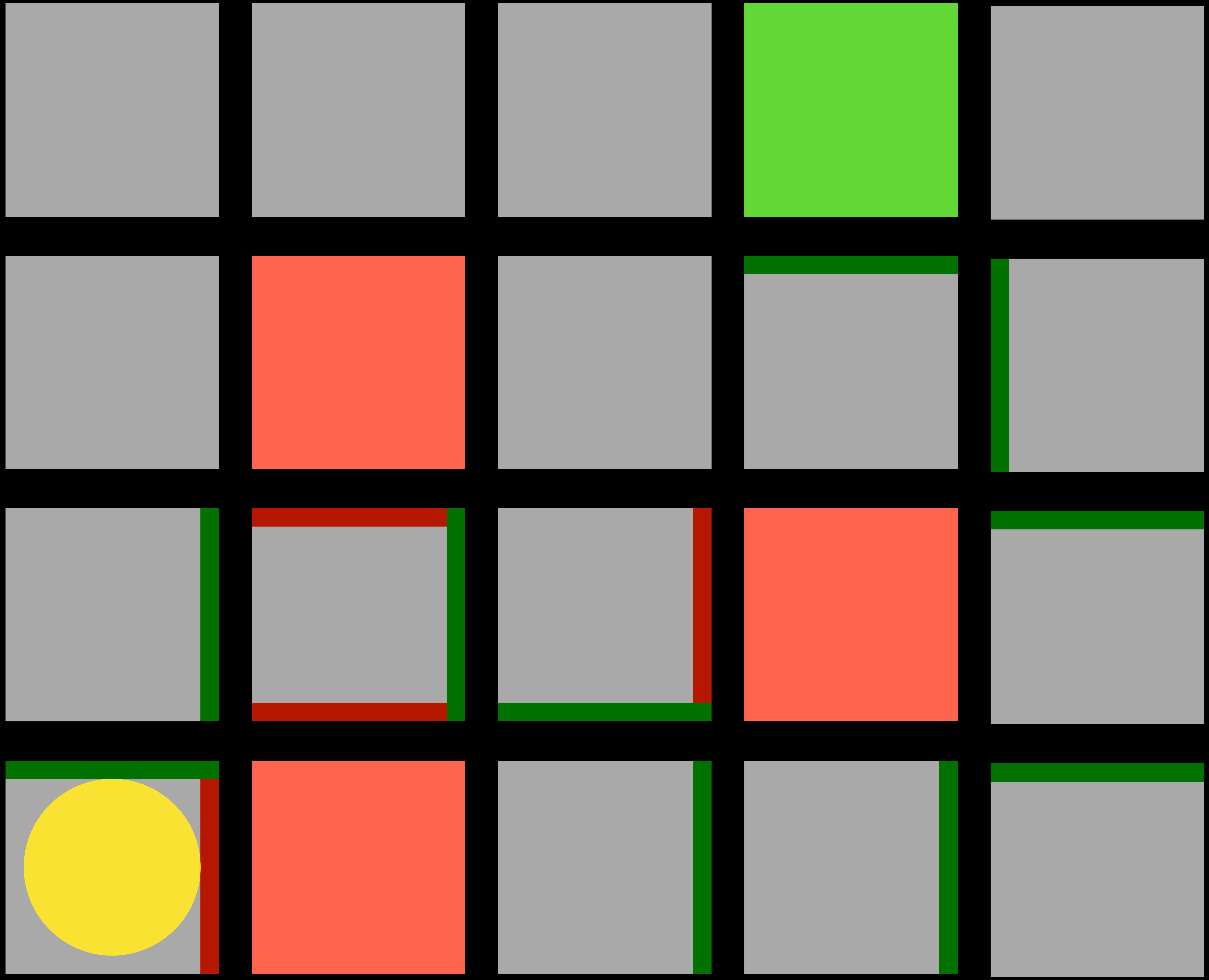












Q-learning

method for learning a function $Q(s, a)$, estimate of the value of performing action a in state s

Q-learning Overview

- Start with $Q(s, a) = 0$ for all s, a
- When we taken an action and receive a reward:
  - Estimate the value of $Q(s, a)$ based on current reward and expected future rewards
  - Update $Q(s, a)$ to take into account old estimate as well as our new estimate

Q-learning

- Start with $Q(s, a) = 0$ for all s, a
- Every time we take an action a in state s and observe a reward r, we update:

  $$Q(s, a) \leftarrow \mathrm{Q}(s, a) + \alpha(\text{new value estimate - old value estimate})$$

Q-learning

- Start with $Q(s, a) = 0$ for all s, a
- Every time we take an action a in state s and observe a reward r, we update:

$$Q(s, a) \leftarrow \mathrm{Q}(s, a) + \alpha(\text{new value estimate - } \mathrm{Q}(s, a))$$

Q-learning

- Start with $Q(s, a) = 0$ for all s, a
- Every time we take an action a in state s and observe a reward r, we update:

  $$Q(s, a) \leftarrow \mathrm{Q}(s, a) + \alpha((\mathrm{r} + \text{future reward estimate}) - \mathrm{Q}(s, a))$$

Q-learning

- Start with $Q(s, a) = 0$ for all s, a
- Every time we take an action a in state s and observe a reward r, we update:

  $$Q(s, a) \leftarrow \mathrm{Q}(s, a) + \alpha((\mathrm{r} + \mathrm{max}_{\mathrm{a'}}\ \mathrm{Q}(\mathrm{s'}, \mathrm{a'})) - \mathrm{Q}(s, a))$$

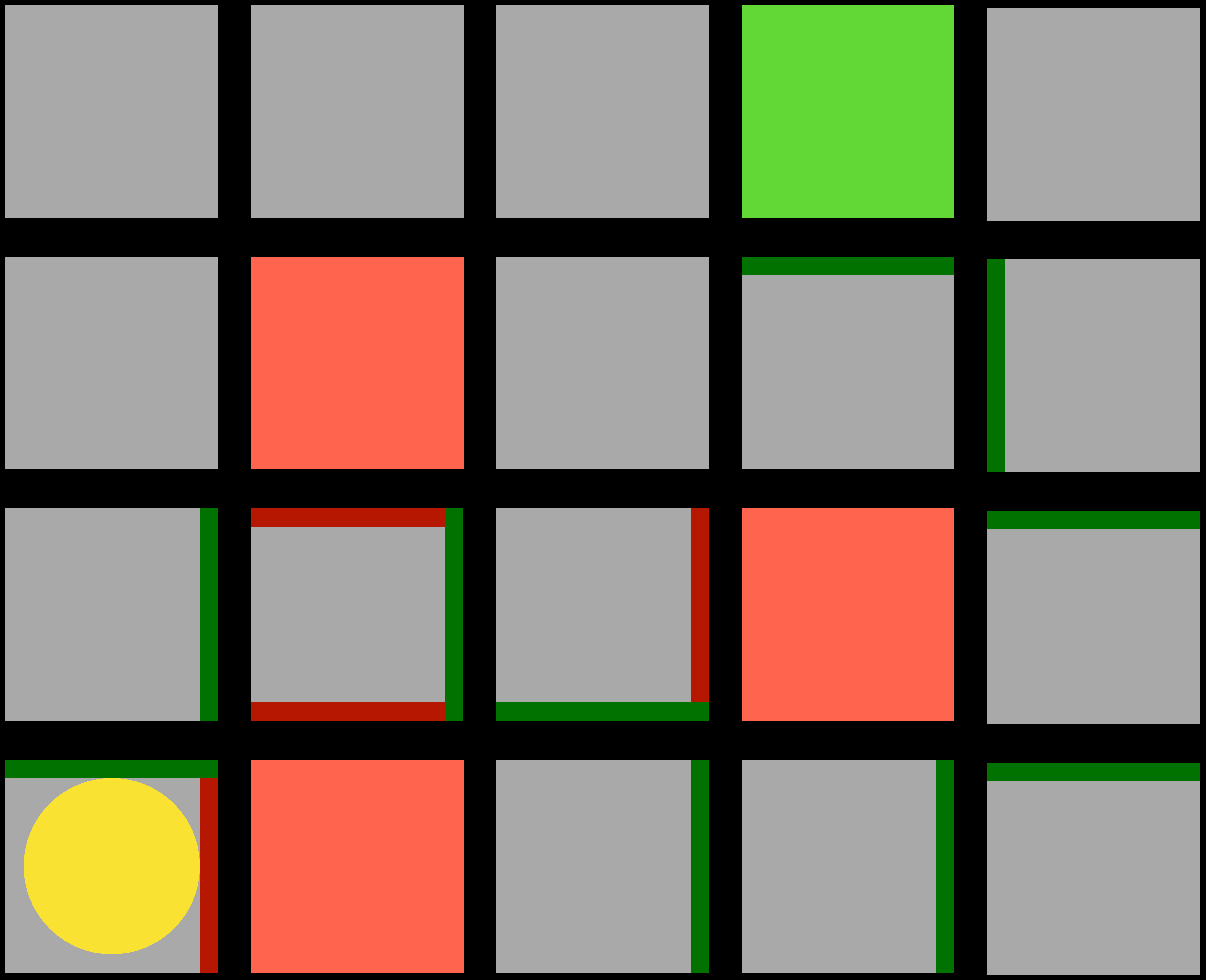
Q-learning

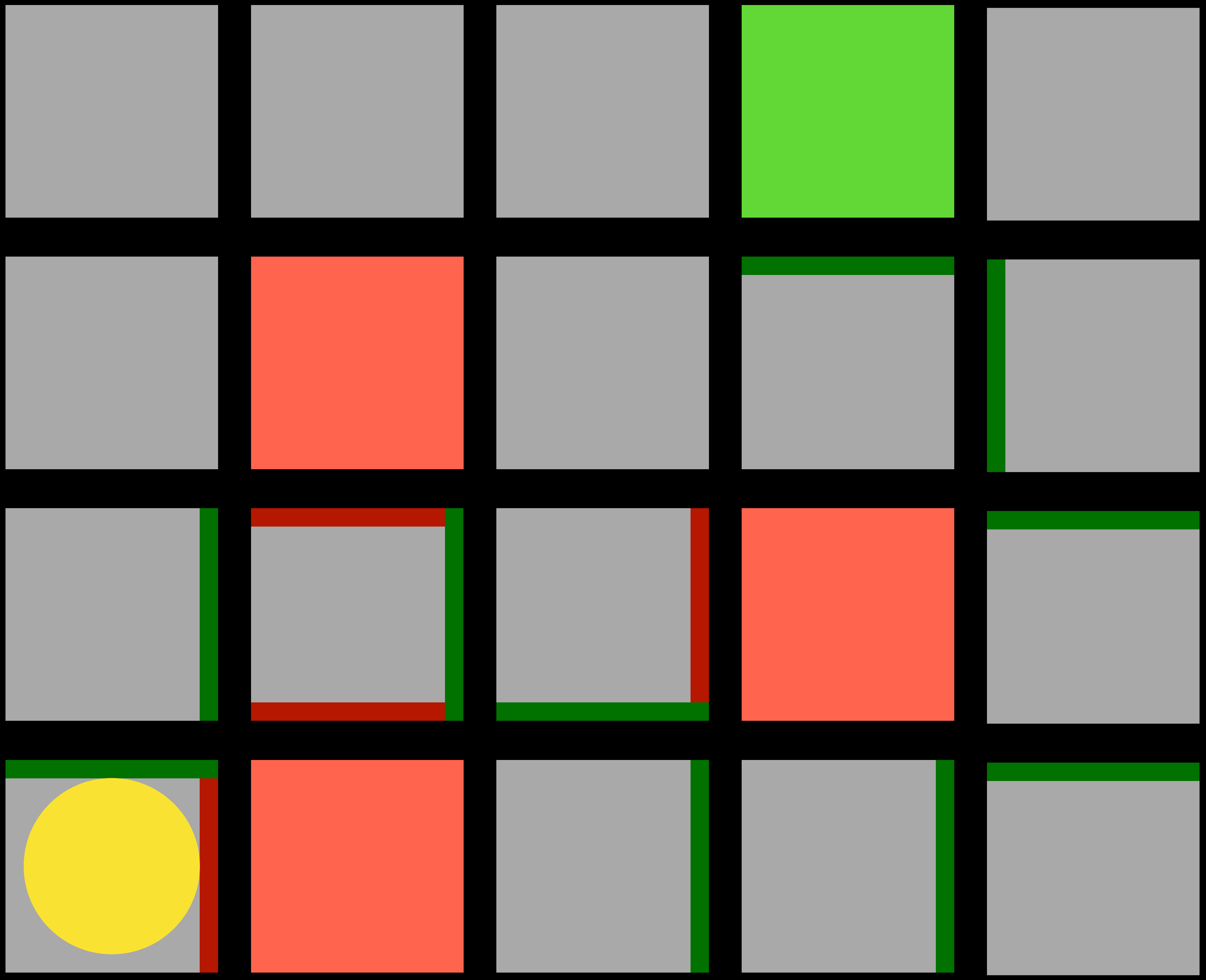
- Start with $Q(s, a) = 0$ for all s, a
- Every time we take an action a in state s and observe a reward r, we update:

  $$Q(s, a) \leftarrow Q(s, a) + \alpha((r + \gamma \max_{a'} Q(s', a')) - Q(s, a))$$

Greedy Decision-Making

- When in state s, choose action a with highest $Q(s, a)$



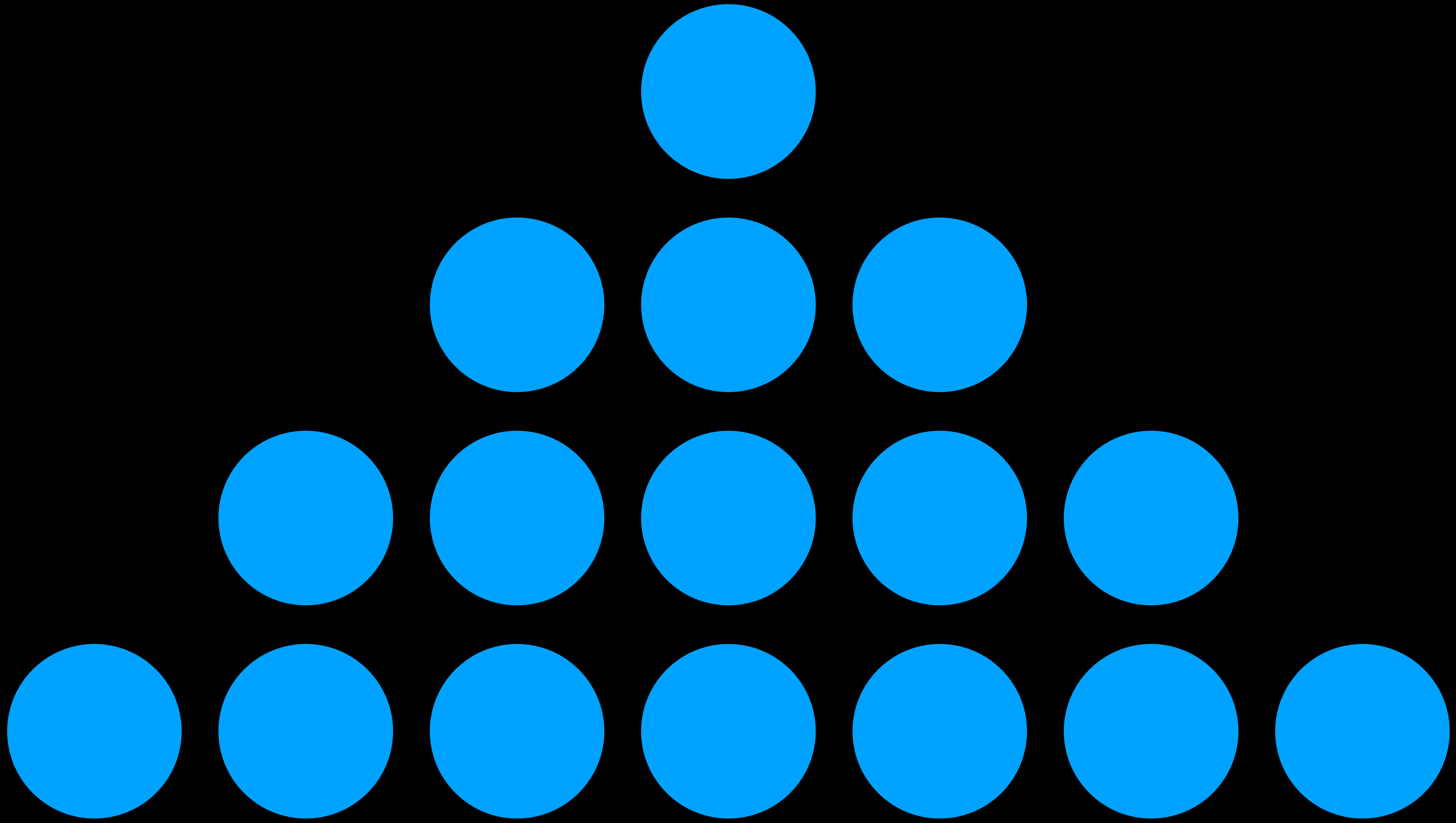


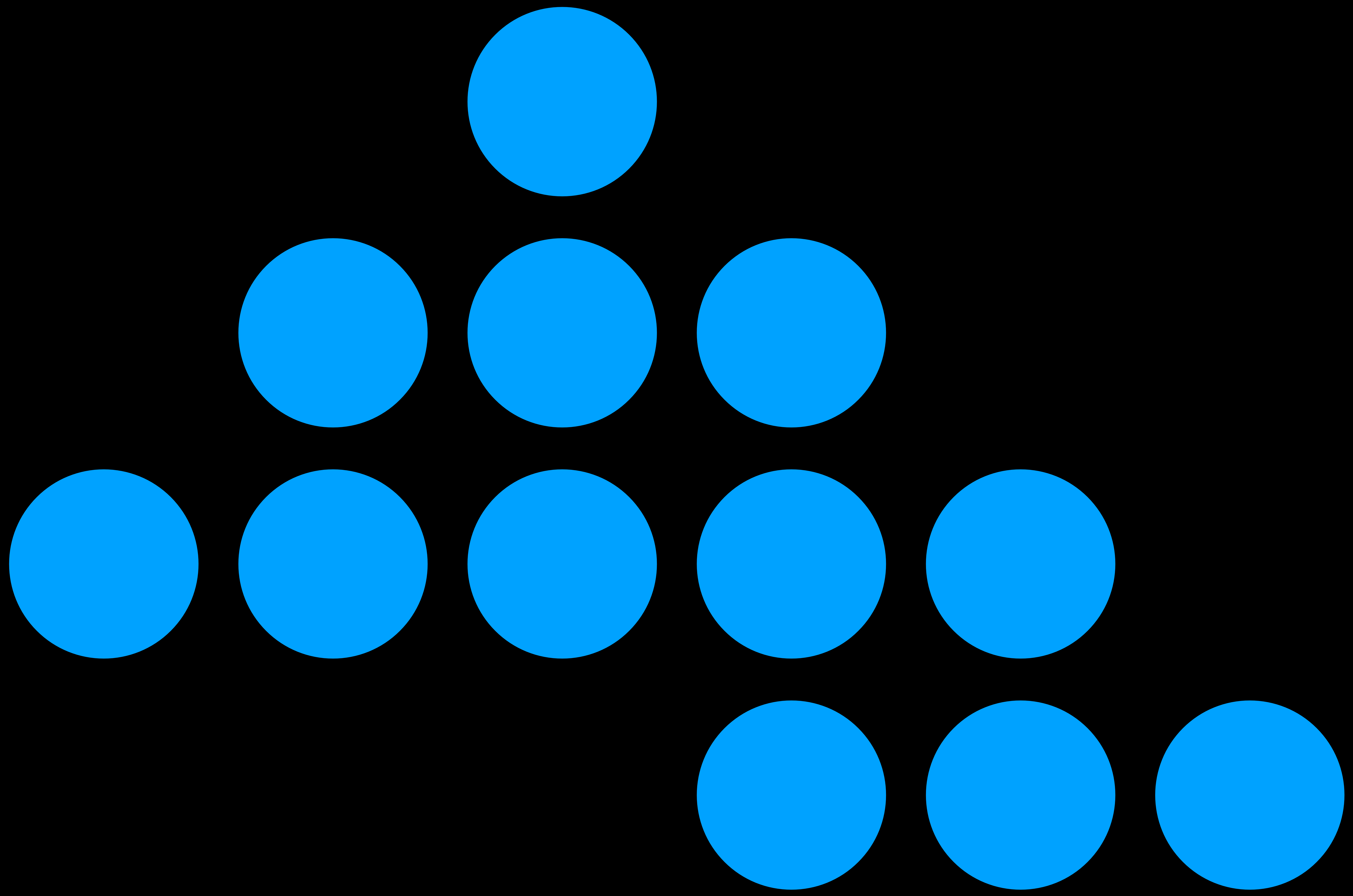
Explore vs. Exploit

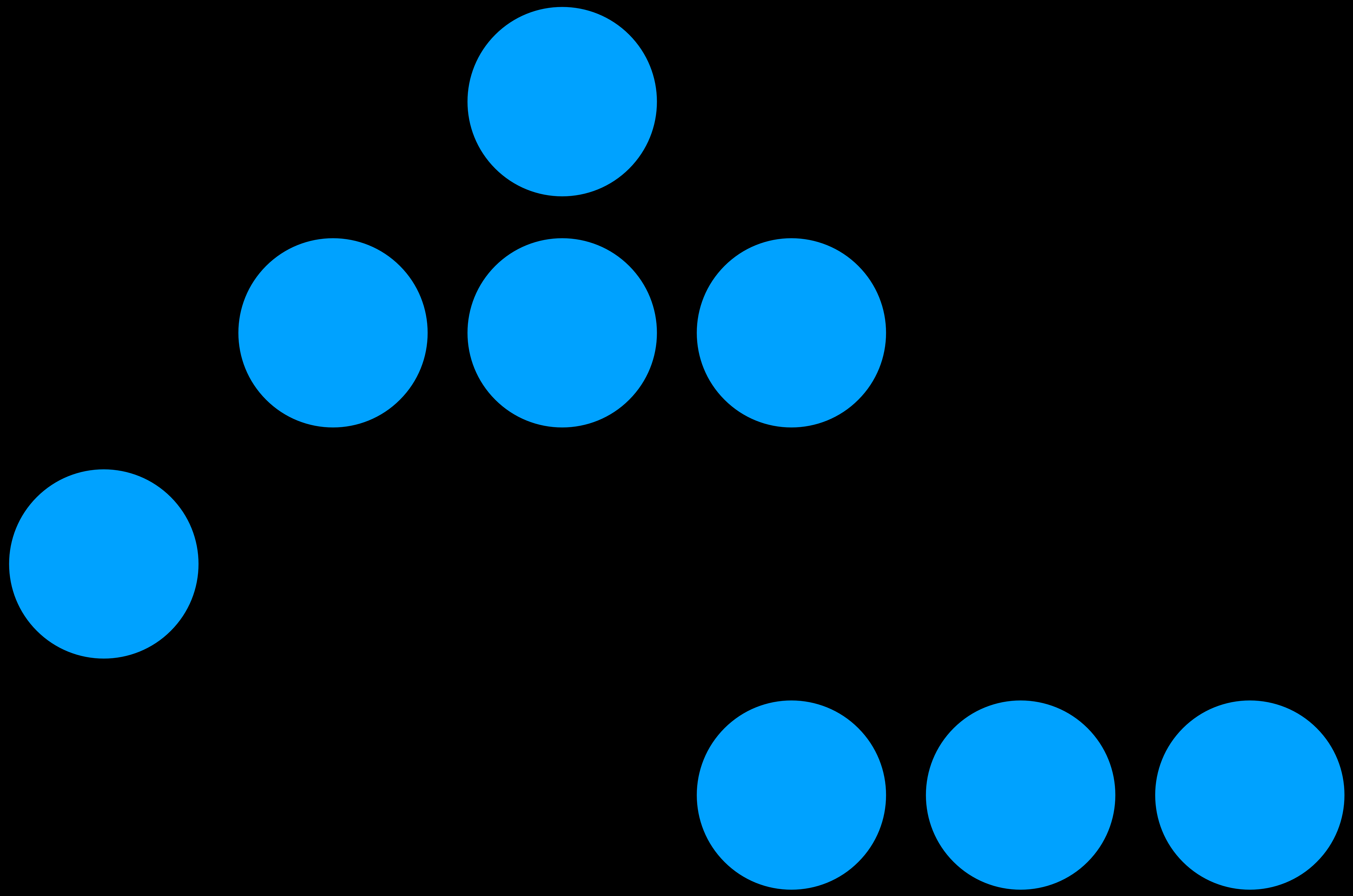
ε-greedy

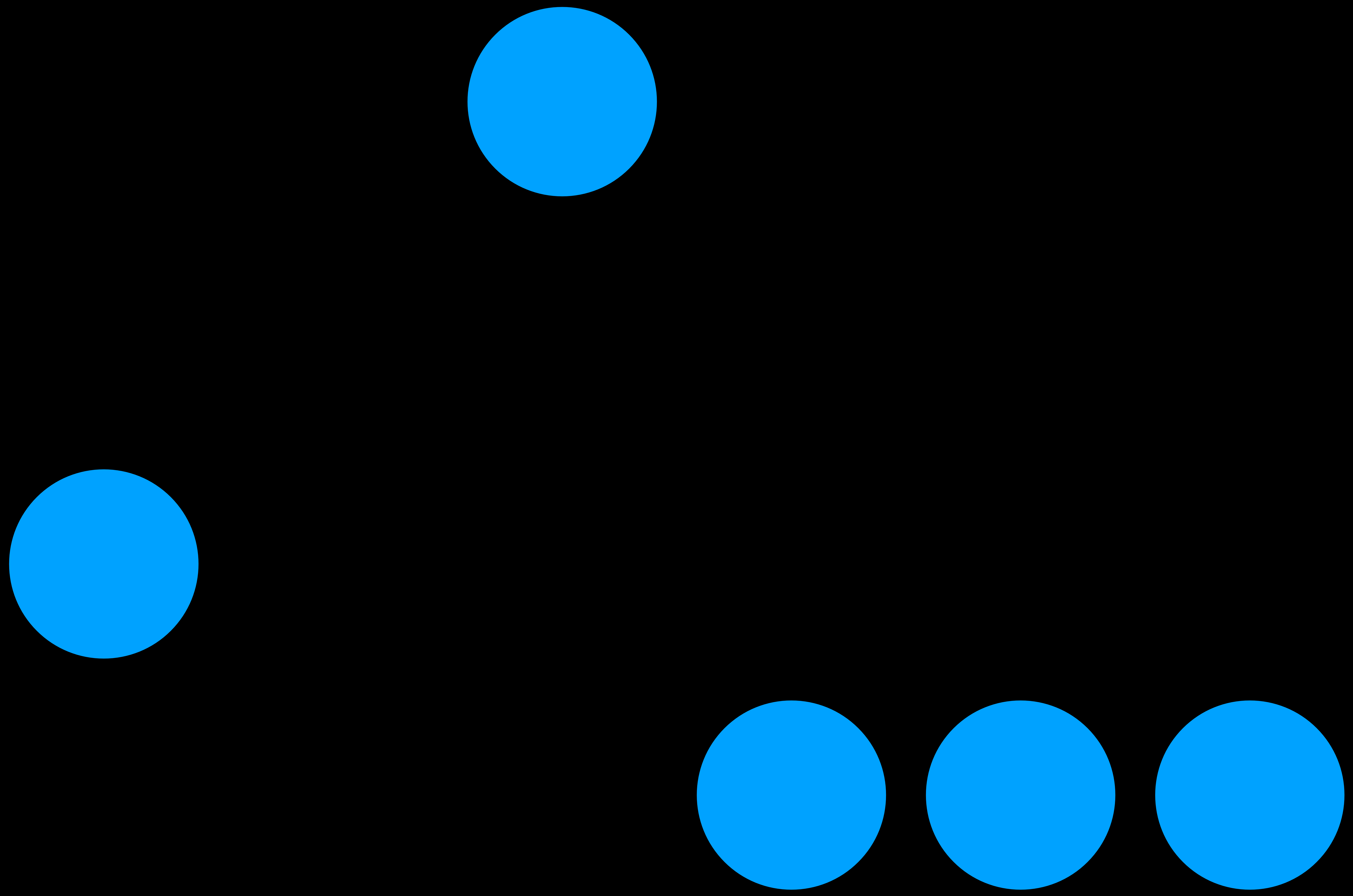
- Set ε equal to how often we want to move randomly.
- With probability $1 - \varepsilon$, choose estimated best move.
- With probability ε, choose a random move.

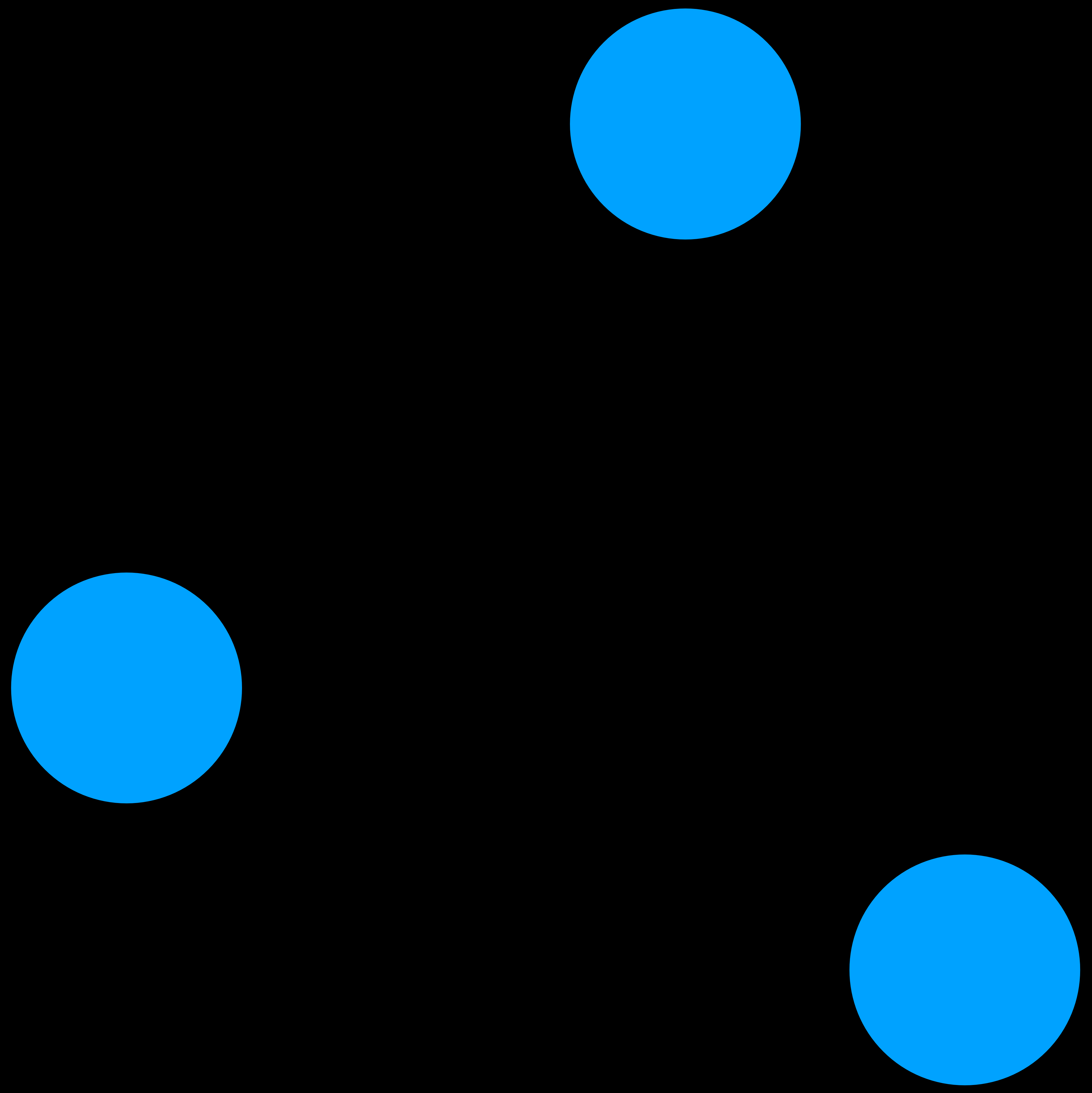
Nim

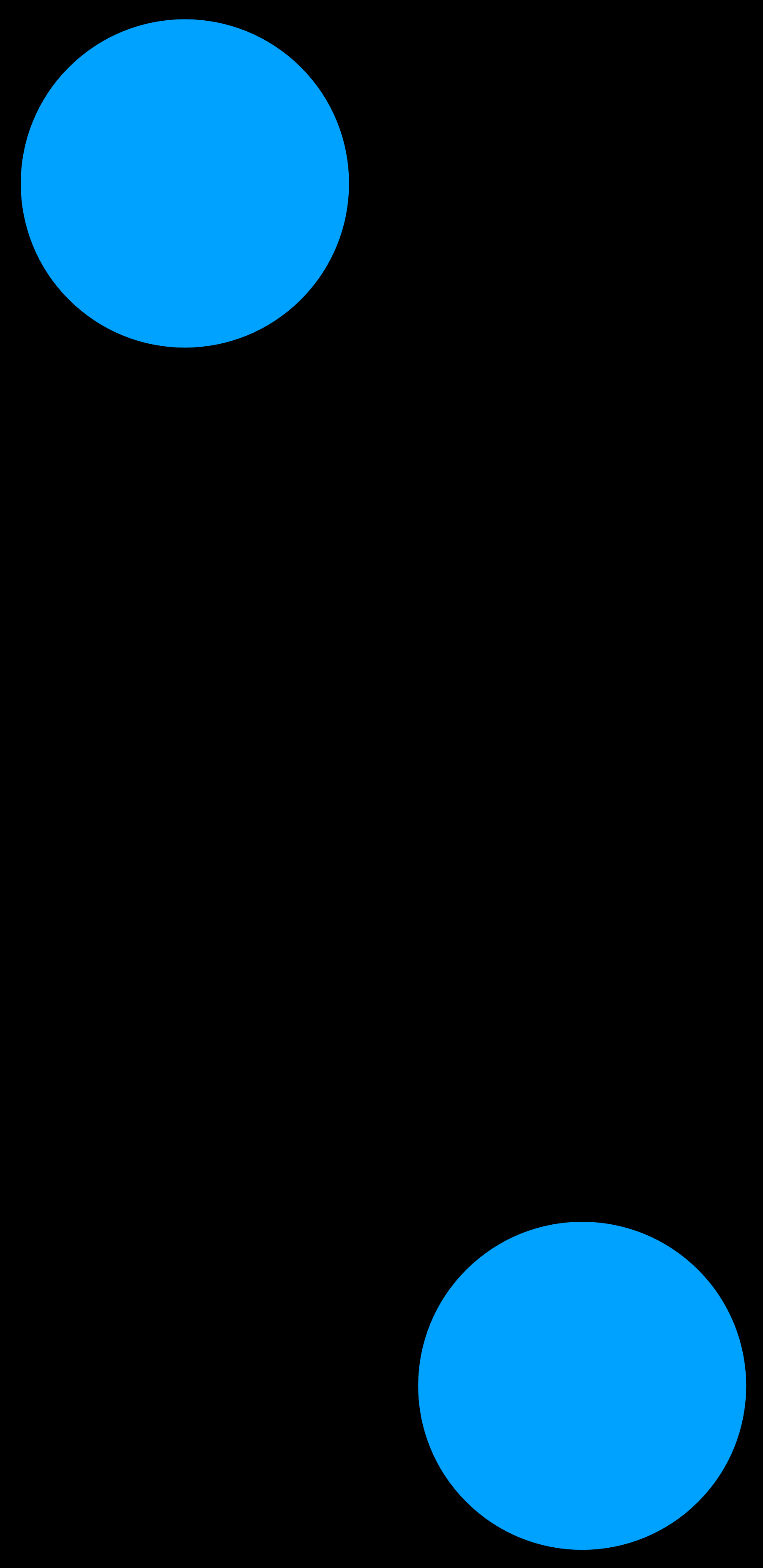


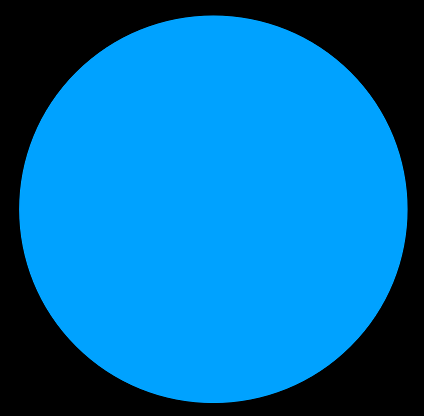












function approximation

approximating $Q(s, a)$, often by a function combining various features, rather than storing one value for every state-action pair

Unsupervised Learning

unsupervised learning

given input data without any additional feedback, learn patterns

Clustering

clustering

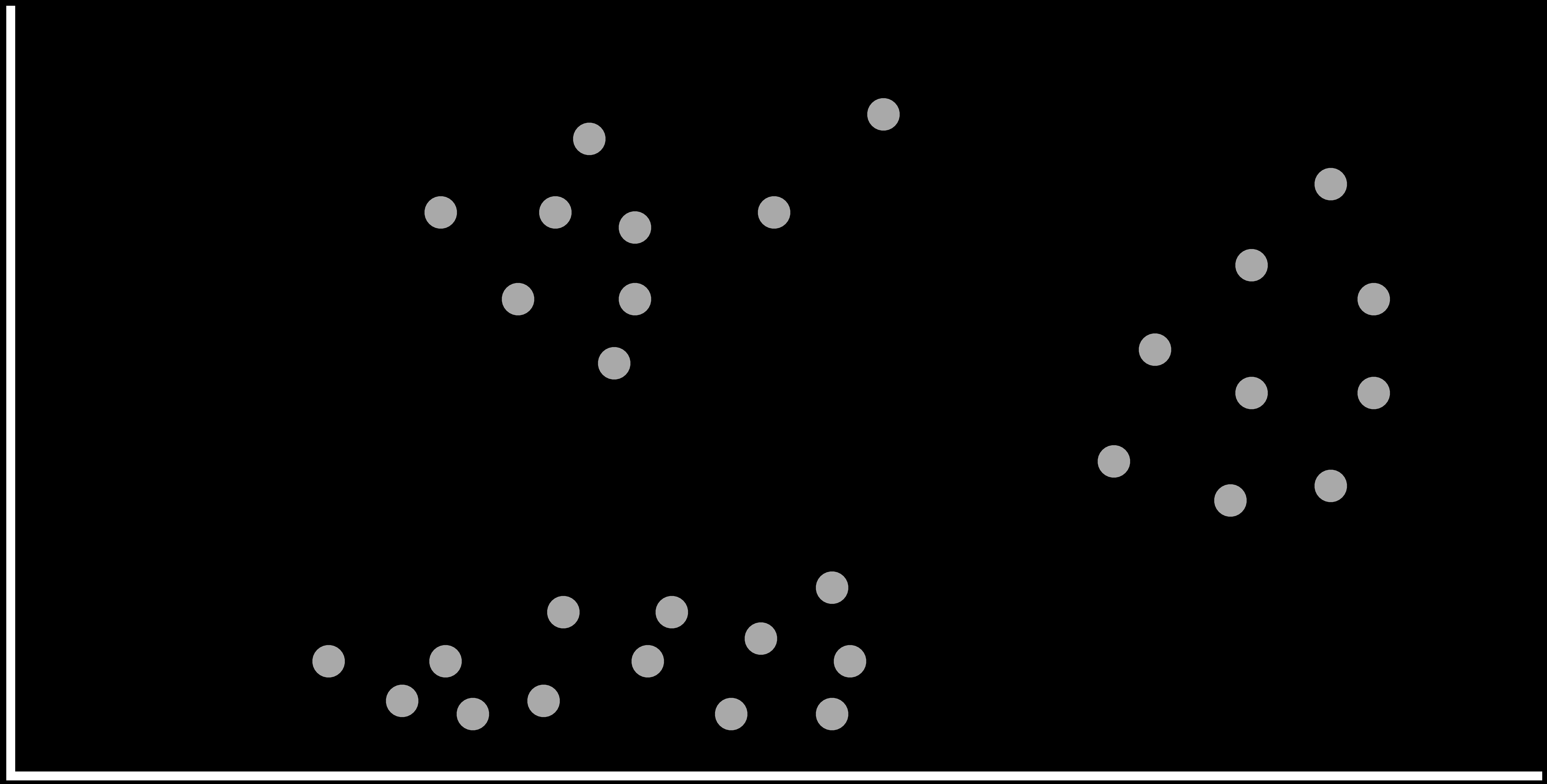
organizing a set of objects into groups in such a way that similar objects tend to be in the same group

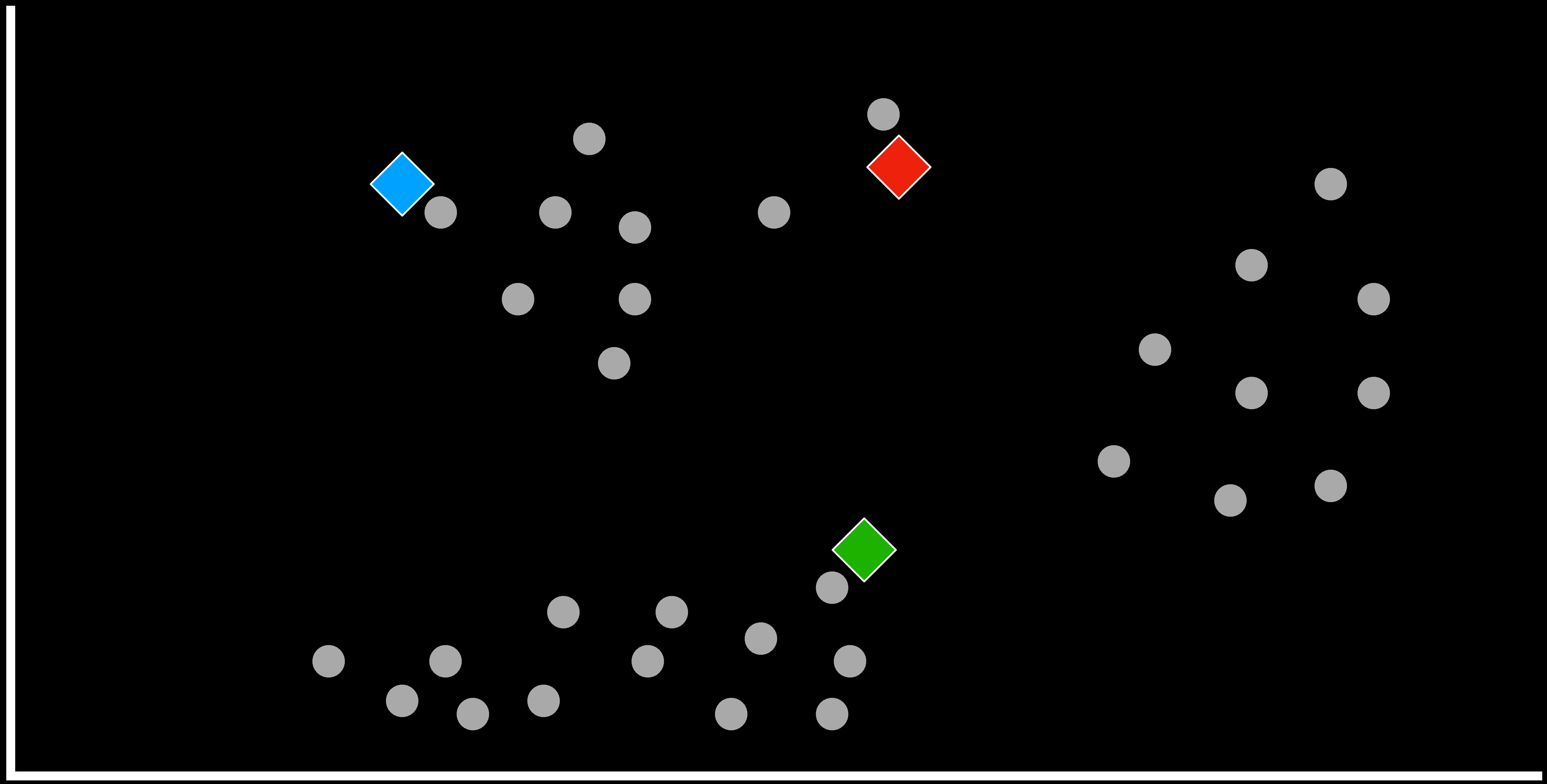
Some Clustering Applications

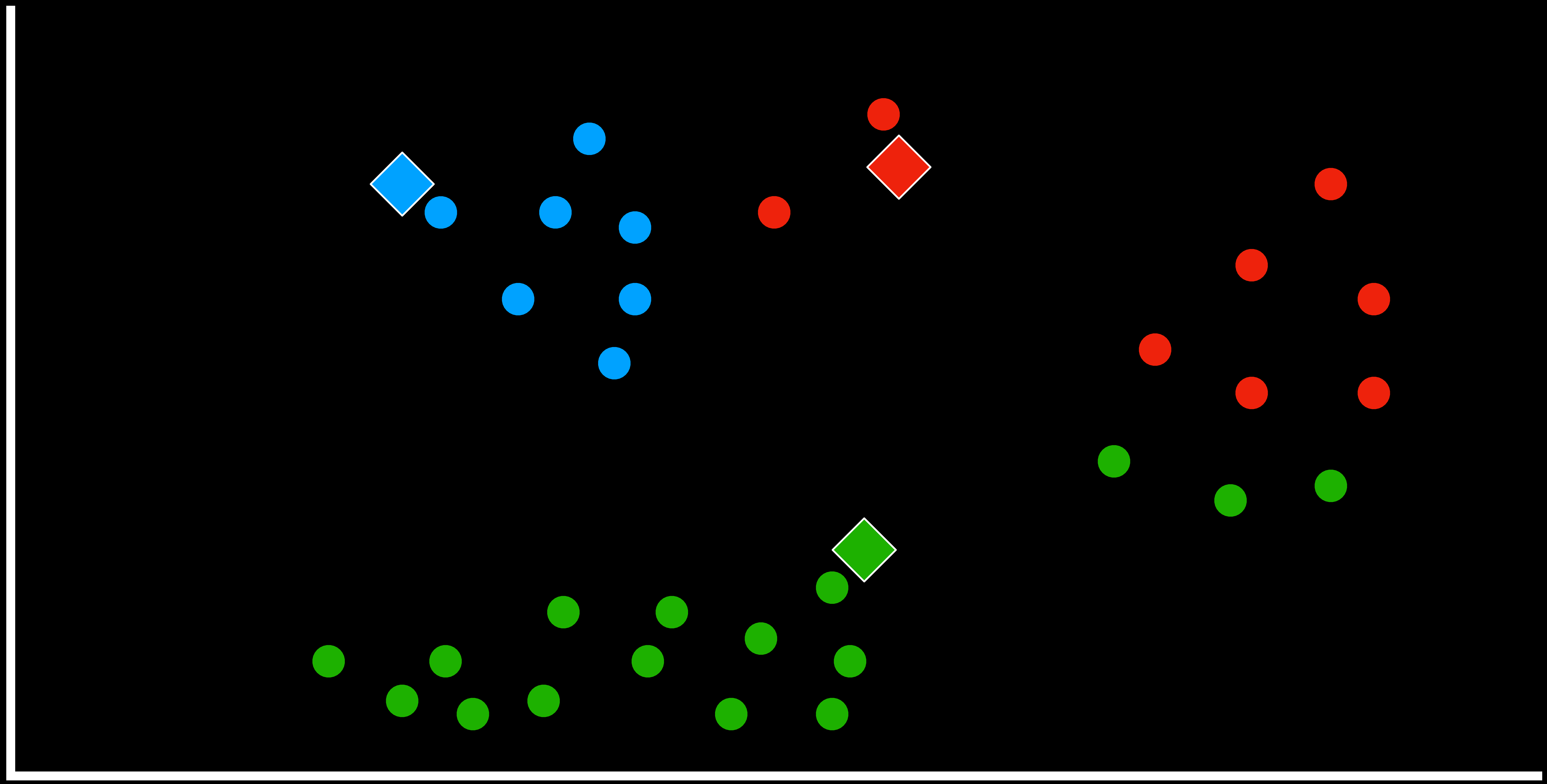
- Genetic research
- Image segmentation
- Market research
- Medical imaging
- Social network analysis.

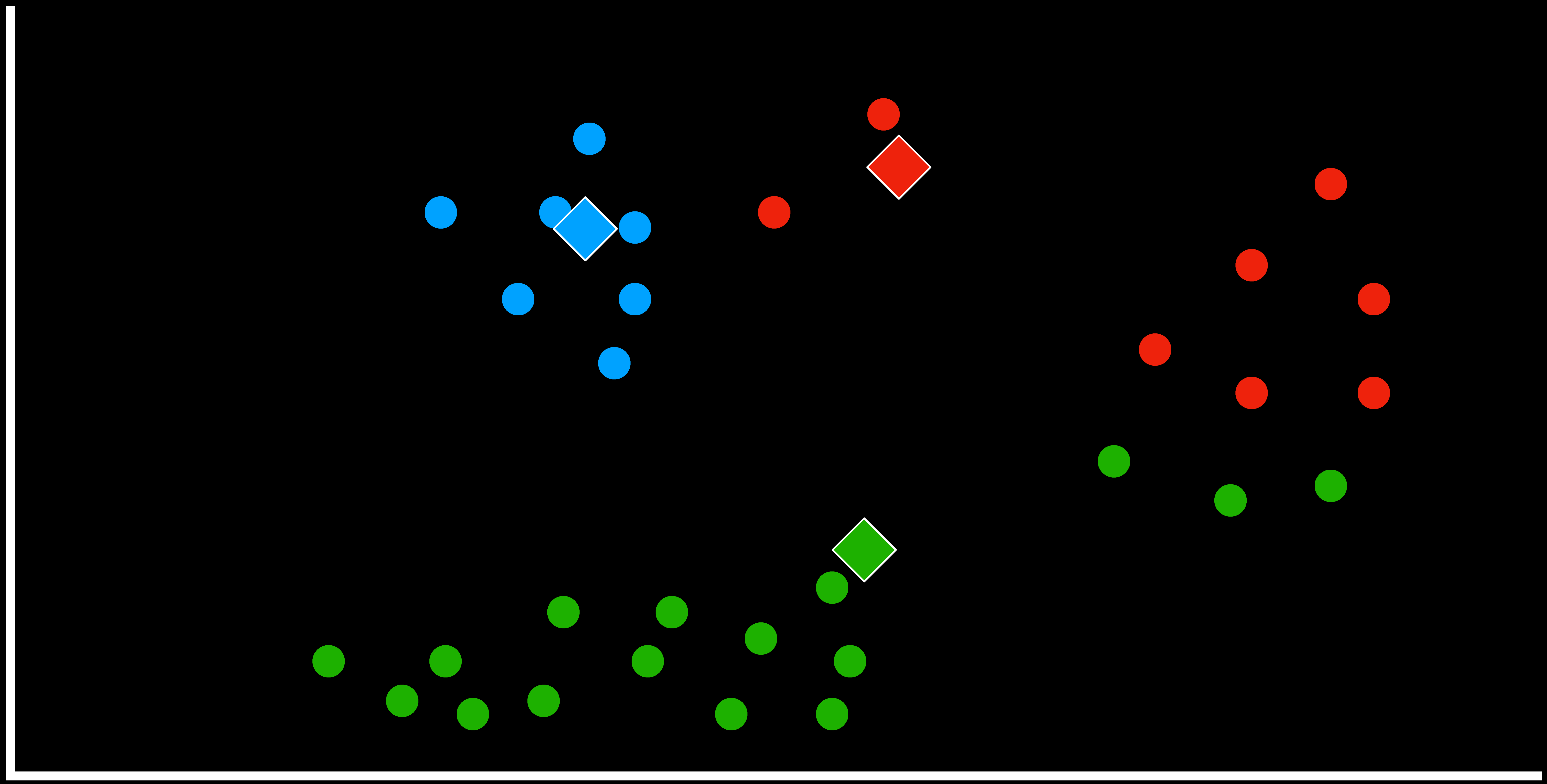
k-means clustering

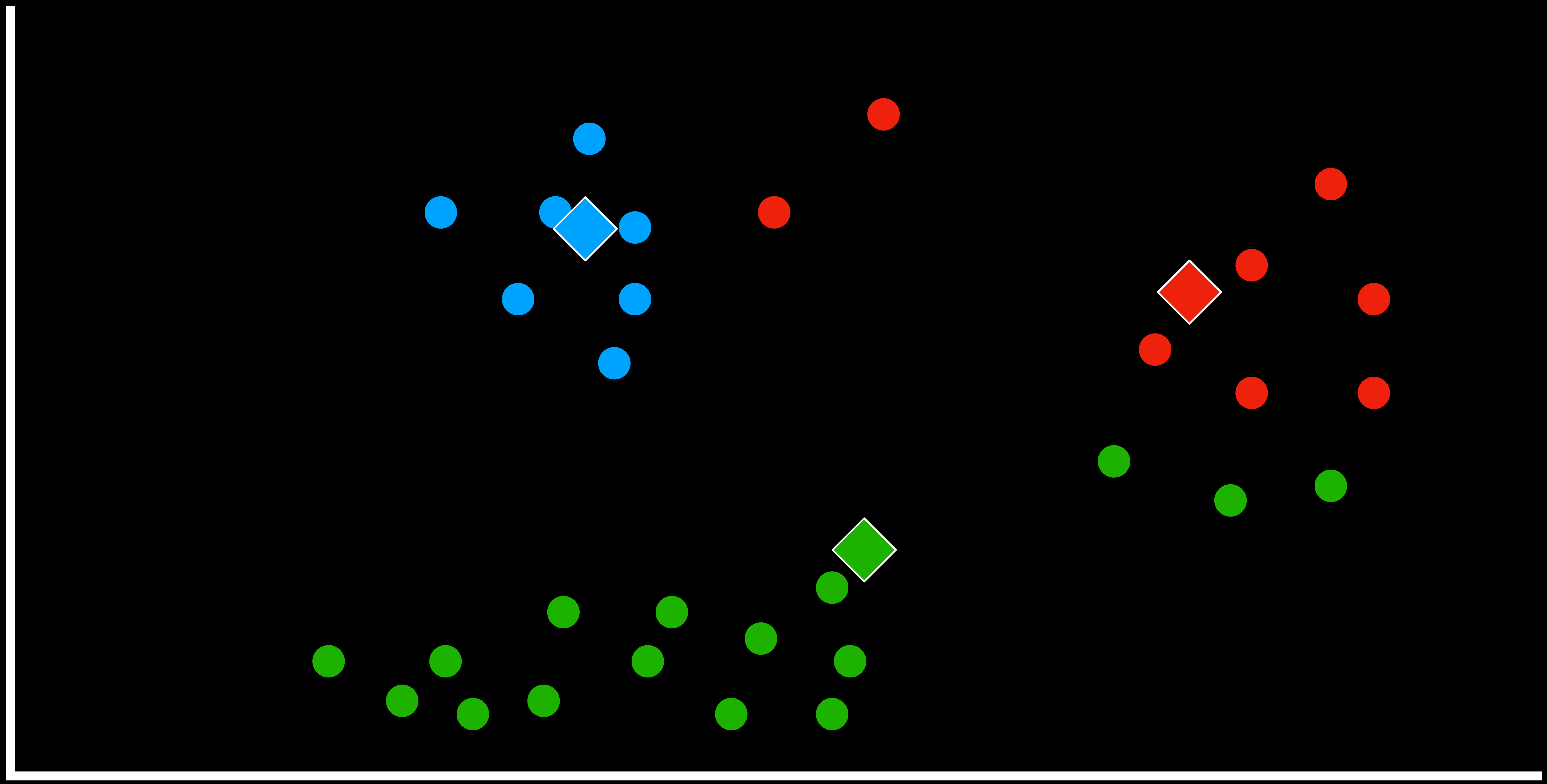
algorithm for clustering data based on repeatedly assigning points to clusters and updating those clusters' centers

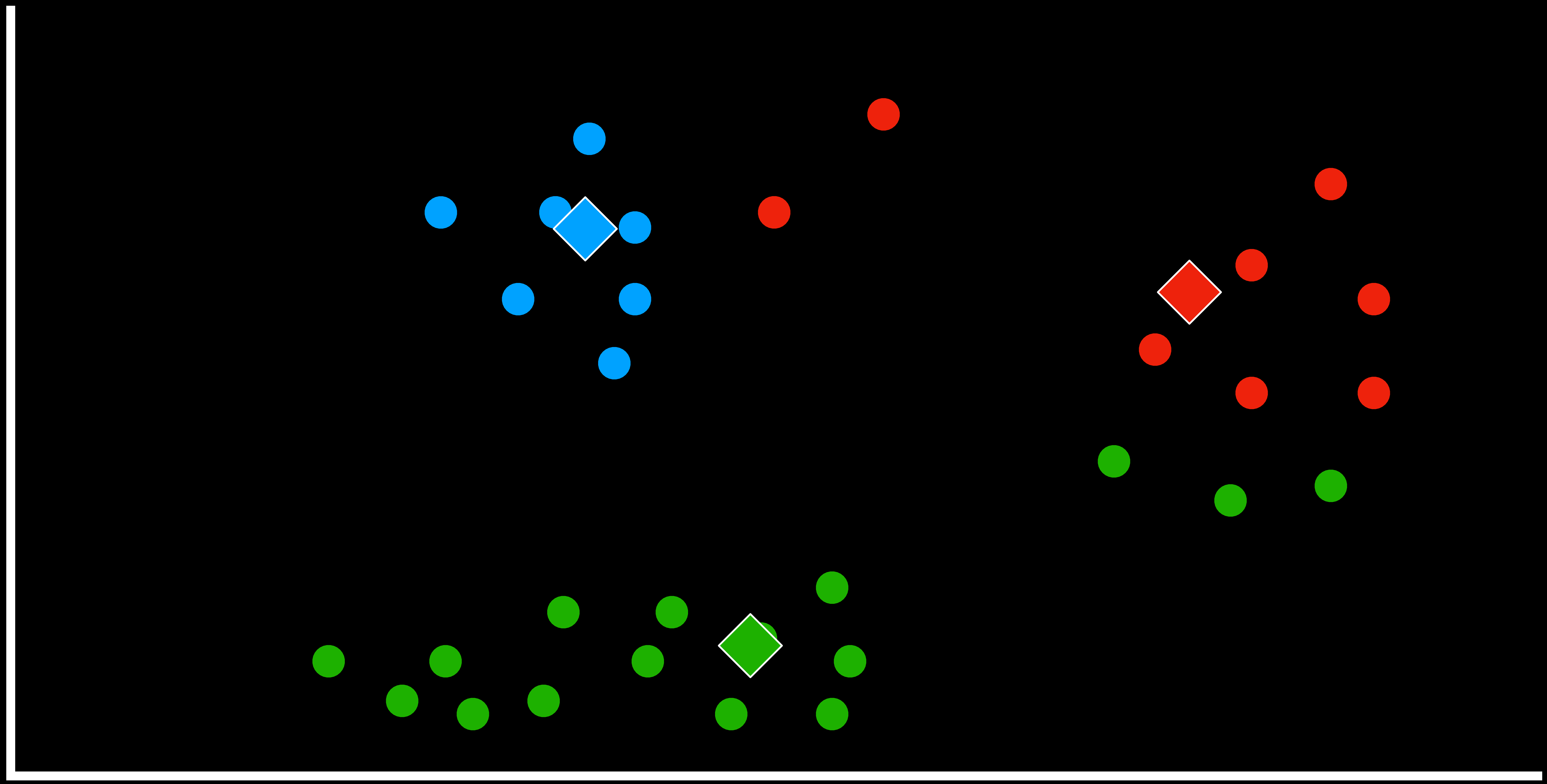


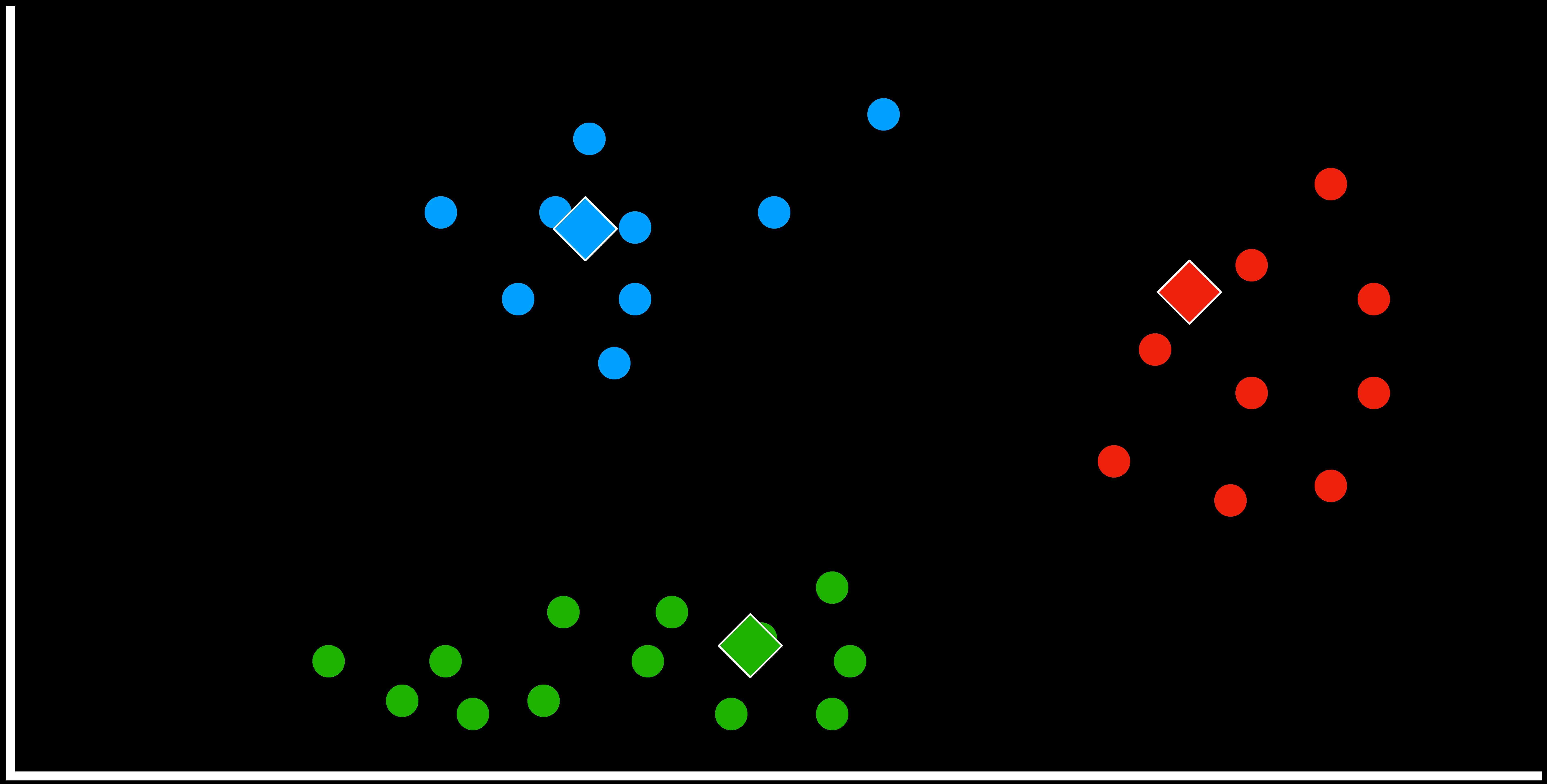


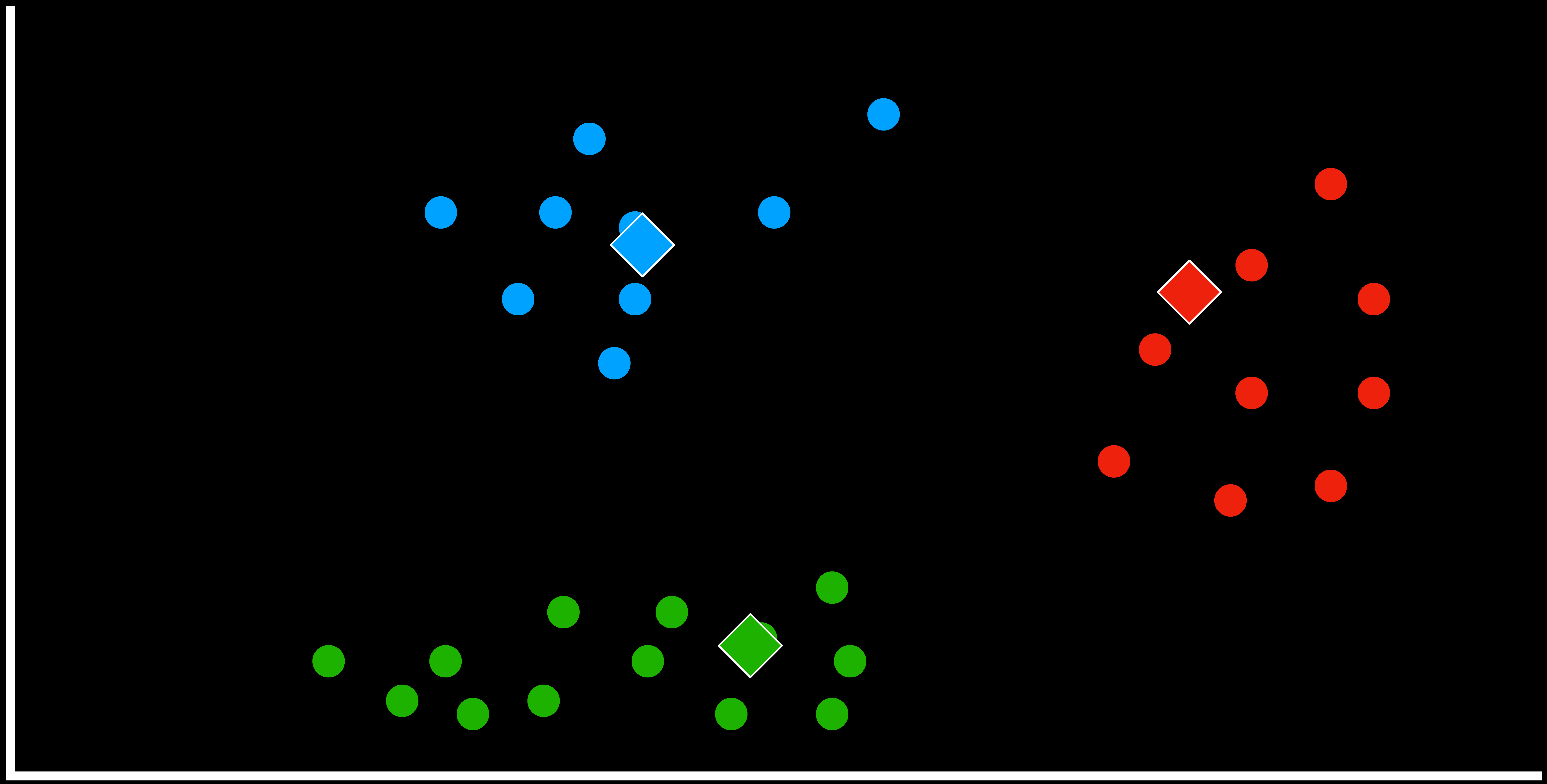


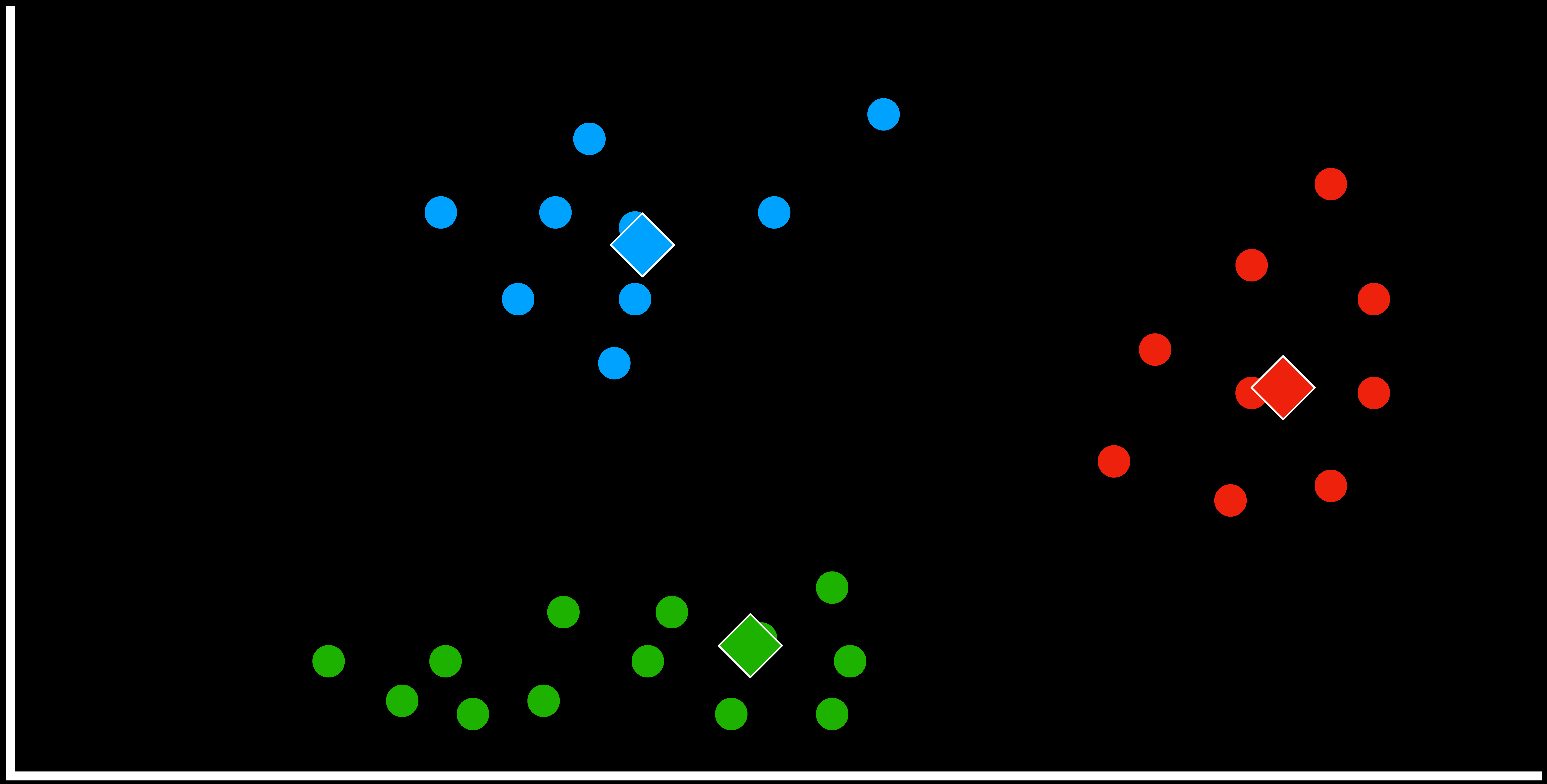


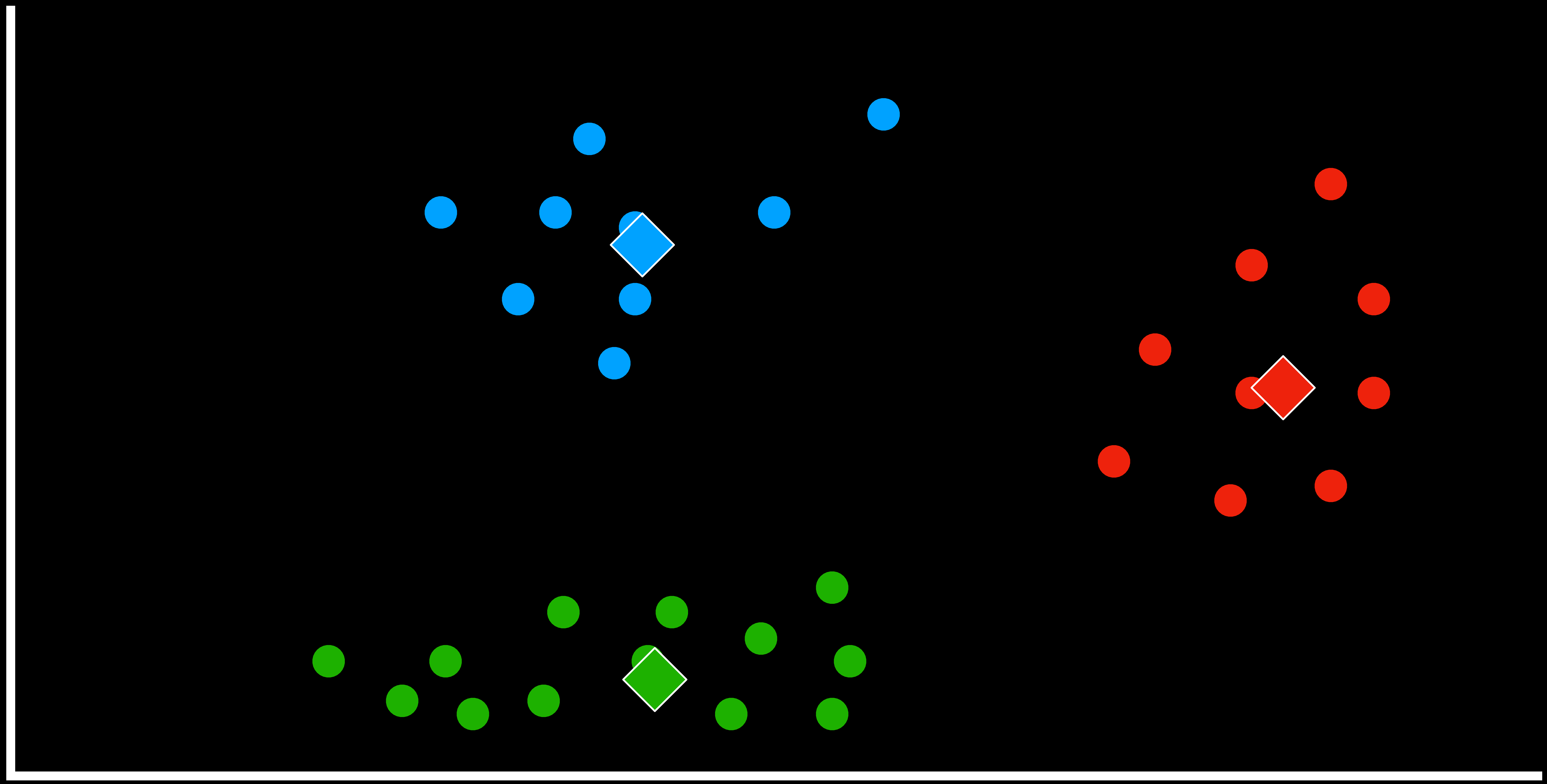


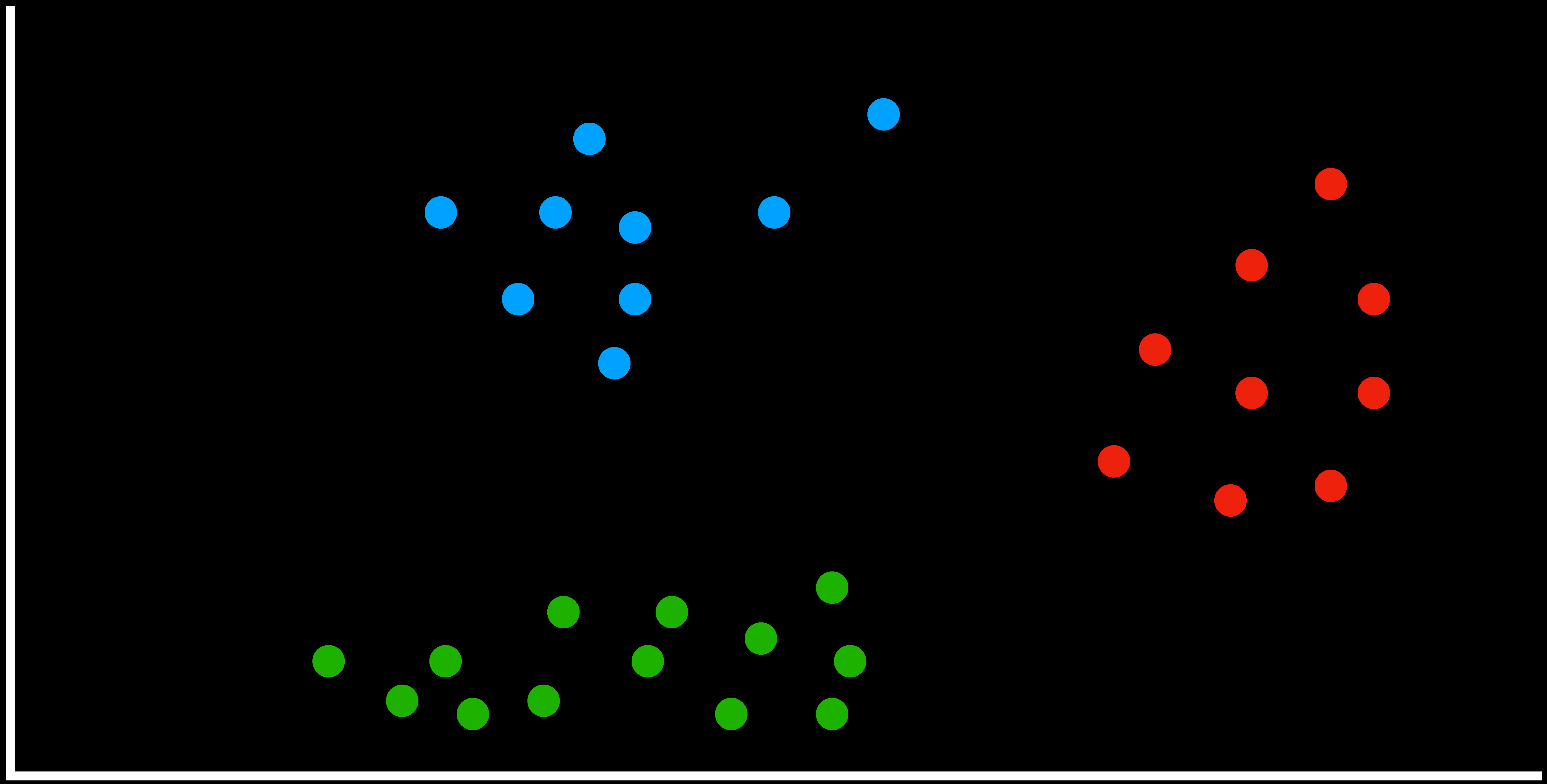












Learning

- Supervised Learning
- Reinforcement Learning
- Unsupervised Learning