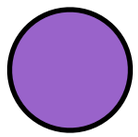
Intro to

Computer Vision

with Prof. Kosta Derpanis

Machine learning



$$\mathbf{x} \in \mathbb{R}^N$$

$m \times n$

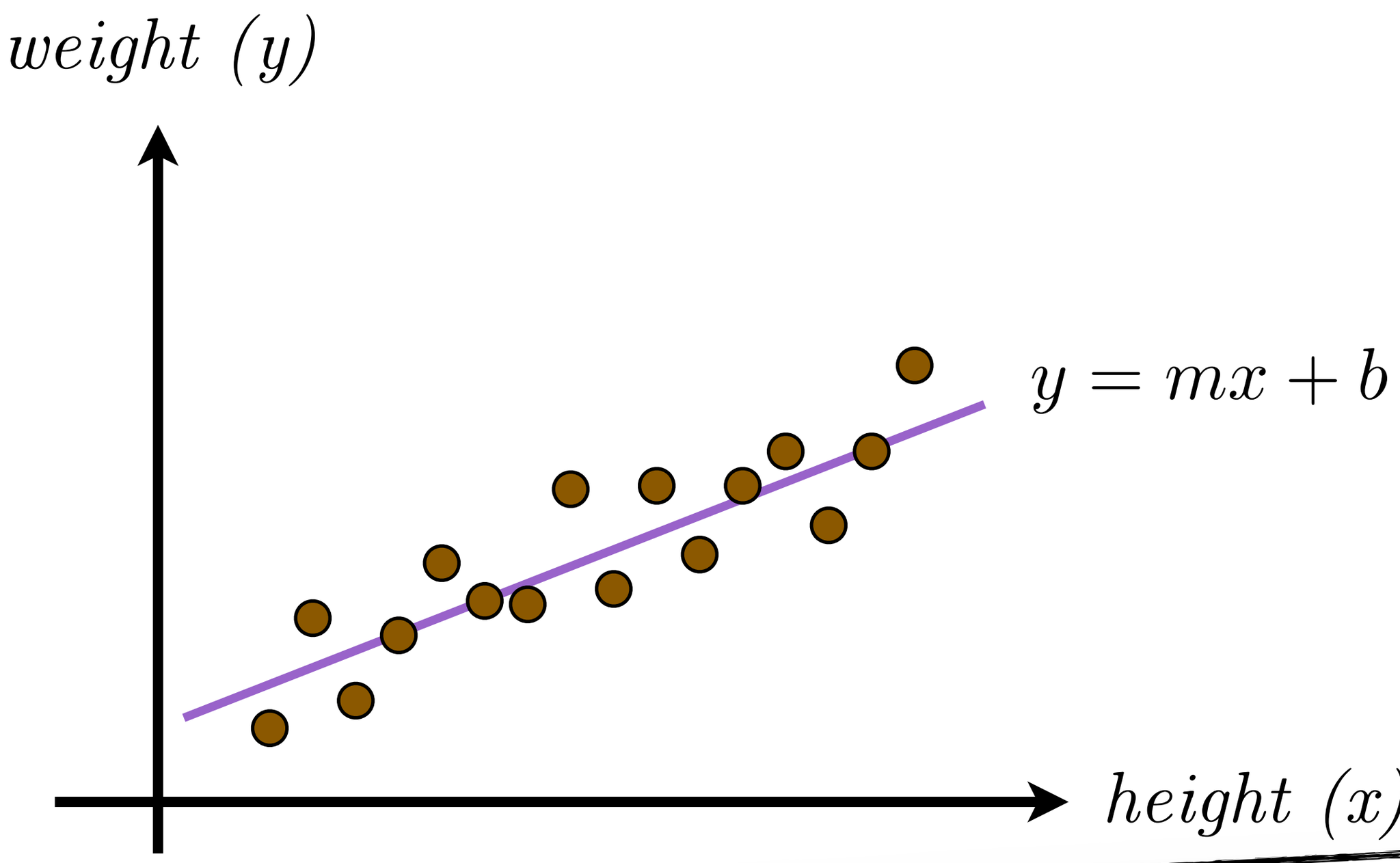
$3mn \times 1$

5

canonical learning problems

1

regression

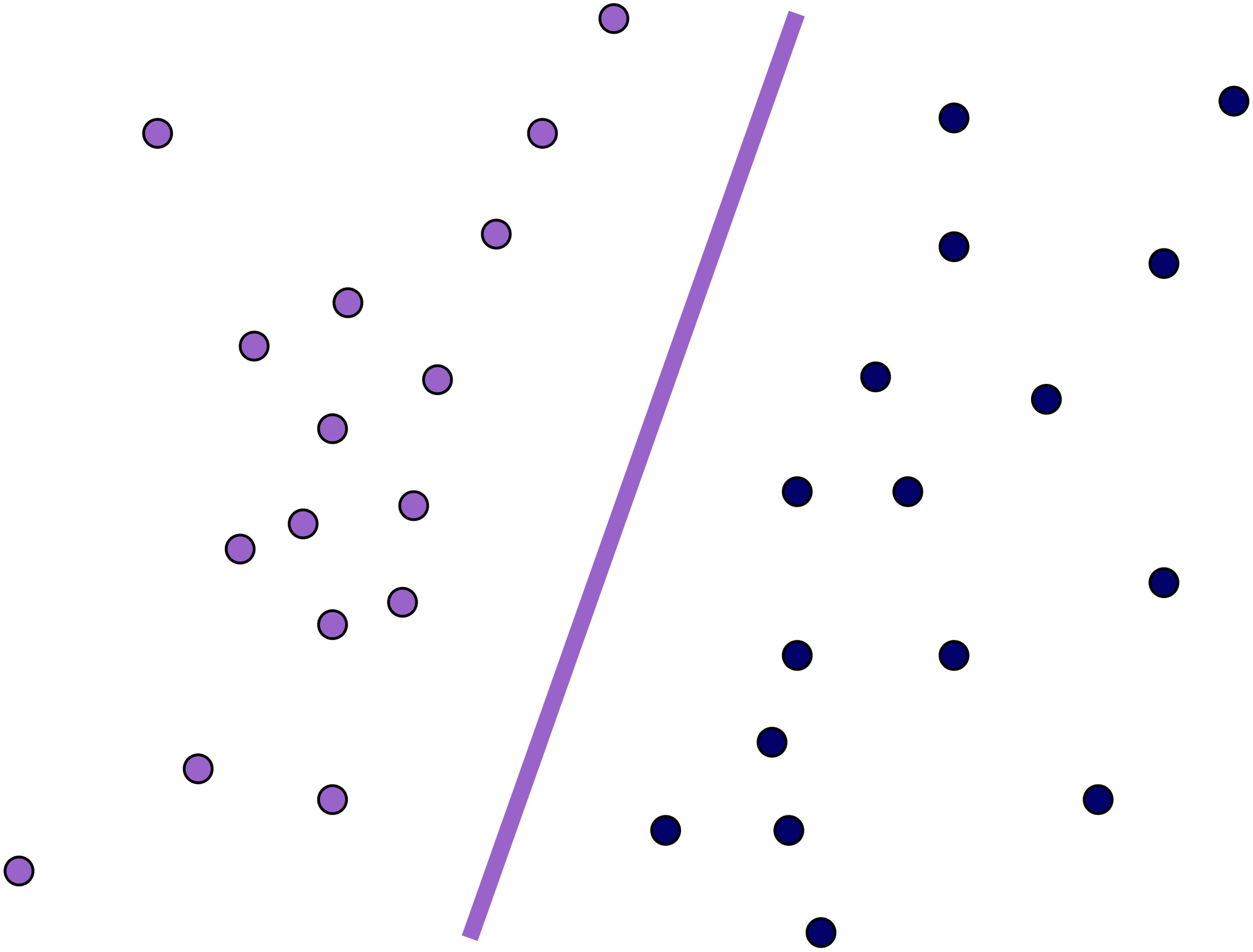


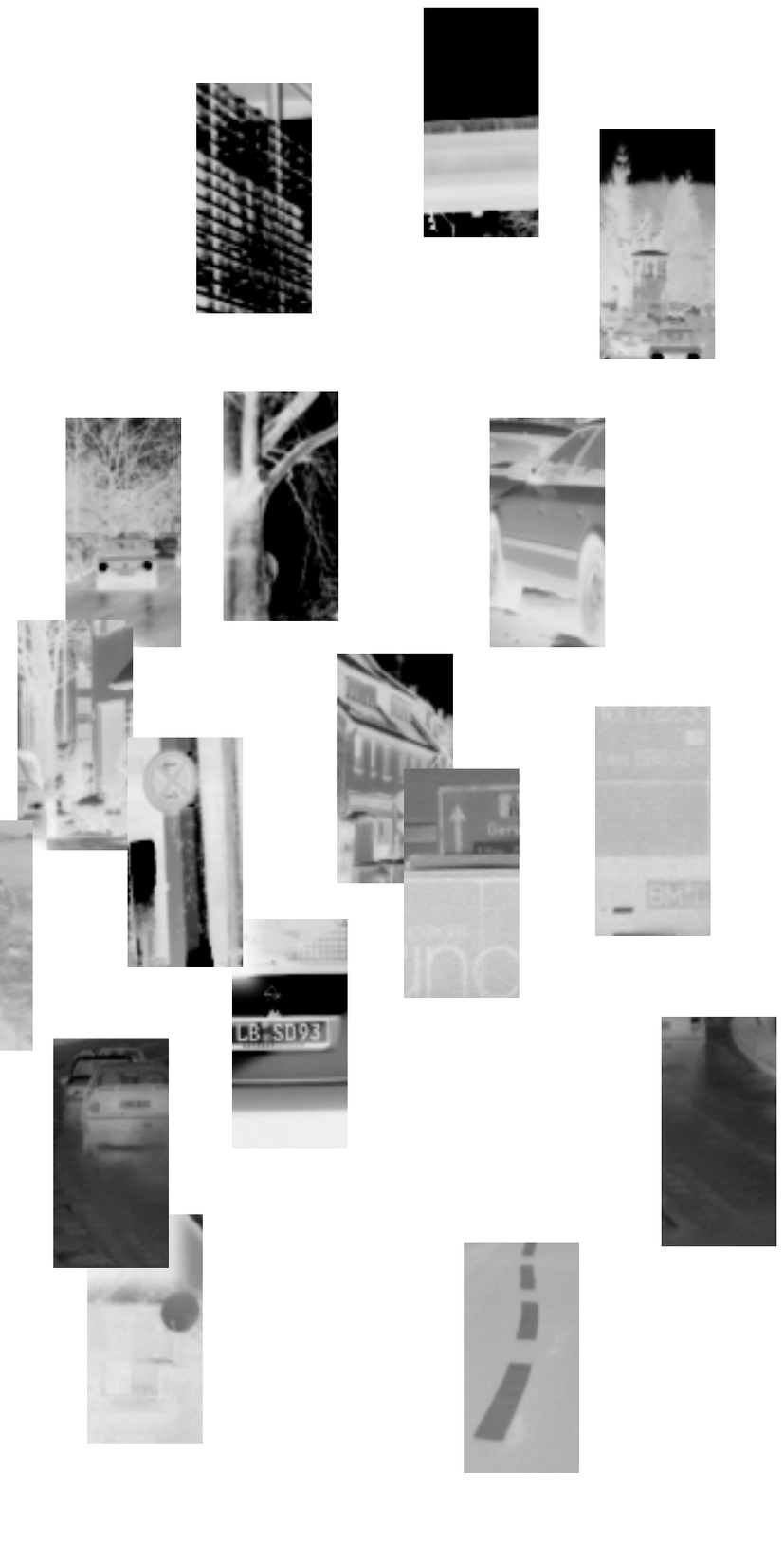
estimate the parameters of the “best” fitting function

2

classification

assign input to one of two or more discrete classes

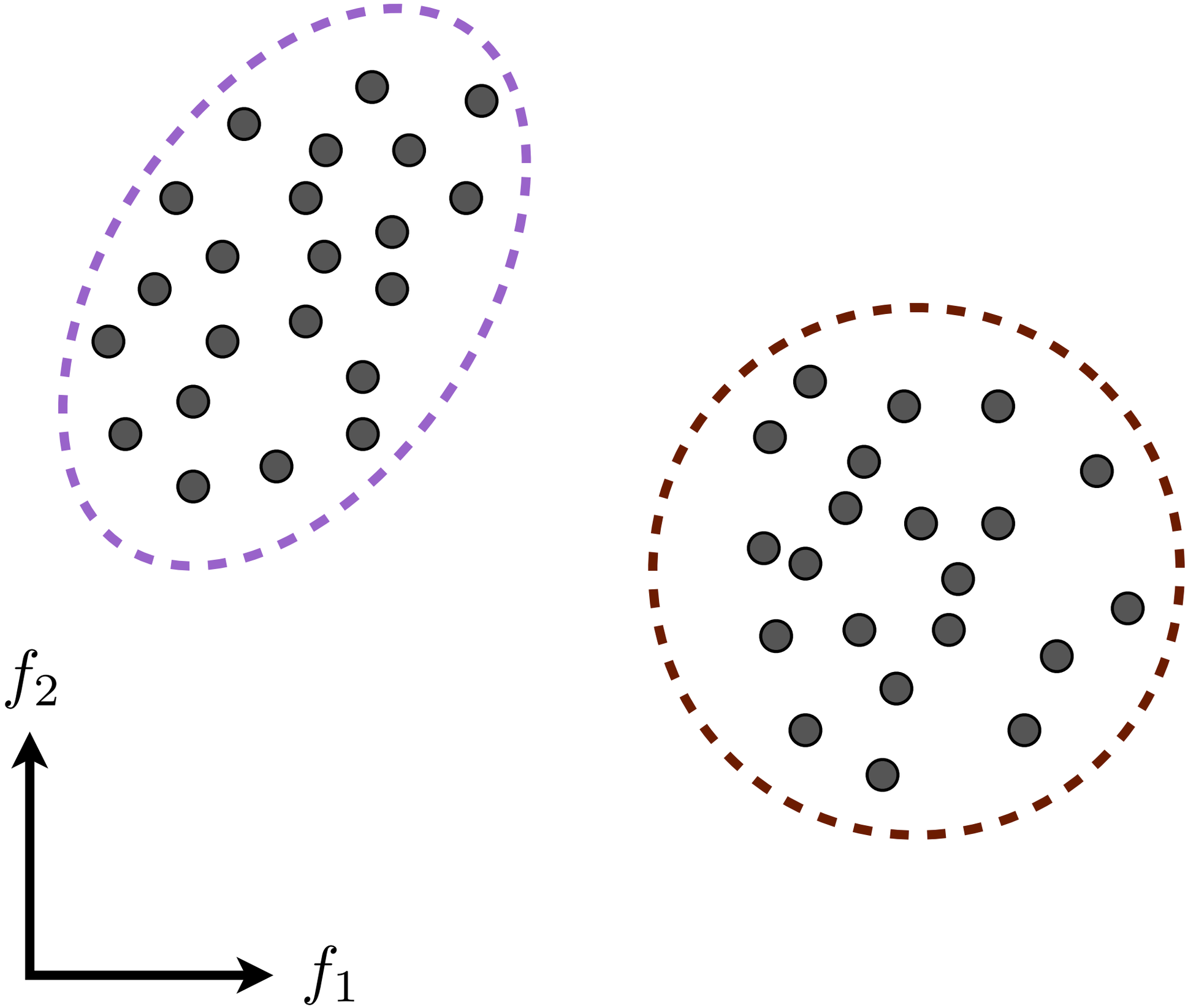



LB SD93

3

clustering

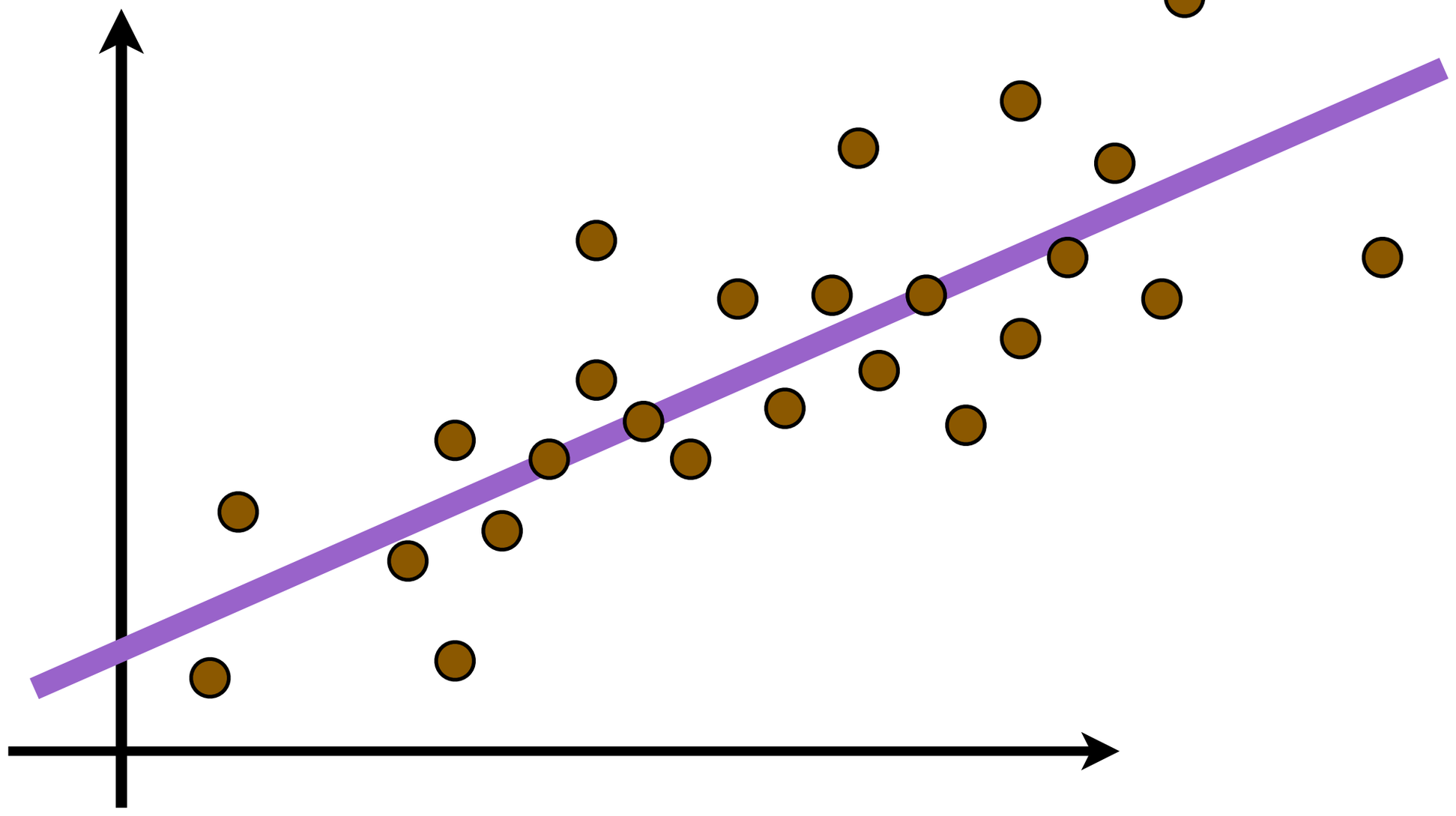
find hidden discrete structure in unlabelled data

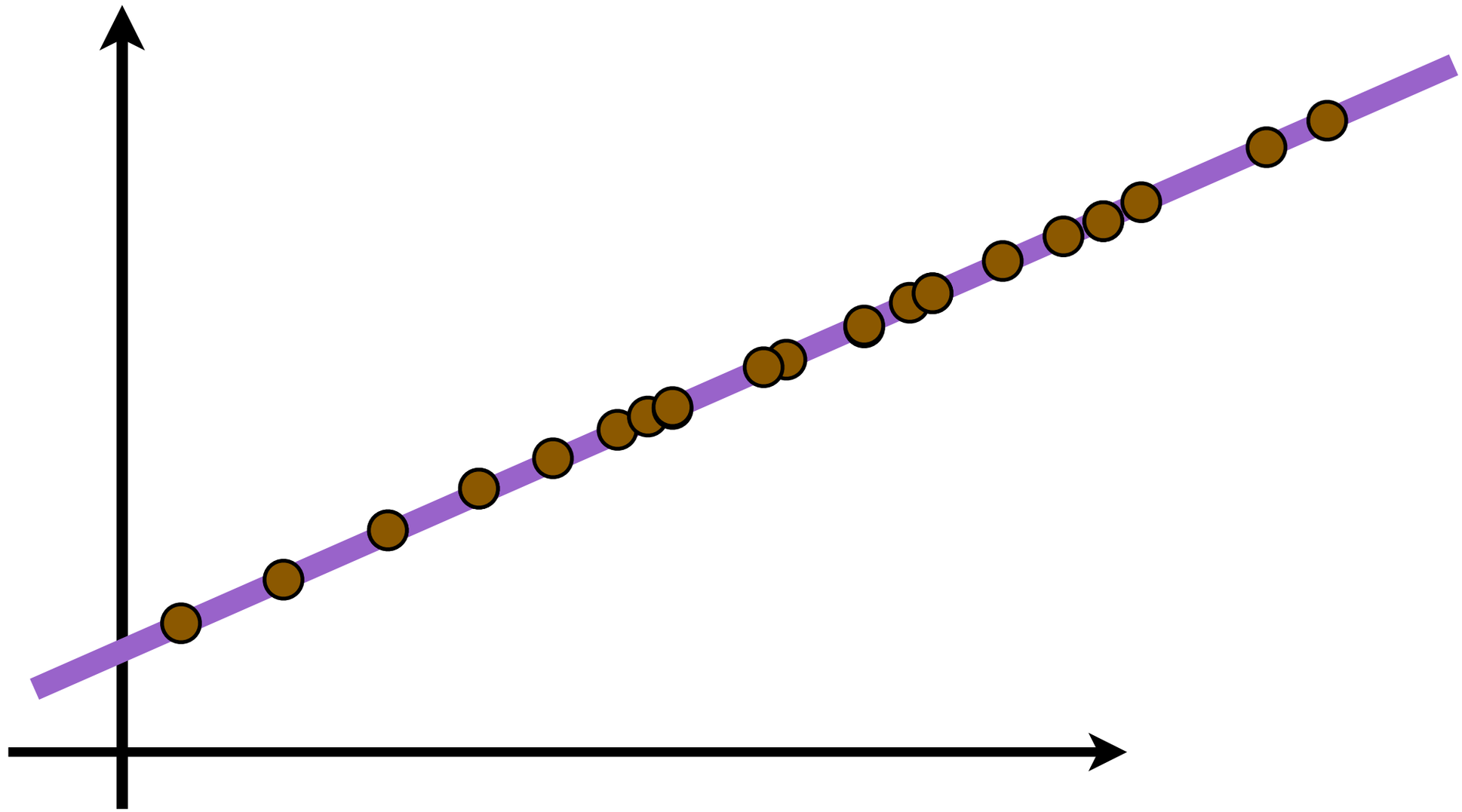

f_2
f_1

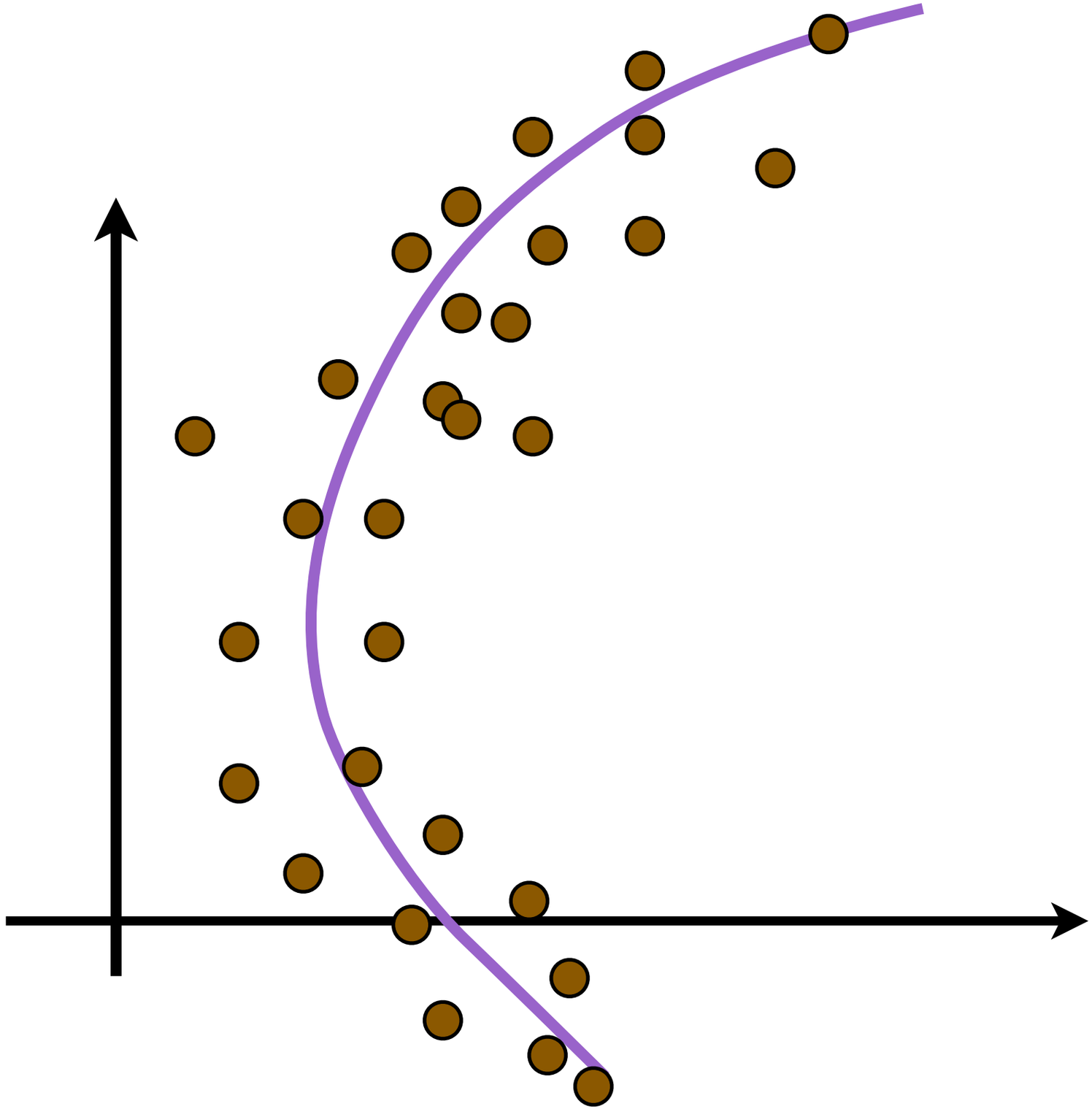
4

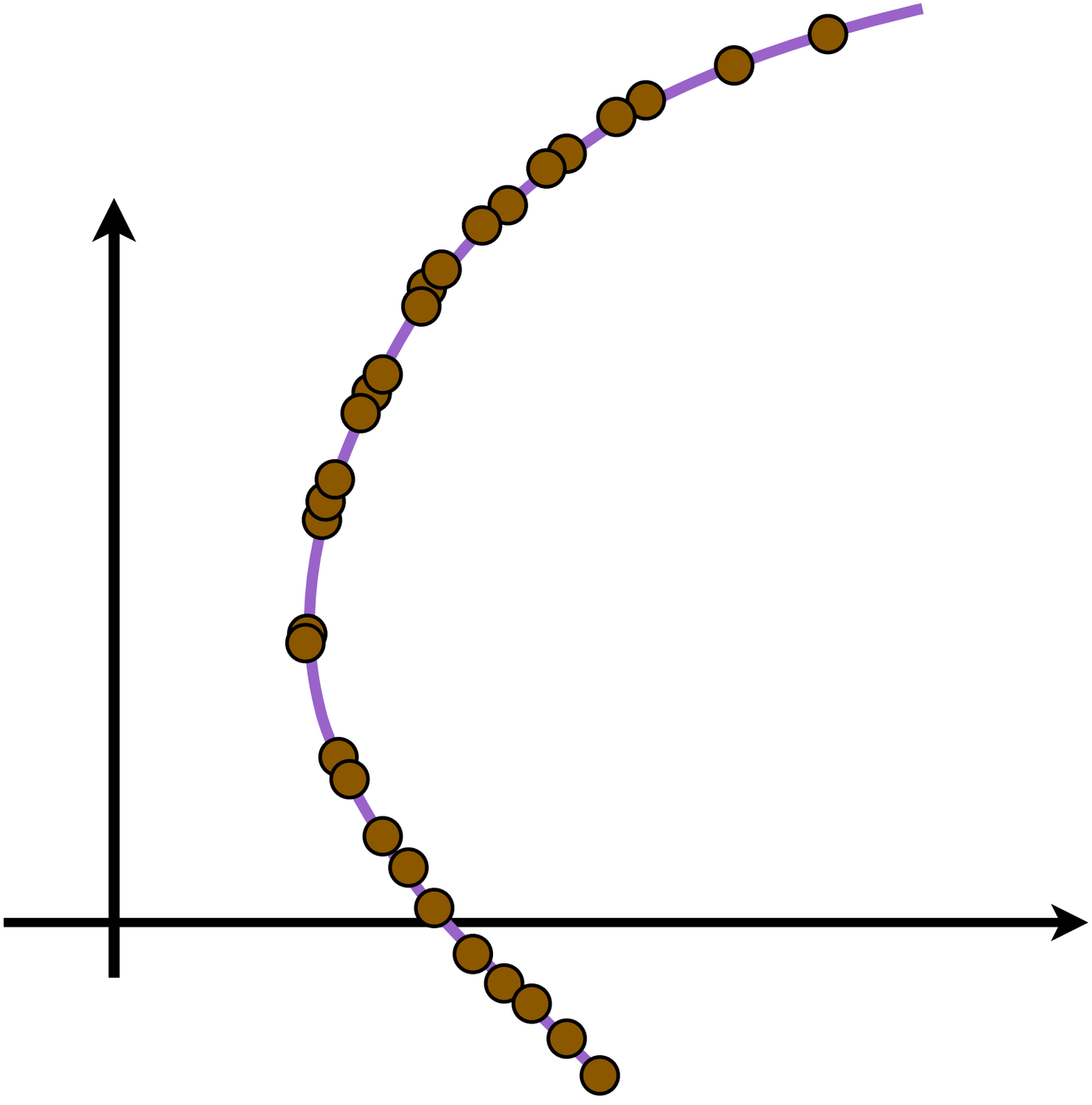
dimensionality reduction

find hidden continuous structure in data







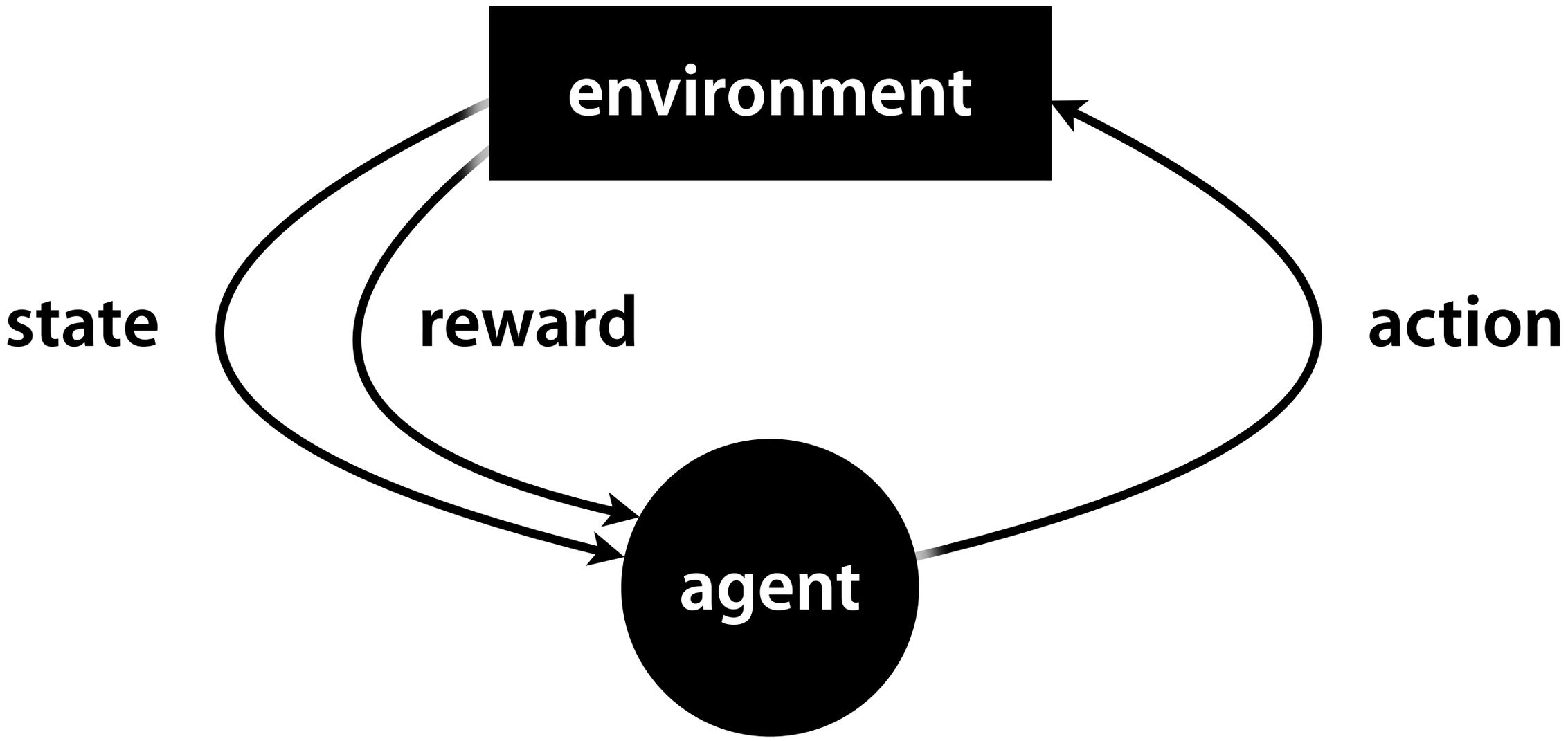


	supervised	unsupervised
discrete	classification	clustering
continuous	regression	dimensionality reduction

5

reinforcement learning

learning by interacting with environment


environment
state
reward
action
agent

240 minutes of training

Image Recognition

image classification

assign an image to a known class based on the objects present in the image

What objects are present in the image?

ImageNet Challenge

ImageNet Challenge

1000 categories, a million images

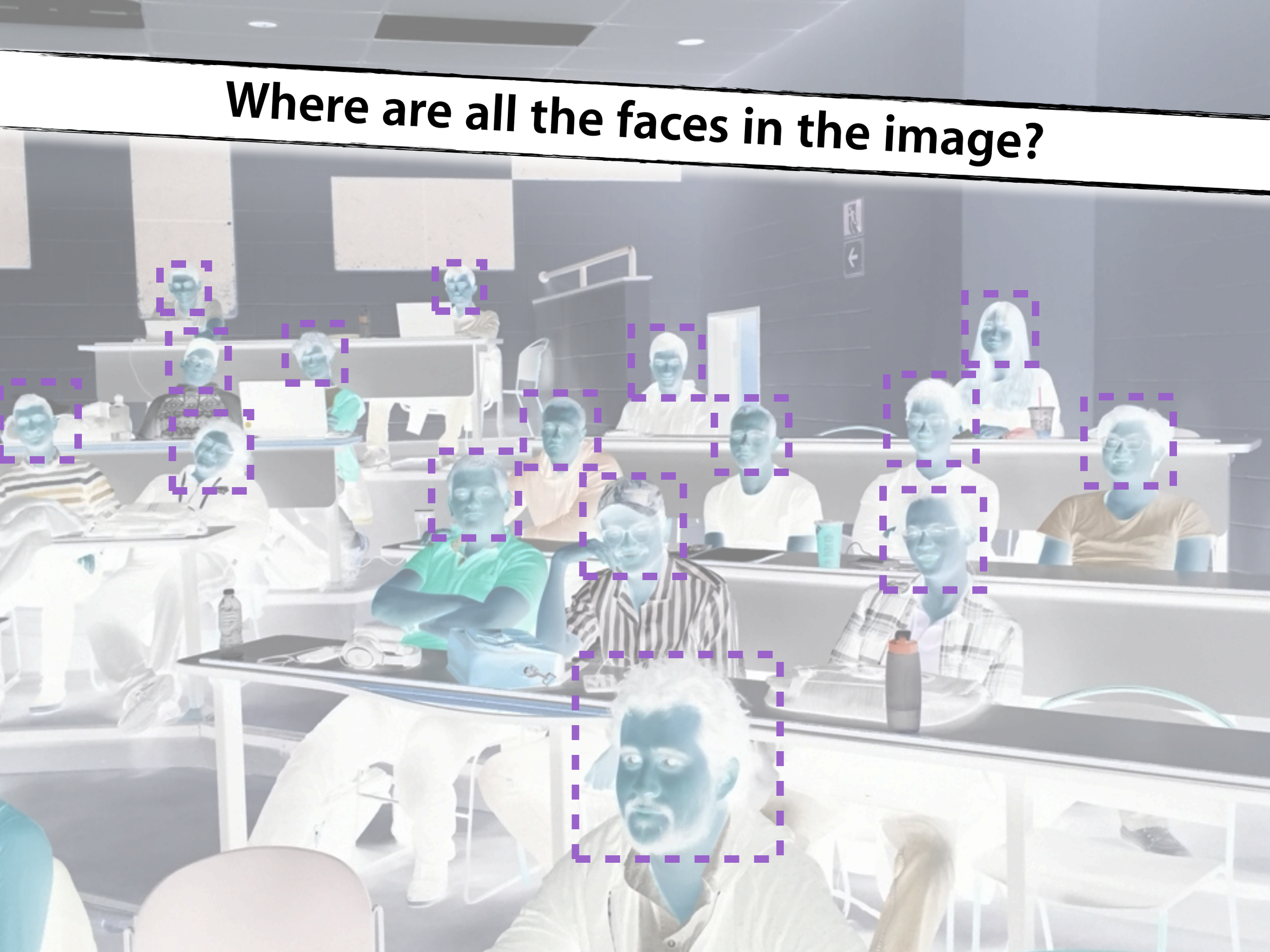
scene classification

assign an image to a known class based on the scene in the image

object detection

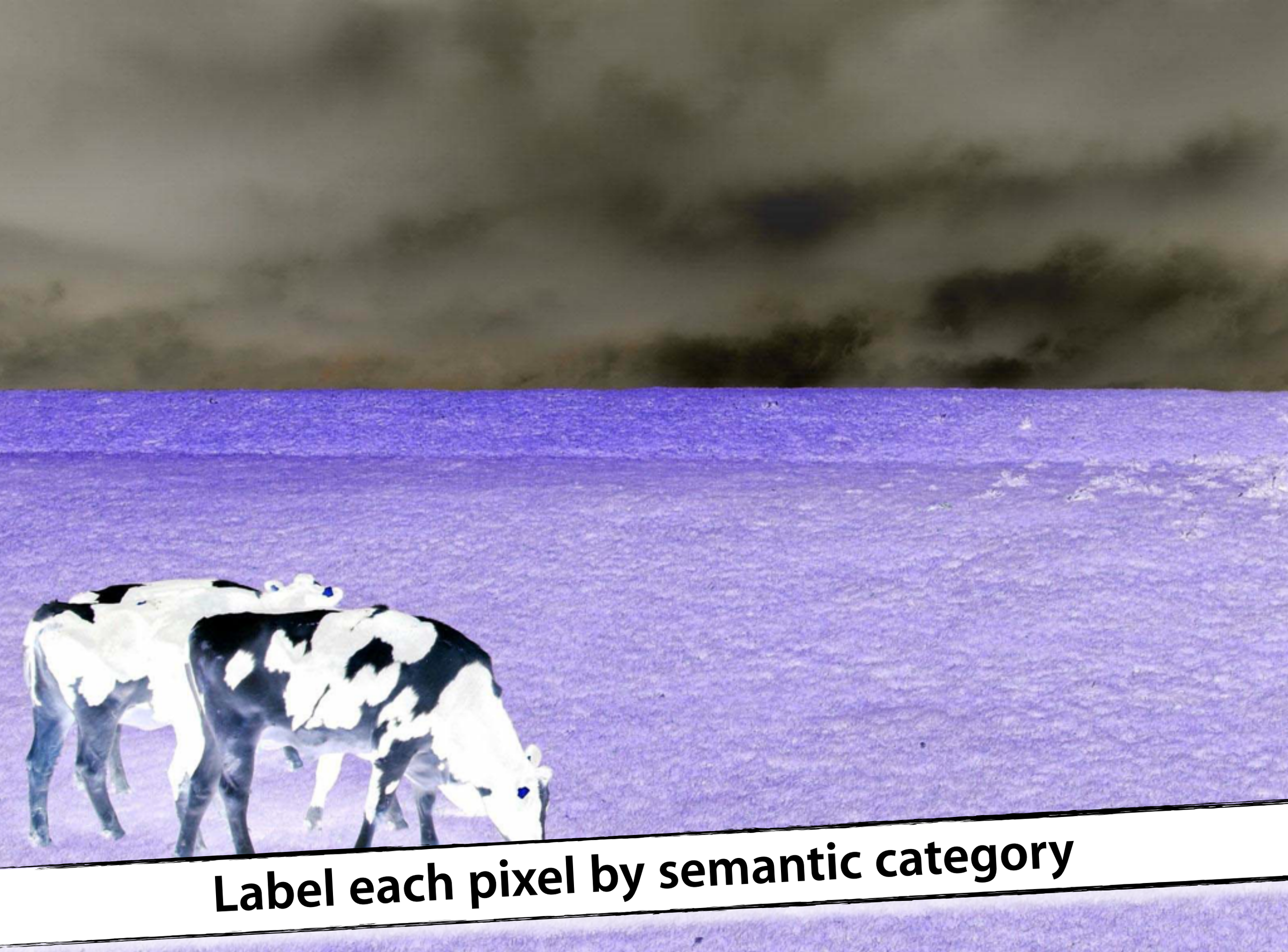
locate where all object instances of known classes are present in the image

Where are all the faces in the image?



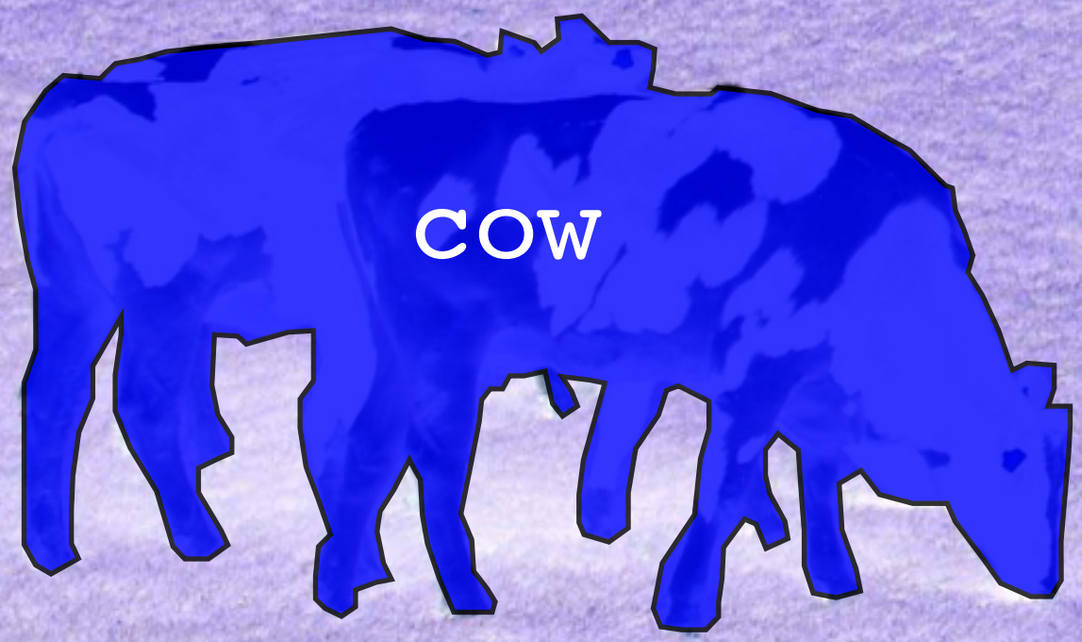
semantic segmentation

assign each image pixel to a known class



Label each pixel by semantic category

sky



grass

image captioning

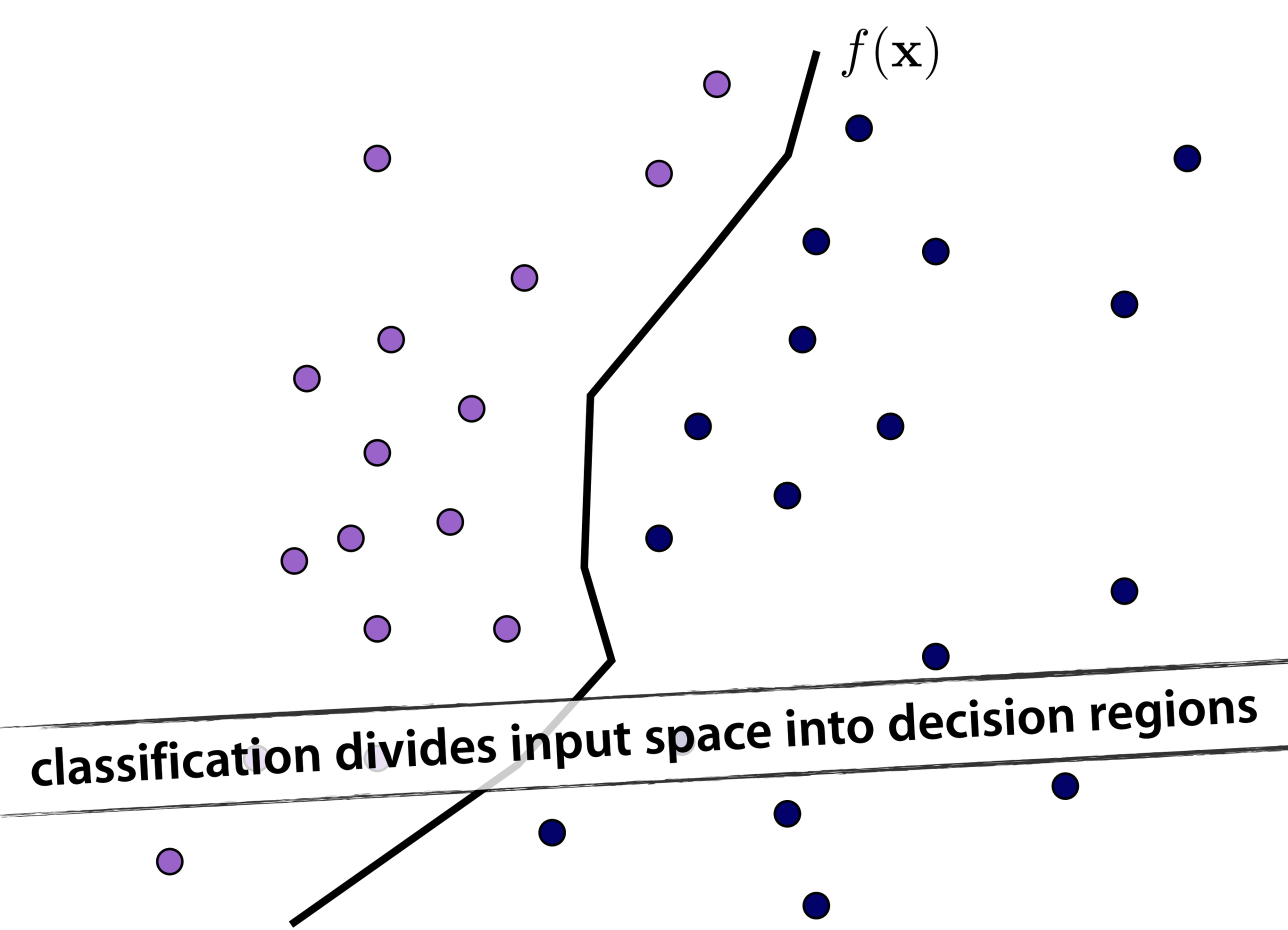
provide a short sentence describing the image

“a group of zebras drinking water”

Classification

Given a training set of N observations

$$\{(\mathbf{x}_i, y_i)\}_{i=1}^{N} \quad \text{where} \quad \mathbf{x}_i \in \mathbb{R}^D \quad \text{and} \quad y_i \in \{-1, 1\}$$



classification divides input space into decision regions

Support Vector Machines

Restricted Boltzmann Machine

Naive Bayes

Bayesian Network

Convolutional Neural Network

Randomized Forest

Boosted Decision Tree

AdaBoost

K-Nearest Neighbour

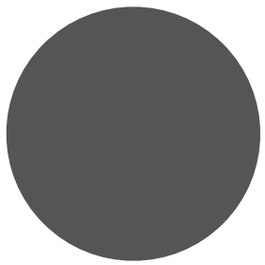
Decision Tree

K-Nearest Neighbour

Classification

For each test point, find the K nearest samples in the training data

Classify the point according to the majority vote of their class label



test point

1- Nearest Neighbour

1- Nearest Neighbour

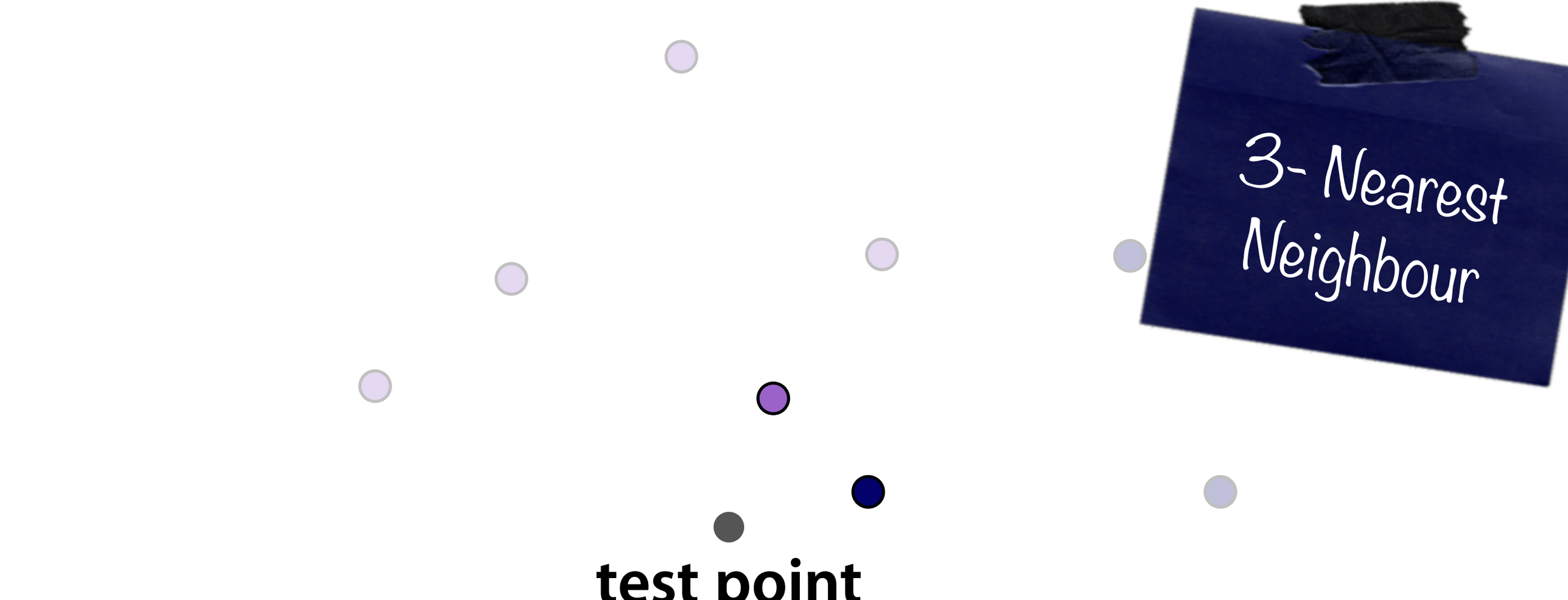
test point

test point

1- Nearest Neighbour

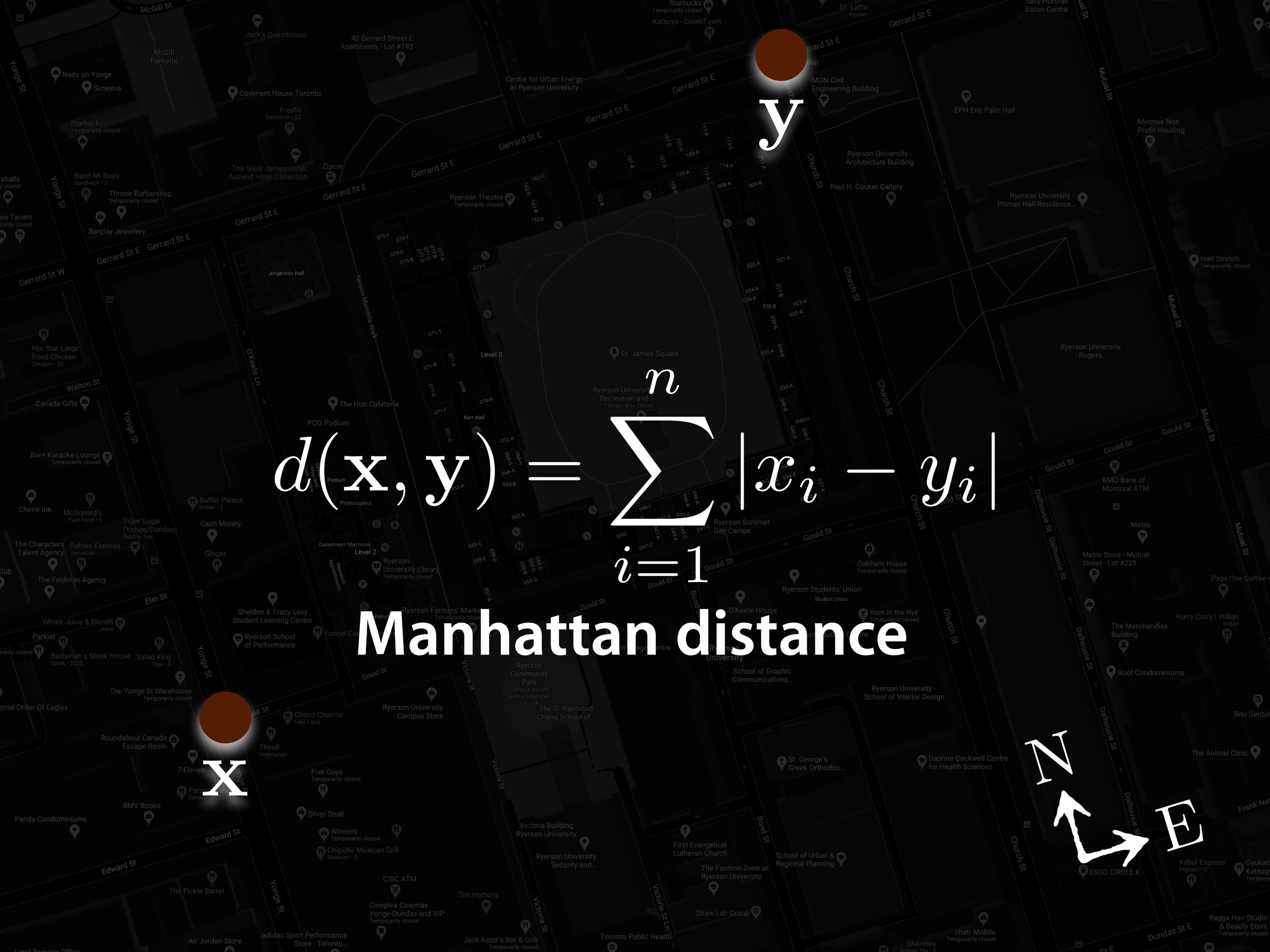
test point

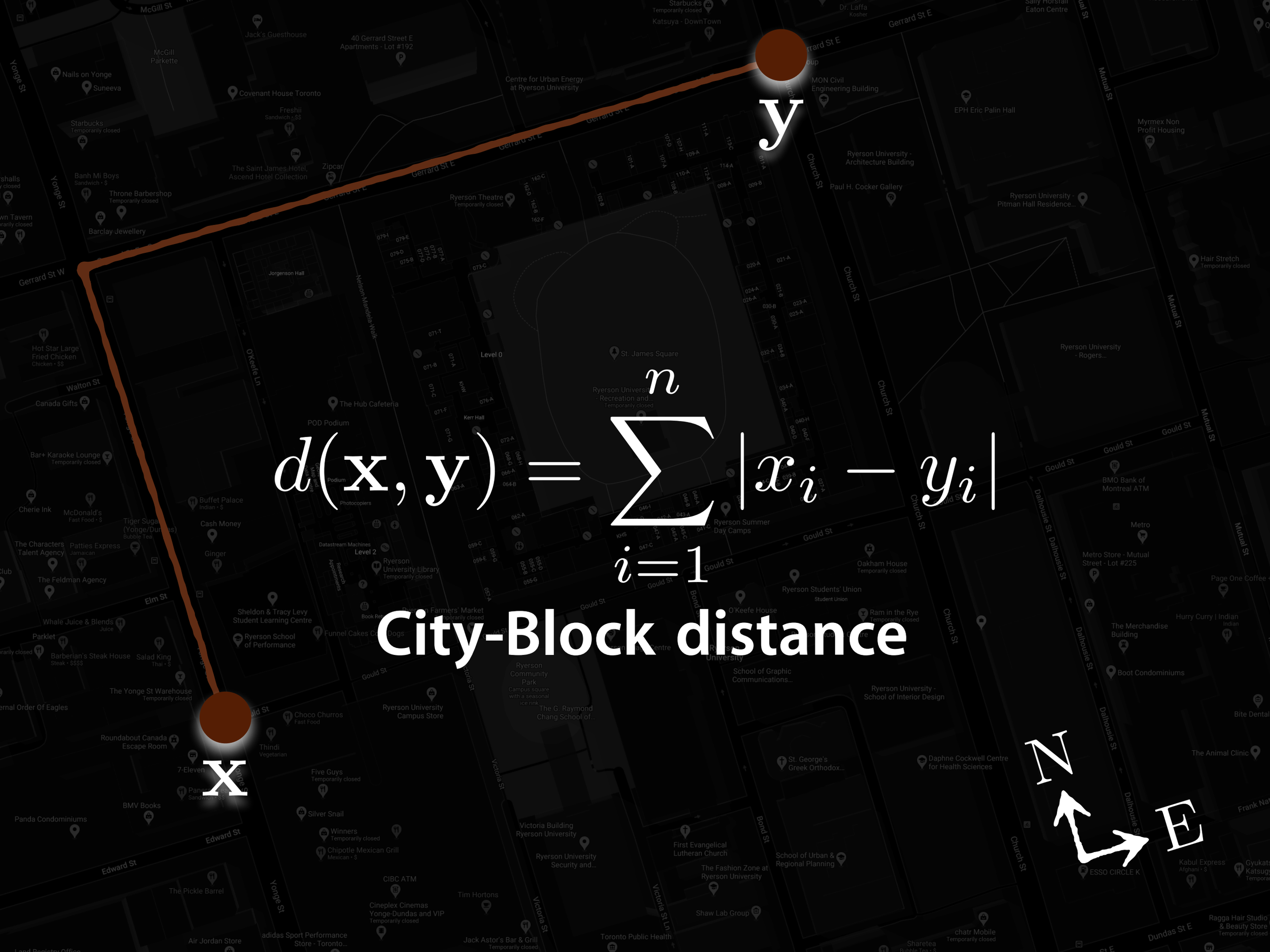
1- Nearest Neighbour



classify point according to the majority vote of labels

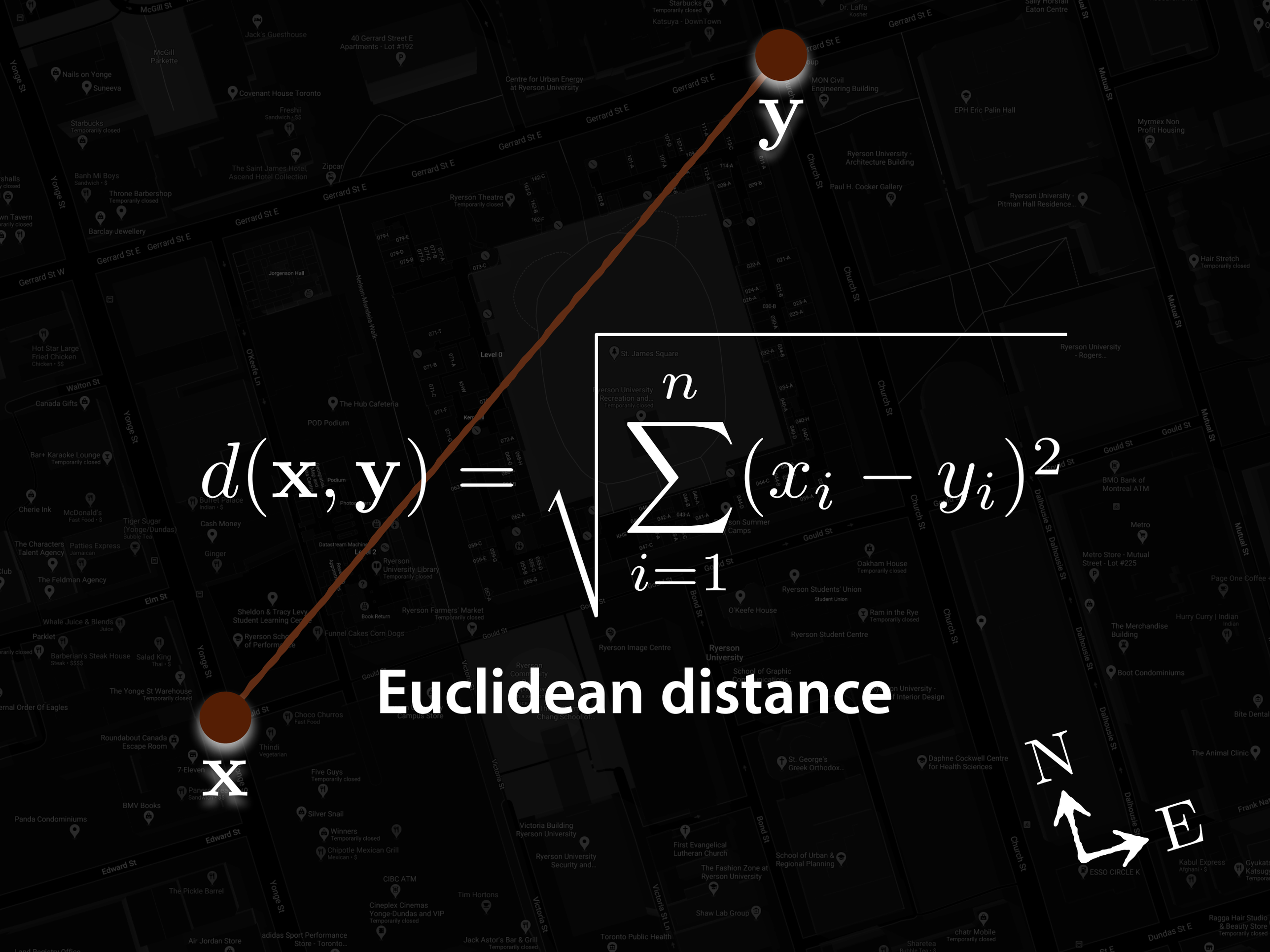
Distance Measures


y
x
N
E
$$d(\mathbf{x}, \mathbf{y}) = \sum_{i=1}^{n} |x_i - y_i|$$
Manhattan distance


y
x
N
E
$$d(\mathbf{x}, \mathbf{y}) = \sum_{i=1}^{n} |x_i - y_i|$$
City-Block distance

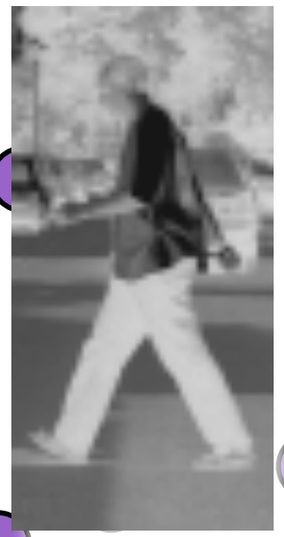
$$d(\mathbf{x}, \mathbf{y}) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

Euclidean distance



Linear Classification

pedestrian

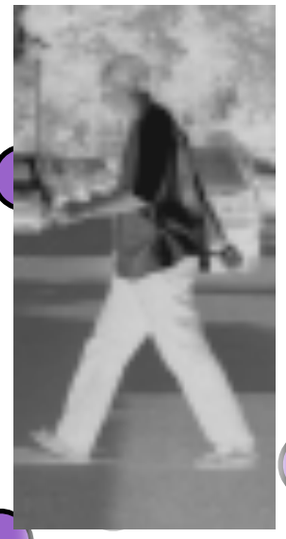


non-pedestrian

Find a linear function that “best” separates the classes

non-linearly separable

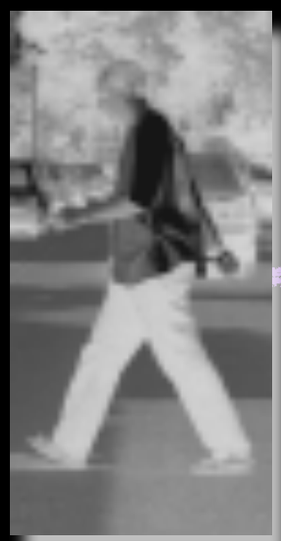
pedestrian



non-pedestrian

At testing, the sign of the score determines the class

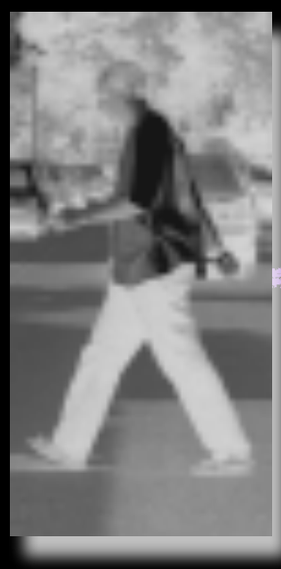
$$f(\mathbf{x}; \mathbf{w}, b) = \mathbf{w} \cdot \mathbf{x} + b$$



$$\mathbf{w} \cdot \mathbf{x} + b$$

score

$\mathbf{x}$



$$\begin{pmatrix} 0.2 \\ -0.8 \\ 0.1 \\ 2.0 \end{pmatrix} \cdot \begin{pmatrix} 56 \\ 231 \\ 24 \\ 2 \end{pmatrix} + 1.1 \rightarrow -96.8$$

$\mathbf{w}$ $\mathbf{x}$ b

What are the best model parameters?

loss function

quantifies agreement between the predicted scores and ground truth labels

scoring function

$$L_i = \max(0, 1 - y_i[\mathbf{w} \cdot \mathbf{x}_i + b])$$

$$L_i = \max(0, 1 - y_i[\mathbf{w} \cdot \mathbf{x}_i + b])$$

training set label, 1 or -1

loss margin

$$L_i = \max(0, 1 - y_i[\mathbf{w} \cdot \mathbf{x}_i + b])$$

$$L_i = \max(0, 1 - y_i[\mathbf{w} \cdot \mathbf{x}_i + b])$$

hinge loss function

0-1 loss

hinge loss

$\delta(y_i f(x_i) < 0)$

$\max(0, 1 - y_i f(x_i))$

$y_i f(\mathbf{x}_i)$

logistic loss

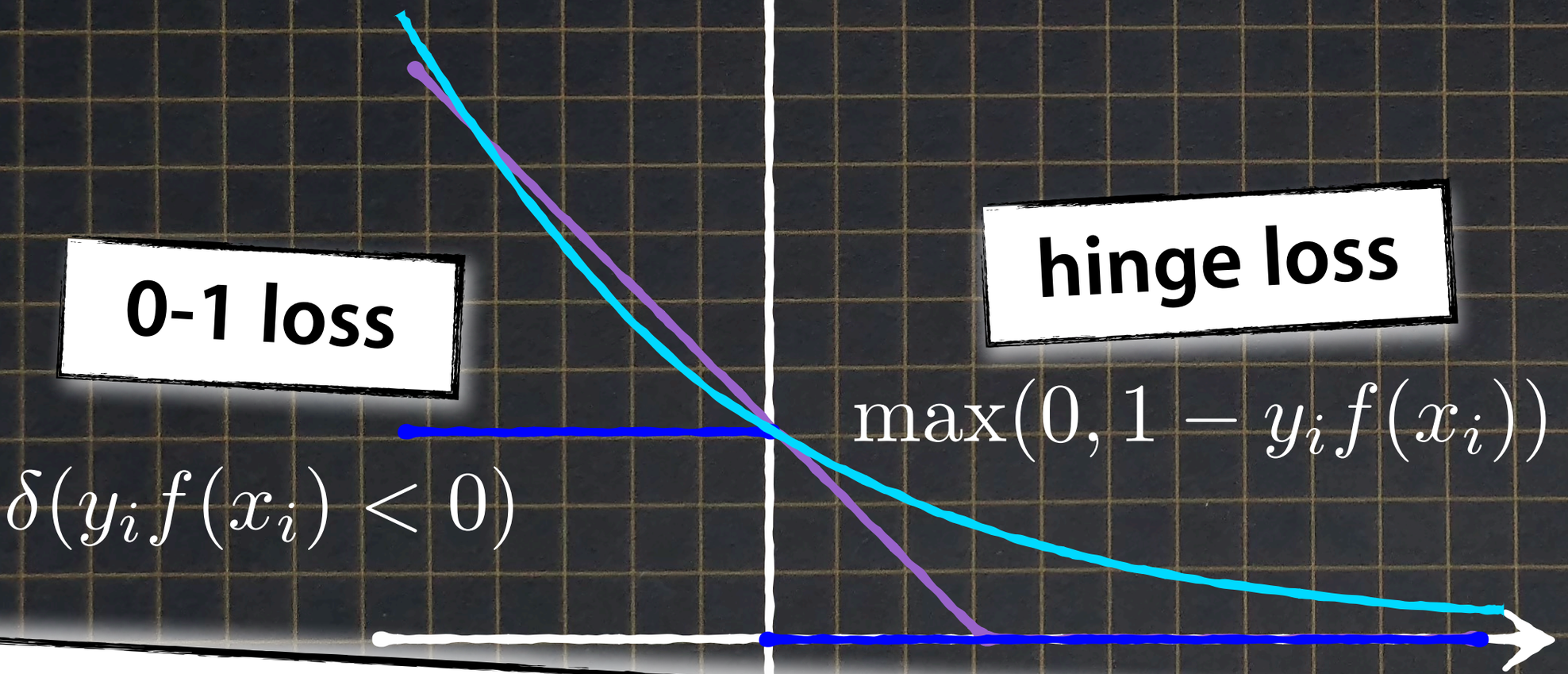
$$\ln(1 + \exp(-y_i f(\mathbf{x}_i)))$$

0-1 loss

$$\delta(y_i f(x_i) < 0)$$

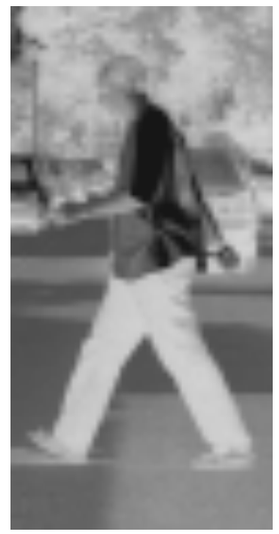
hinge loss

$$\max(0, 1 - y_i f(x_i))$$



hinge and logistic losses are convex approximations of 0-1 loss

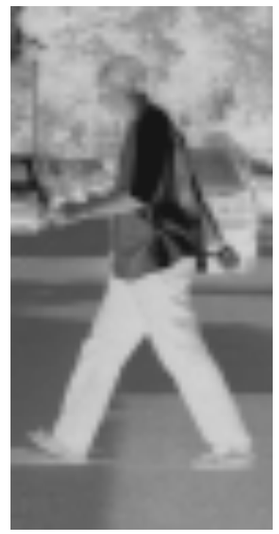
$$L_i = \max(0, 1 - y_i[\mathbf{w} \cdot \mathbf{x}_i + b])$$



score	0.3	-30	-96.8
loss	0.7	0	97.8

Overall loss is the average loss over the training set

$$L_i = \max(0, 1 - y_i[\mathbf{w} \cdot \mathbf{x}_i + b])$$



score	0.3	-30	-96.8
loss	0.7	0	97.8

Overall loss is the average loss over the training set

$$L = \frac{1}{N}\sum_{i=1}^{N} L_i = \frac{1}{N}\sum_{i=1}^{N} \max(0, 1 - y_i[\mathbf{w} \cdot \mathbf{x}_i + b])$$

$$L = \frac{1}{N} \sum_{i=1}^{N} \max(0, 1 - y_i[\mathbf{w} \cdot \mathbf{x}_i + b])$$

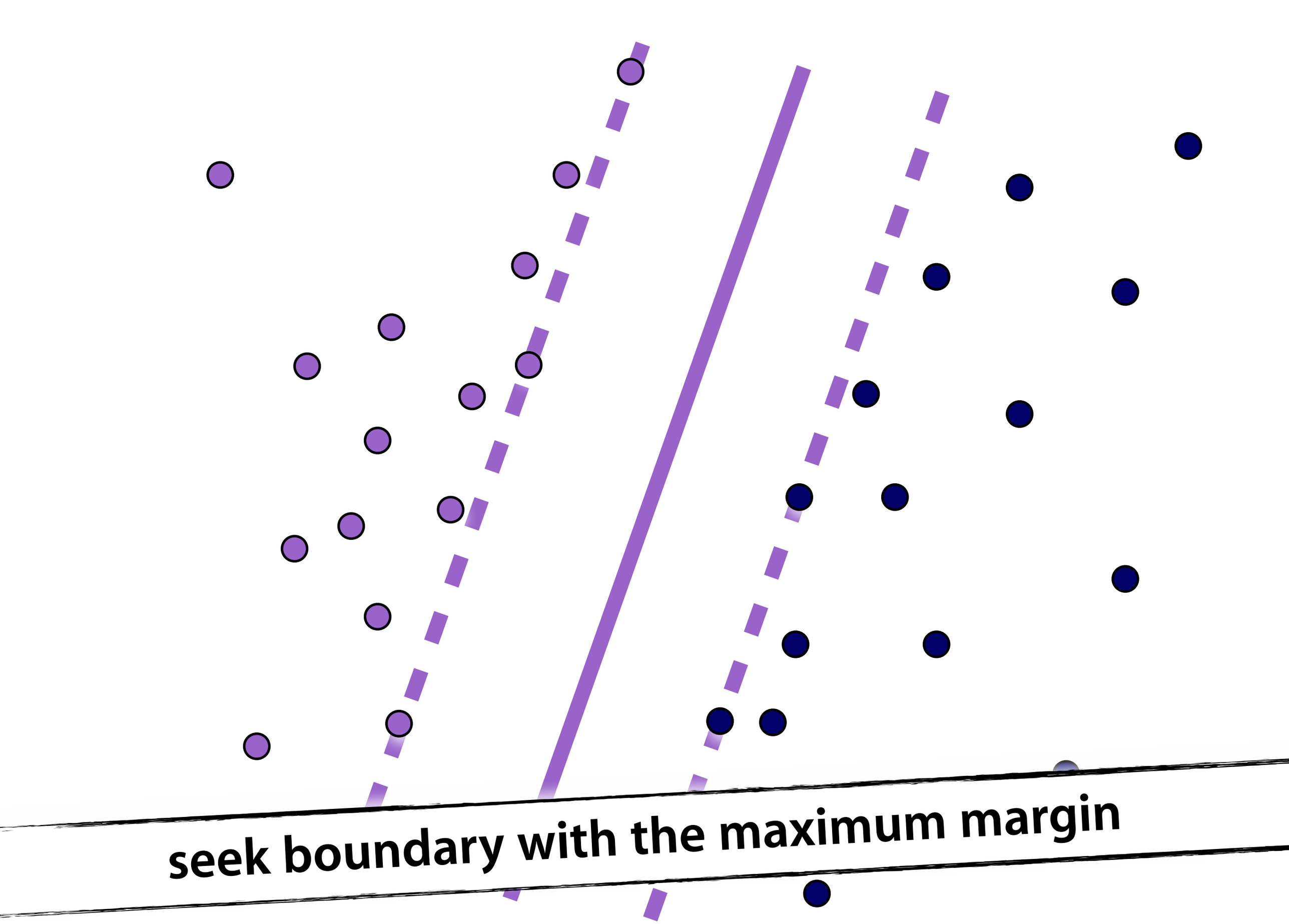
Loss function admits multiple solutions

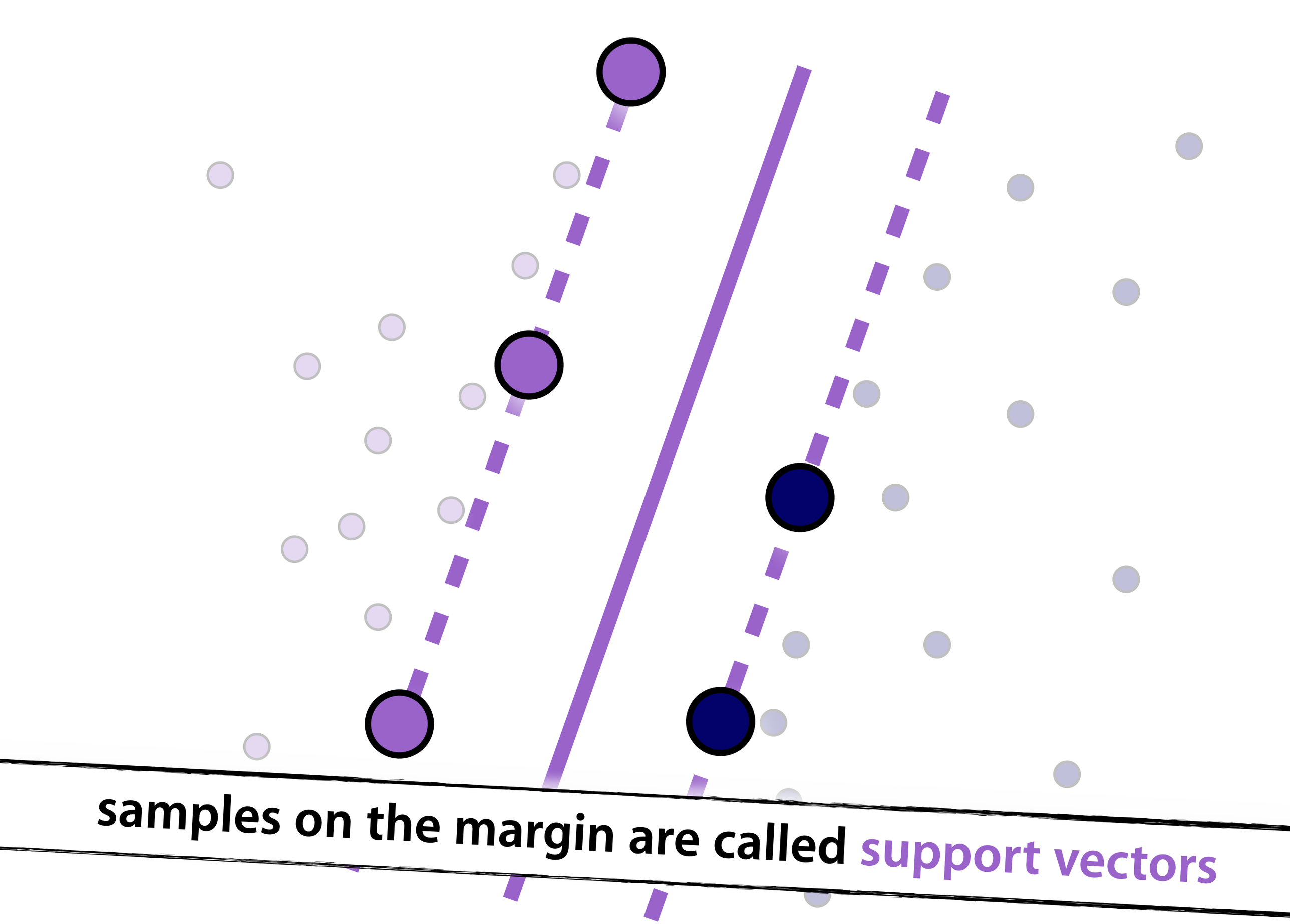
$$L = \frac{1}{N}\sum_{i=1}^{N} \max(0, 1 - y_i[\mathbf{w} \cdot \mathbf{x}_i + b]) + \lambda R(\mathbf{w})$$

L2 norm is a common regularizer

$$R(\mathbf{w}) = \|\mathbf{w}\|_2^2$$

Support Vector Machine (SVM)


seek boundary with the maximum margin



samples on the margin are called support vectors

$$f(\mathbf{x}; \mathbf{w}) = \mathbf{w} \cdot \mathbf{x} + b$$

scoring function

$$L = \frac{1}{N}\sum_{i=1} \max(0, 1 - y_i[\mathbf{w} \cdot \mathbf{x}_i + b]) + \lambda R(\mathbf{w})$$

loss function

How do we find the optimal model parameters?

gradient

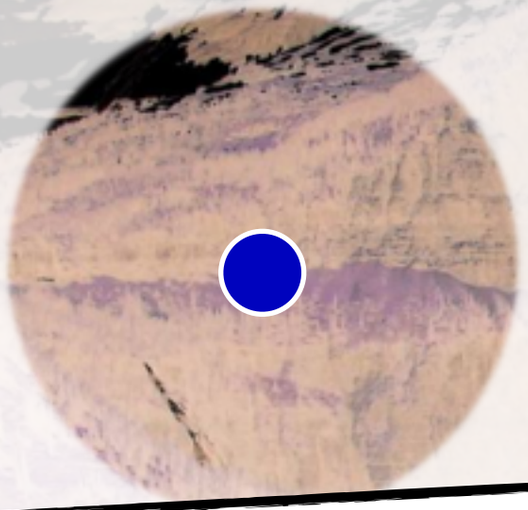
$$\nabla f(x_1, x_2, \ldots, x_N) = \begin{pmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \\ \vdots \\ \frac{\partial f}{\partial x_N} \end{pmatrix}$$

points in the direction of greatest rate of increase

gradient

$$\nabla f(x_1, x_2, \ldots, x_N) = \begin{pmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \\ \vdots \\ \frac{\partial f}{\partial x_N} \end{pmatrix}$$

magnitude is the rate of increase

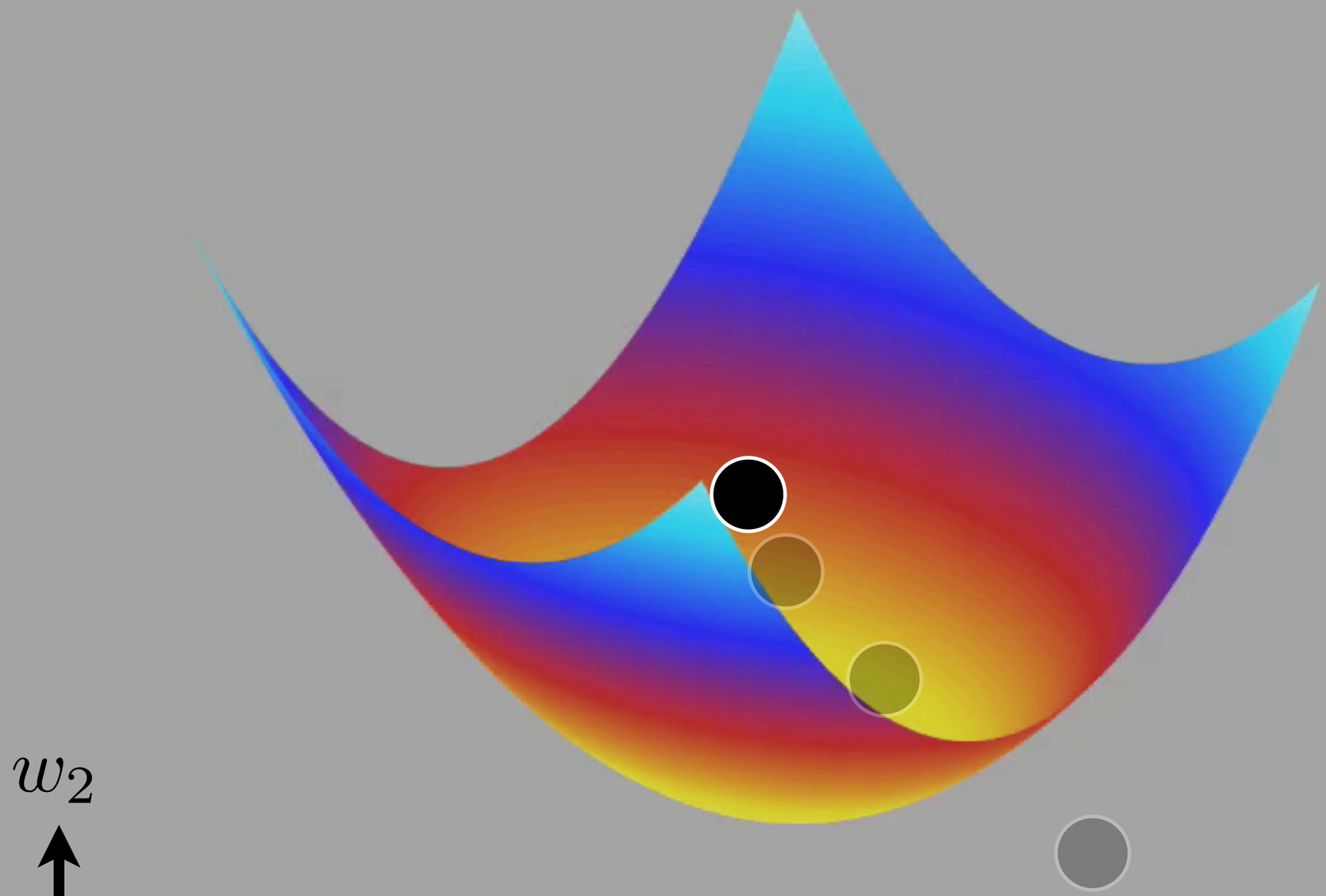


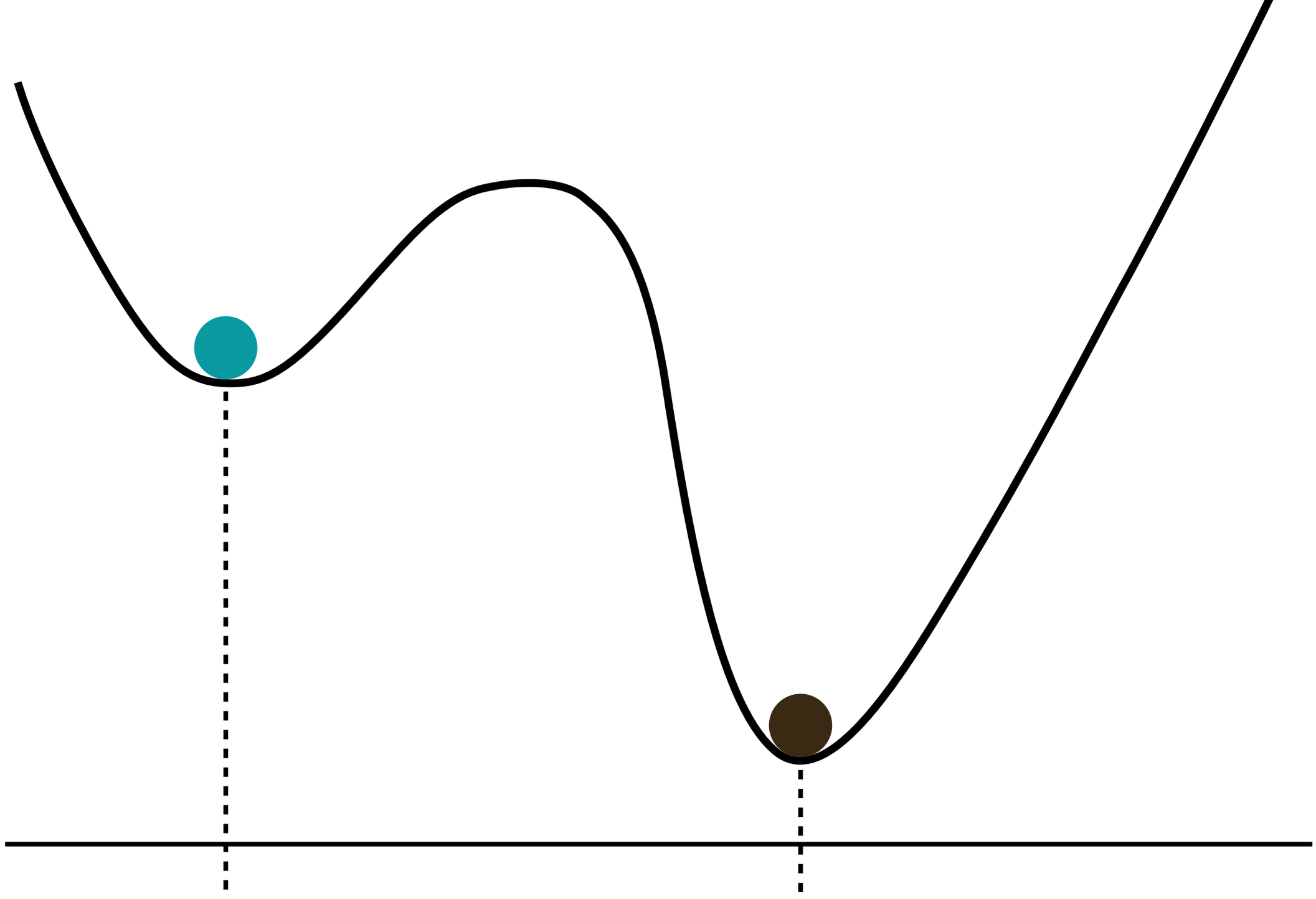
What is the direction of greatest descent?

$$-\nabla L(\mathbf{w}_t)$$

update parameters in negative gradient direction

$$\mathbf{w}_{t+1} = \mathbf{w}_t - \eta_t \nabla L(\mathbf{w}_t)$$

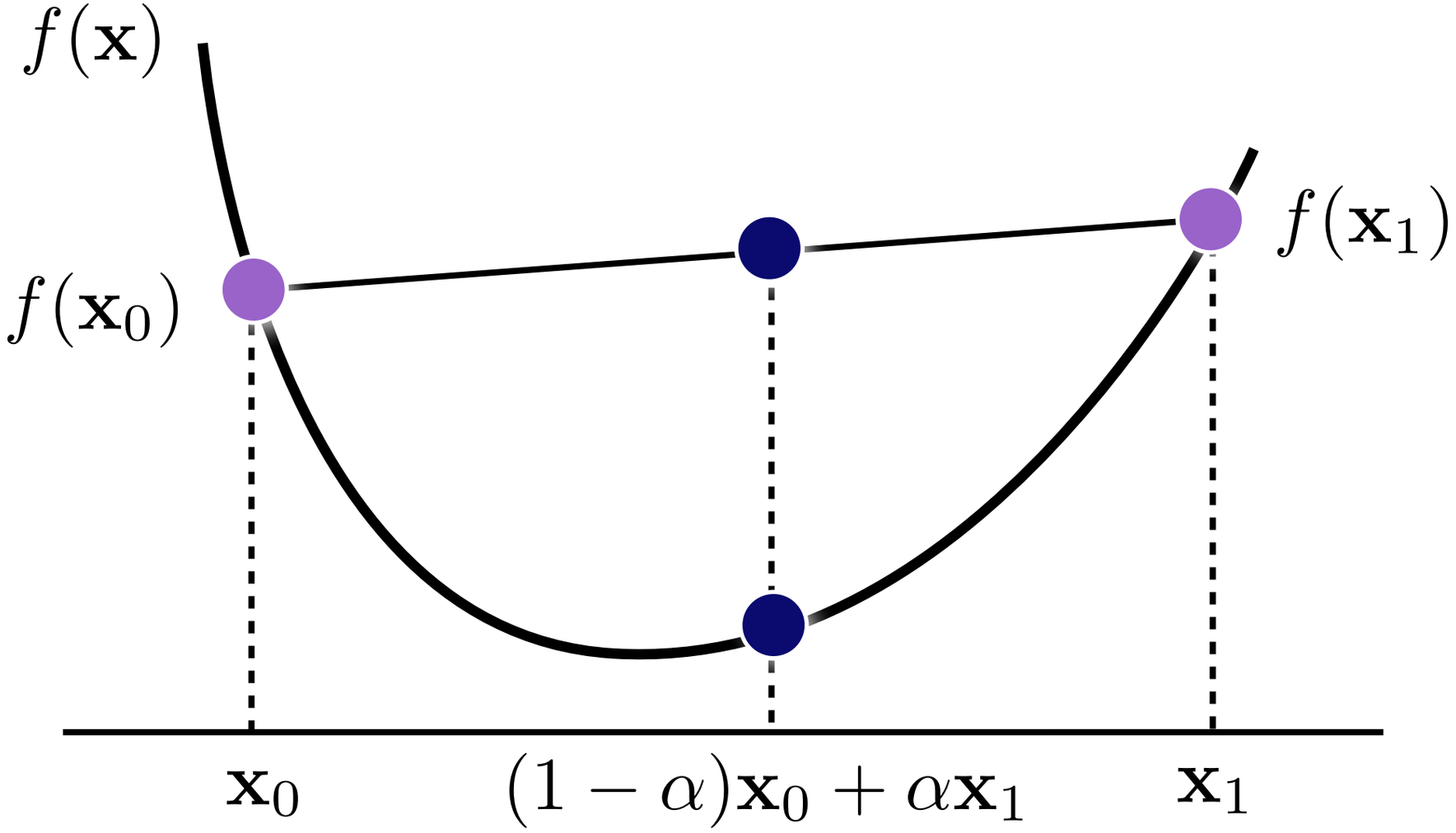

w_2
w_1

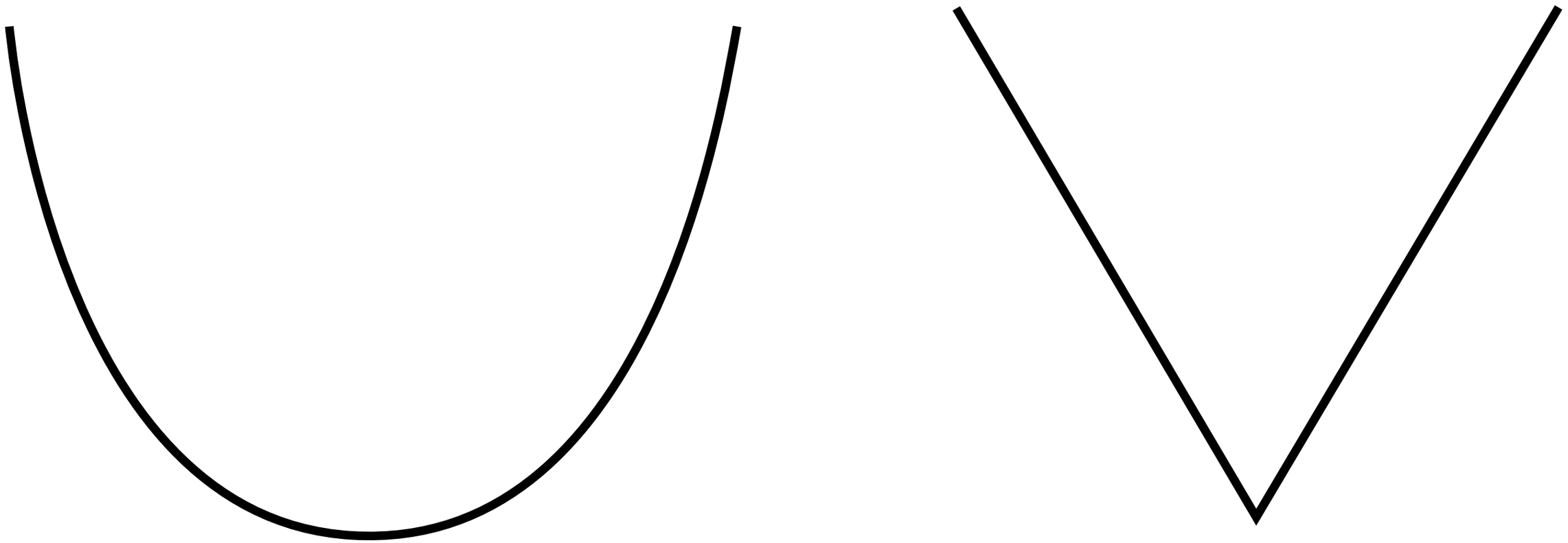

local
minima
global
minimum

Definition:

A function, $f : D \to \mathbb{R}$, is said to be convex if for any $\mathbf{x}_0$ and $\mathbf{x}_1$ in D and $0 \leq \alpha \leq 1$ **:**

$$f((1-\alpha)\mathbf{x}_0 + \alpha\mathbf{x}_1) \leq (1-\alpha)f(\mathbf{x}_0) + \alpha f(\mathbf{x}_1).$$

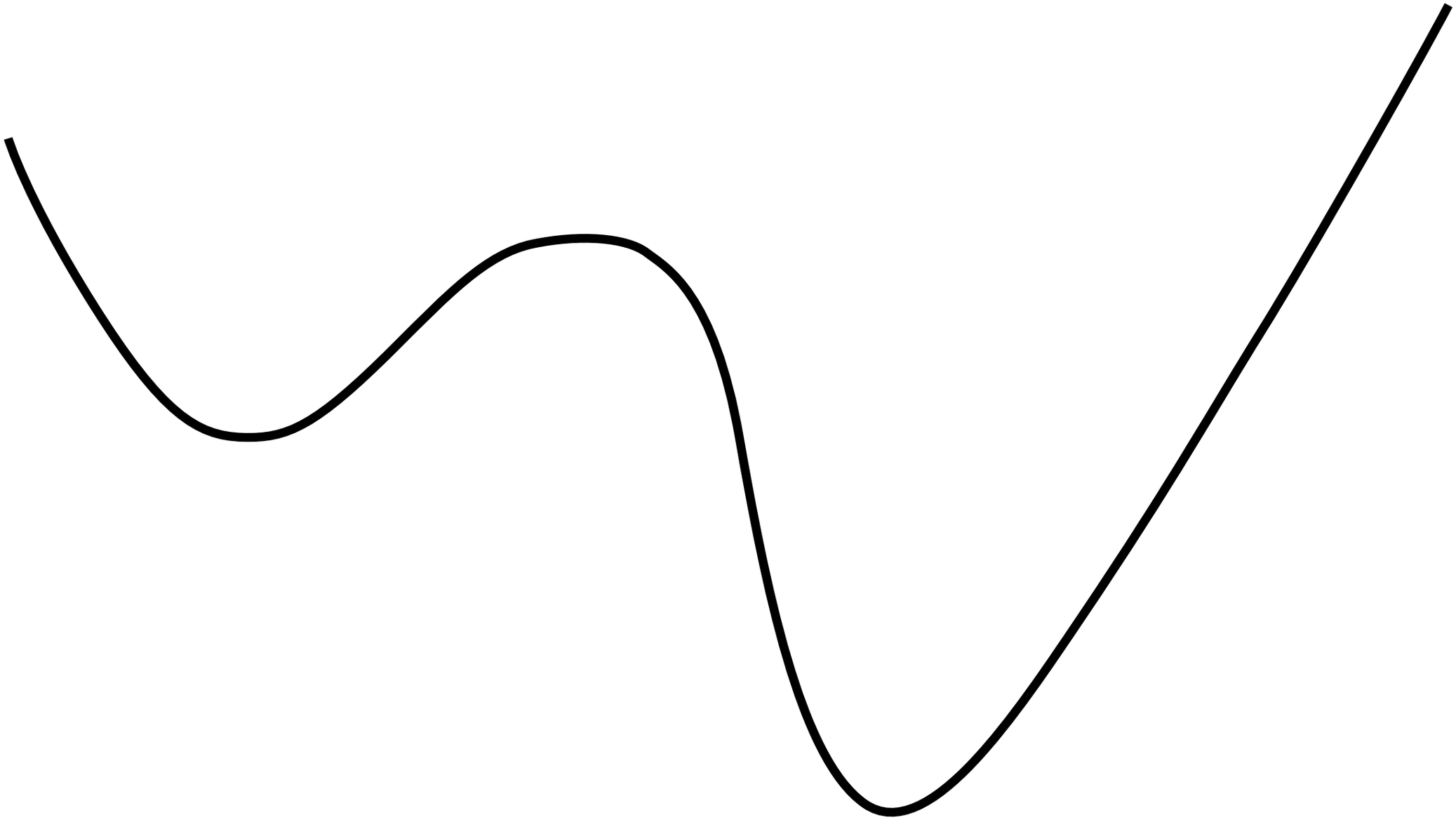




convex functions

$$L = \frac{1}{N}\sum_{i=1}^{N} \max(0, 1 - y_i[\mathbf{w} \cdot \mathbf{x}_i + b]) + \lambda R(\mathbf{w})$$

SVM cost function is convex



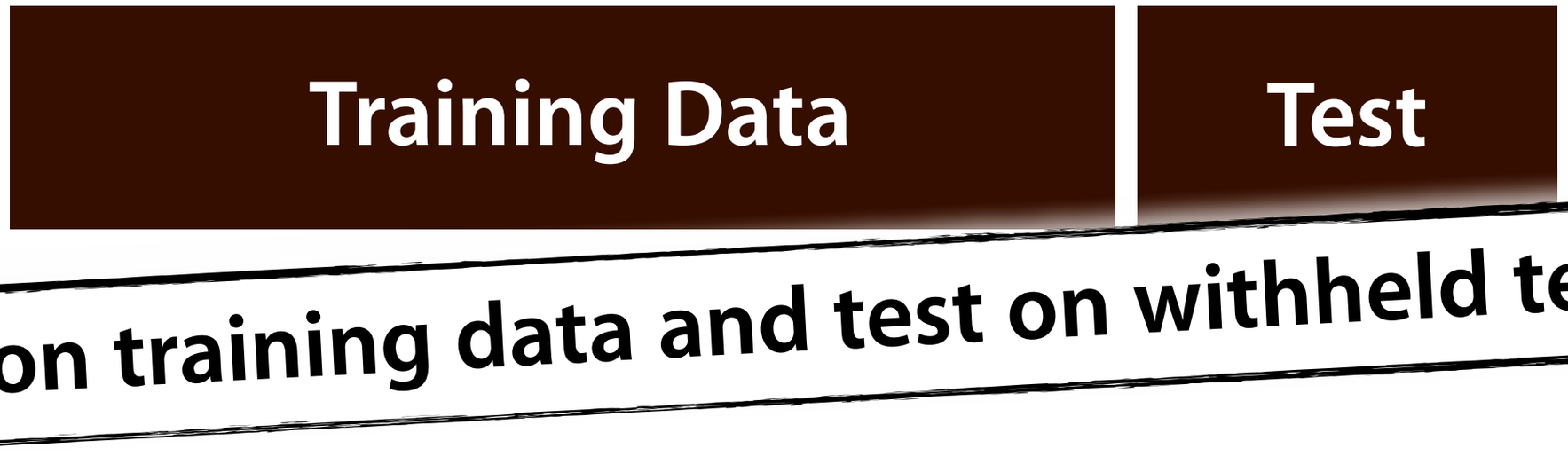
non-convex function

GENERALIZATION

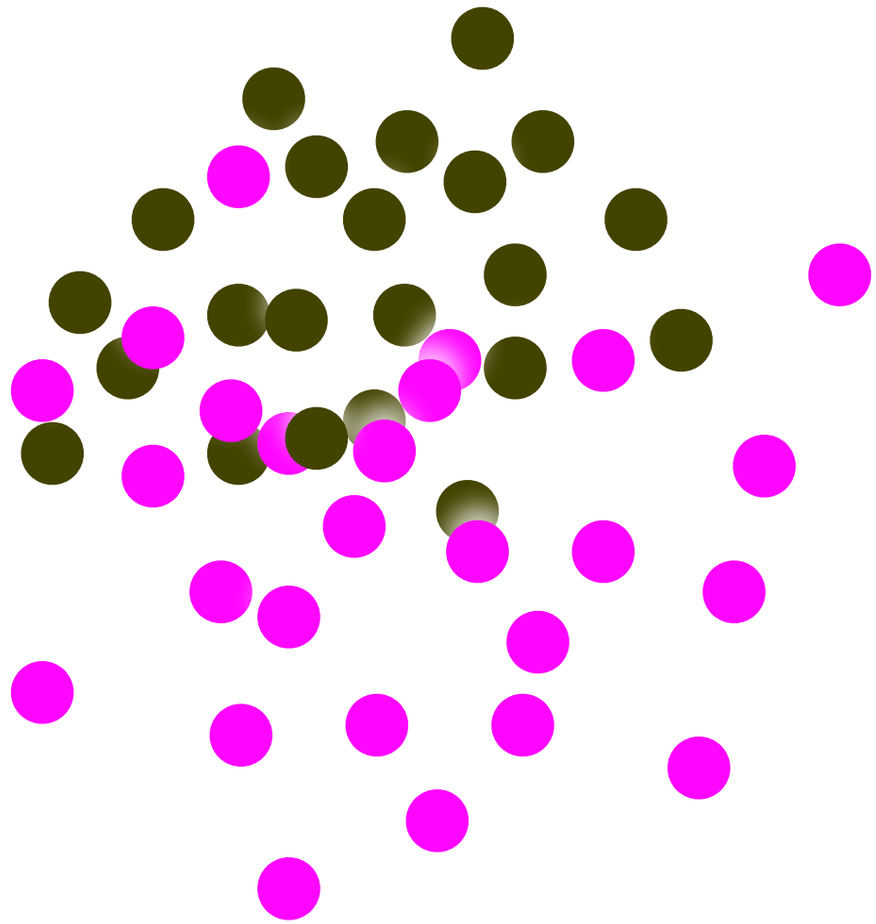
objective of machine learning

Data

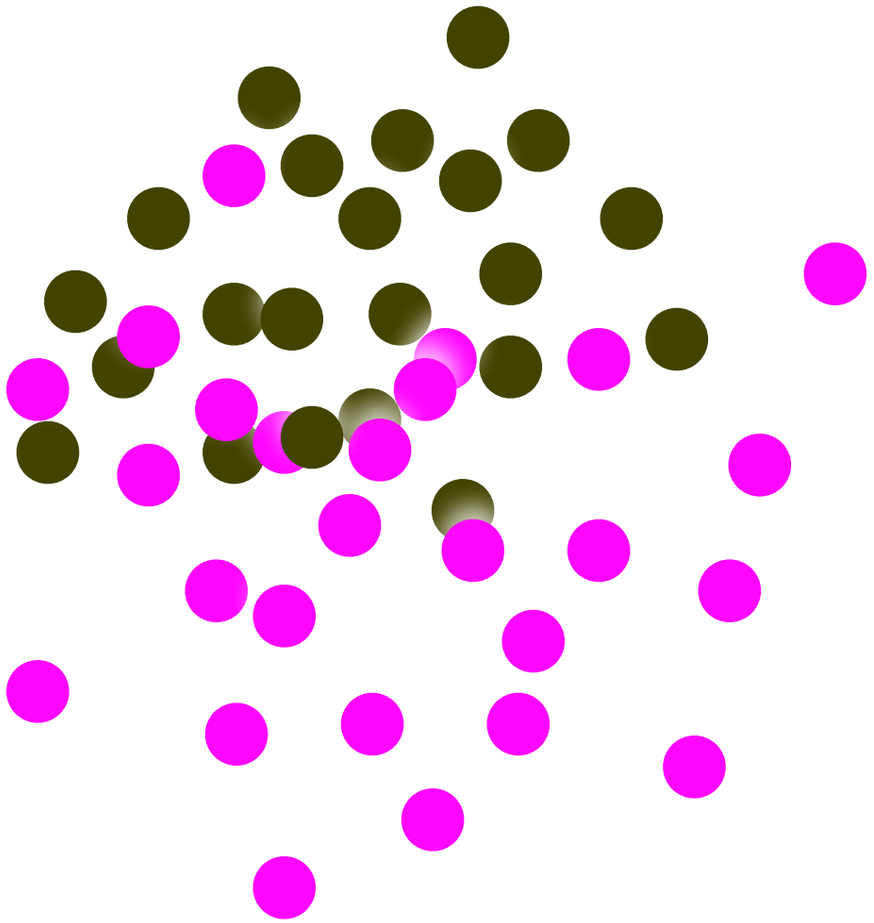
NEVER train and test on the same data


Training Data
Test
Train on training data and test on withheld test set

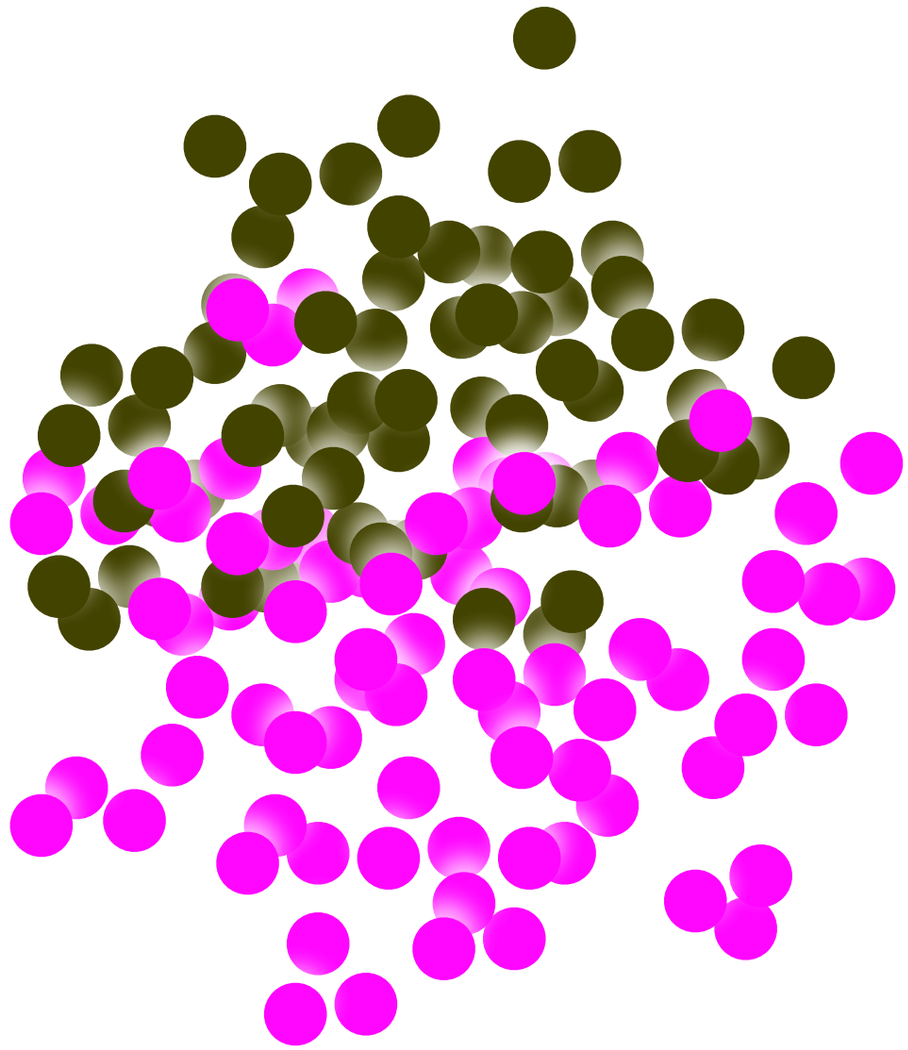
Assume training and testing data drawn independently from the same distribution



training data



training data



testing data

How do we set the hyperparameters?

K- Nearest Neighbour

What is the best distance metric to use?

K- Nearest Neighbour

What is the best value of K?

Linear Classifiers

$$L = \frac{1}{N}\sum_{i=1}^{N} \max(0, 1 - y_i[\mathbf{w} \cdot \mathbf{x}_i + b]) + \lambda R(\mathbf{w})$$

What is the best regularizer?

Linear Classifiers

$$L = \frac{1}{N}\sum_{i=1}^{N} \max(0, 1 - y_i[\mathbf{w} \cdot \mathbf{x}_i + b]) + \lambda R(\mathbf{w})$$

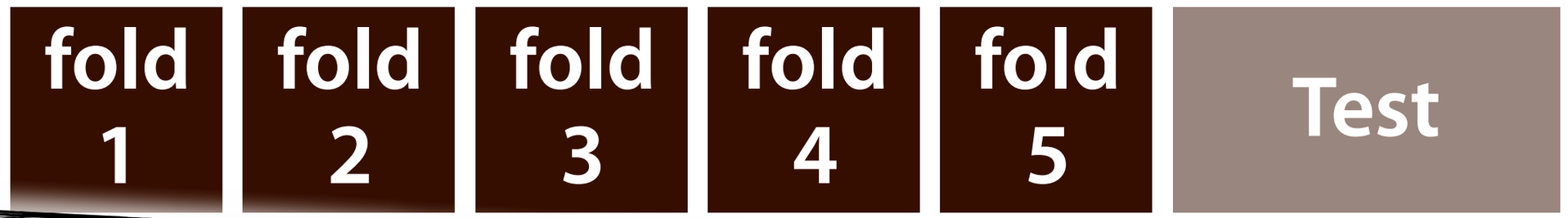
What is the best regularization parameter?

Training Data

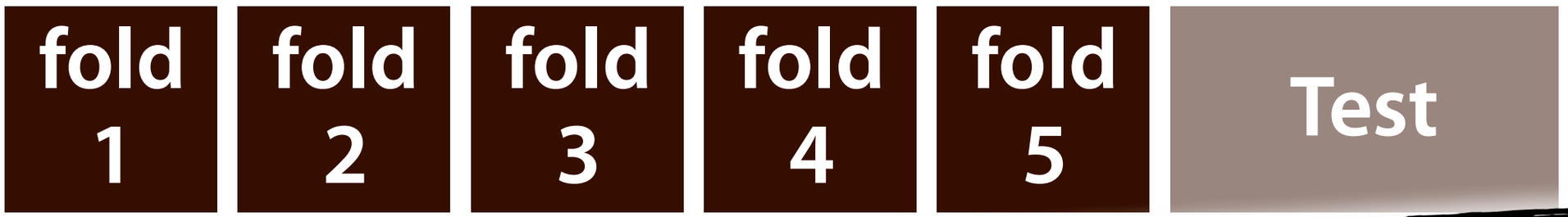
Validation

Test


Training Data
Test



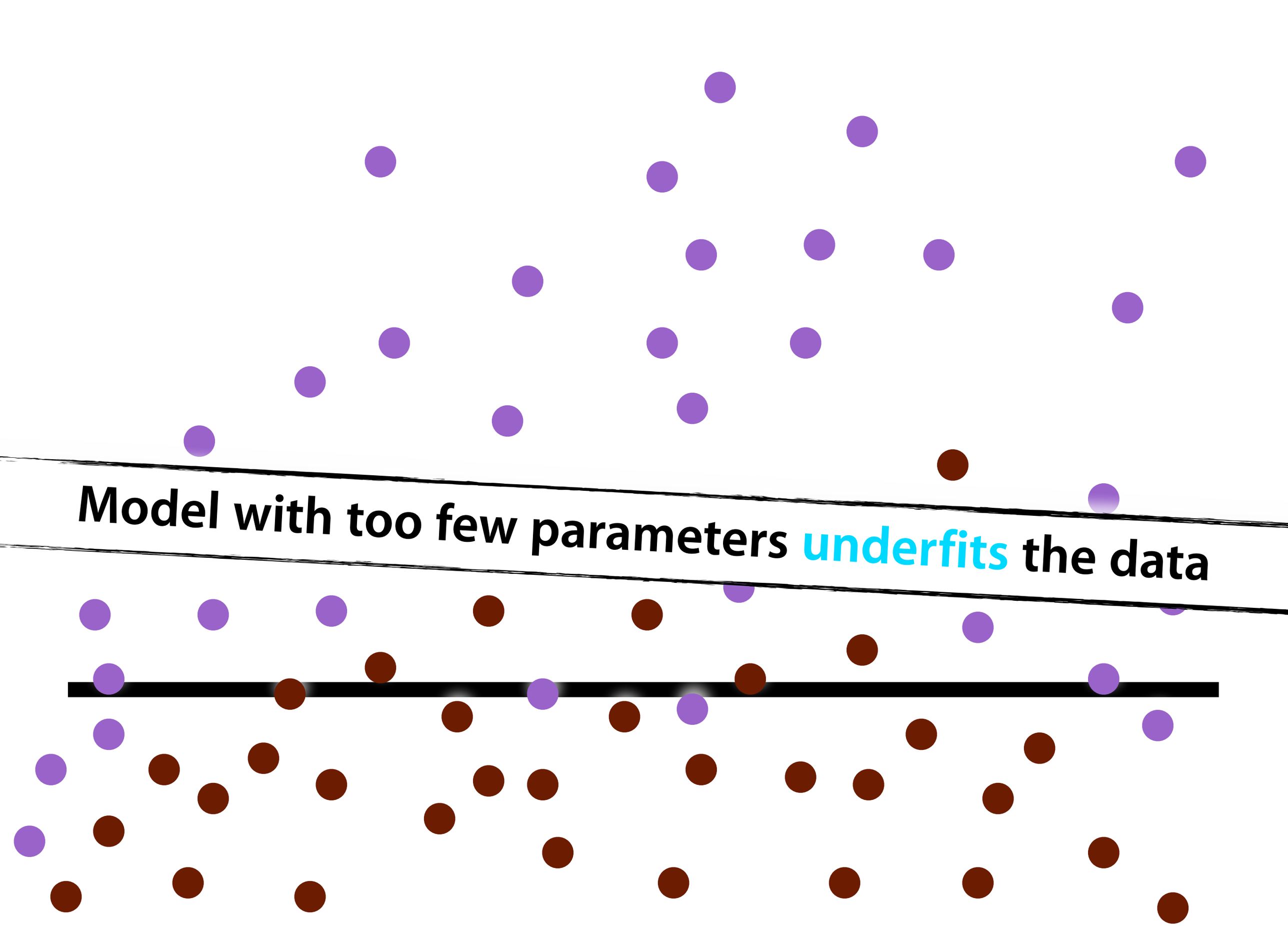
Use a fold as validation data and train on other folds



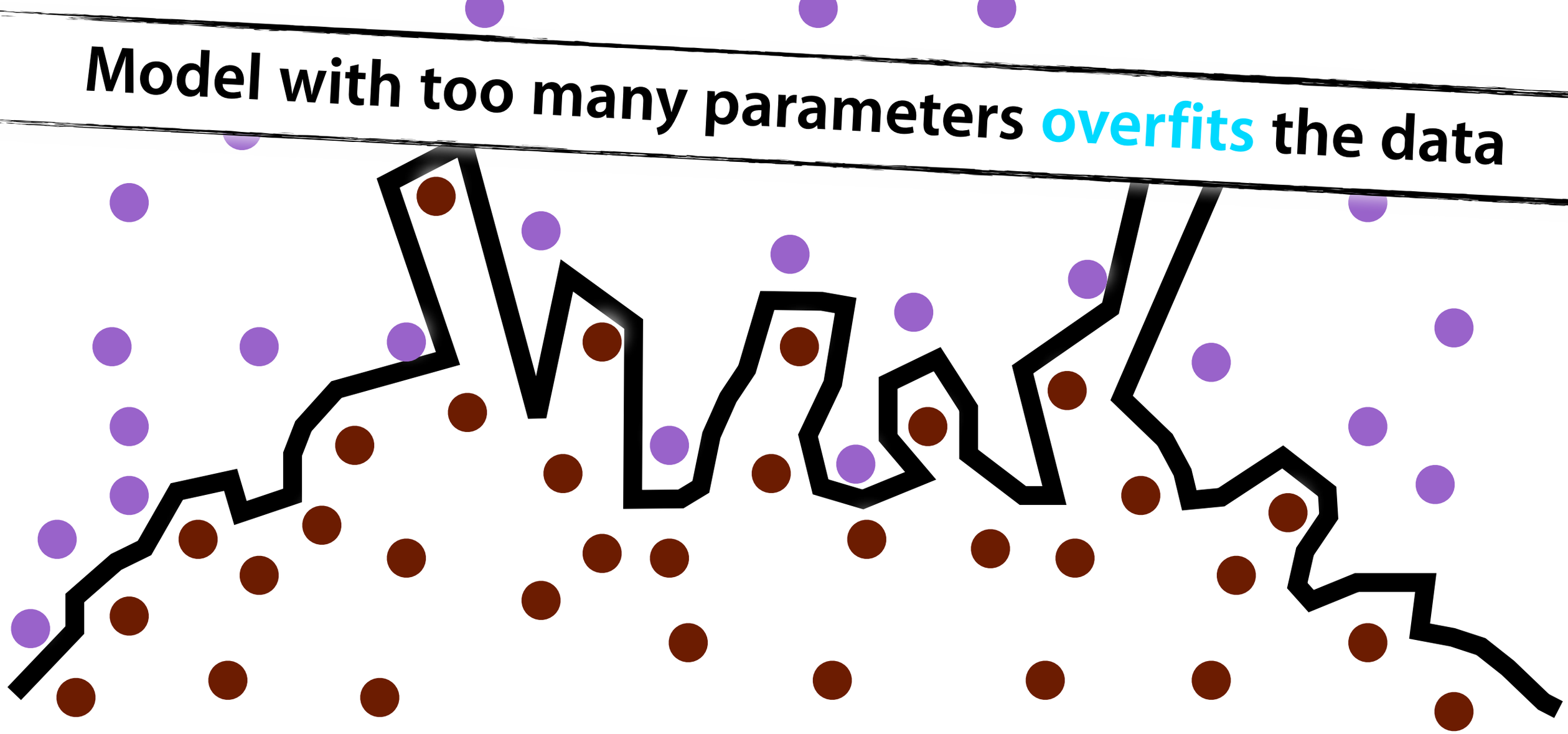
Cross-validation

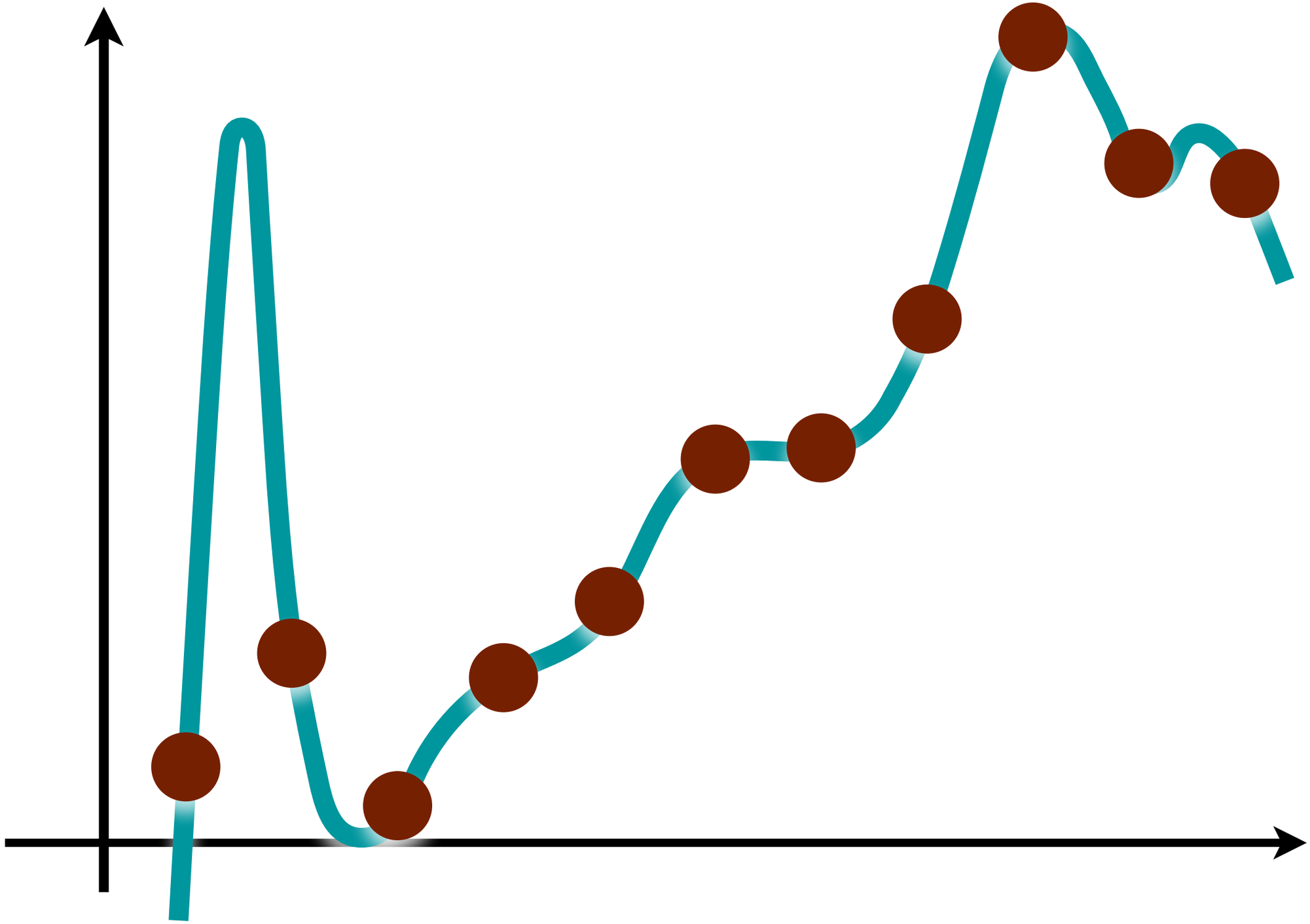
Select each fold in turn as validation data and average results

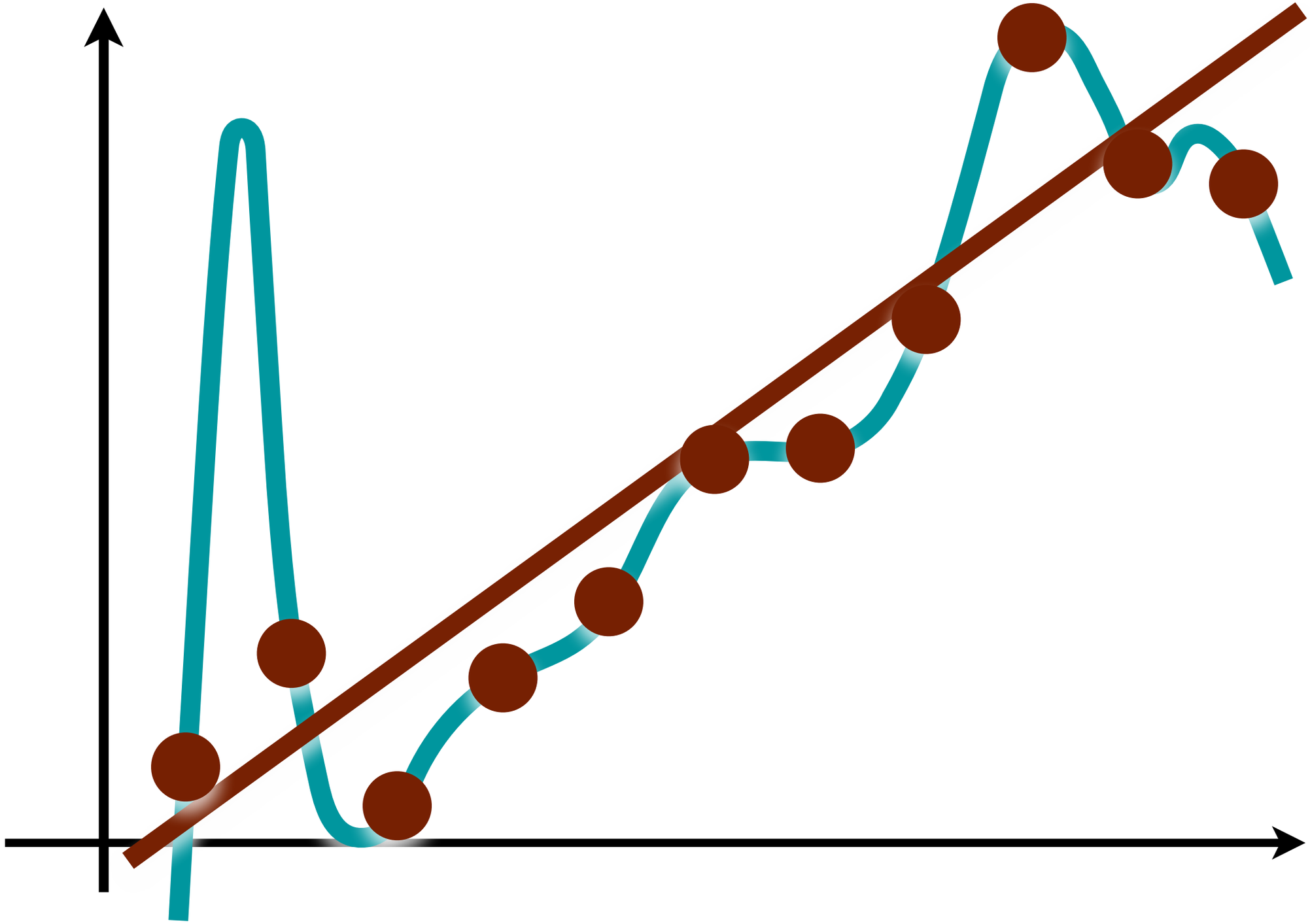
Model with too few parameters underfits the data



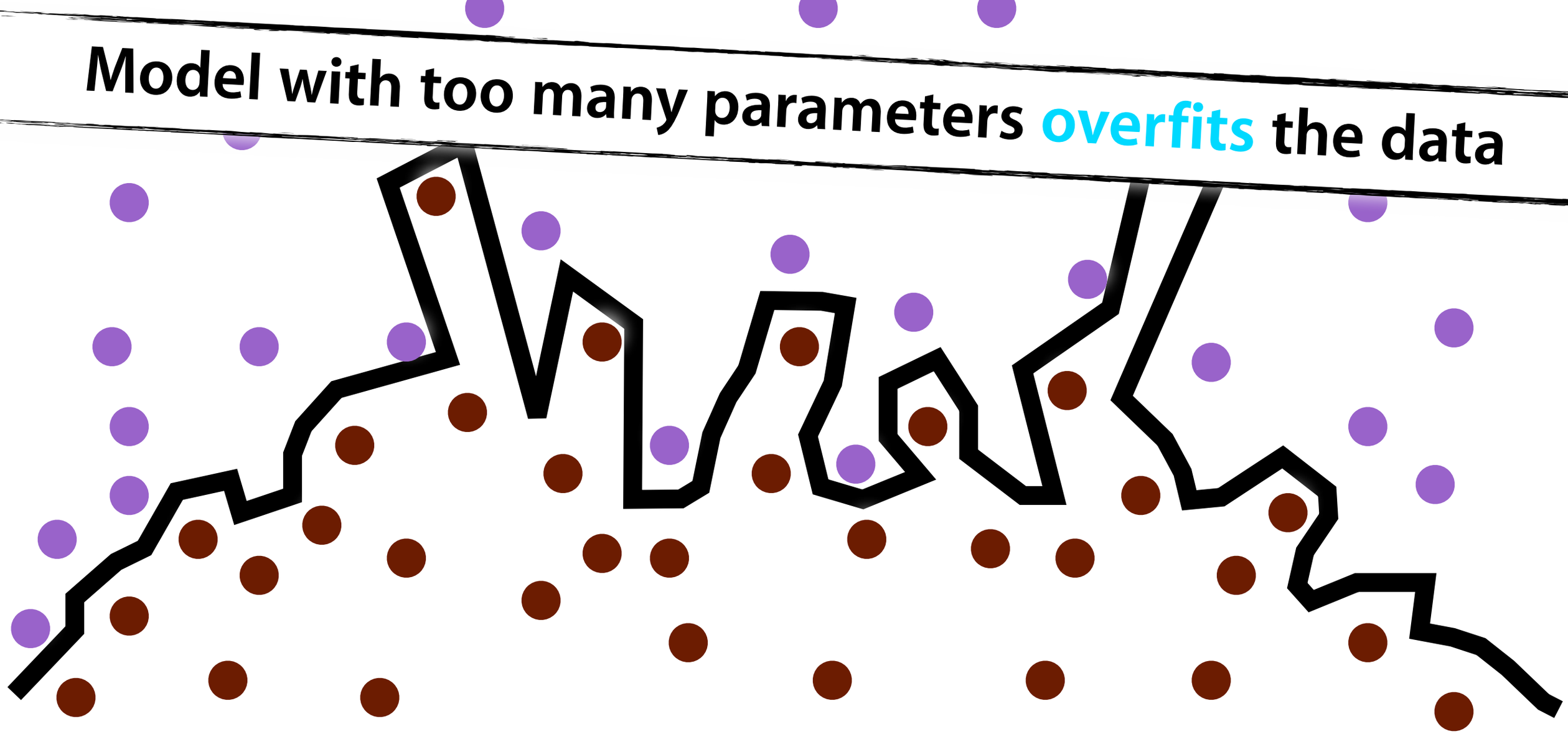
Model with too many parameters overfits the data



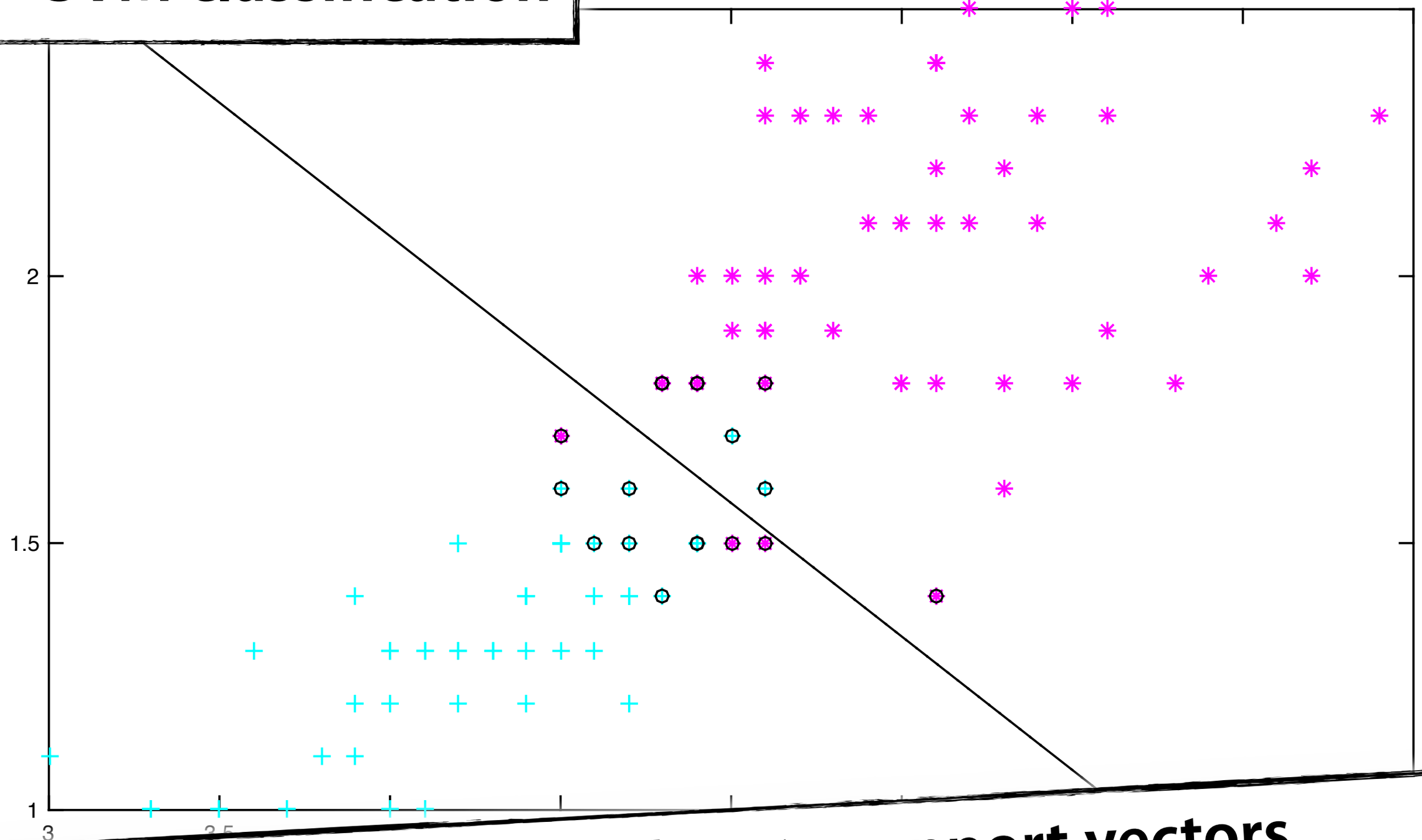




Model with too many parameters overfits the data



SVM classification



circled features denote support vectors

```
load fisheriris

% --- training phase
features = meas(51:end, 3:4);
labels = species(51:end);
svmStruct = svmtrain(features, labels, ...
 'ShowPlot', true);

% --- test phase
testDataSet = meas(1:50, 3:4);

predictClass = svmclassify(svmStruct, ...
    testDataSet);
```

Object Detection

Where are all the pedestrians?

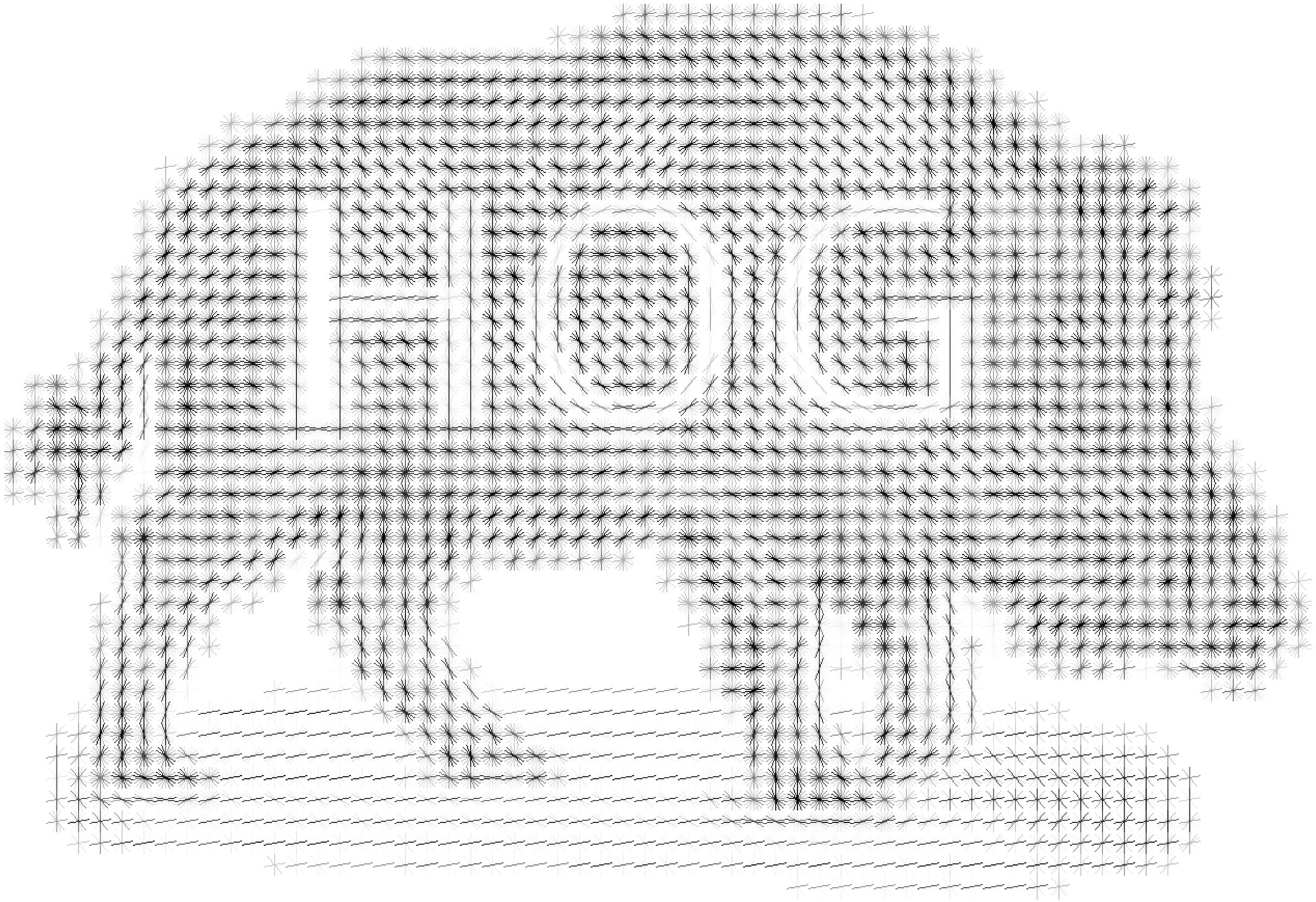
4

major steps

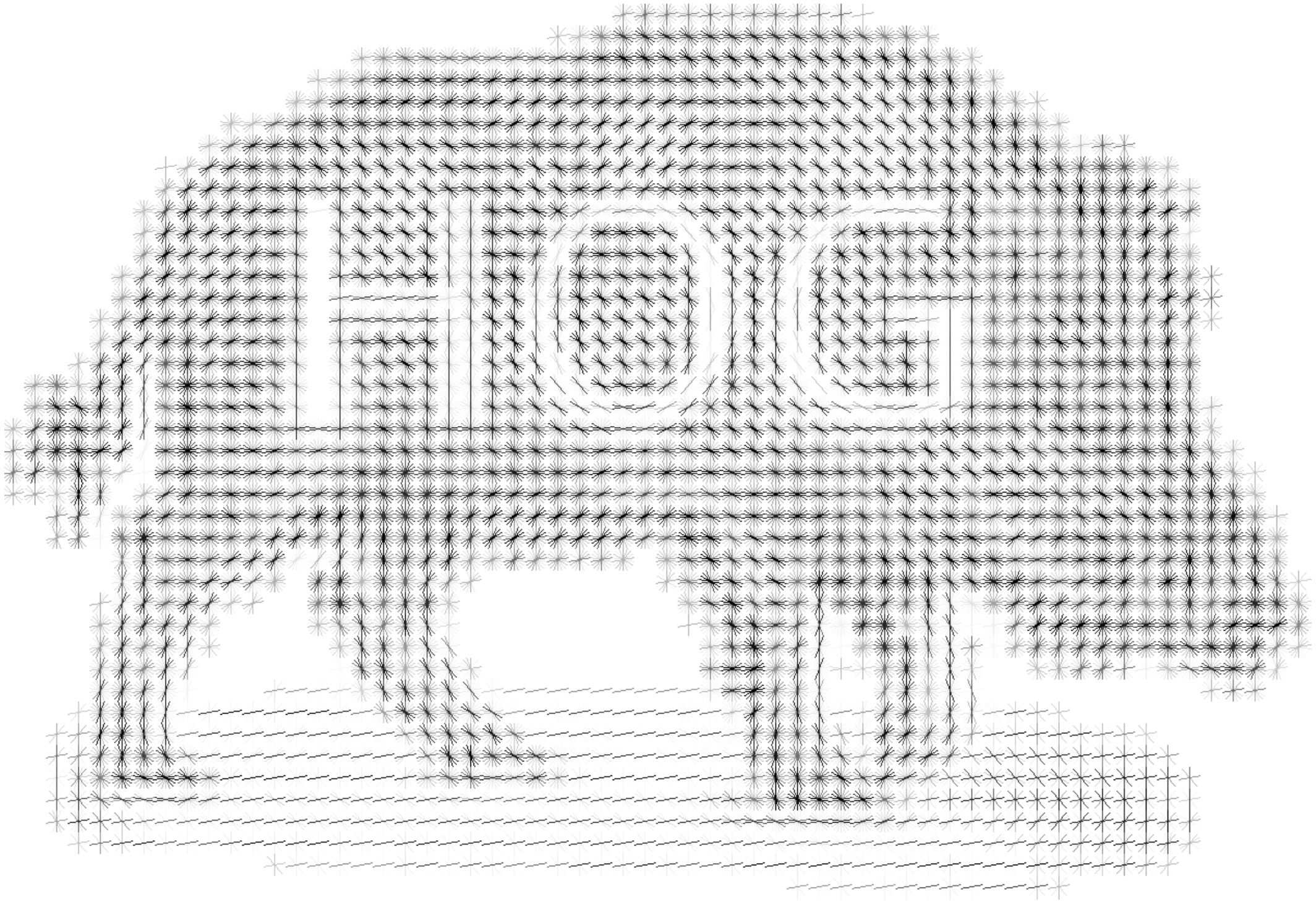
object detection using sliding windows

Step 1

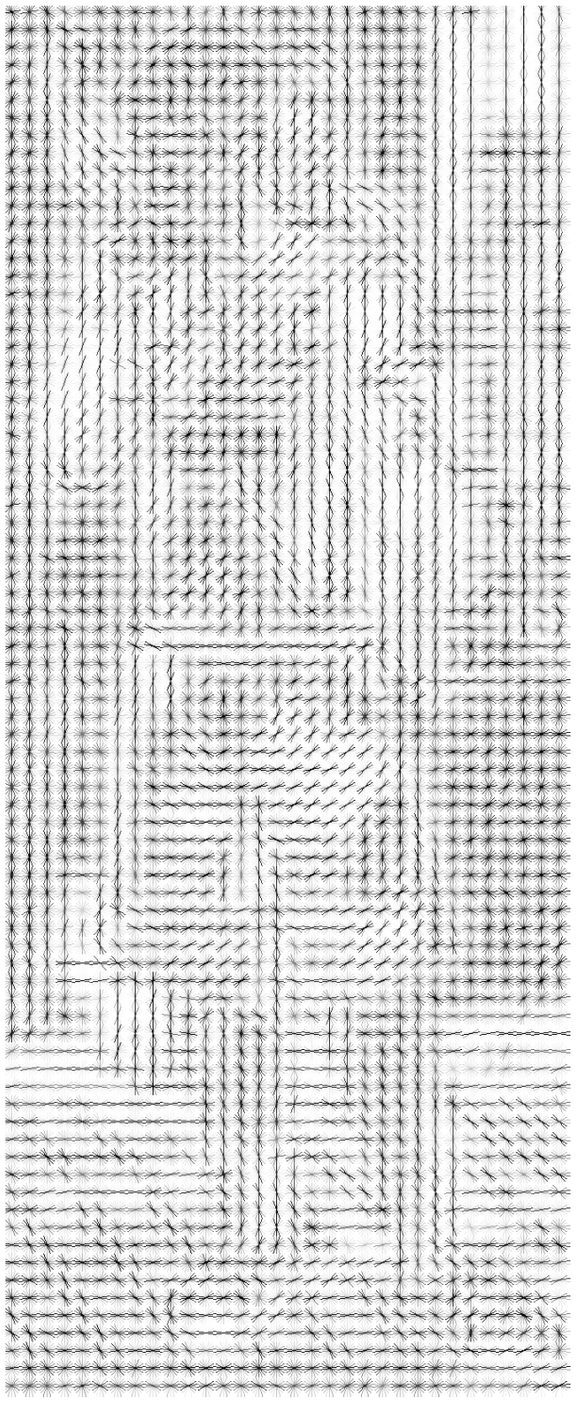
Select feature set



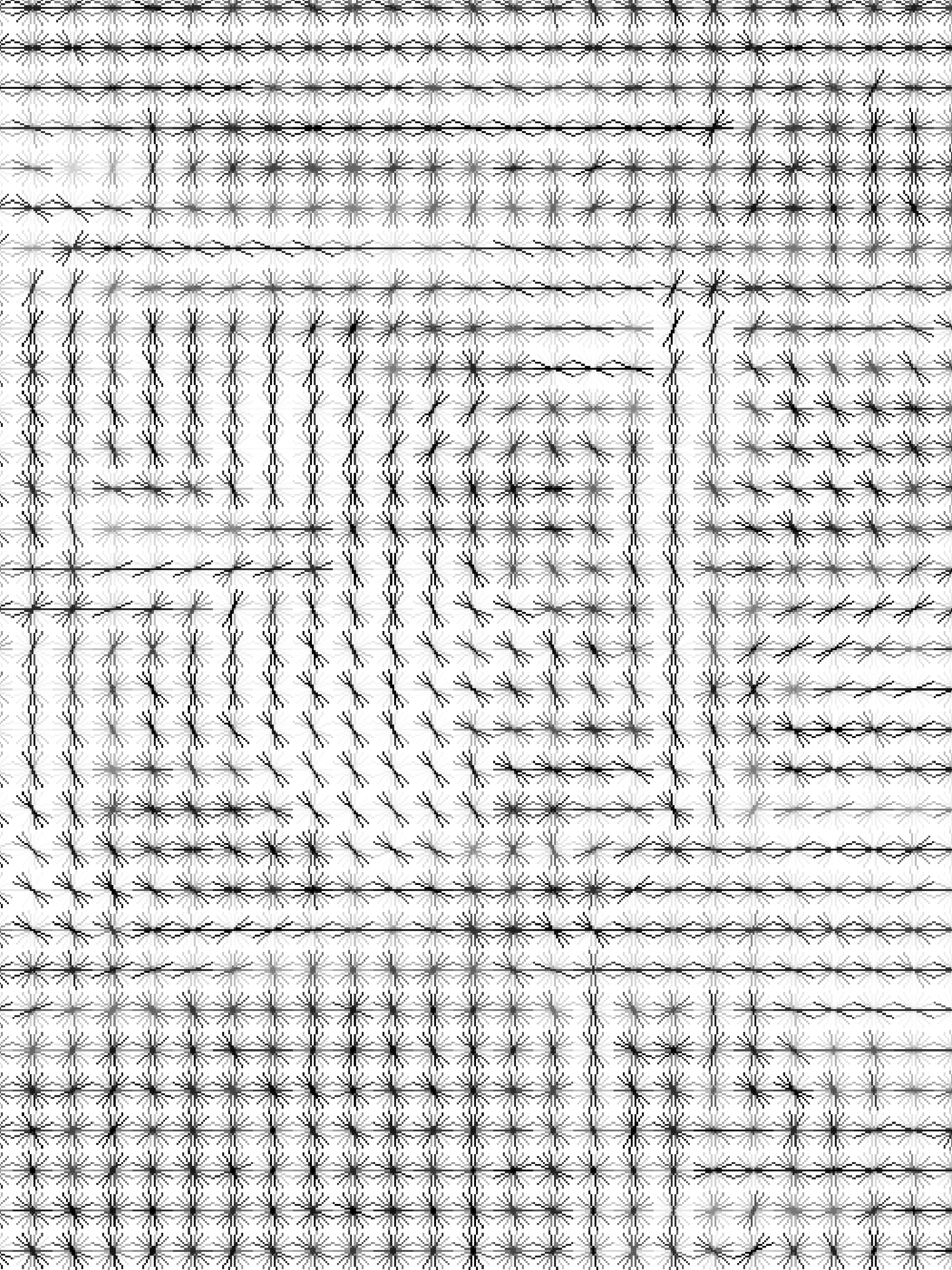
Histogram of Oriented Gradients



Histogram of Oriented Gradients



compute histograms of gradients in non-overlapping blocks



SIFT Descriptor

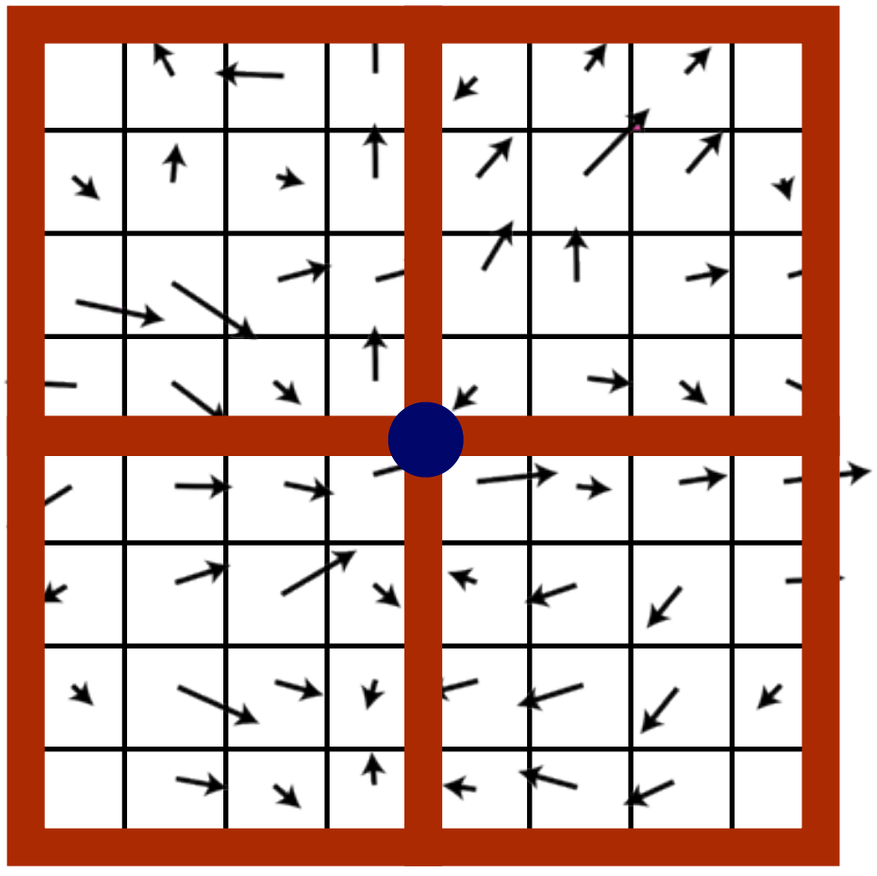
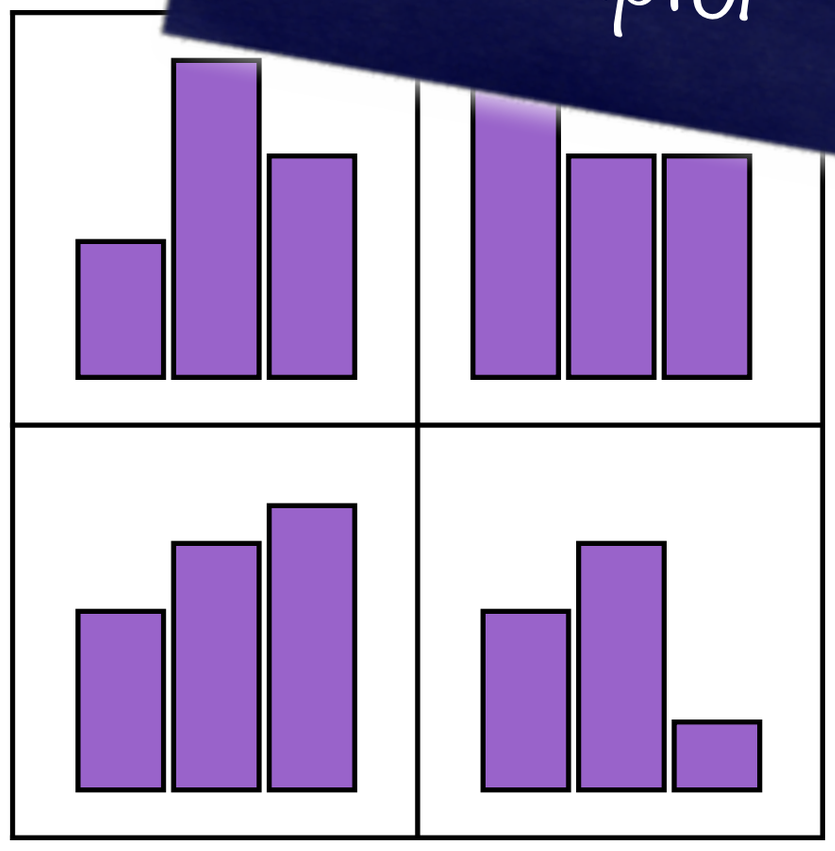
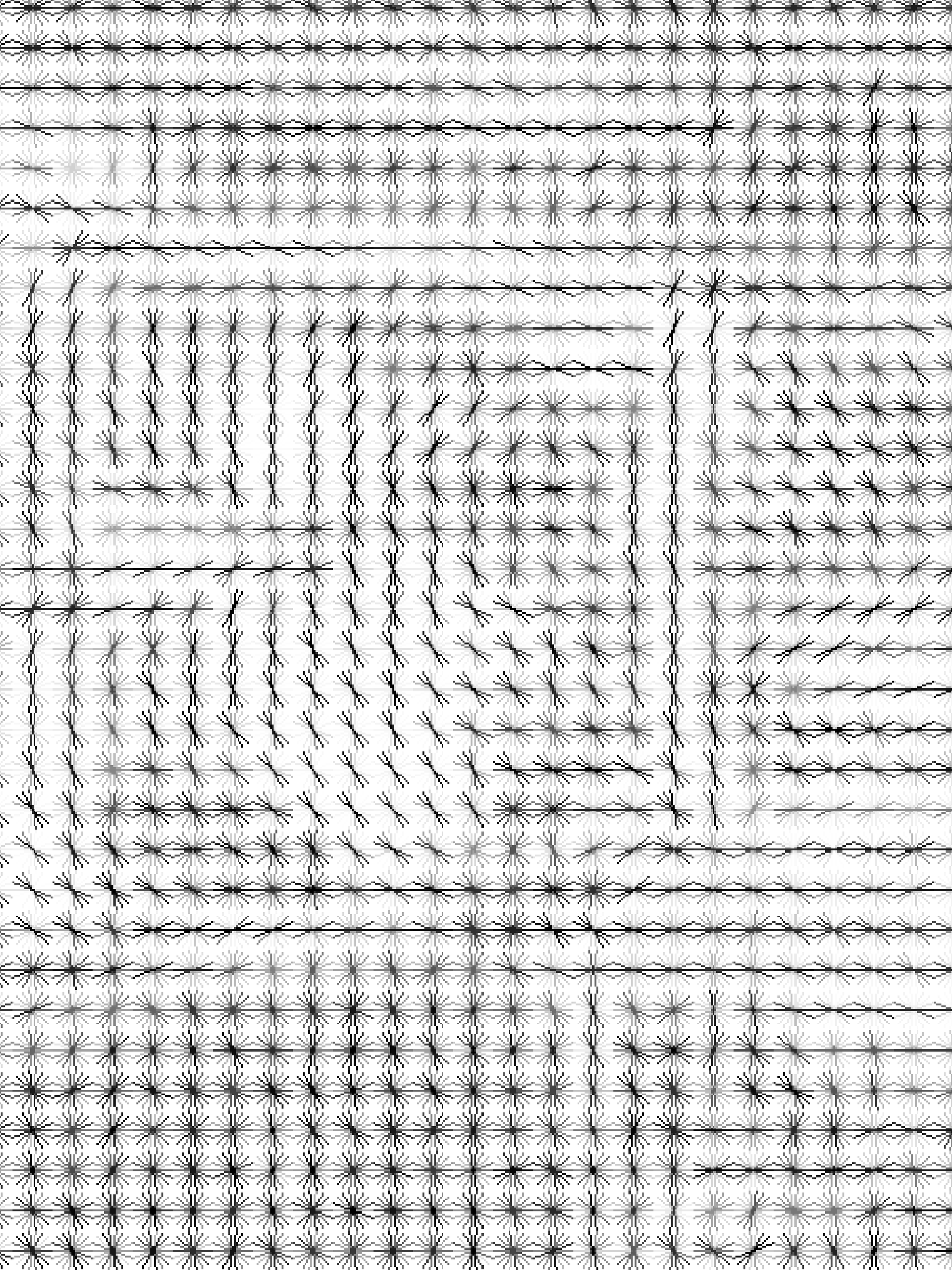


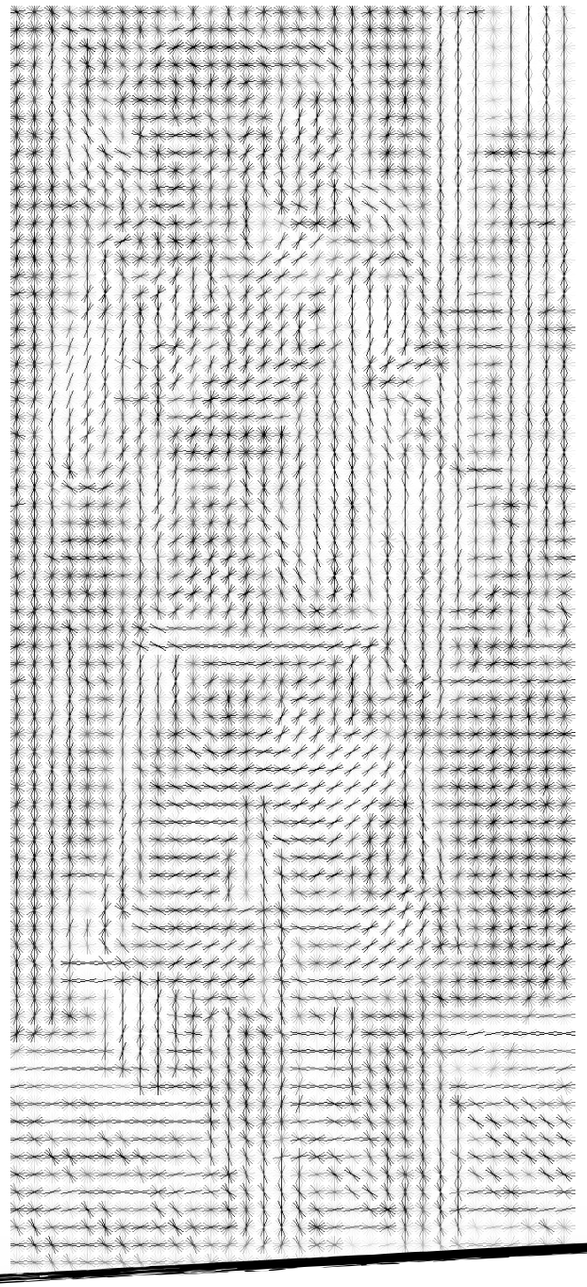
image gradients



keypoint descriptor

16 cells x 8 bins = 128 dimensional descriptor





collect HOGs over all blocks and form a feature vector

Dalal-Triggs feature vector is 3780 dimensional

Step 2

Build object model

training set of positive and negative examples

for each training image compute features

$$L = \frac{1}{N}\sum_{i=1}^{N} \max(0, 1 - y_i[\mathbf{w} \cdot \mathbf{x}_i + b]) + \lambda R(\mathbf{w})$$

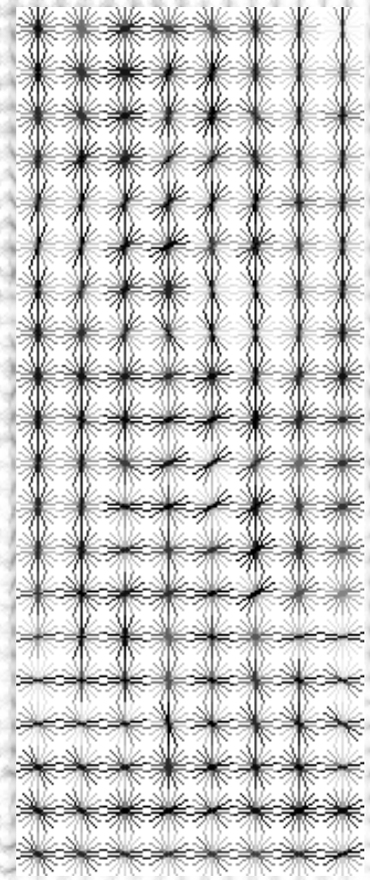
support vector machine (SVM) classifier

Step 3

Score image locations

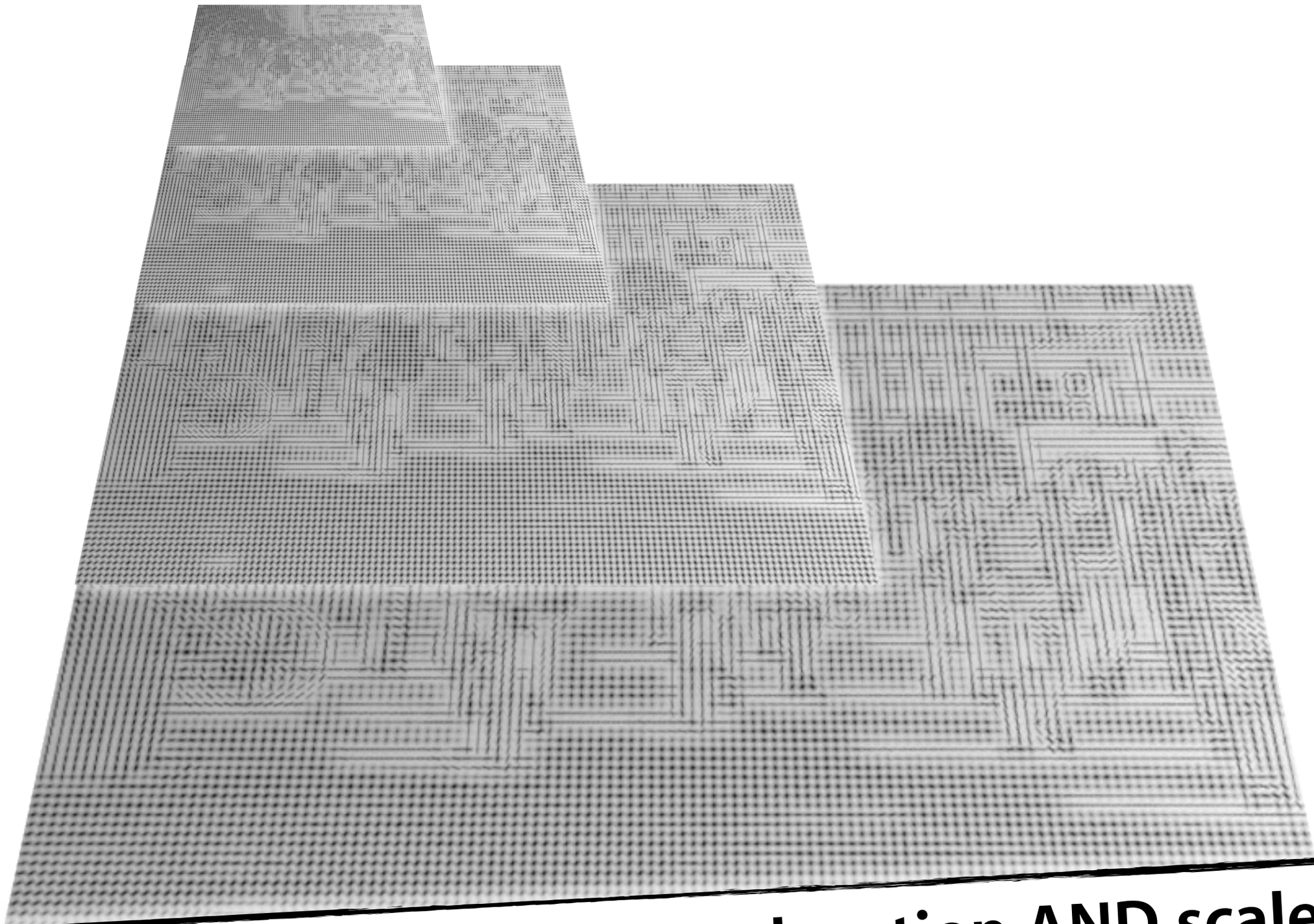

Public
Parking
P

test model at each image location



test model at each image location

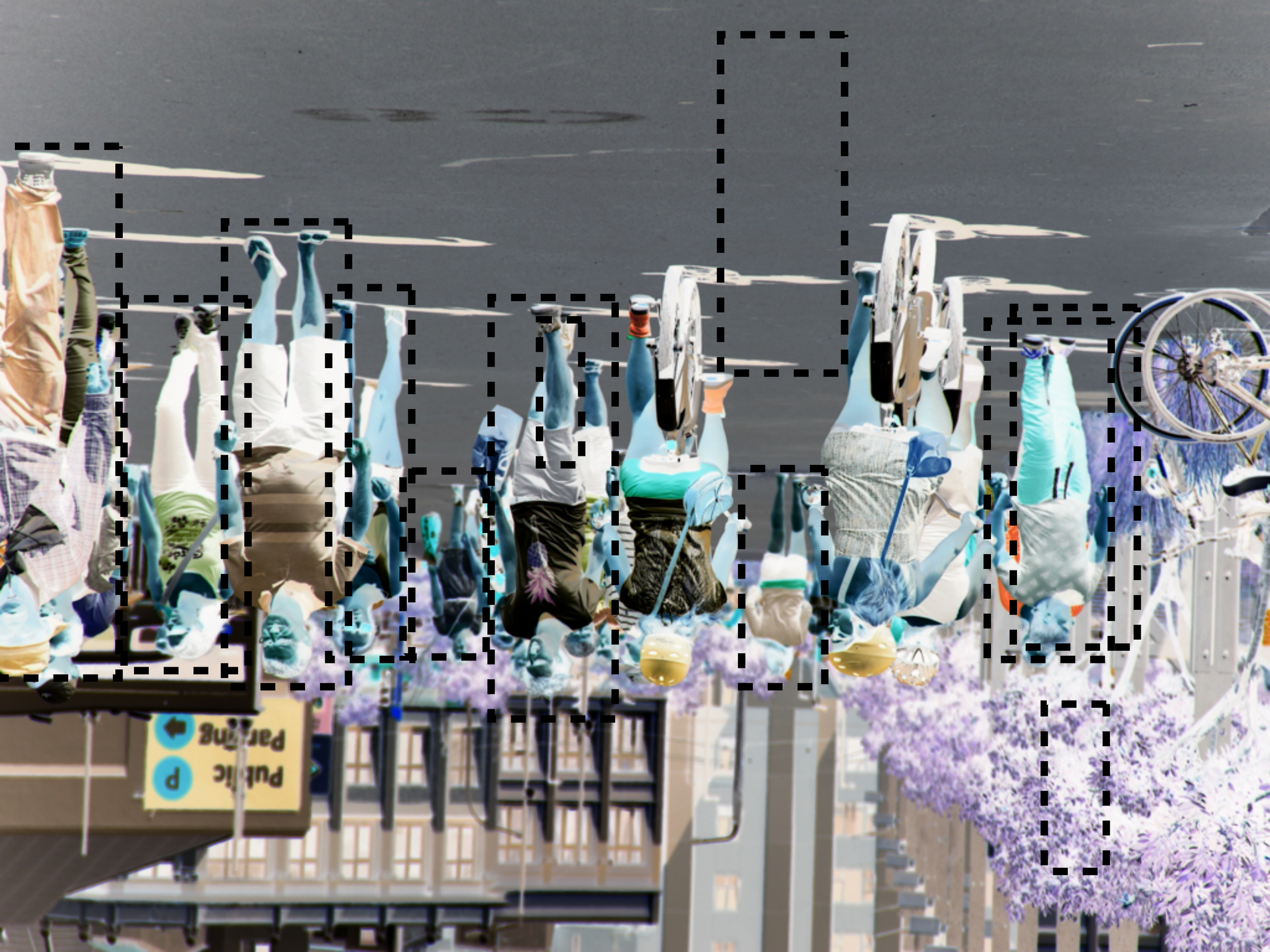
What if the instance size differs from the model?

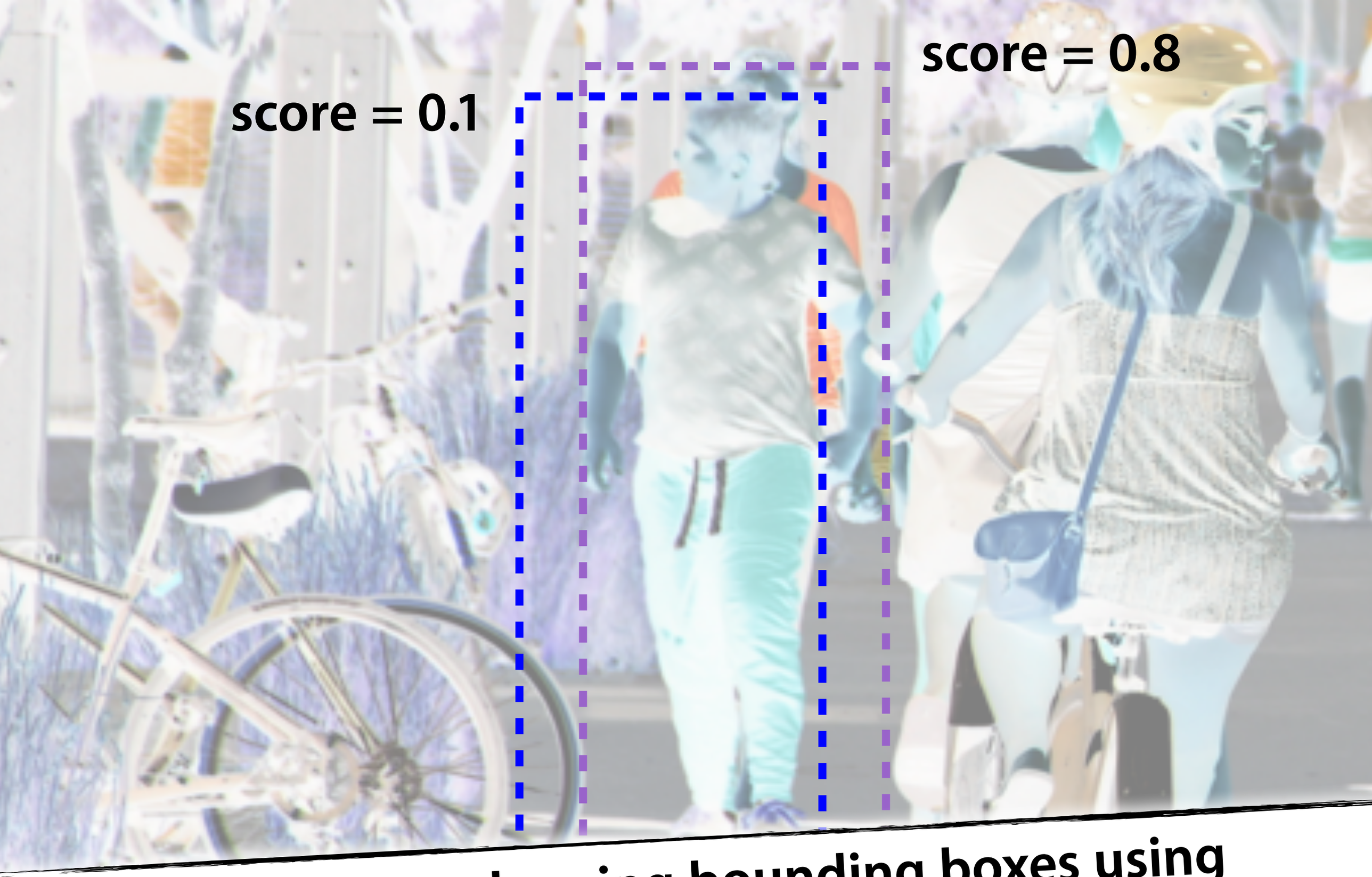


test model at each image location AND scale

Step 4

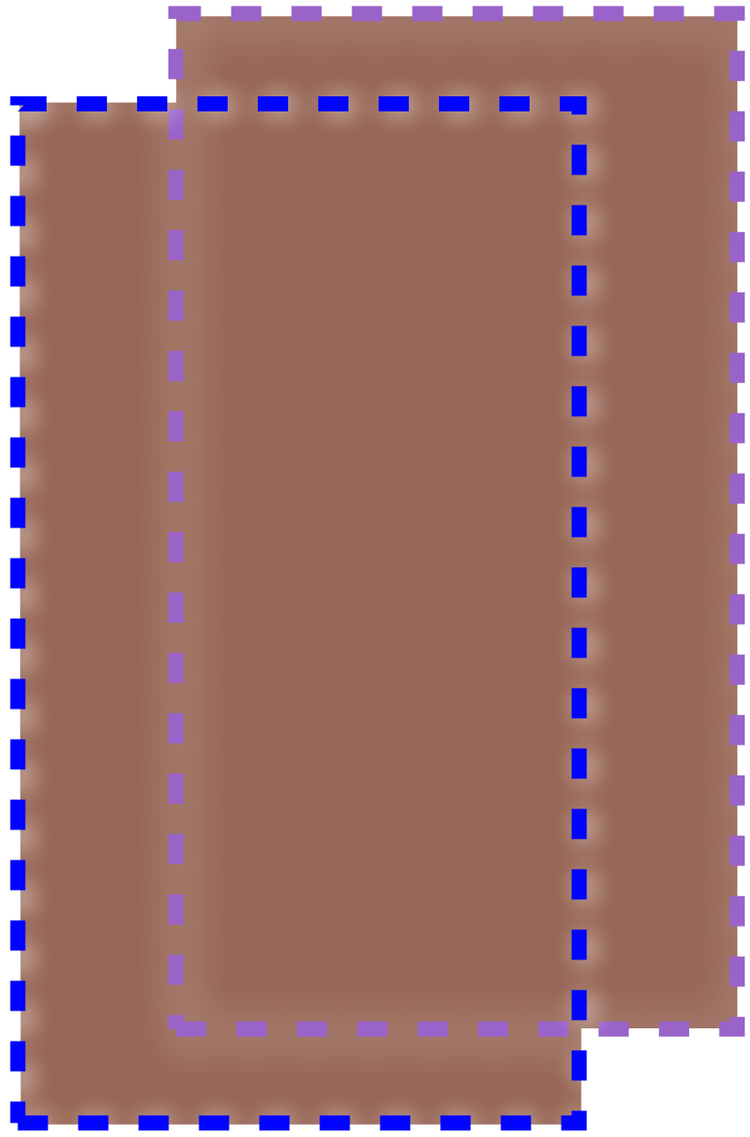
Resolve detections


Public
Parking
P

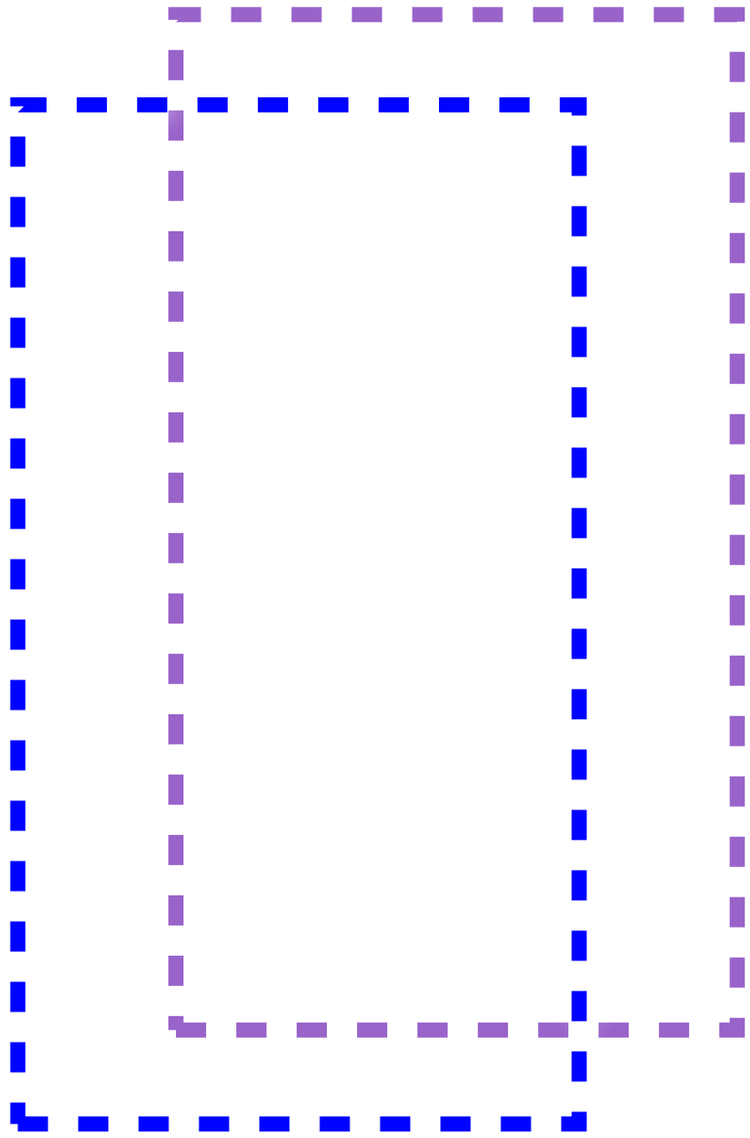


eliminate overlapping bounding boxes using

non-maximum suppression

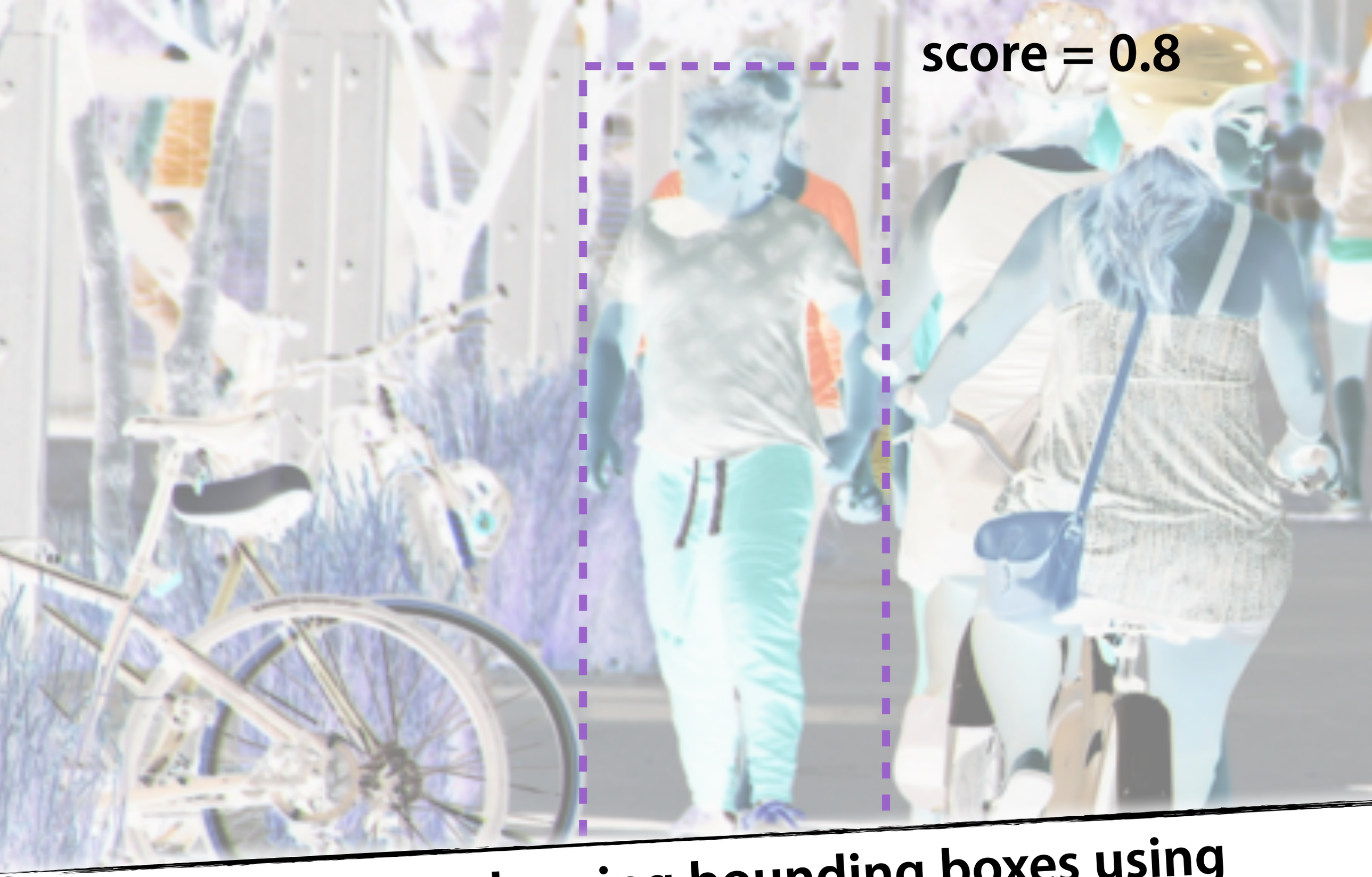


$$\text{overlap} = \frac{\text{area}(\text{box}_1 \cap \text{box}_2)}{\text{area}(\text{box}_1 \cup \text{box}_2)}$$



$$\text{overlap} = \frac{\text{area}(\text{box}_1 \cap \text{box}_2)}{\text{area}(\text{box}_1 \cup \text{box}_2)} > \text{threshold}$$

threshold is typically set to 50%



eliminate overlapping bounding boxes using

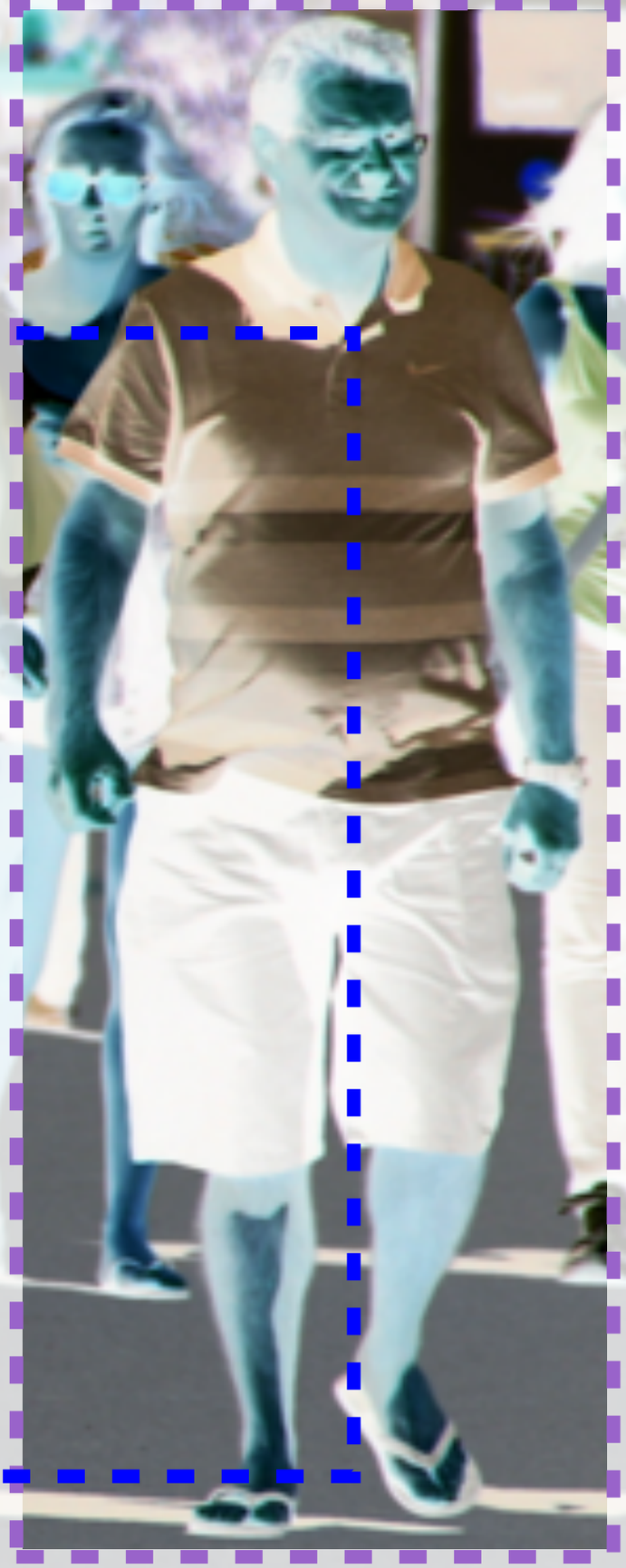
non-maximum suppression

Given a test set, how do we evaluate performance?

true positive

$$\frac{\text{area}(\text{box}_1 \cap \text{box}_2)}{\text{area}(\text{box}_1 \cup \text{box}_2)} > .5$$

ground truth



detection

precision

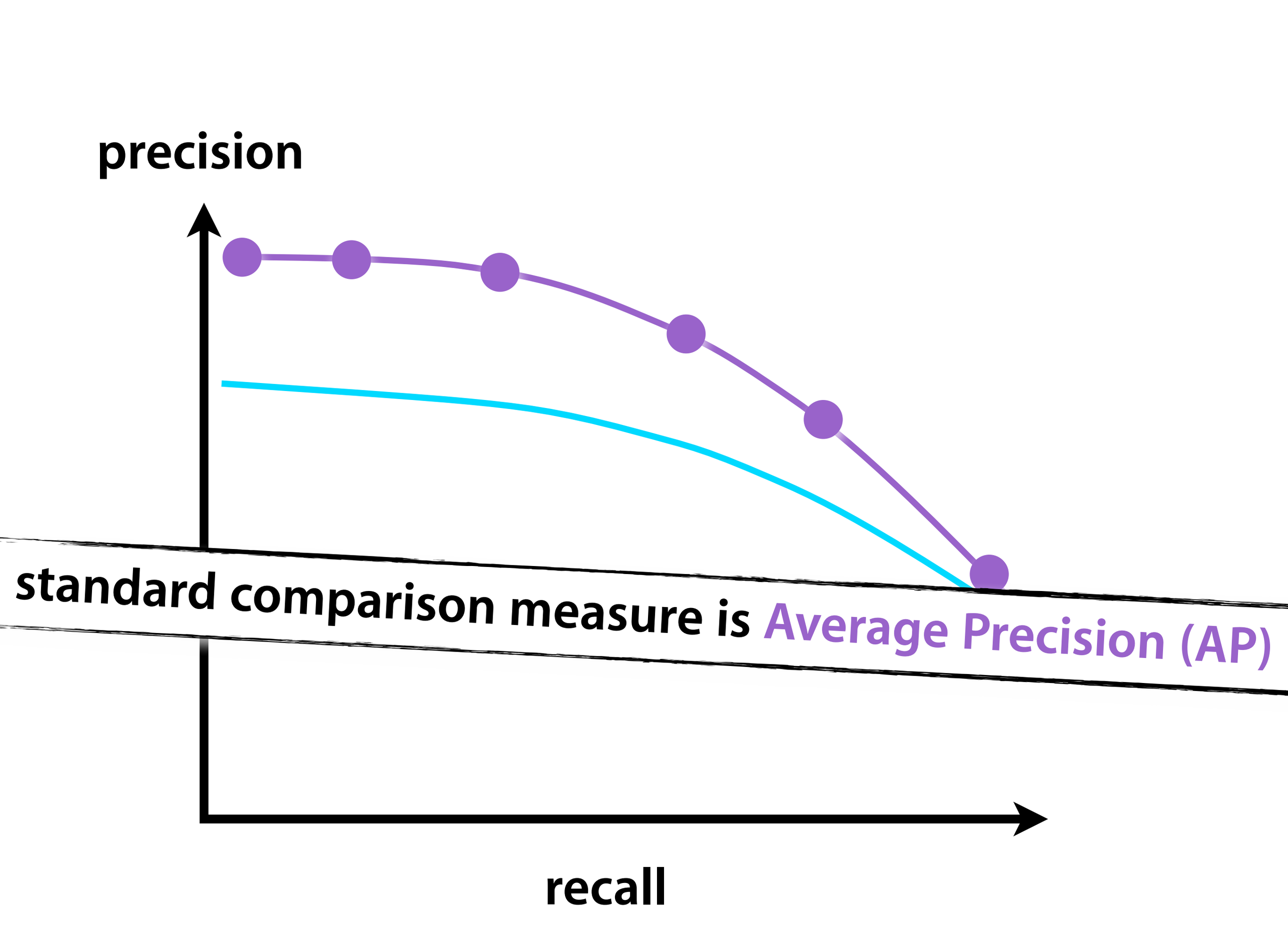
recall: percentage of true positives detected

recall

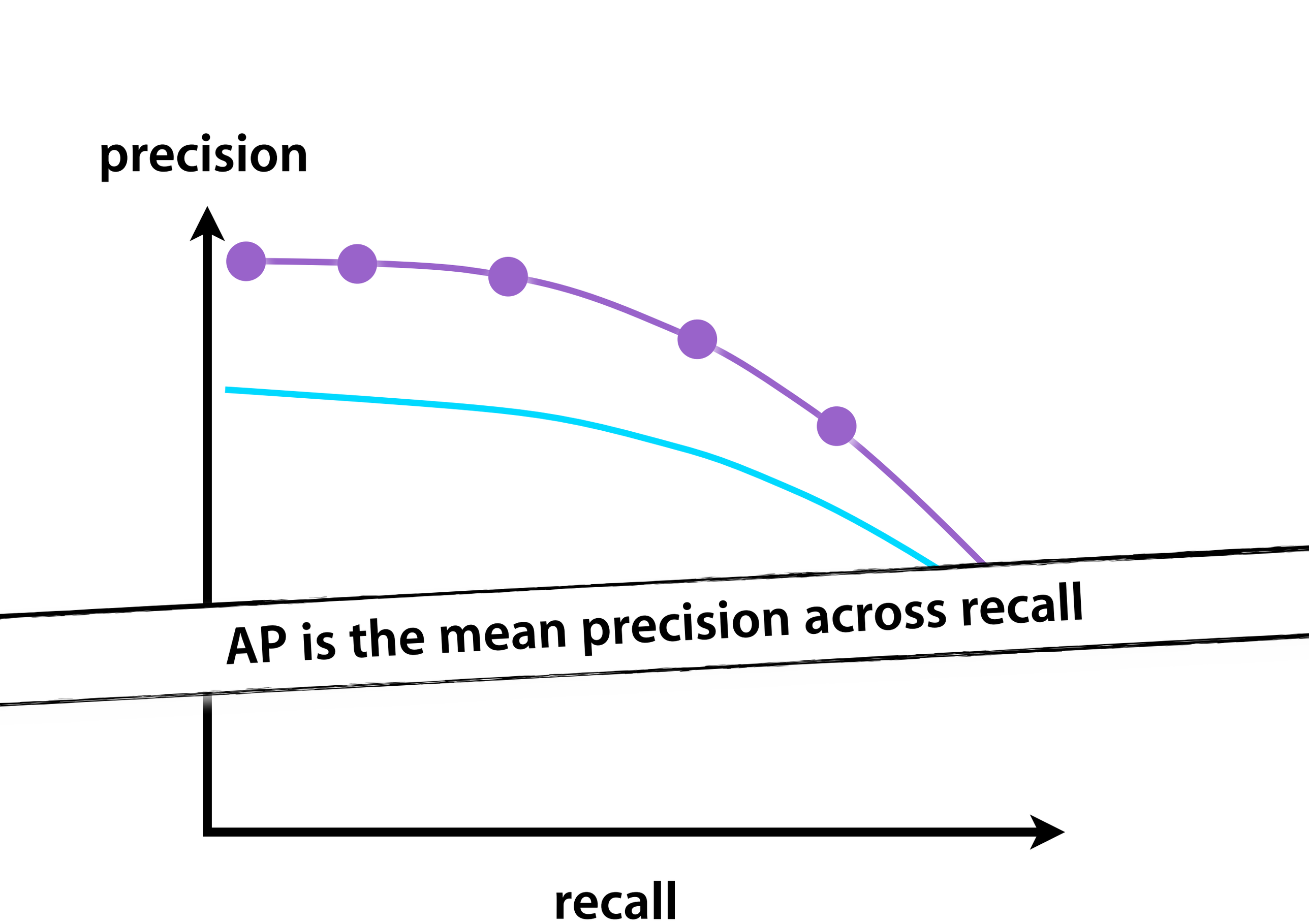
precision

precision: percentage of detections that are correct

recall



standard comparison measure is Average Precision (AP)


precision
AP is the mean precision across recall
recall