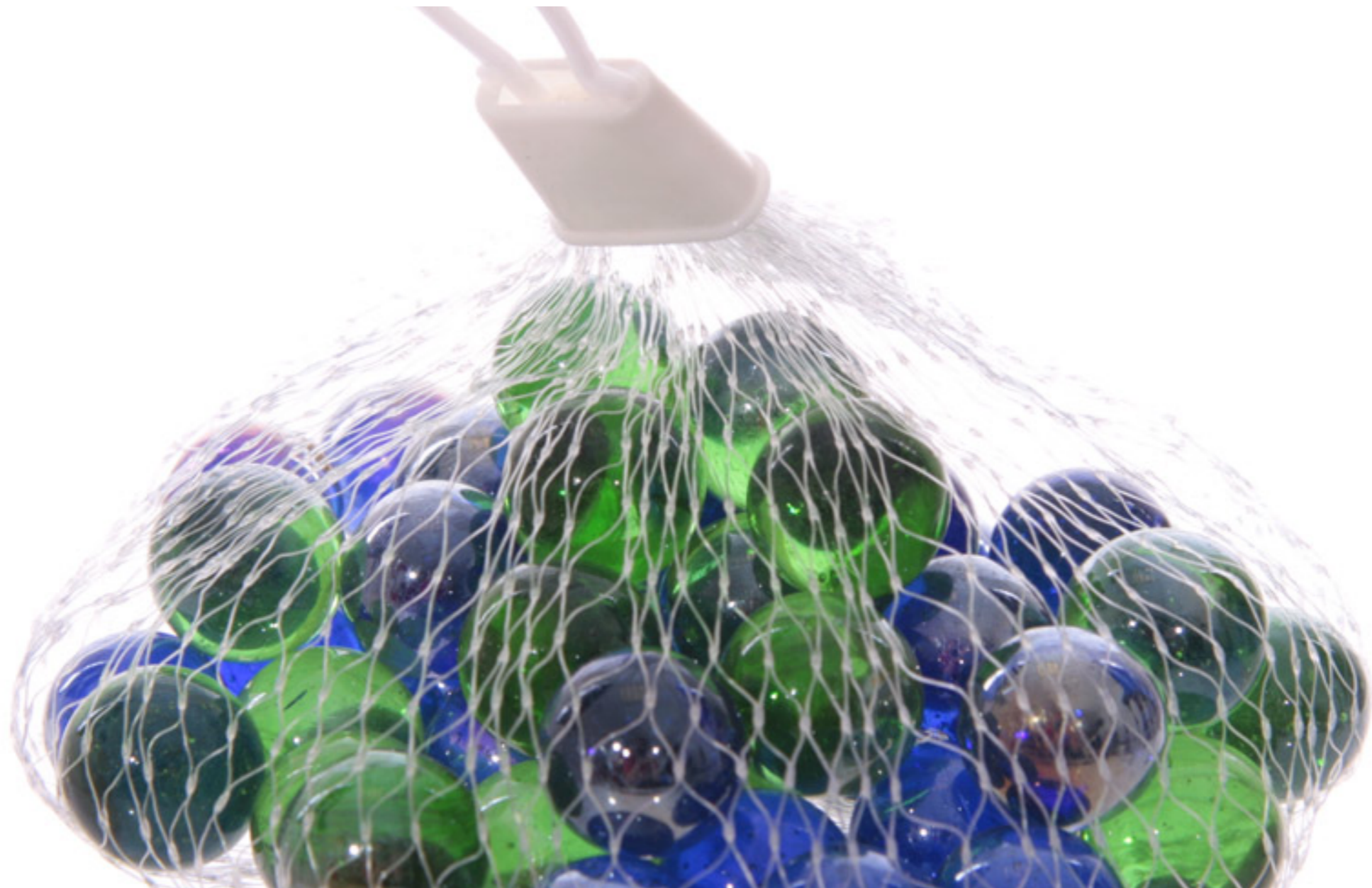


Image classification



Overview of today's lecture

- Introduction to learning-based vision.
- Image classification.
- Bag-of-words.
- K-means clustering.
- Classification.
- K nearest neighbors.
- Naïve Bayes.
- Support vector machine.

Slide credits

Most of these slides were adapted from:

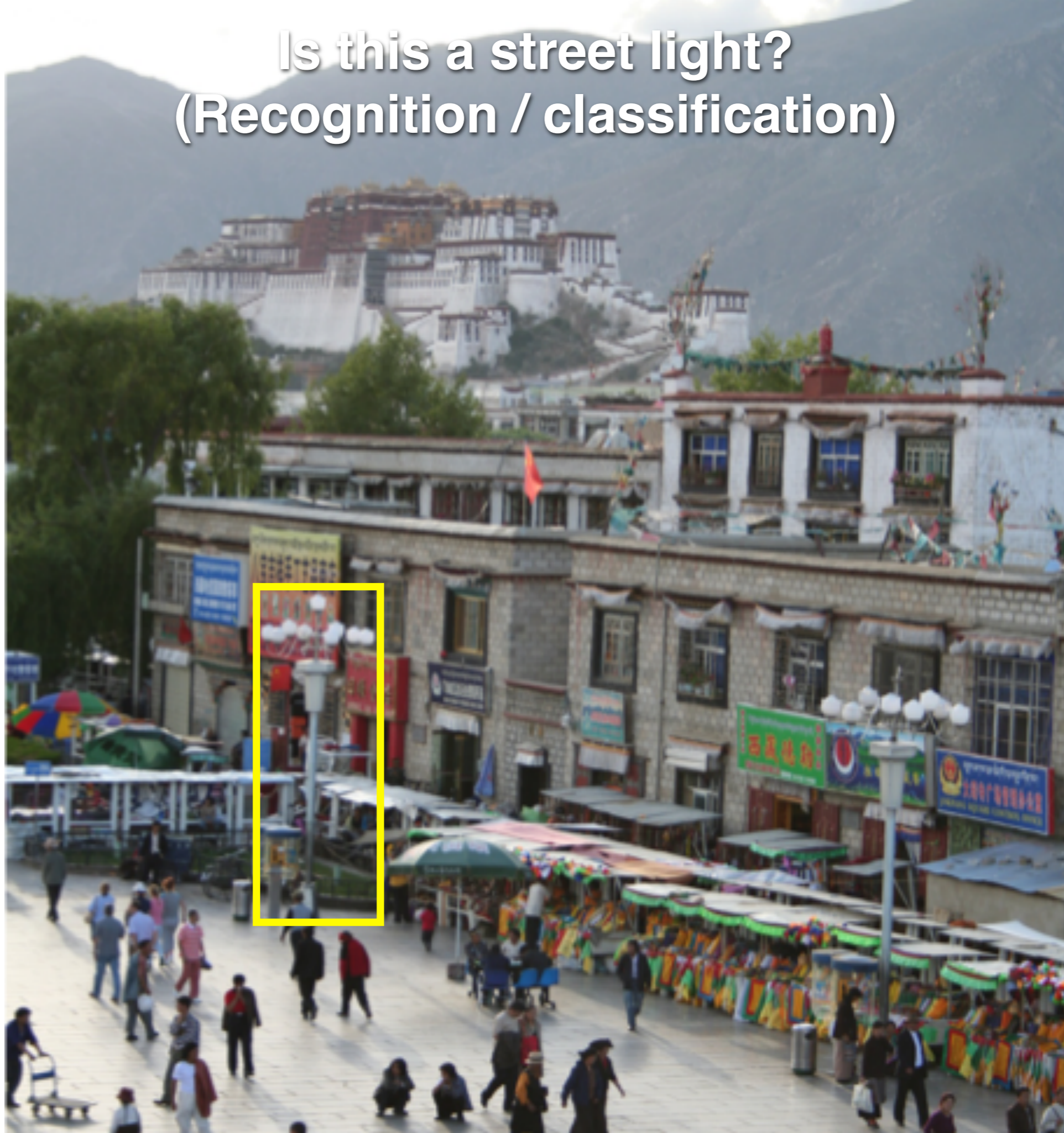
- Kris Kitani (16-385, Spring 2017).
- Noah Snavely (Cornell University).
- Fei-Fei Li (Stanford University).

Course overview

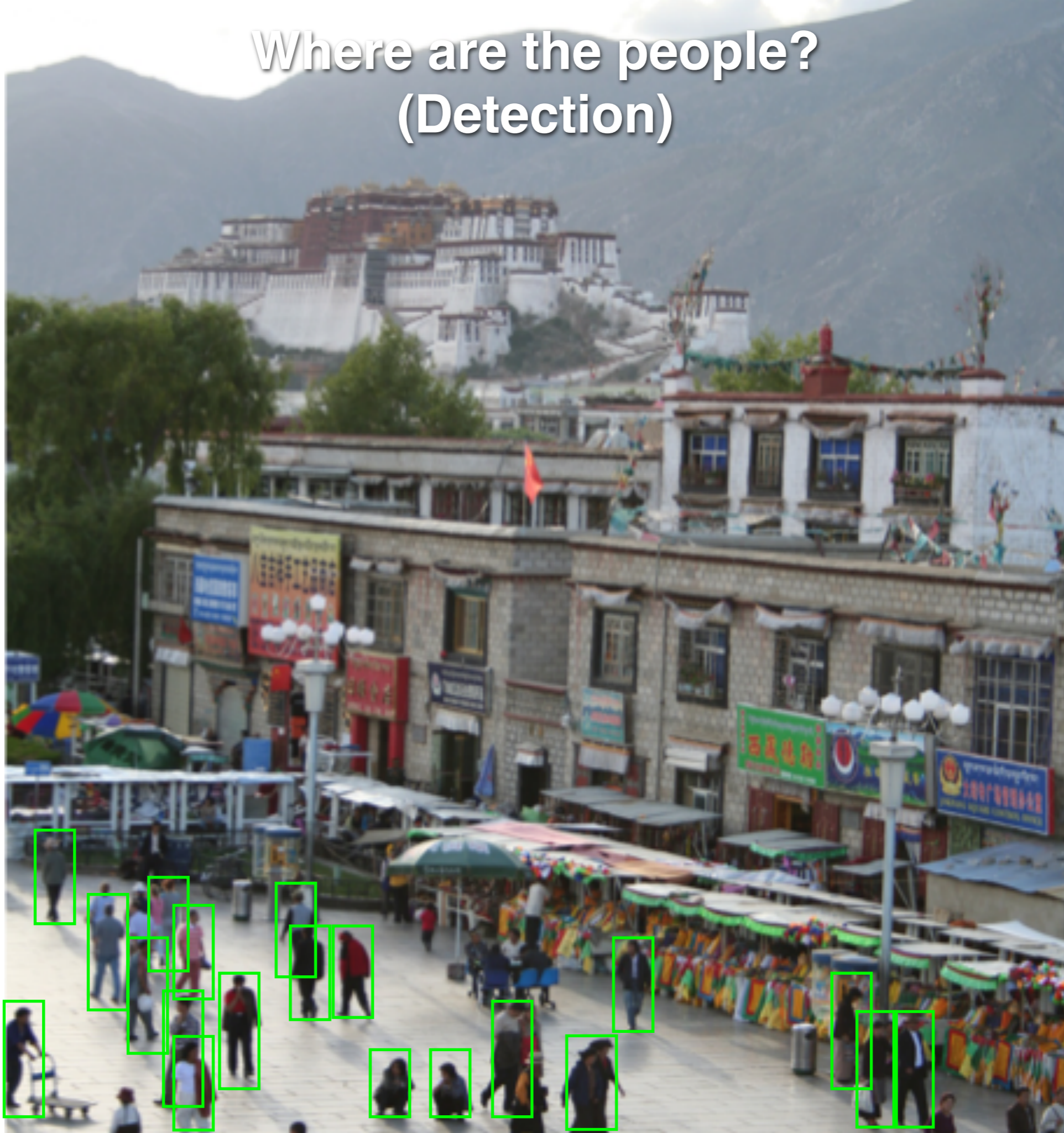
1. Image processing. ← Lectures 1 – 6
See also 18-793: Image and Video Processing
2. Geometry-based vision. ← Lectures 7 – 12
See also 16-822: Geometry-based Methods in Vision
3. Learning-based vision. ← We are starting this part now
4. Dealing with motion.
5. Physics-based vision.

What do we mean by learning-based vision or 'semantic vision'?

Is this a street light?
(Recognition / classification)



Where are the people? (Detection)

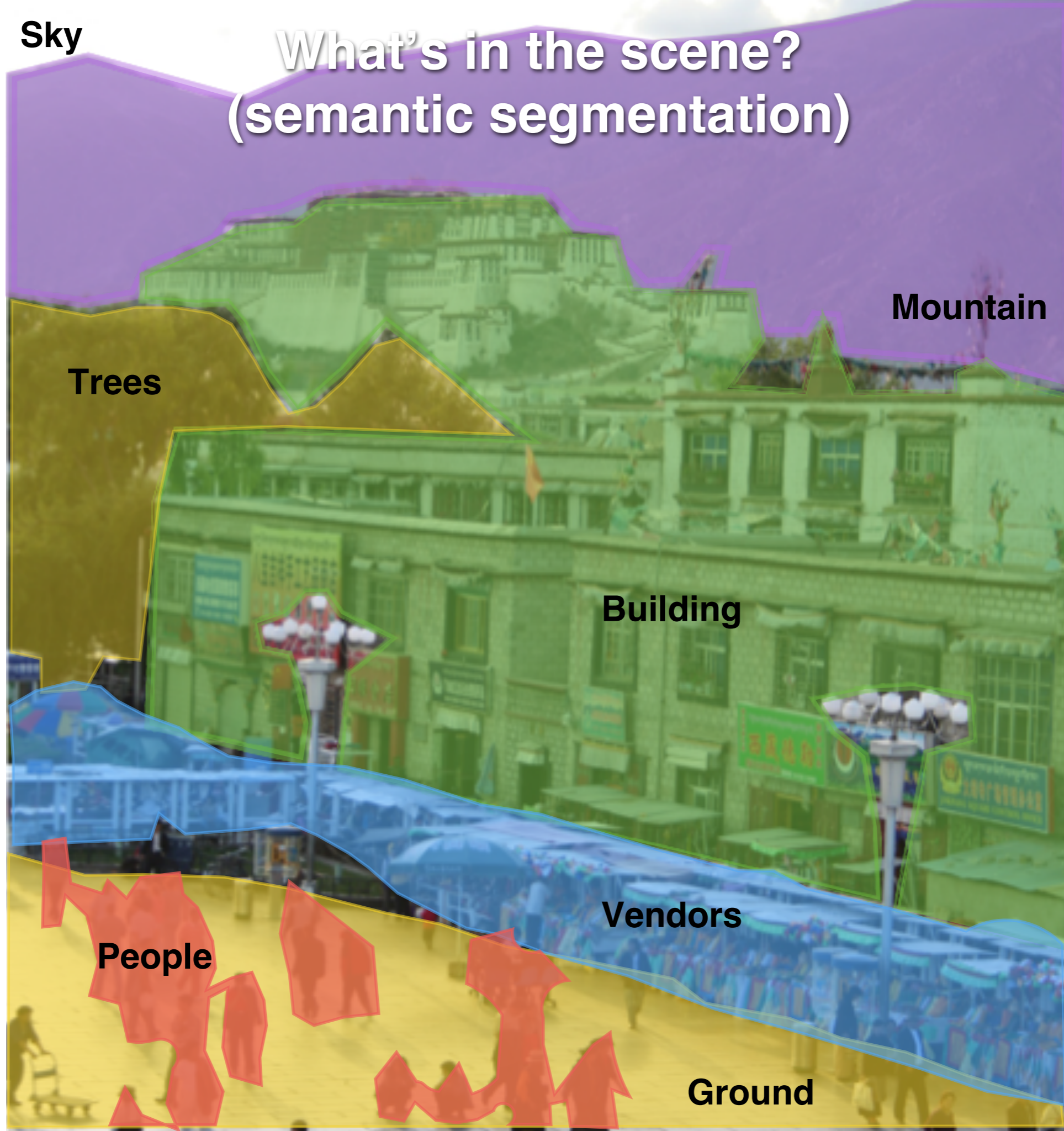


Is that Potala palace? (Identification)



Sky

What's in the scene? (semantic segmentation)



Mountain

Trees

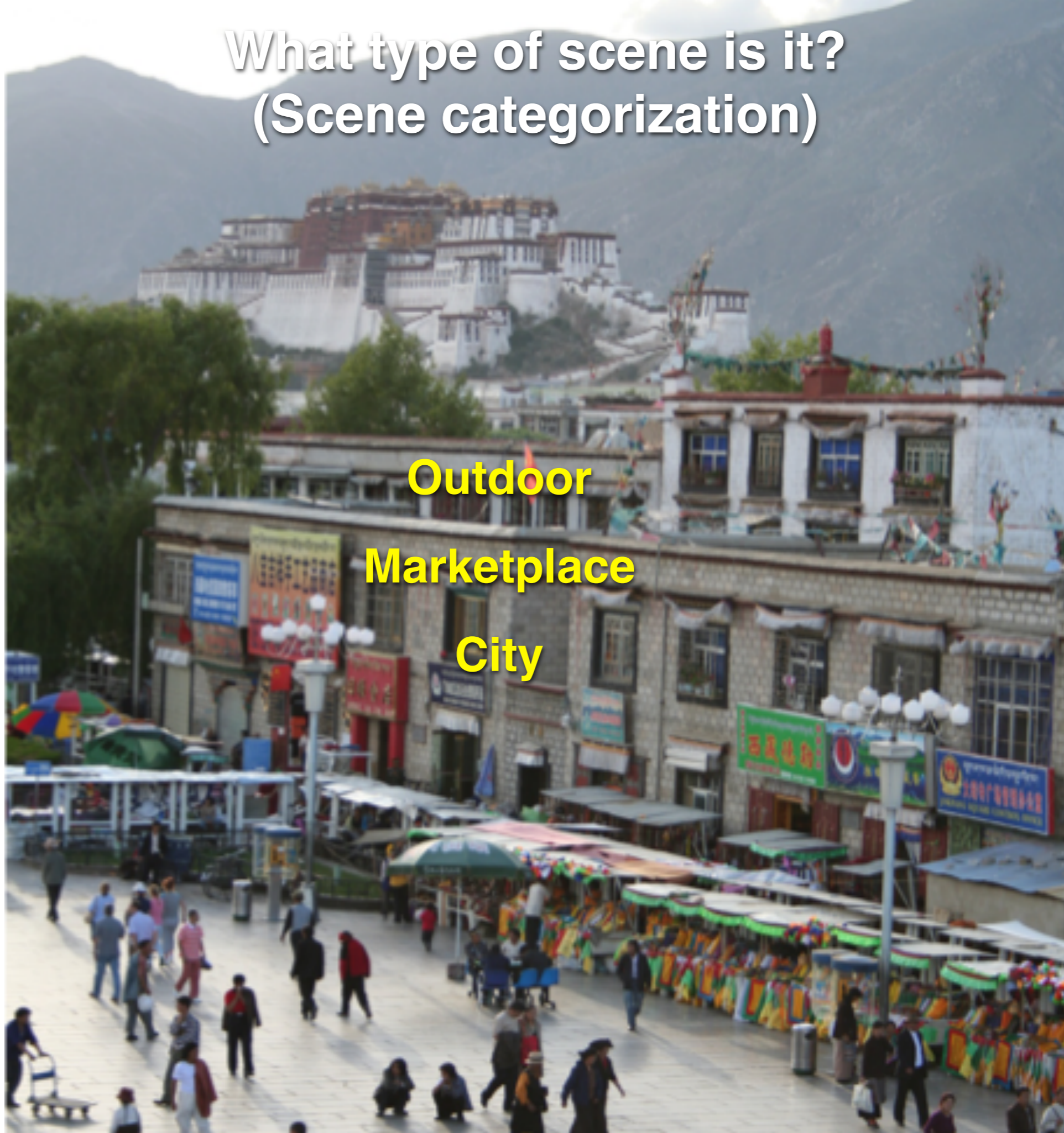
Building

Vendors

People

Ground

What type of scene is it?
(Scene categorization)

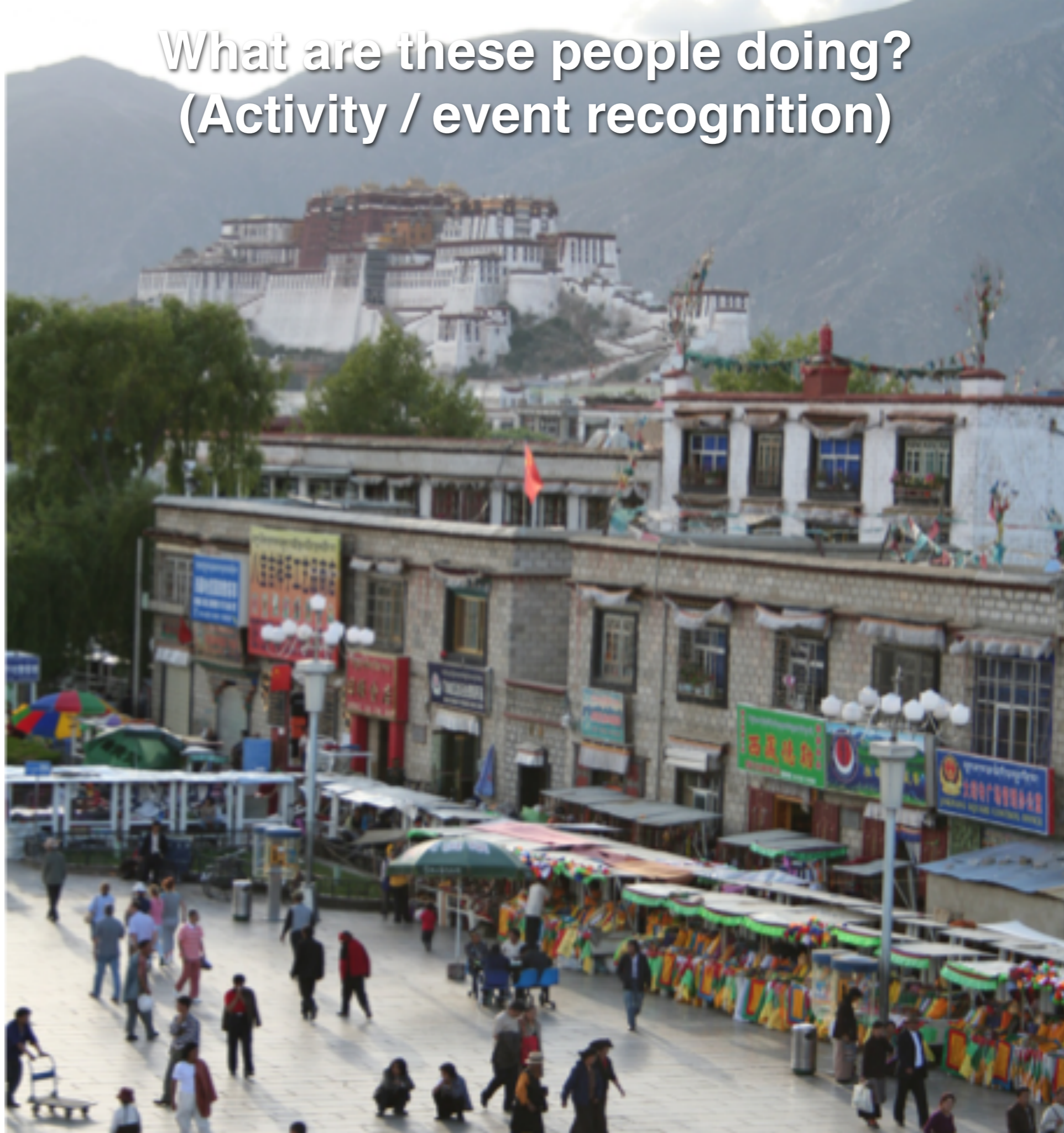


Outdoor

Marketplace

City

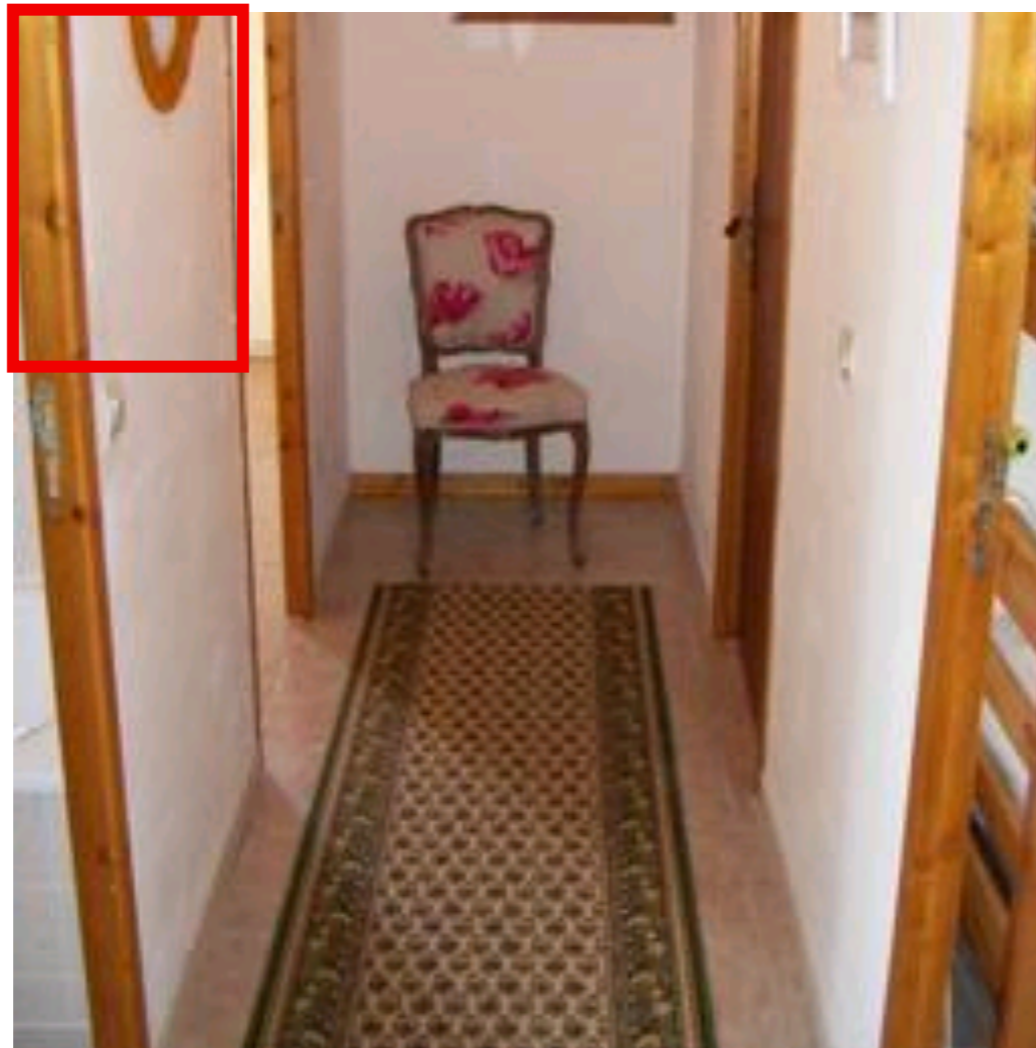
What are these people doing?
(Activity / event recognition)



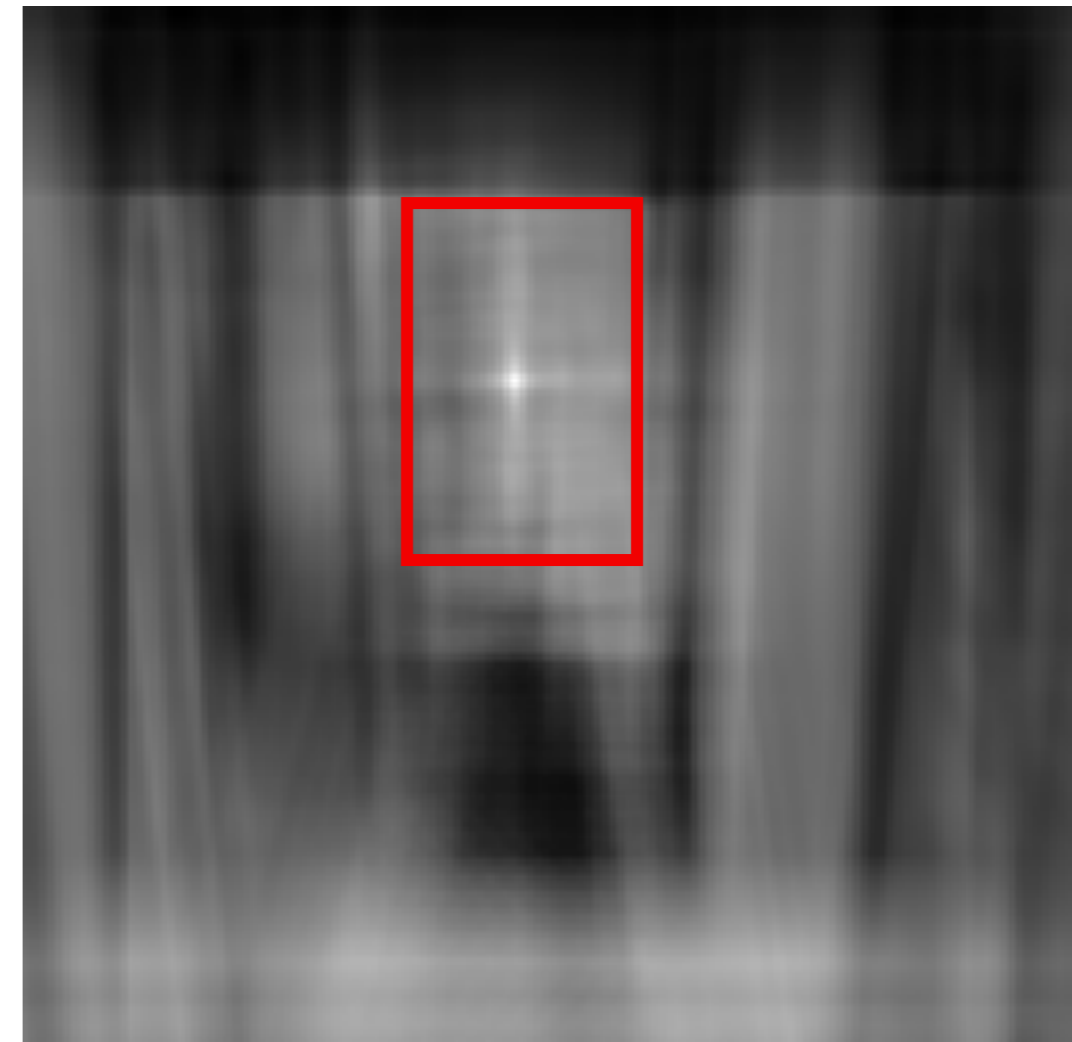
Object recognition

Is it really so hard?

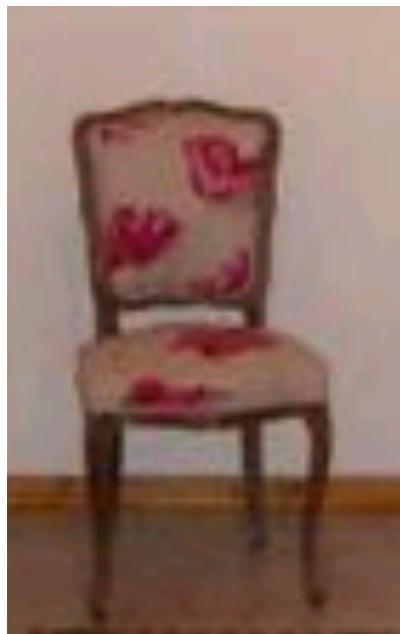
Find the chair in this image

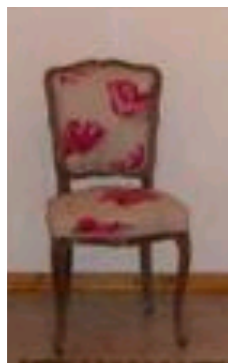


Output of normalized correlation



This is a chair

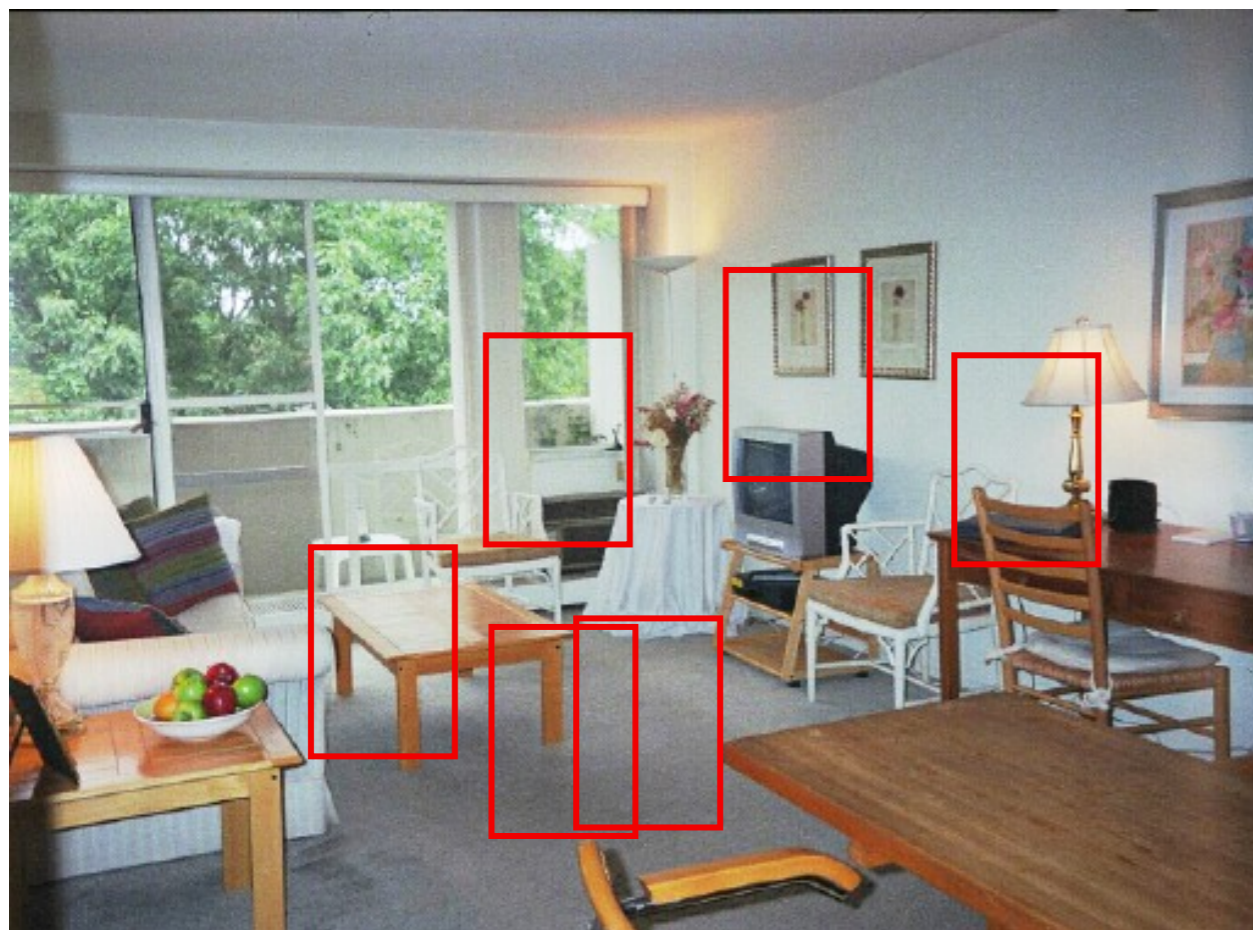




Object recognition

Is it really so hard?

Find the chair in this image



Pretty much garbage

Simple template matching is not going to make it

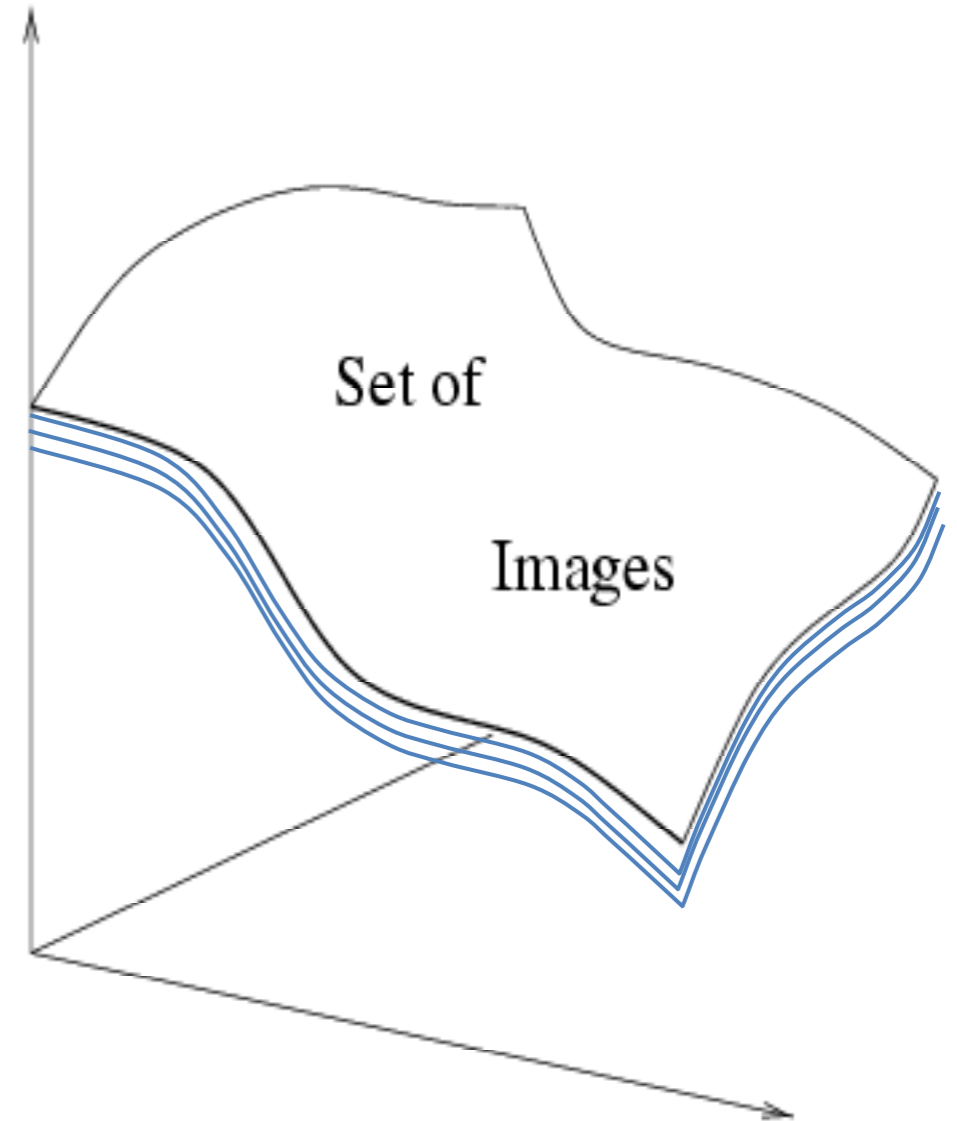
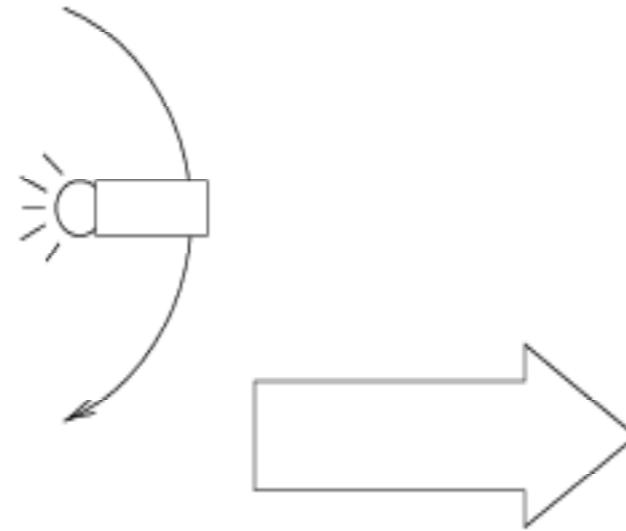
A “popular method is that of template matching, by point to point correlation of a model pattern with the image pattern. These techniques are inadequate for three-dimensional scene analysis for many reasons, such as occlusion, changes in viewing angle, and articulation of parts.” Nivatia & Binford, 1977.

And it can get a lot harder



Brady, M. J., & Kersten, D. (2003). Bootstrapped learning of novel objects. *J Vis*, 3(6), 413-422

Why is this hard?



Variability: Camera position
Illumination
Shape parameters

How many object categories are there?

~10,000 to 30,000

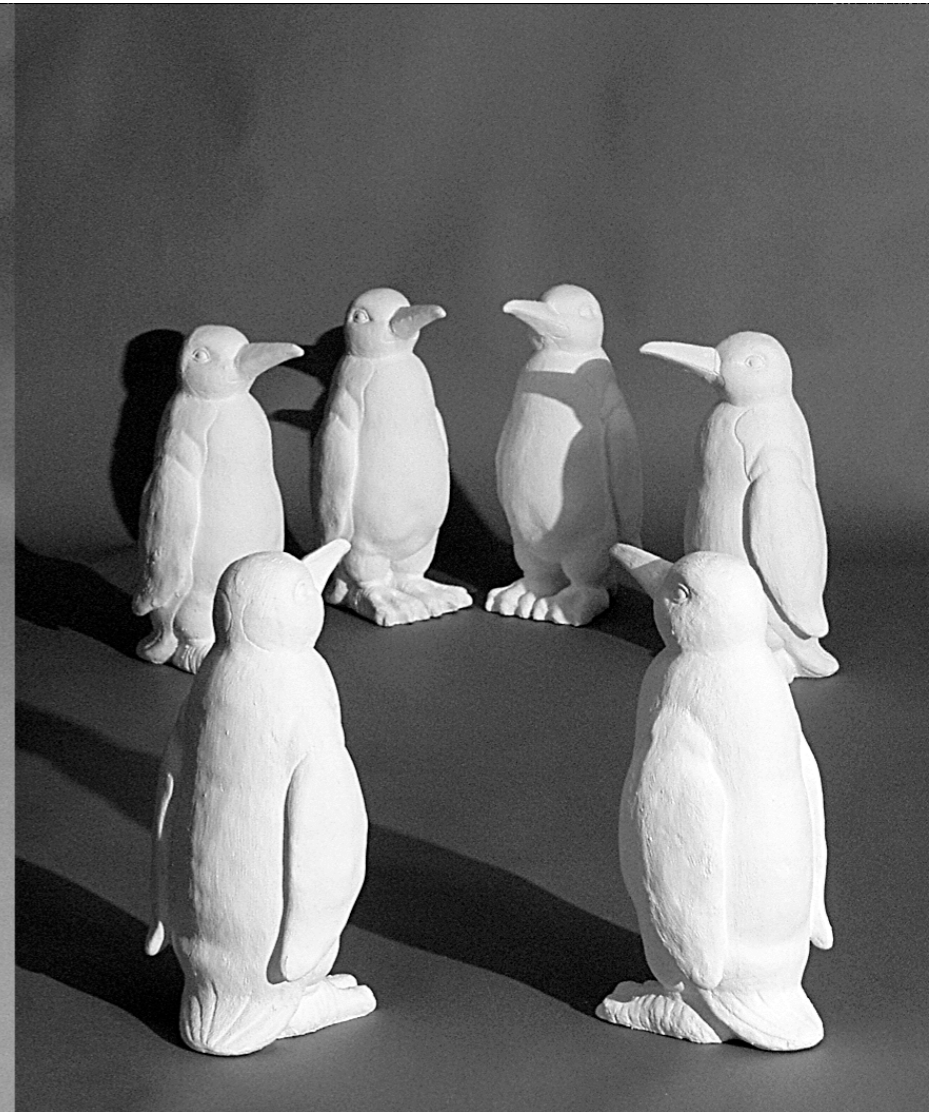
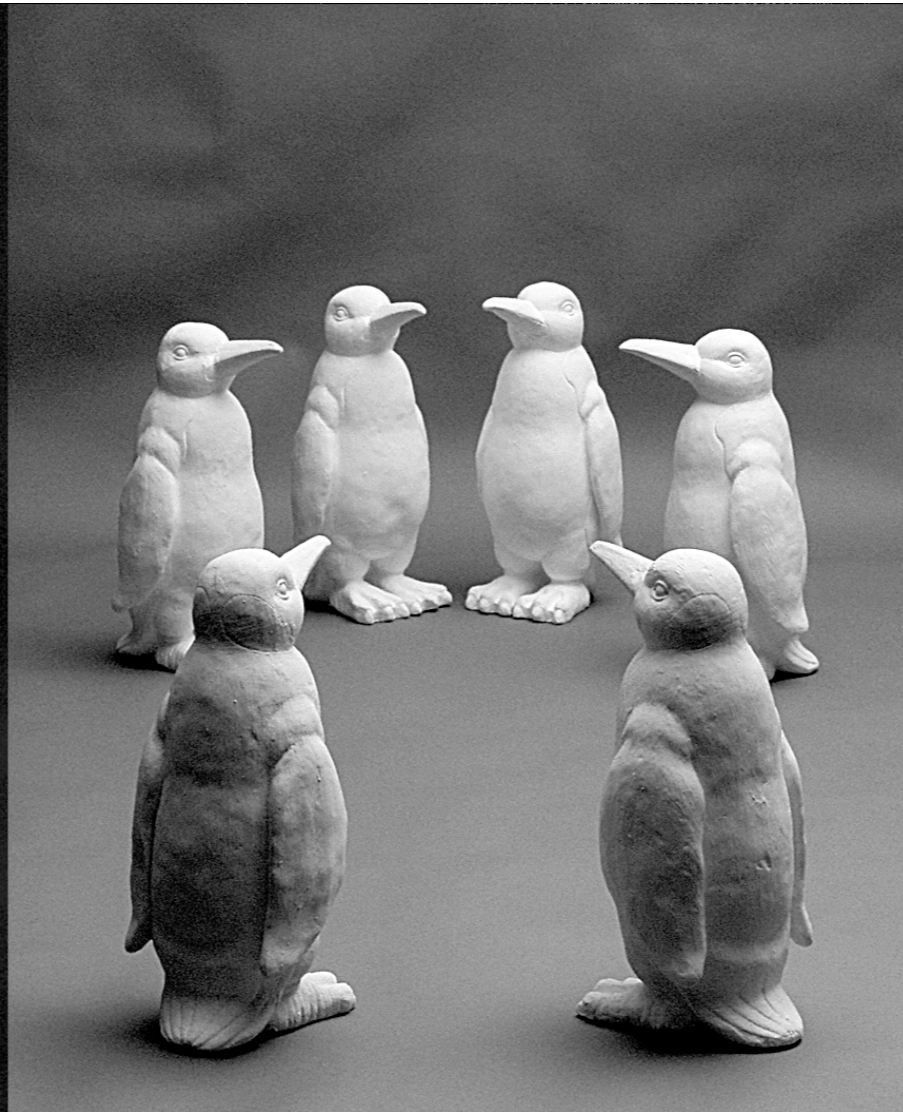
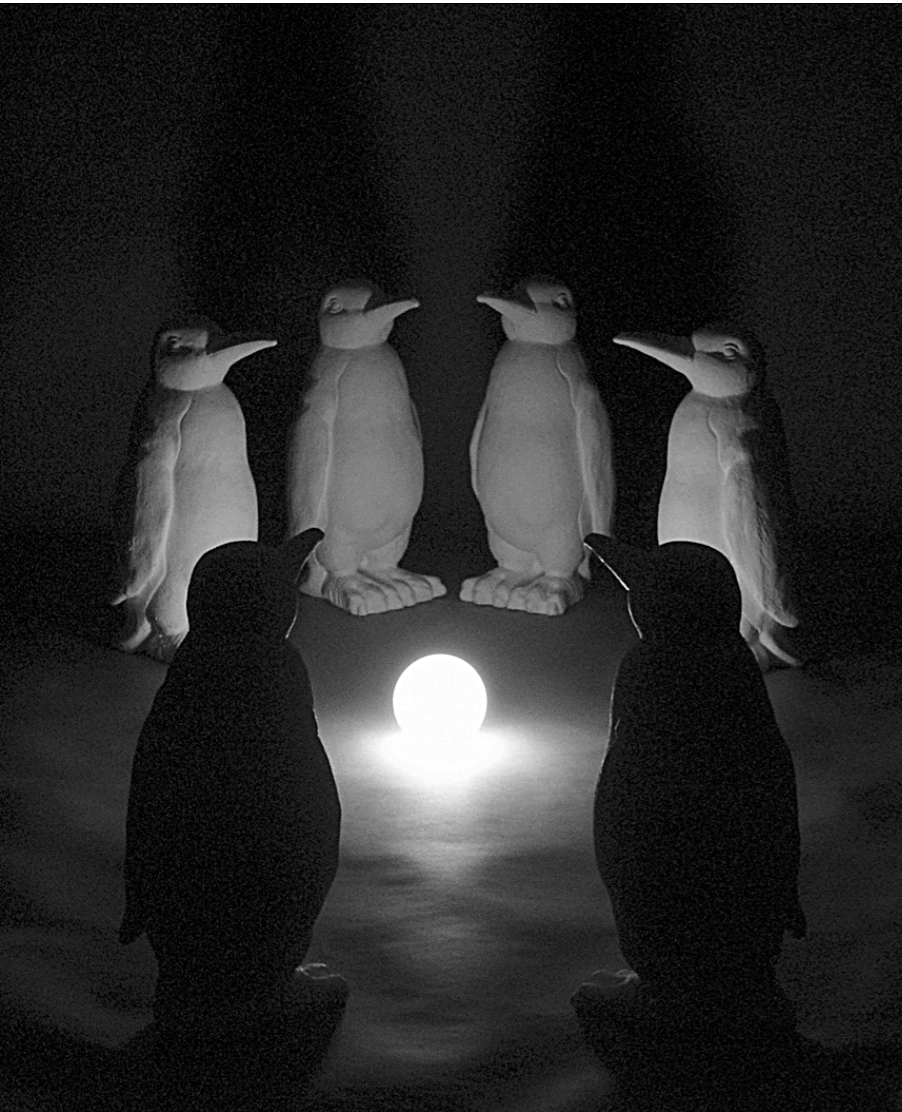


Challenge: variable viewpoint



Michelangelo 1475-1564

Challenge: variable illumination



Challenge: scale



Challenge: deformation



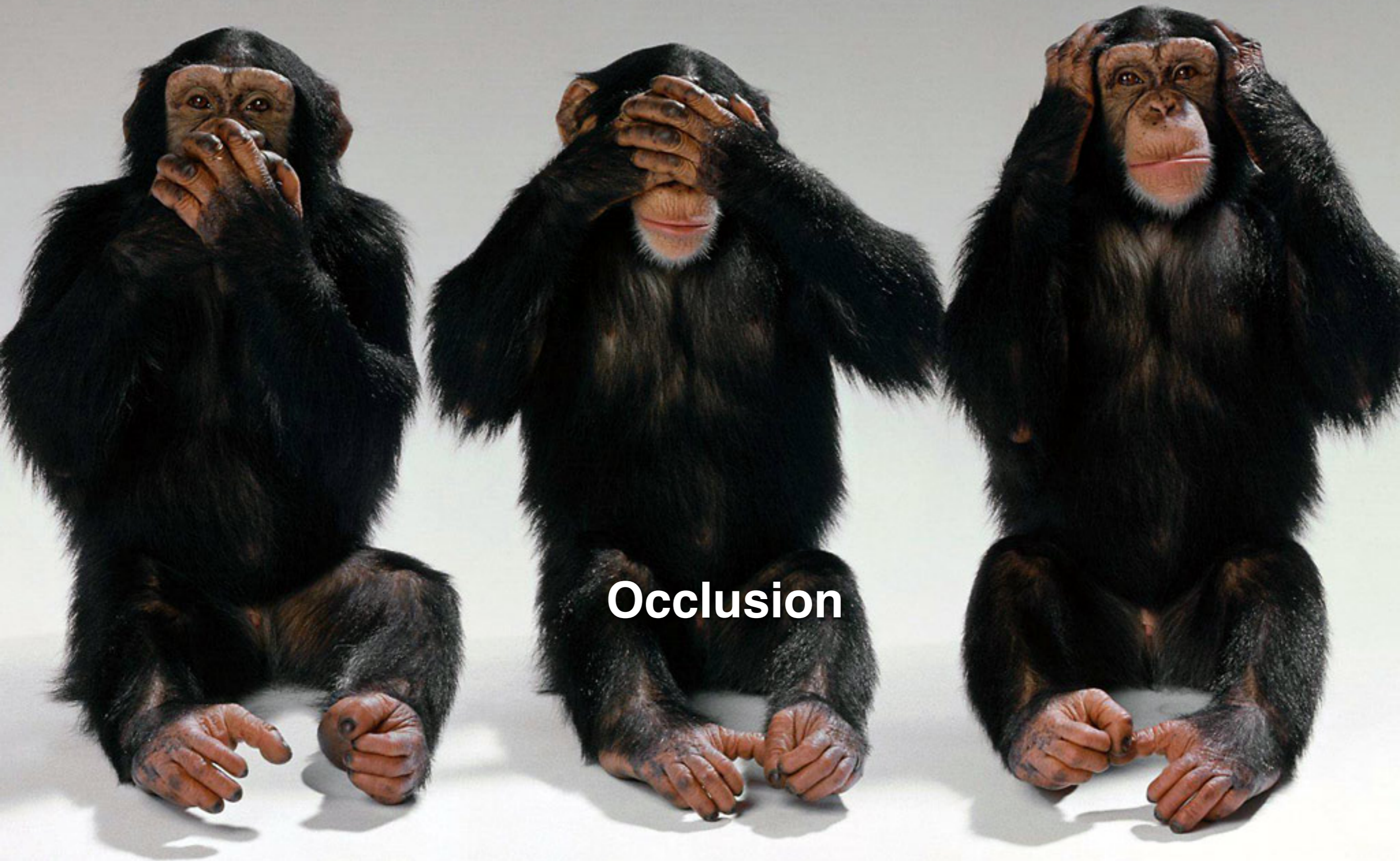


Deformation

Challenge: Occlusion



Magritte, 1957



Occlusion

Challenge: background clutter



Kilmeny Niland. 1995



Challenge: Background clutter

Challenge: intra-class variations



Image Classification

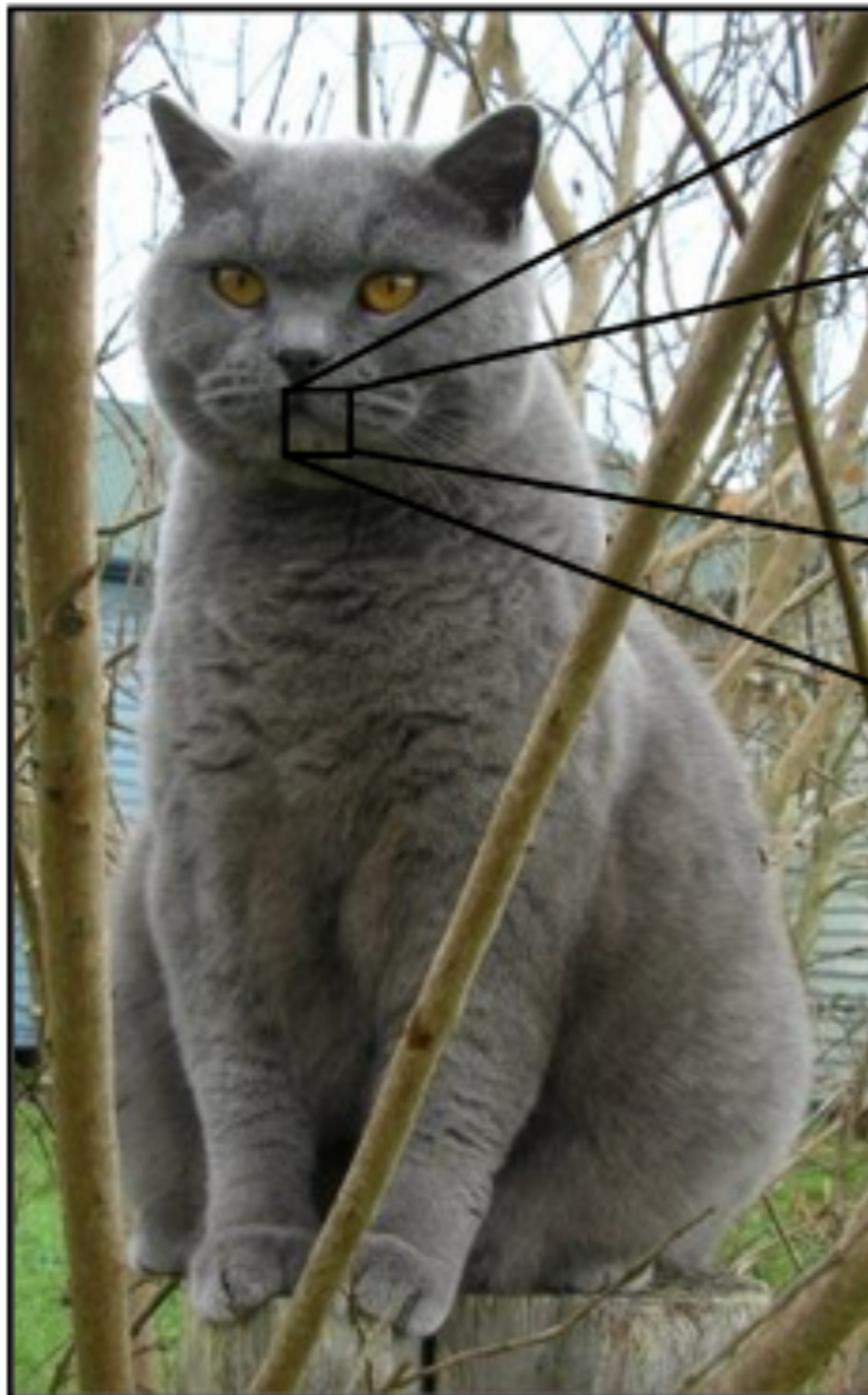


(assume given set of discrete labels)
{dog, cat, truck, plane, ...}



cat

Image Classification: Problem



08	02	22	97	38	15	00	40	00	75	04	05	07	78	52	12	50	77	91	05
49	49	99	40	17	81	18	57	60	87	17	40	98	43	69	48	04	56	62	00
81	49	31	73	55	79	14	29	93	71	40	67	58	88	30	03	49	13	36	65
52	70	95	23	04	60	11	42	69	21	68	56	01	32	56	71	37	02	36	91
22	31	16	71	51	62	63	89	41	92	36	54	22	40	40	28	66	33	13	80
24	47	38	60	99	03	45	02	44	75	33	53	78	36	84	20	35	17	12	50
32	98	81	28	64	23	67	10	26	38	40	67	59	54	70	66	18	38	64	70
67	26	20	68	02	62	12	20	95	63	94	39	63	08	40	91	66	49	94	21
24	55	58	05	66	73	99	26	97	17	78	78	96	83	14	88	34	89	63	72
21	36	23	09	75	00	76	44	20	45	35	14	00	61	33	97	34	31	33	95
78	17	53	28	22	75	31	67	15	94	03	80	04	62	16	14	09	53	56	92
16	39	05	42	96	35	31	47	55	58	88	24	00	17	54	24	36	29	85	57
86	56	00	48	35	71	89	07	05	44	44	37	44	60	21	58	51	54	17	58
19	80	81	68	05	94	47	69	28	73	92	13	86	52	17	77	04	89	55	40
04	52	08	83	97	35	99	16	07	97	57	32	16	26	26	79	33	27	98	66
55	46	68	87	57	62	20	72	03	46	33	67	46	55	12	32	63	93	53	69
04	42	16	73	35	35	39	11	24	94	72	18	08	46	29	32	40	62	76	36
20	69	36	41	72	30	23	88	34	82	99	69	82	67	59	85	74	04	36	16
20	73	35	29	78	31	90	01	74	31	49	71	48	58	81	16	23	57	05	54
01	70	54	71	83	51	54	69	16	92	33	48	61	43	52	01	89	17	67	48

What the computer sees

image classification → 82% cat
15% dog
2% hat
1% mug

Data-driven approach

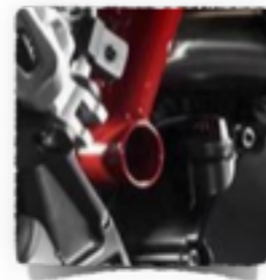
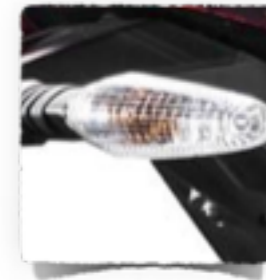
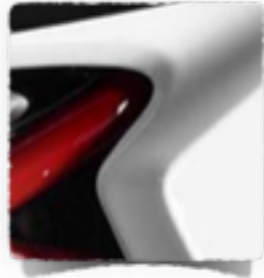
- Collect a database of images with labels
- Use ML to train an image classifier
- Evaluate the classifier on test images

Example training set

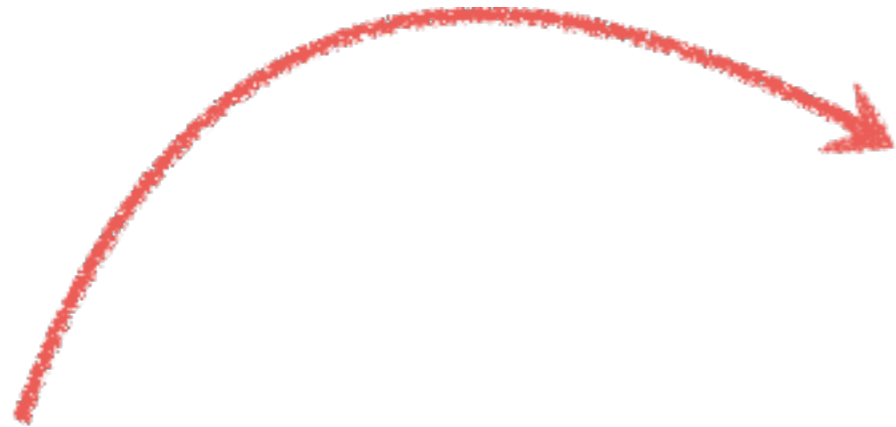


Bag of words

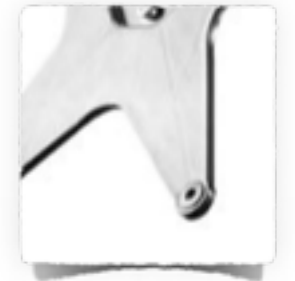
What object do these parts belong to?



Some local features
are very informative



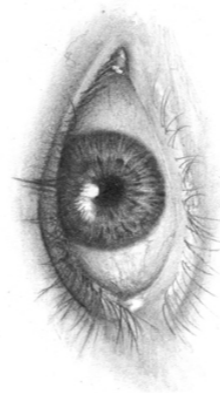
An object as



a collection of local features
(bag-of-features)

- deals well with occlusion
- scale invariant
- rotation invariant

(not so) crazy assumption



spatial information of local features
can be ignored for object recognition

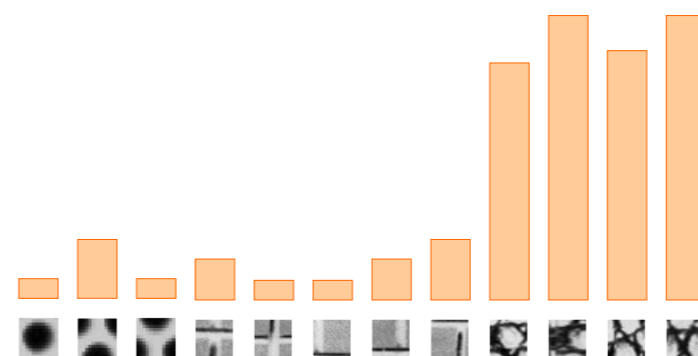
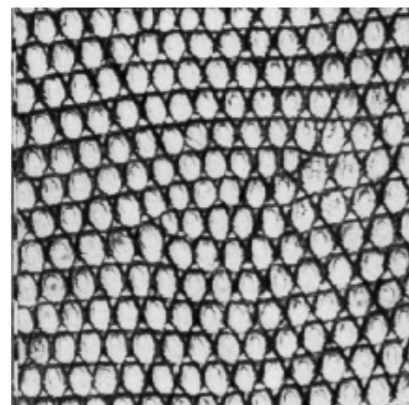
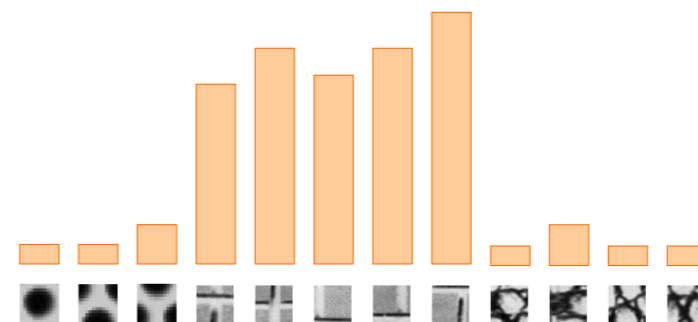
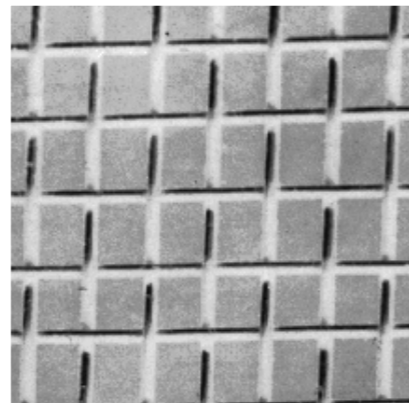
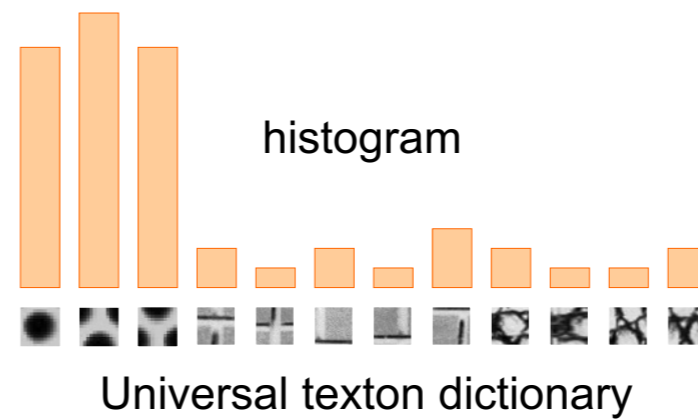
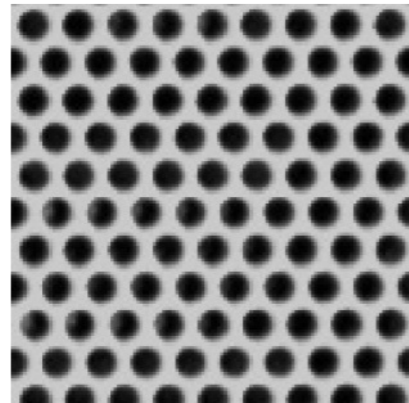
Bag-of-features

represent a data item (document, texture, image)
as a histogram over features

an old idea

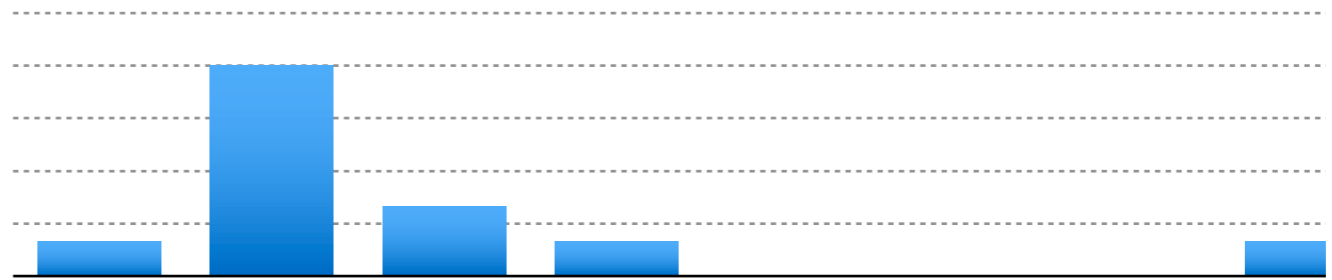
(e.g., texture recognition and information retrieval)

Texture recognition

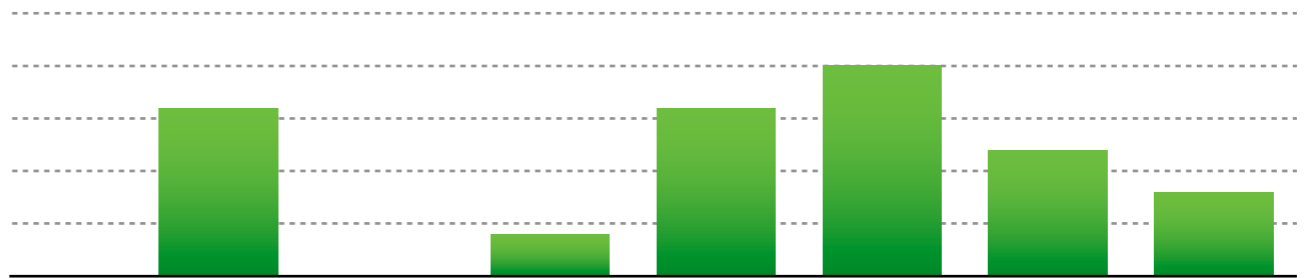


Vector Space Model

G. Salton. 'Mathematics and Information Retrieval' Journal of Documentation, 1979



1	6	2	1	0	0	0	1
Tartan	robot	CHIMP	CMU	bio	soft	ankle	sensor



0	4	0	1	4	5	3	2
Tartan	robot	CHIMP	CMU	bio	soft	ankle	sensor

A document (datapoint) is a vector of counts over each word (feature)

$$\mathbf{v}_d = [n(w_{1,d}) \quad n(w_{2,d}) \quad \cdots \quad n(w_T,d)]$$

$n(\cdot)$ counts the number of occurrences



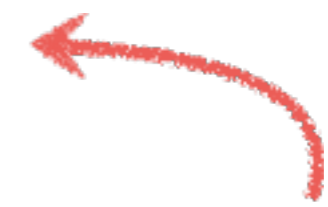
just a histogram over words

What is the similarity between two documents?



A document (datapoint) is a vector of counts over each word (feature)

$$\mathbf{v}_d = [n(w_{1,d}) \quad n(w_{2,d}) \quad \cdots \quad n(w_T,d)]$$



$n(\cdot)$ counts the number of occurrences

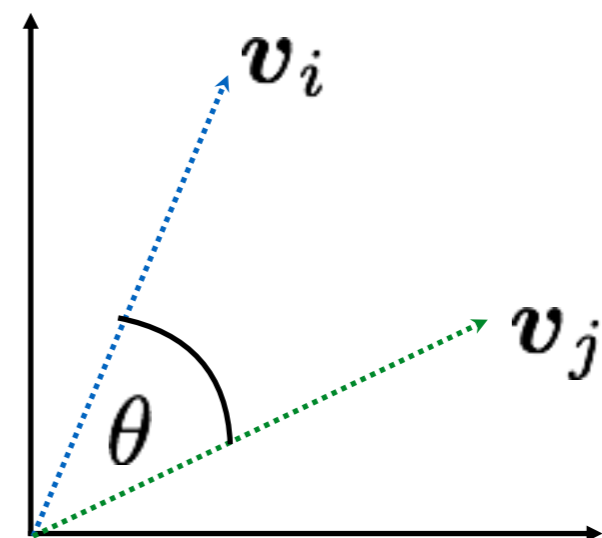
just a histogram over words

What is the similarity between two documents?

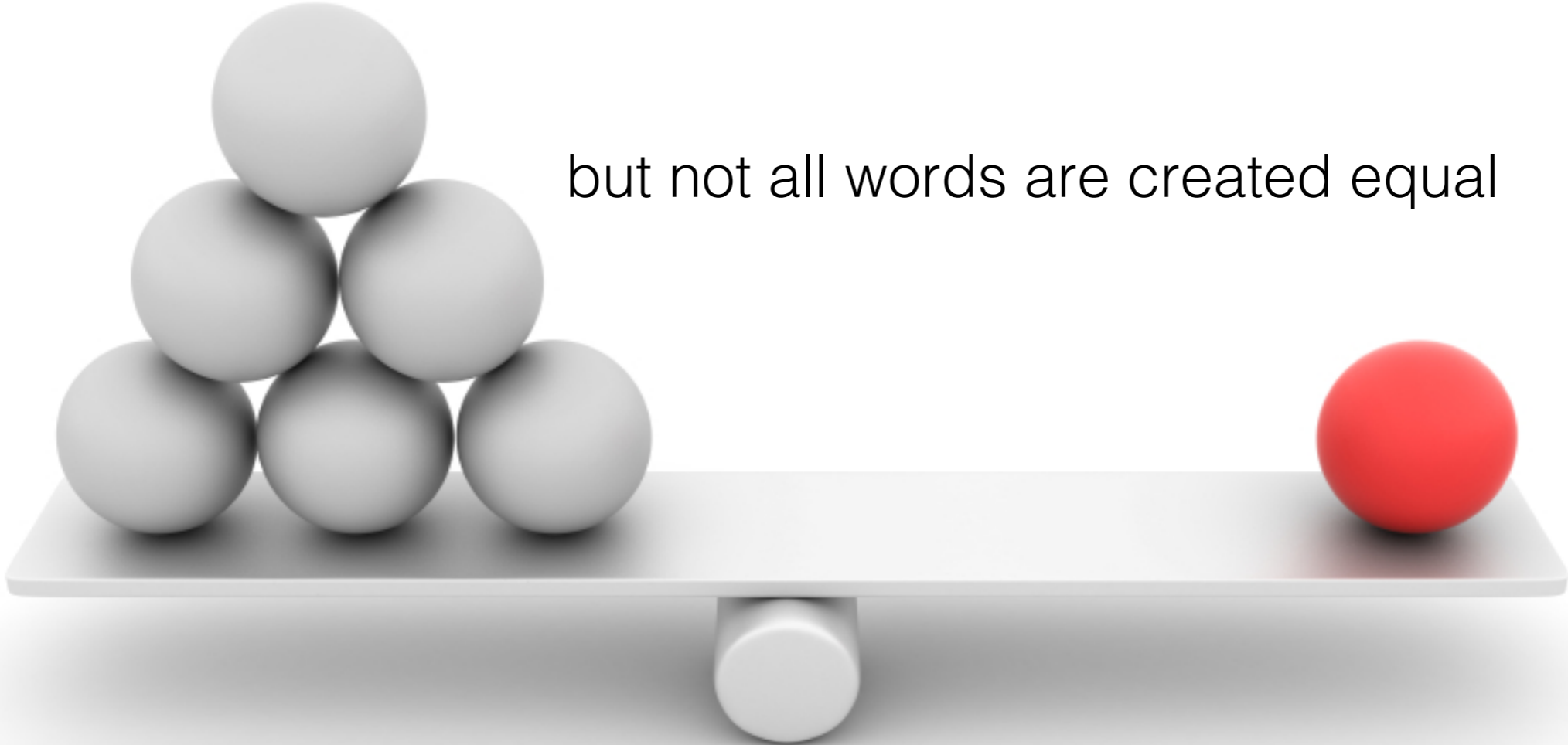


Use any distance you want but the cosine distance is fast.

$$d(\mathbf{v}_i, \mathbf{v}_j) = \cos \theta$$
$$= \frac{\mathbf{v}_i \cdot \mathbf{v}_j}{\|\mathbf{v}_i\| \|\mathbf{v}_j\|}$$



but not all words are created equal



TF-IDF

Term **F**requency Inverse **D**ocument **F**requency

$$\mathbf{v}_d = [n(w_{1,d}) \quad n(w_{2,d}) \quad \cdots \quad n(w_{T,d})]$$

weigh each word by a heuristic

$$\mathbf{v}_d = [n(w_{1,d})\alpha_1 \quad n(w_{2,d})\alpha_2 \quad \cdots \quad n(w_{T,d})\alpha_T]$$

$$n(w_{i,d})\alpha_i = \underbrace{n(w_{i,d})}_{\text{term frequency}} \log \left\{ \underbrace{\frac{D}{\sum_{d'} \mathbf{1}[w_i \in d']}}_{\text{inverse document frequency}} \right\}$$

(down-weights **common** terms)

Standard BOW pipeline

(for image classification)

Dictionary Learning:

Learn Visual Words using clustering

Encode:

build Bags-of-Words (BOW) vectors
for each image

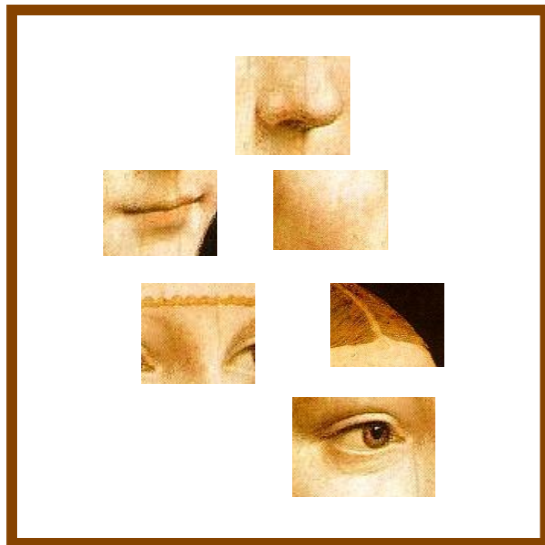
Classify:

Train and test data using BOWs

Dictionary Learning:

Learn Visual Words using clustering

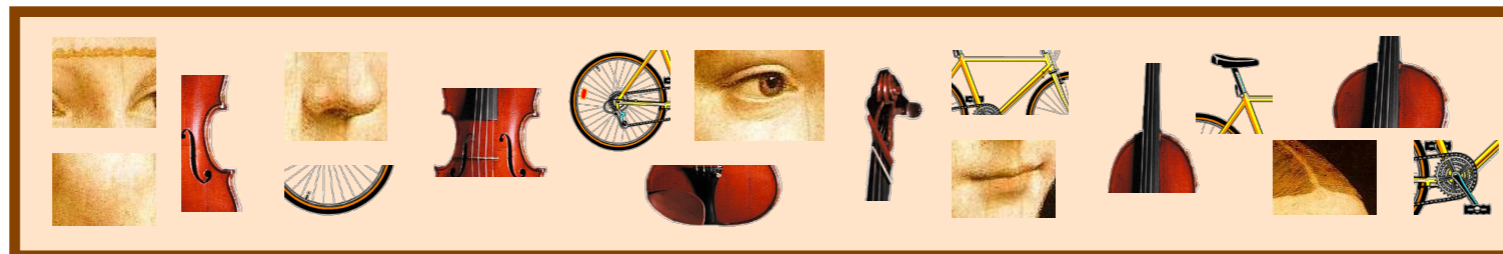
1. extract features (e.g., SIFT) from images



Dictionary Learning:

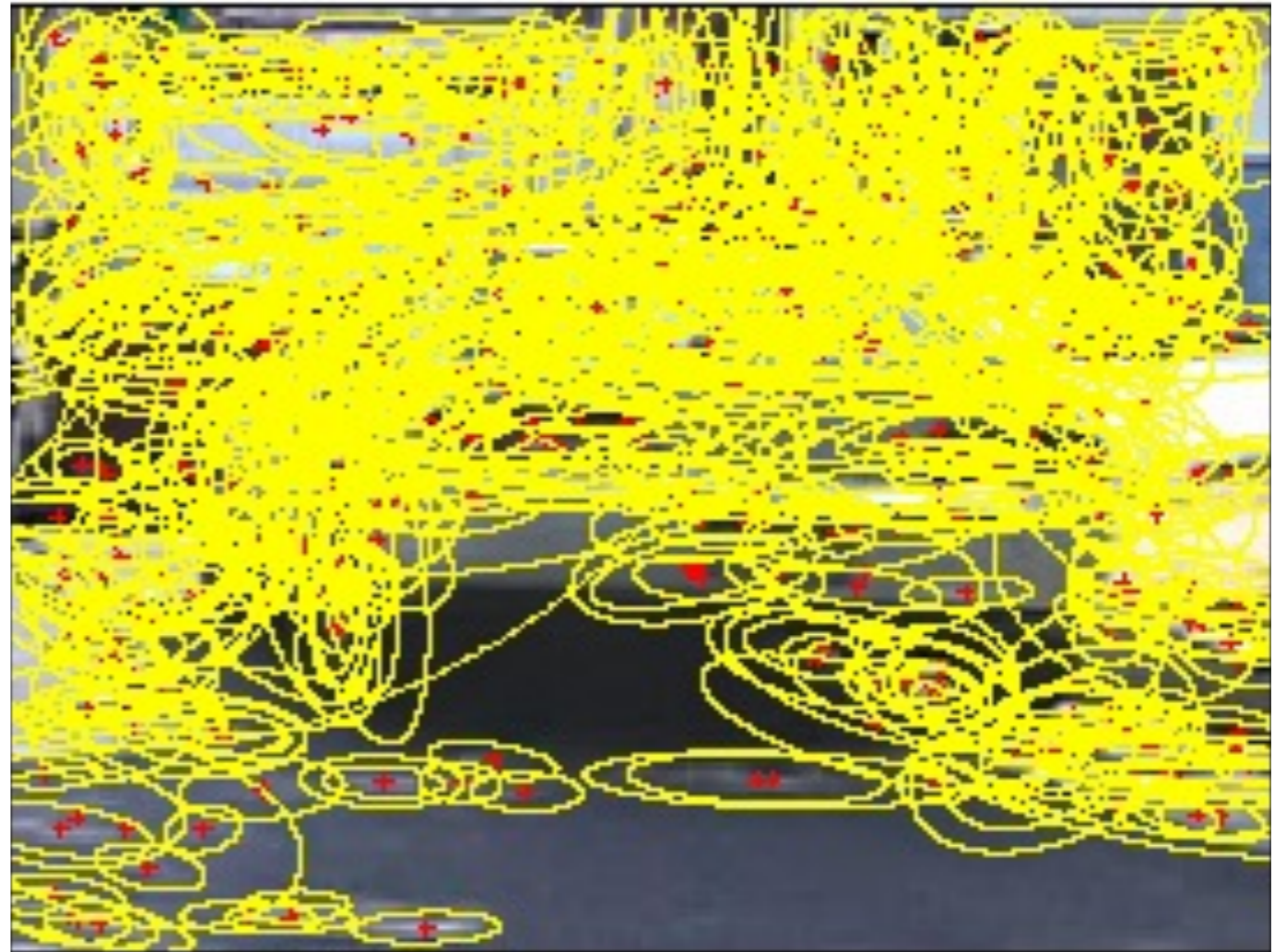
Learn Visual Words using clustering

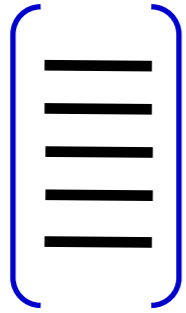
2. Learn visual dictionary (e.g., K-means clustering)



What kinds of features can we extract?

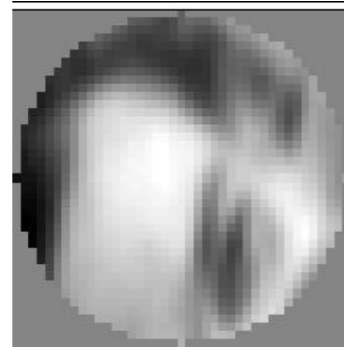
- **Regular grid**
 - Vogel & Schiele, 2003
 - Fei-Fei & Perona, 2005
- **Interest point detector**
 - Csurka et al. 2004
 - Fei-Fei & Perona, 2005
 - Sivic et al. 2005
- **Other methods**
 - Random sampling (Vidal-Naquet & Ullman, 2002)
 - Segmentation-based patches (Barnard et al. 2003)



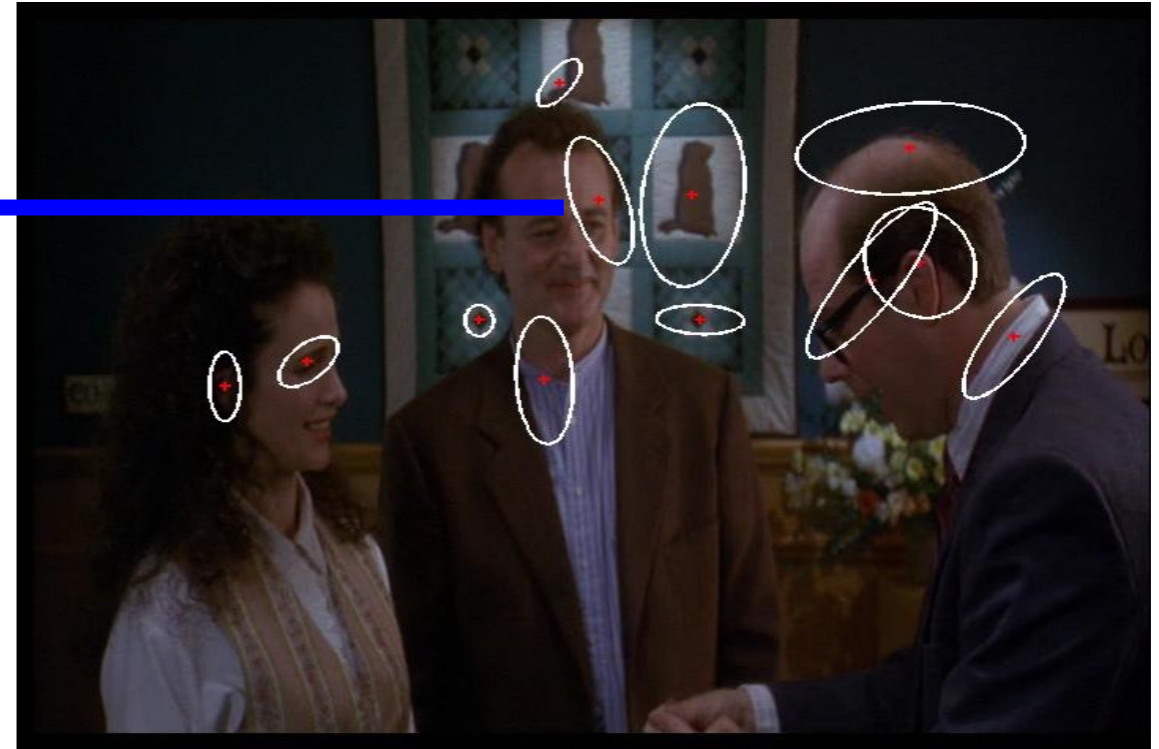


**Compute SIFT
descriptor**

[Lowe'99]



Normalize patch

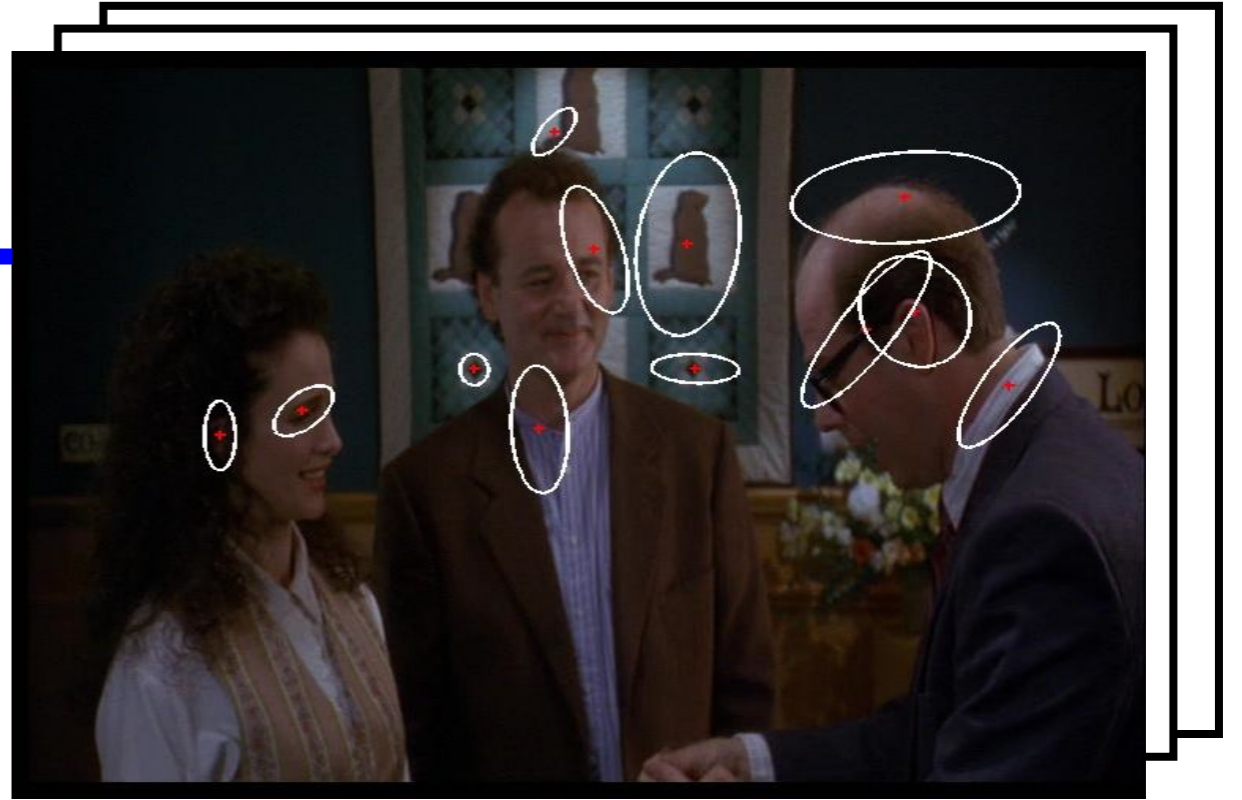
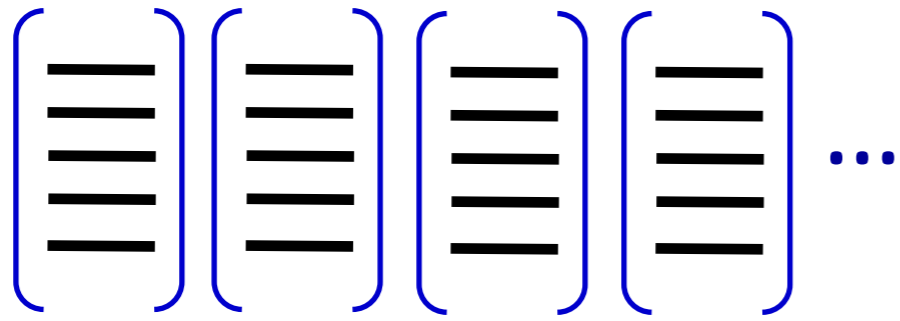


Detect patches

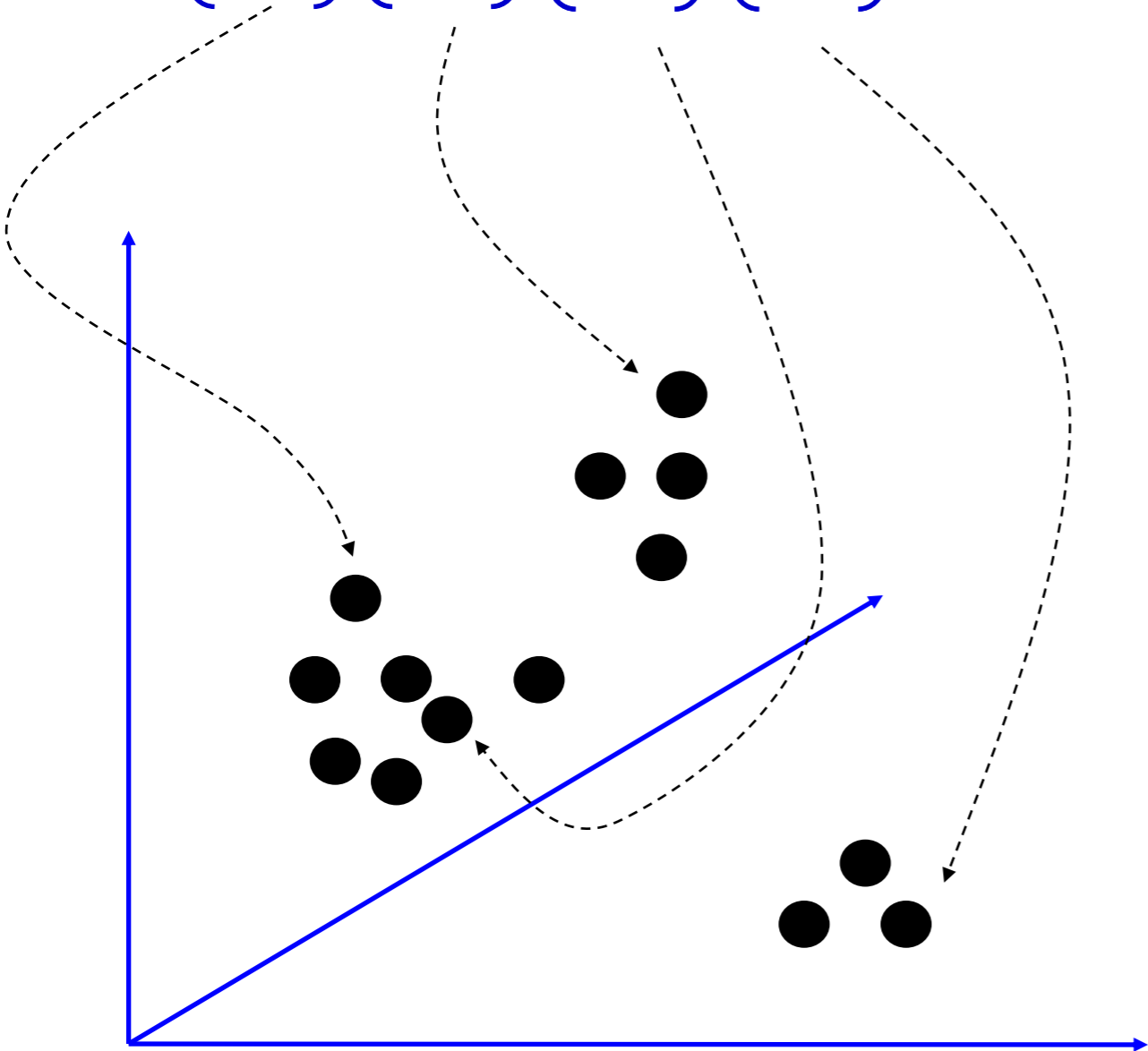
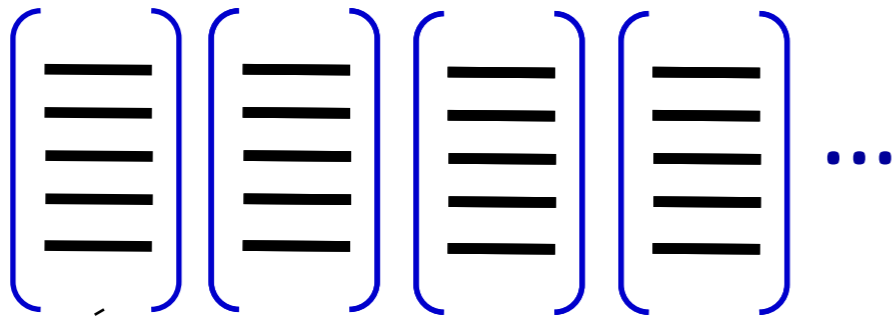
[Mikojaczyk and Schmid '02]

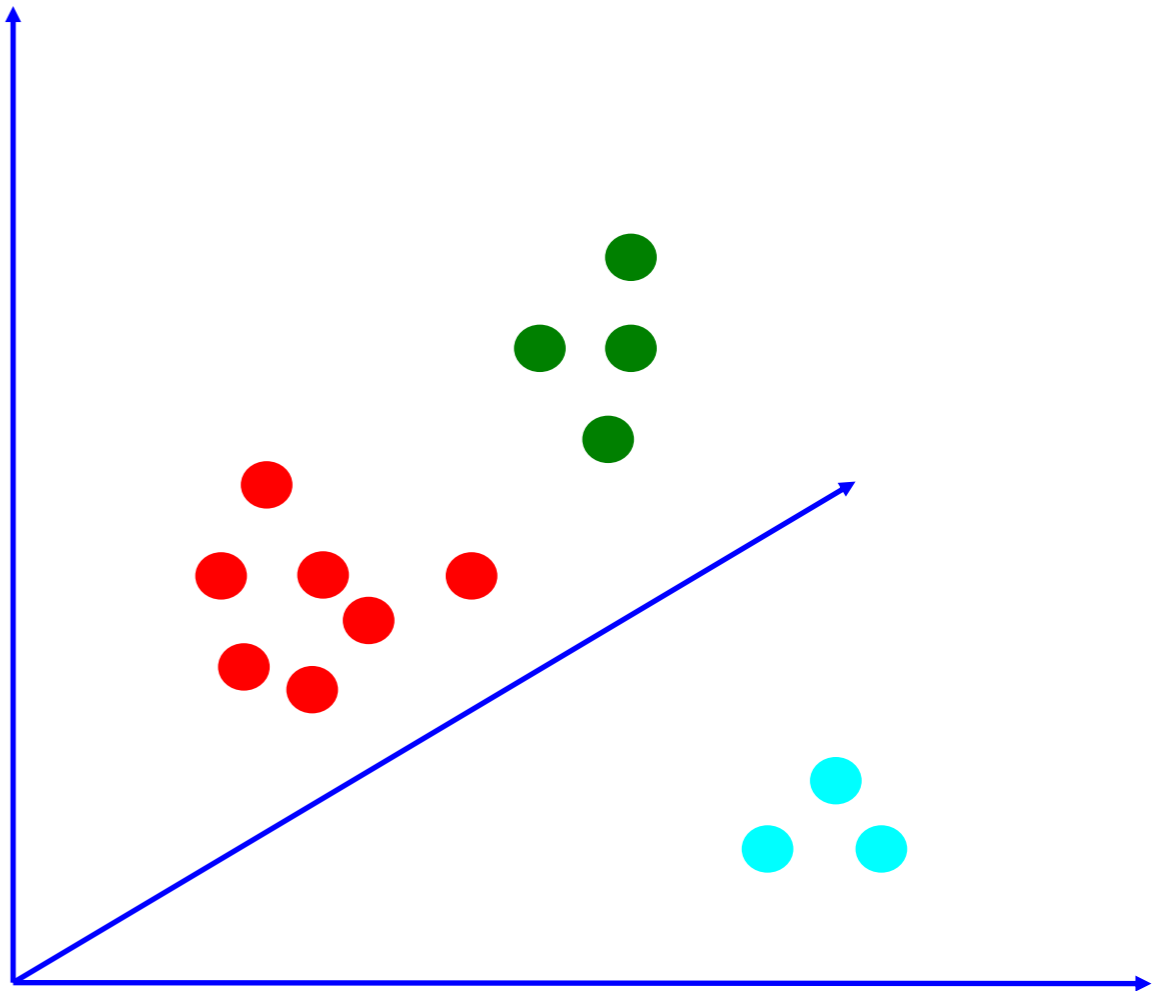
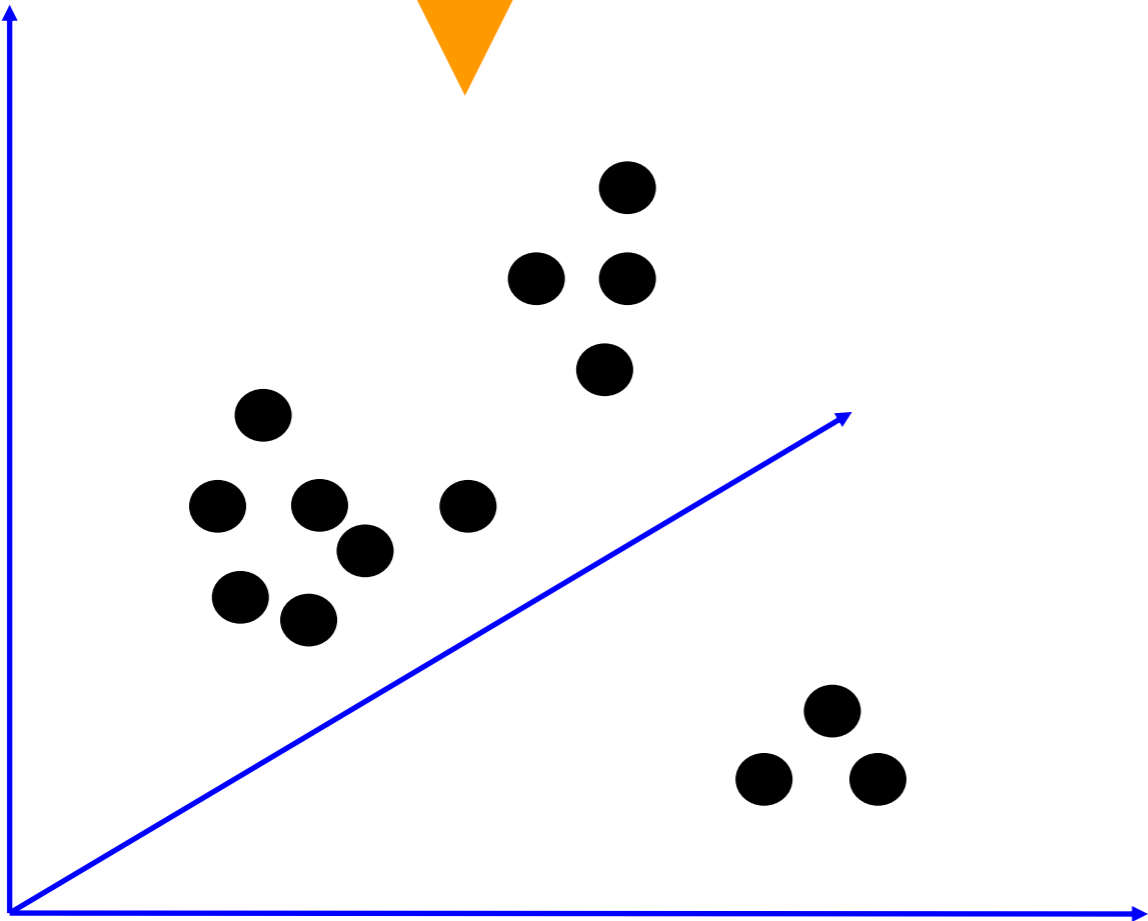
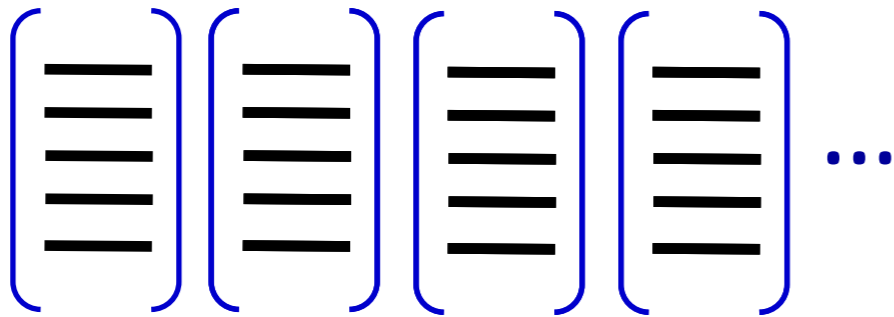
[Mata, Chum, Urban & Pajdla, '02]

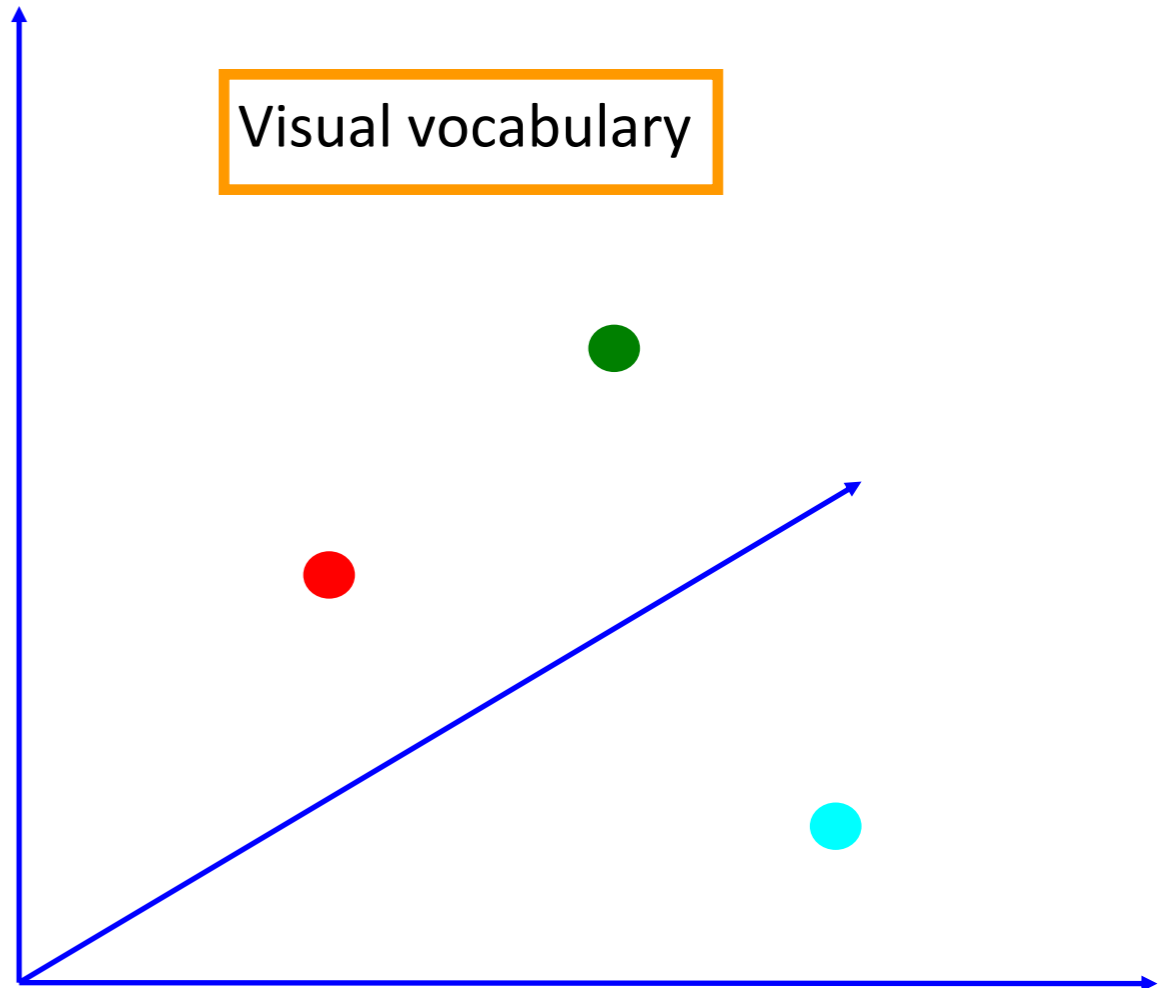
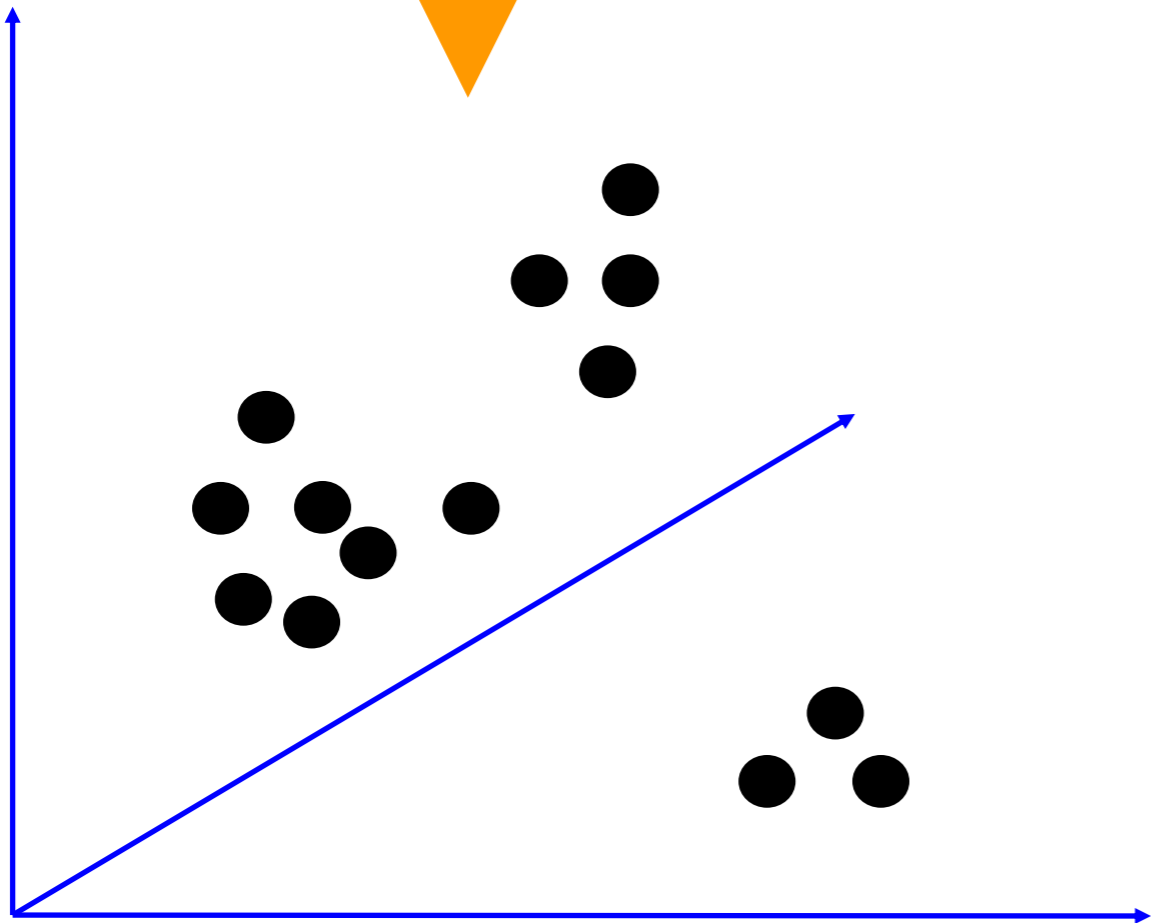
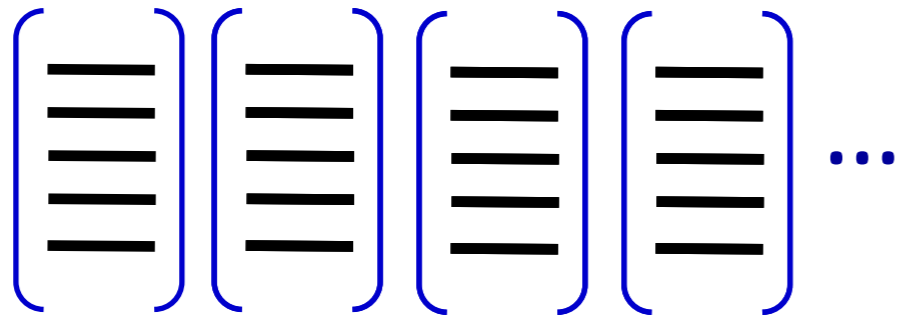
[Sivic & Zisserman, '03]



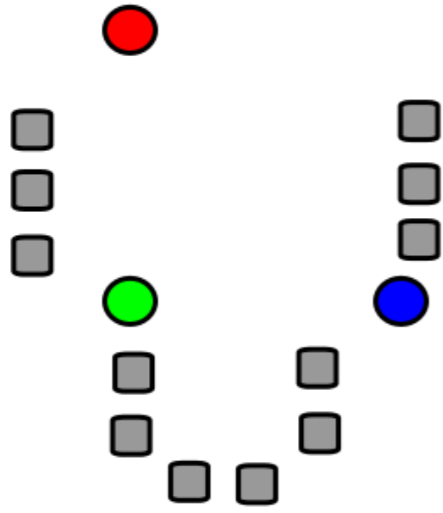
How do we learn the dictionary?



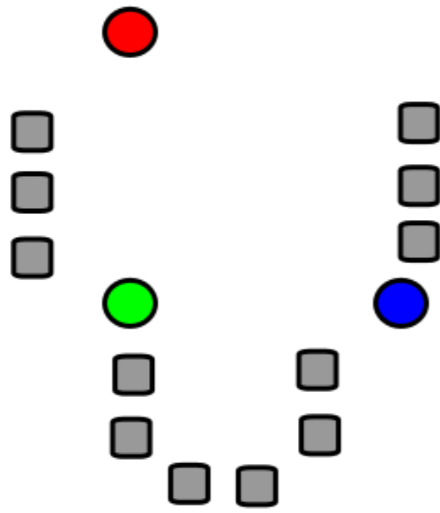




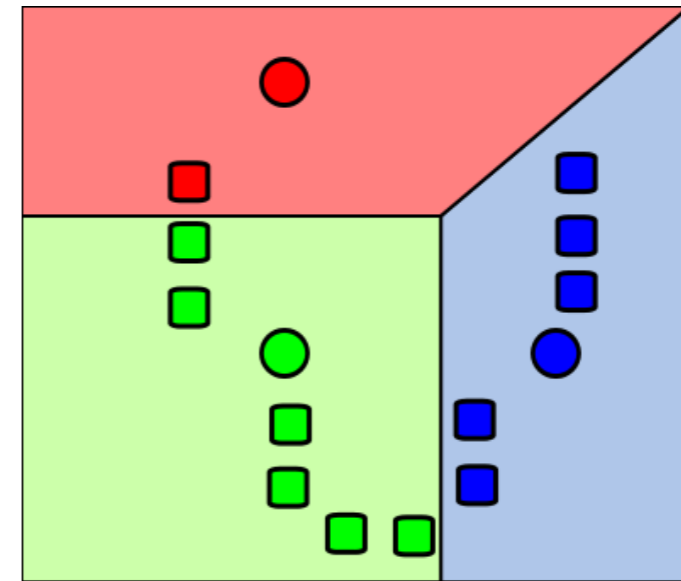
K-means clustering



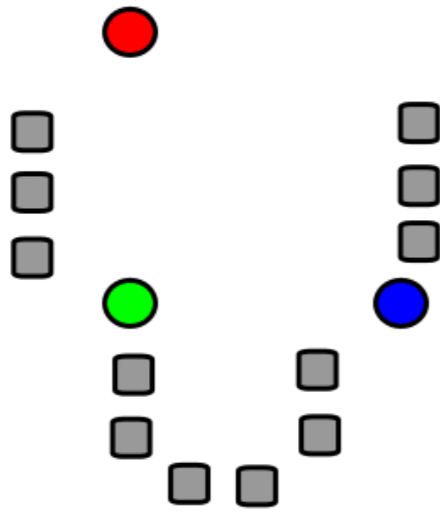
1. Select initial centroids at random



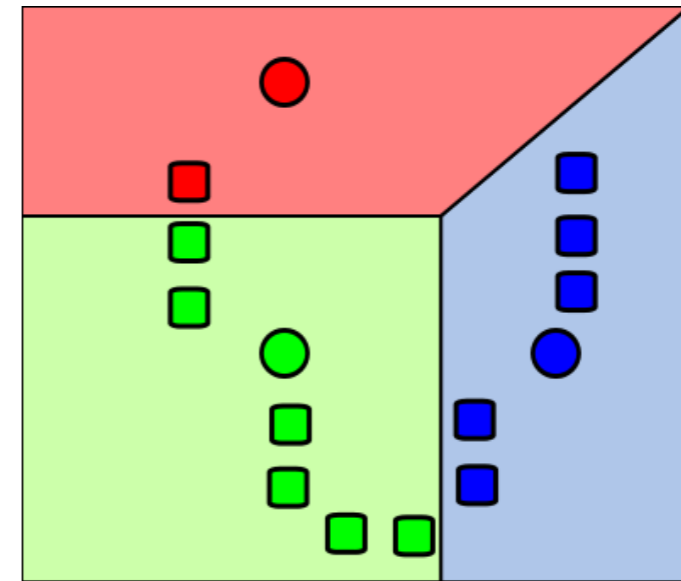
1. Select initial centroids at random



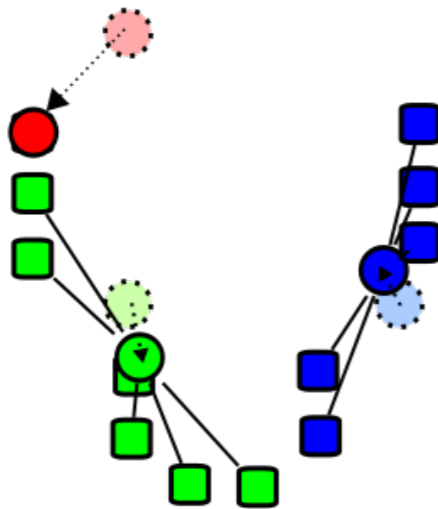
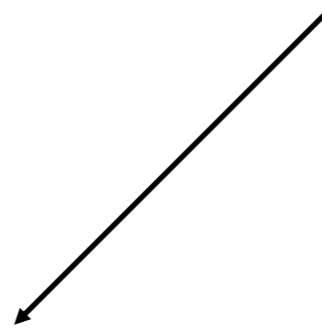
2. Assign each object to the cluster with the nearest centroid.



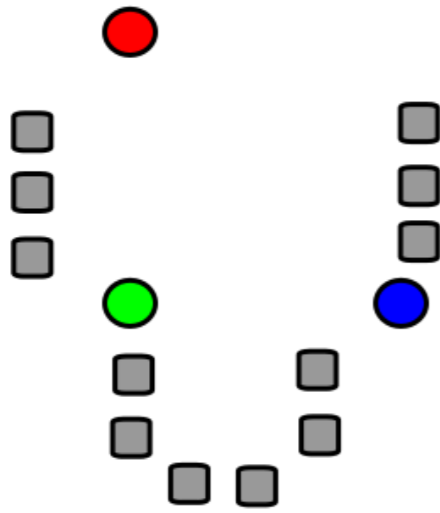
1. Select initial centroids at random



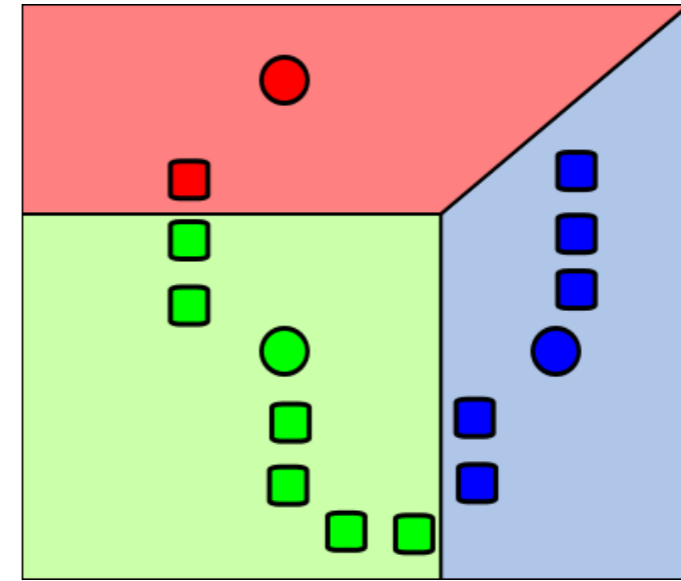
2. Assign each object to the cluster with the nearest centroid.



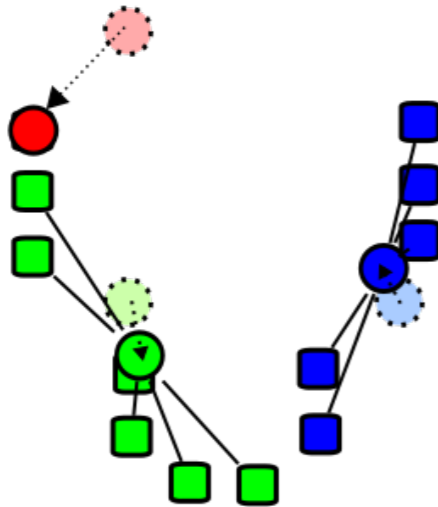
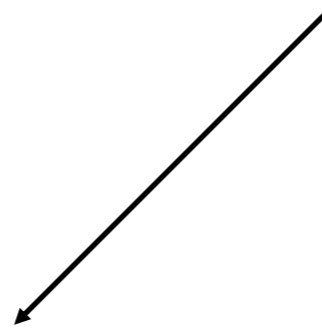
3. Compute each centroid as the mean of the objects assigned to it (go to 2)



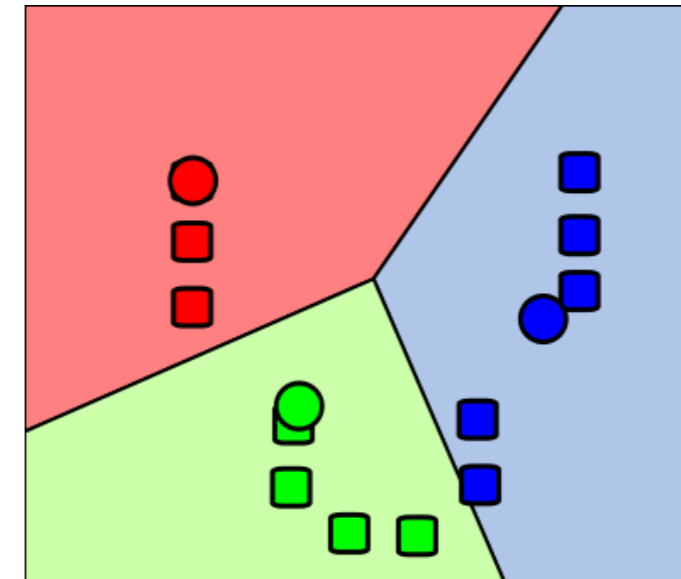
1. Select initial centroids at random



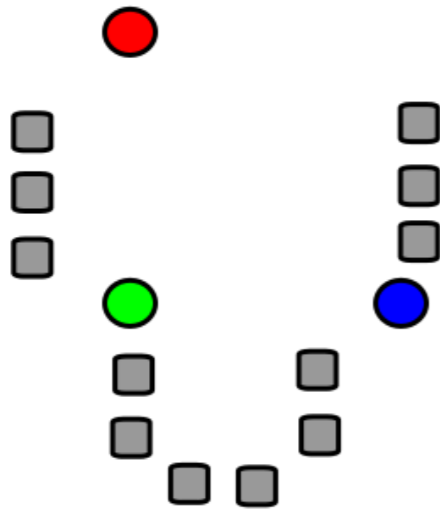
2. Assign each object to the cluster with the nearest centroid.



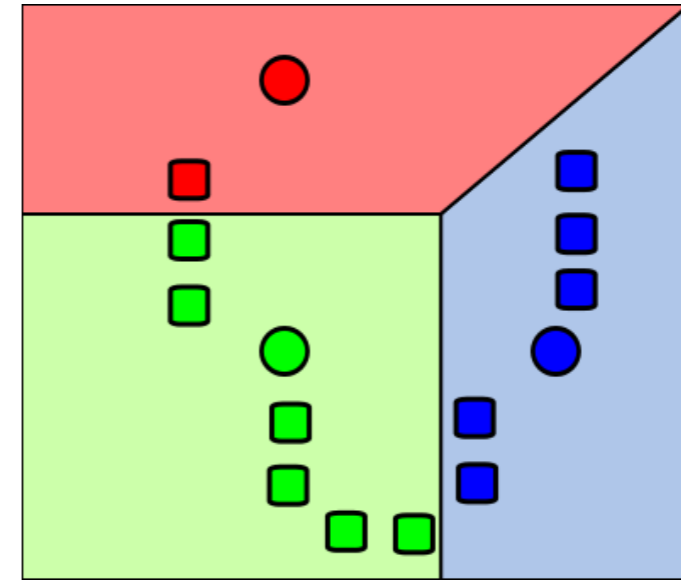
3. Compute each centroid as the mean of the objects assigned to it (go to 2)



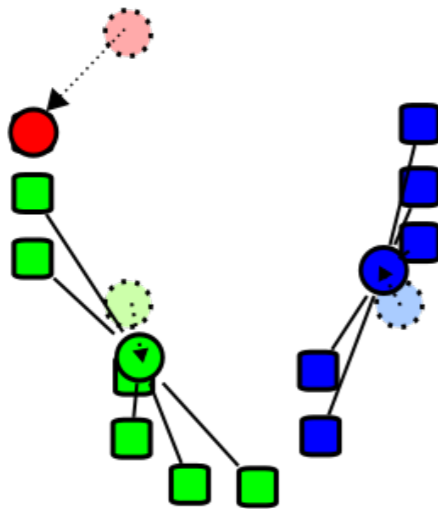
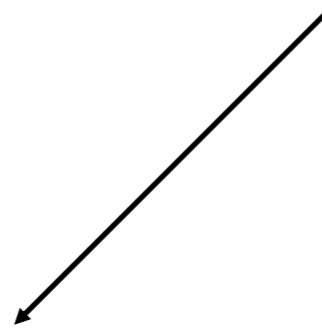
2. Assign each object to the cluster with the nearest centroid.



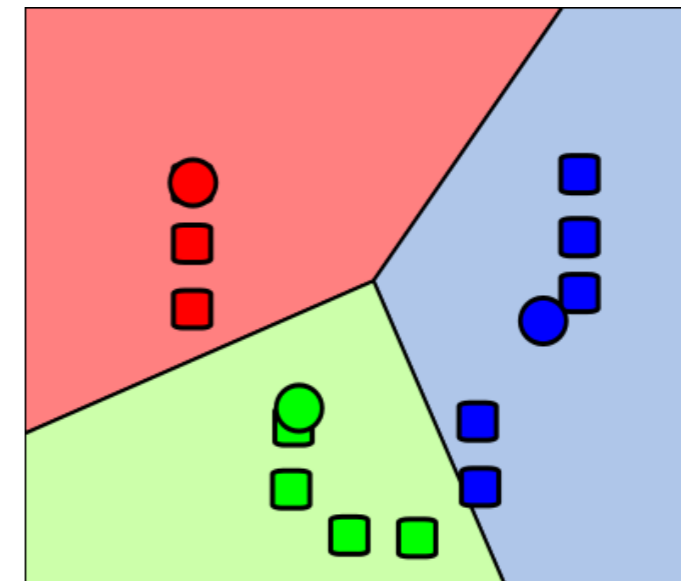
1. Select initial centroids at random



2. Assign each object to the cluster with the nearest centroid.



3. Compute each centroid as the mean of the objects assigned to it (go to 2)



2. Assign each object to the cluster with the nearest centroid.

Repeat previous 2 steps until no change

K-means Clustering

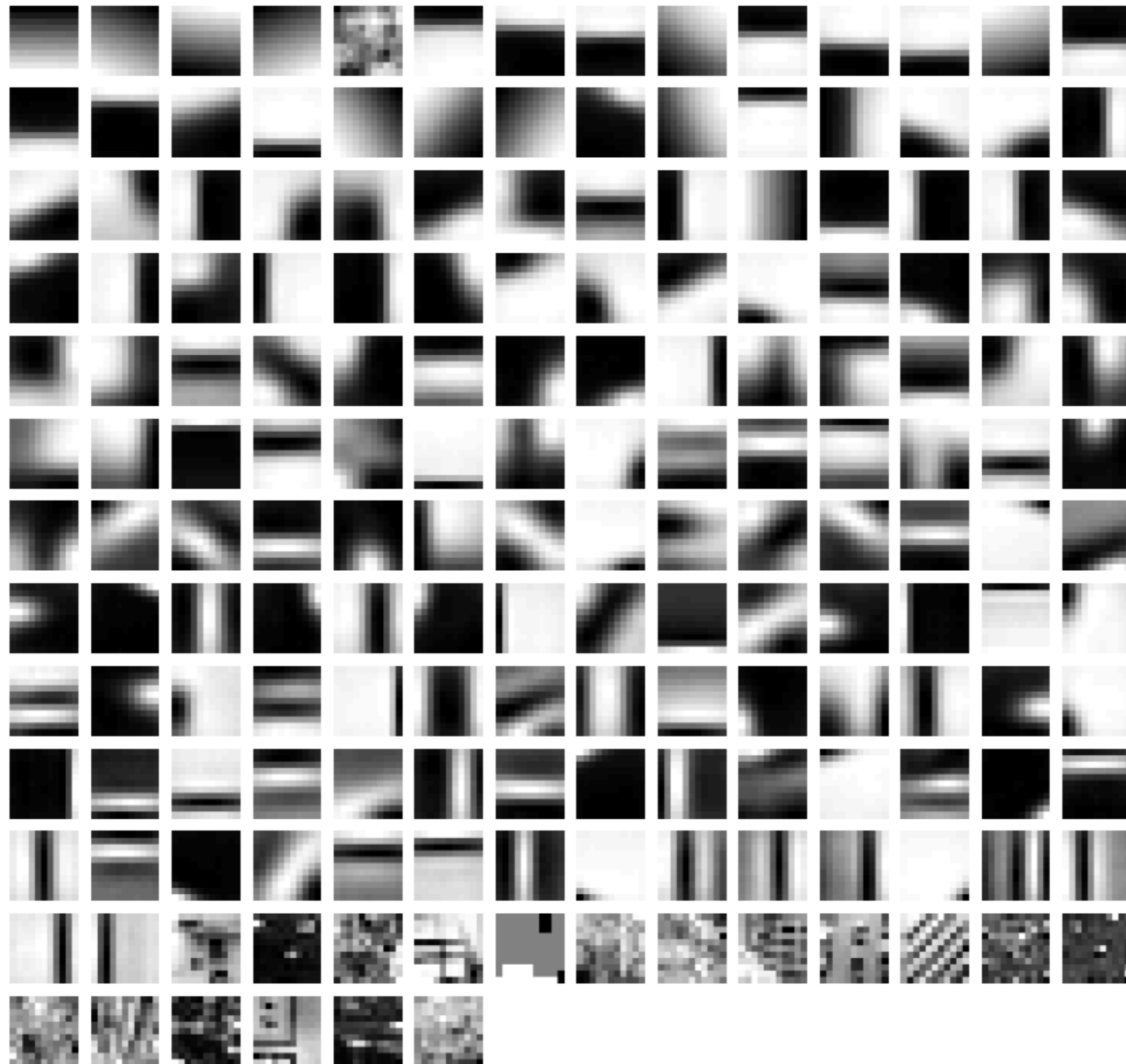
Given k :

1. Select initial centroids at random.
2. Assign each object to the cluster with the nearest centroid.
3. Compute each centroid as the mean of the objects assigned to it.
4. Repeat previous 2 steps until no change.

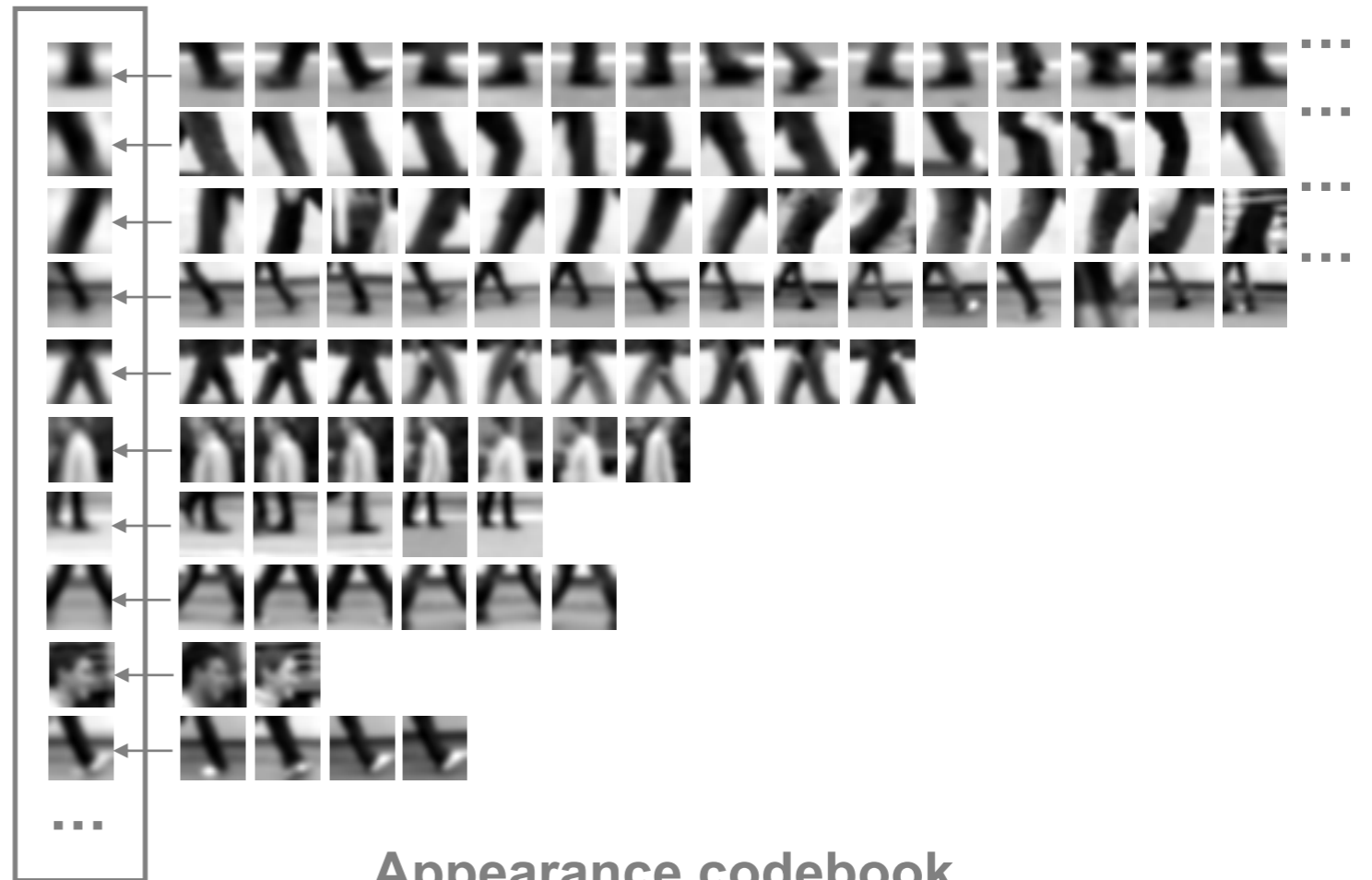
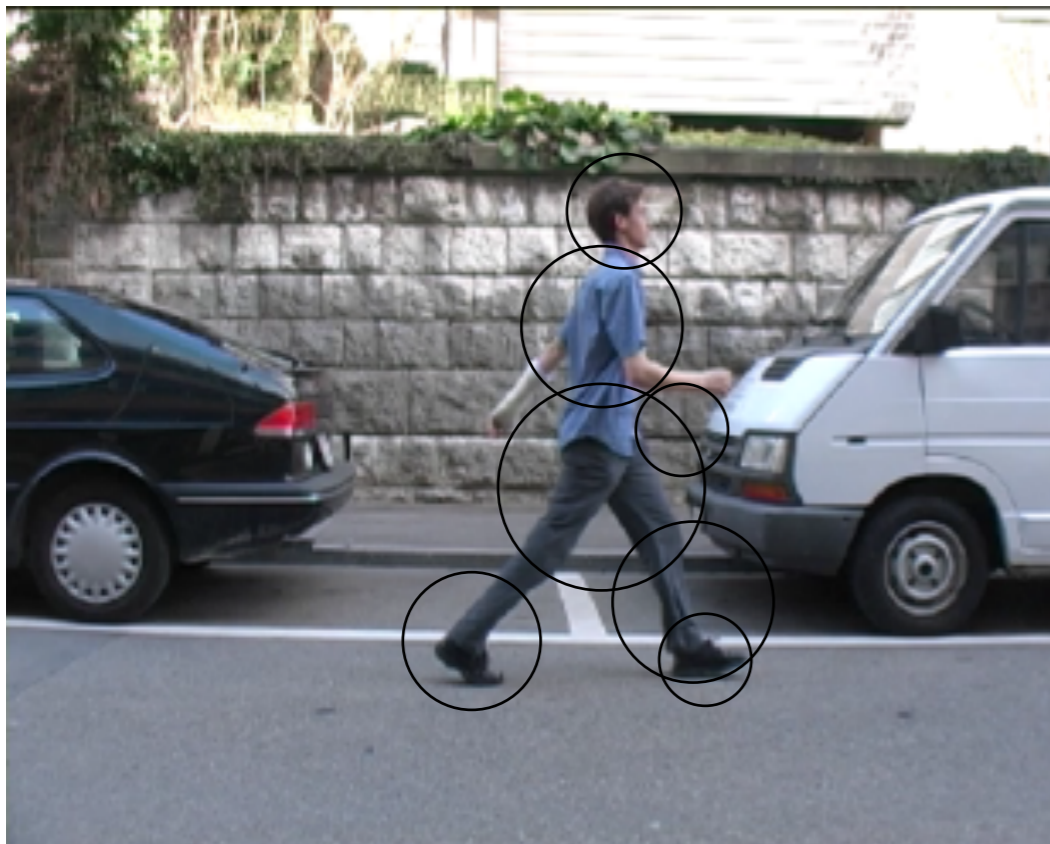
*From what **data** should I learn the dictionary?*

- Dictionary can be learned on separate training set
- Provided the training set is sufficiently representative, the dictionary will be “universal”

Example visual dictionary



Another dictionary



Appearance codebook

Dictionary Learning:

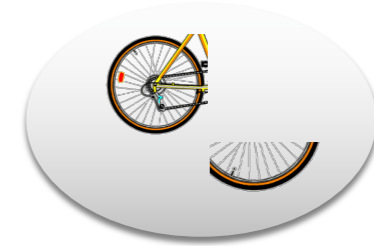
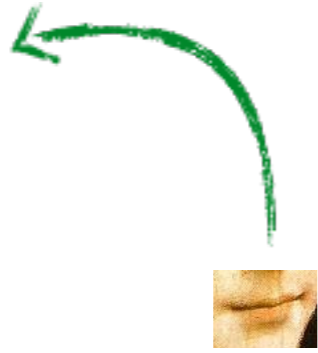
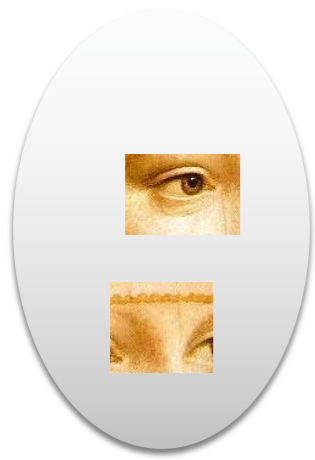
Learn Visual Words using clustering

Encode:

build Bags-of-Words (BOW) vectors
for each image

Classify:

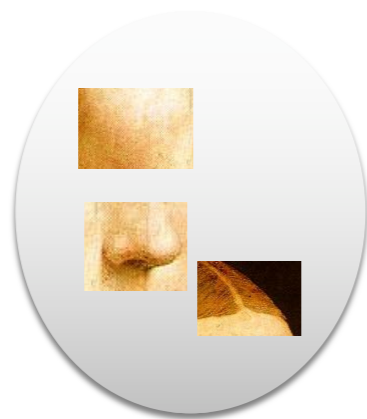
Train and test data using BOWs



1. Quantization: image features gets associated to a visual word (nearest cluster center)

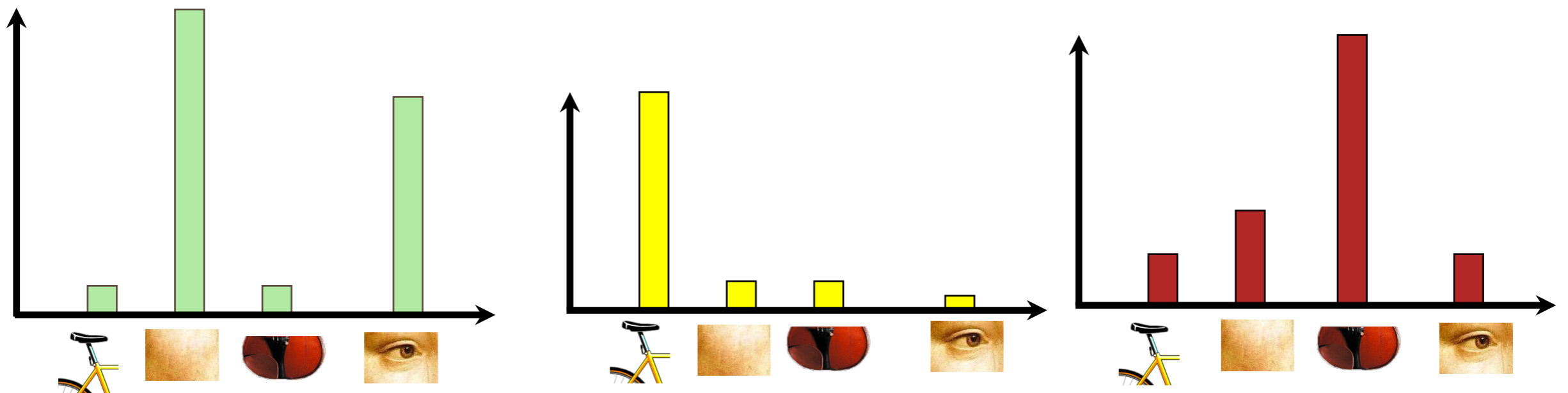
Encode:

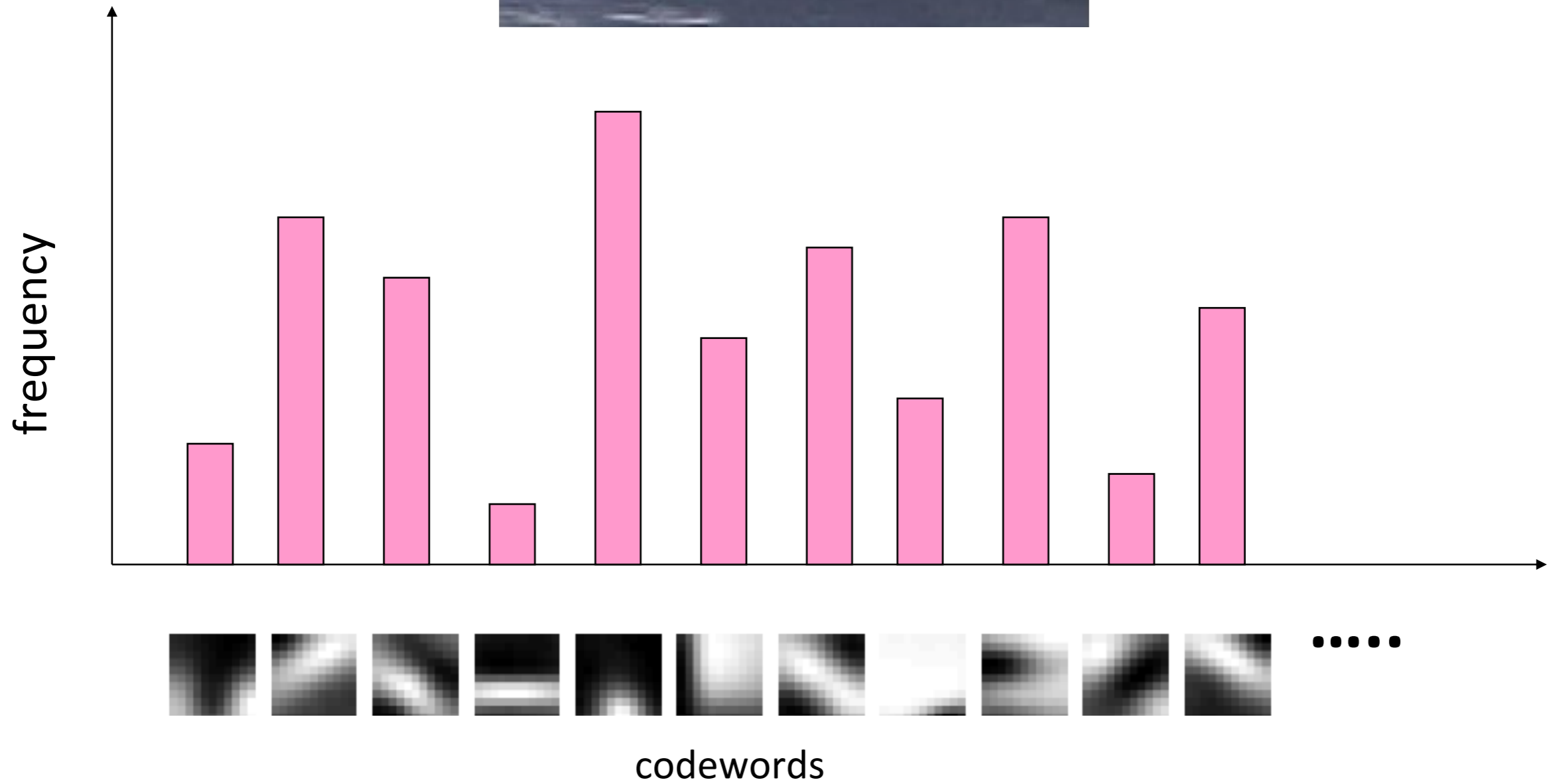
build Bags-of-Words (BOW) vectors for each image



Encode:
build Bags-of-Words (BOW) vectors
for each image

2. Histogram: count the
number of visual word
occurrences





Dictionary Learning:

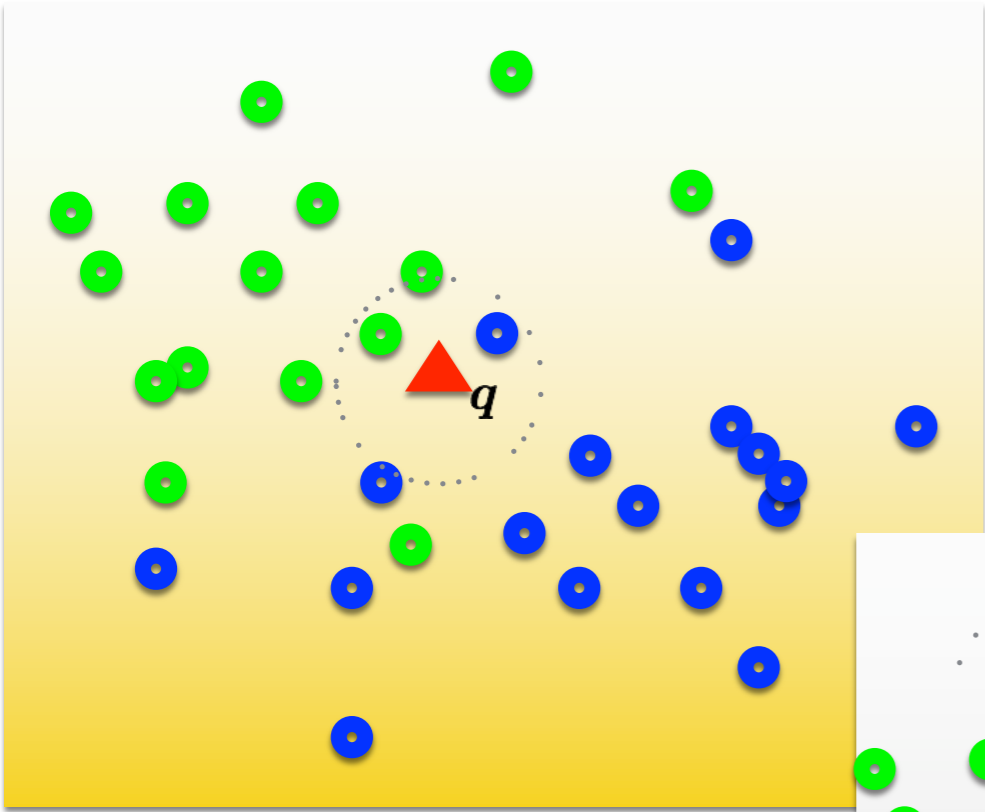
Learn Visual Words using clustering

Encode:

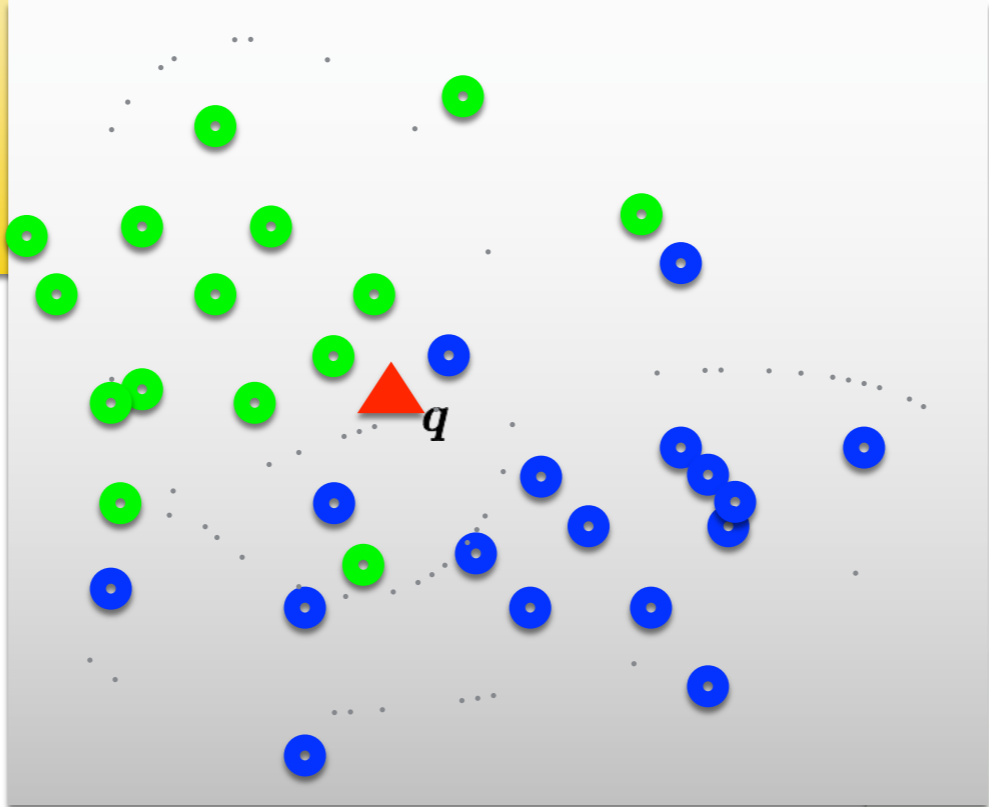
build Bags-of-Words (BOW) vectors
for each image

Classify:

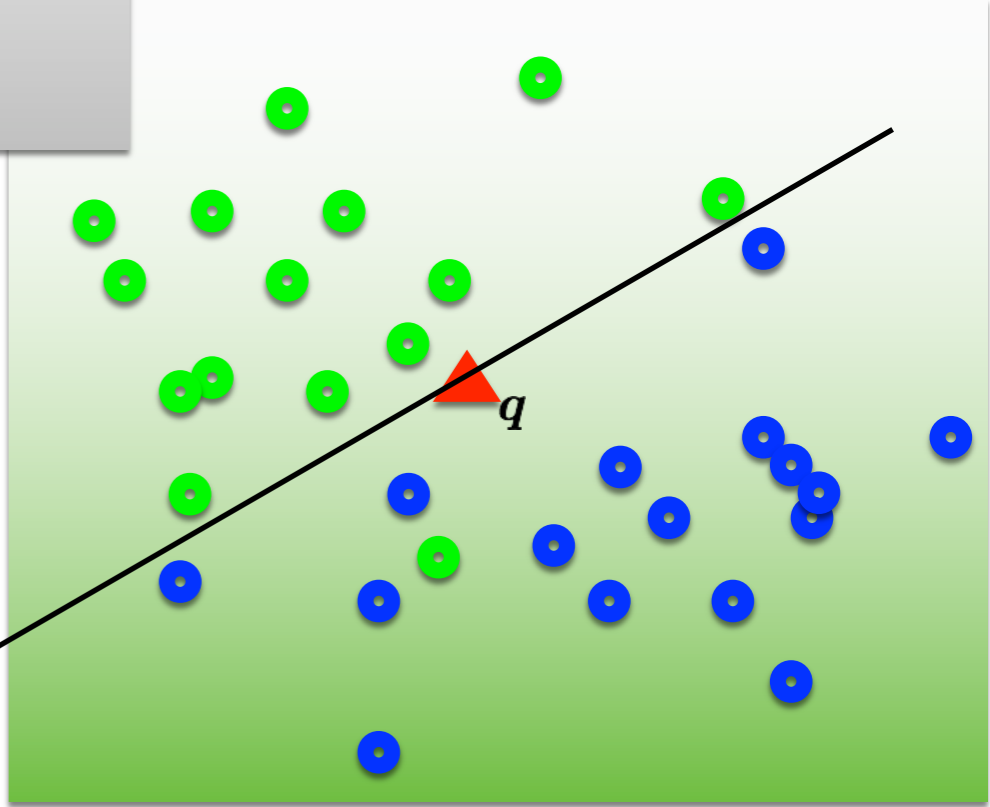
Train and test data using BOWs



K nearest neighbors



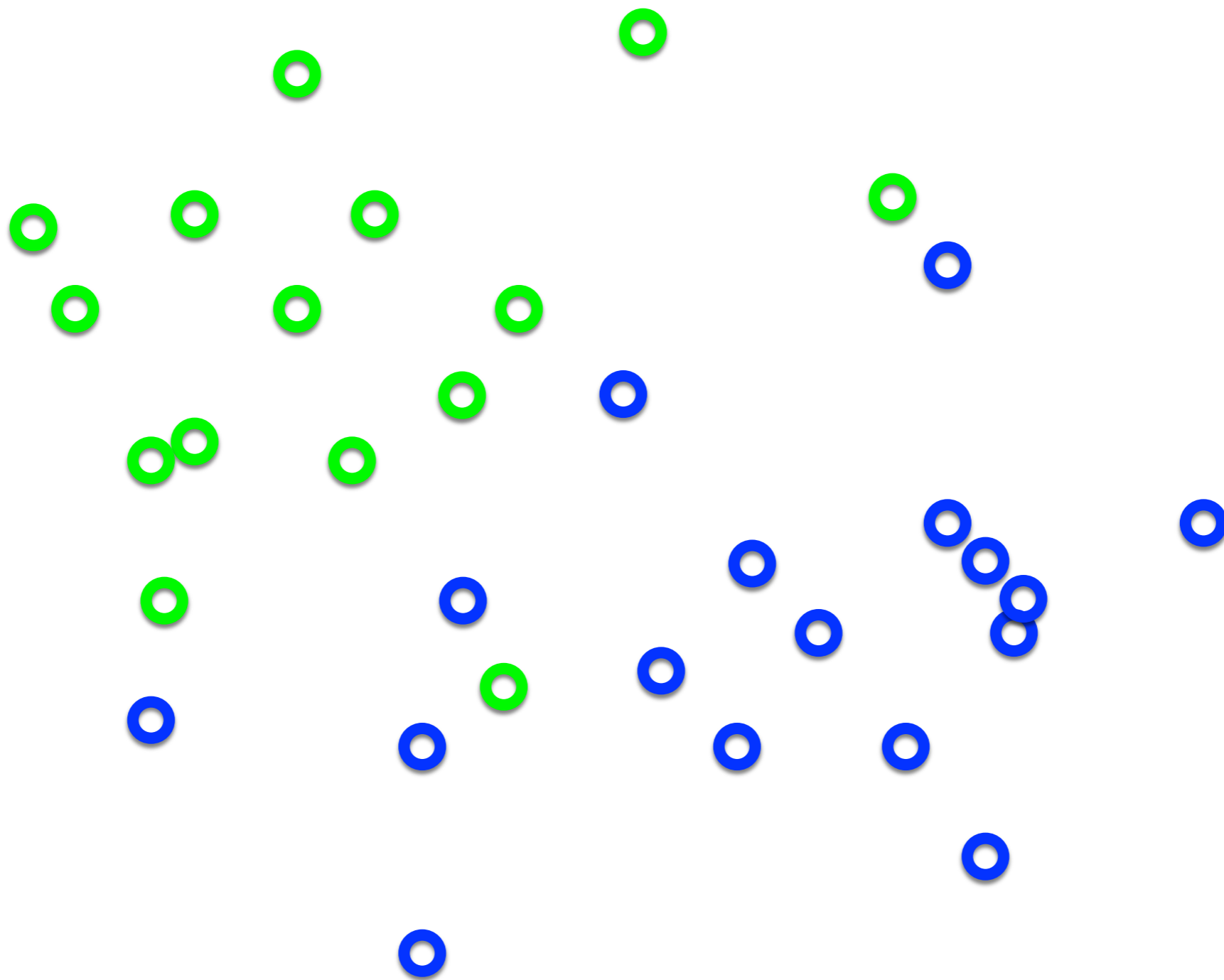
Naïve Bayes



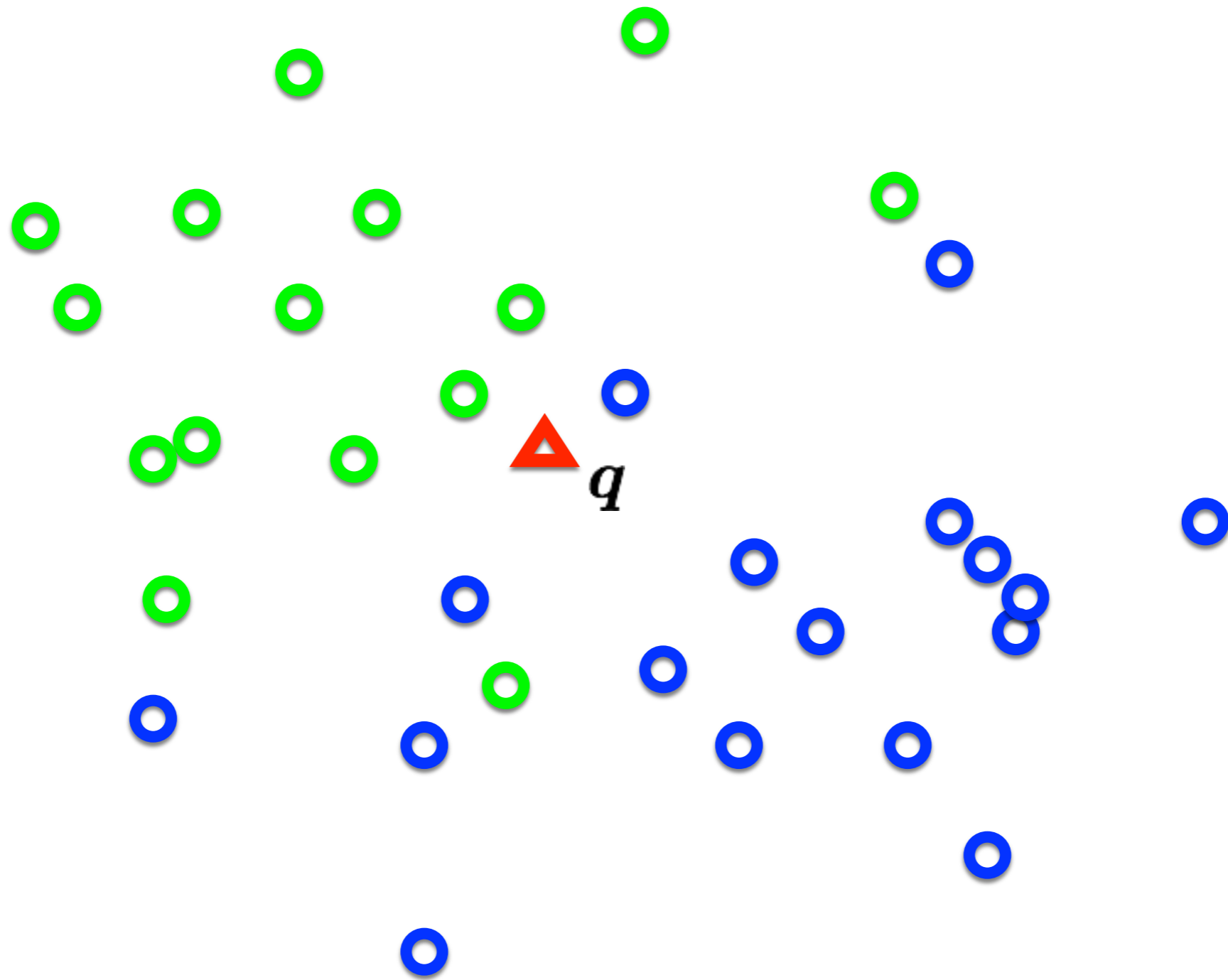
Support Vector Machine

K nearest neighbors

Distribution of data from two classes

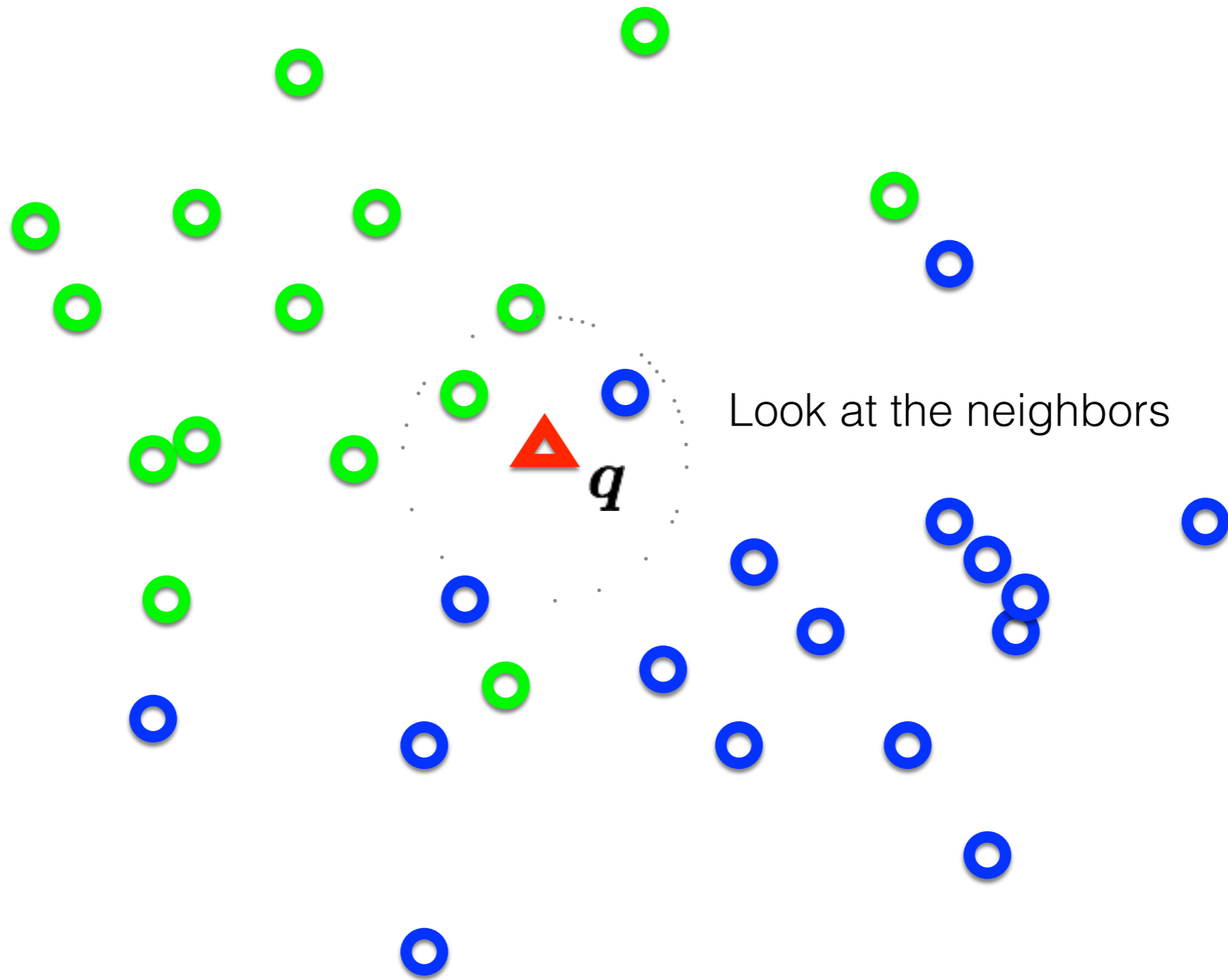


Distribution of data from two classes

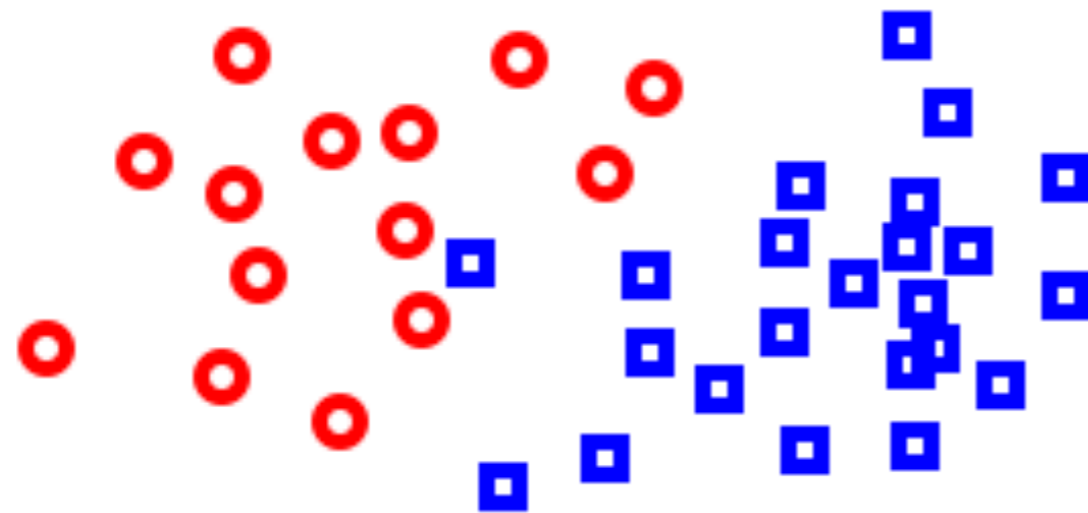


Which class does q belong too?

Distribution of data from two classes



K-Nearest Neighbor (KNN) Classifier

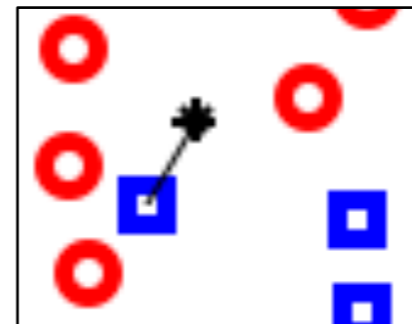


Non-parametric pattern classification approach

Consider a two class problem where each sample consists of two measurements (x,y).

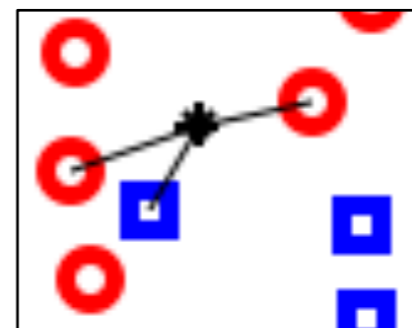
For a given query point q , assign the class of the nearest neighbor

$k = 1$

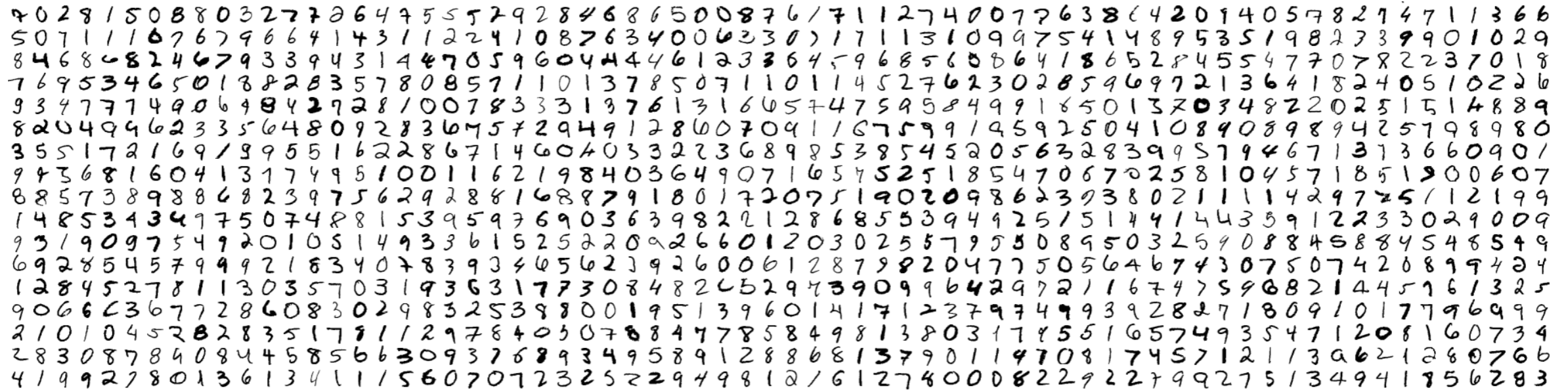


Compute the k nearest neighbors and assign the class by majority vote.

$k = 3$



Nearest Neighbor is competitive



MNIST Digit Recognition

- Handwritten digits
- 28x28 pixel images: $d = 784$
- 60,000 training samples
- 10,000 test samples

Yann LeCunn

	Test Error Rate (%)
Linear classifier (1-layer NN)	12.0
K-nearest-neighbors, Euclidean	5.0
K-nearest-neighbors, Euclidean, deskewed	2.4
K-NN, Tangent Distance, 16x16	1.1
K-NN, shape context matching	0.67
1000 RBF + linear classifier	3.6
SVM deg 4 polynomial	1.1
2-layer NN, 300 hidden units	4.7
2-layer NN, 300 HU, [deskewing]	1.6
LeNet-5, [distortions]	0.8
Boosted LeNet-4, [distortions]	0.7

What is the best distance metric between data points?

- Typically Euclidean distance
- Locality sensitive distance metrics
- Important to normalize.
Dimensions have different scales

How many K?

- Typically $k=1$ is good
- Cross-validation (try different k !)

Distance metrics

$$D(\mathbf{x}, \mathbf{y}) = \sqrt{(x_1 - y_1)^2 + \cdots + (x_N - y_N)^2} \quad \text{Euclidean}$$

$$D(\mathbf{x}, \mathbf{y}) = \frac{\mathbf{x} \cdot \mathbf{y}}{\|\mathbf{x}\| \|\mathbf{y}\|} = \frac{x_1 y_1 + \cdots + x_N y_N}{\sqrt{\sum_n x_n^2} \sqrt{\sum_n y_n^2}} \quad \text{Cosine}$$

$$D(\mathbf{x}, \mathbf{y}) = \frac{1}{2} \sum_n \frac{(x_n - y_n)^2}{(x_n + y_n)} \quad \text{Chi-squared}$$

Choice of distance metric

- Hyperparameter

L1 (Manhattan) distance

$$d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$$

L2 (Euclidean) distance

$$d_2(I_1, I_2) = \sqrt{\sum_p (I_1^p - I_2^p)^2}$$

- Two most commonly used special cases of p-norm

$$\|x\|_p = (|x_1|^p + \dots + |x_n|^p)^{\frac{1}{p}} \quad p \geq 1, x \in \mathbb{R}^n$$

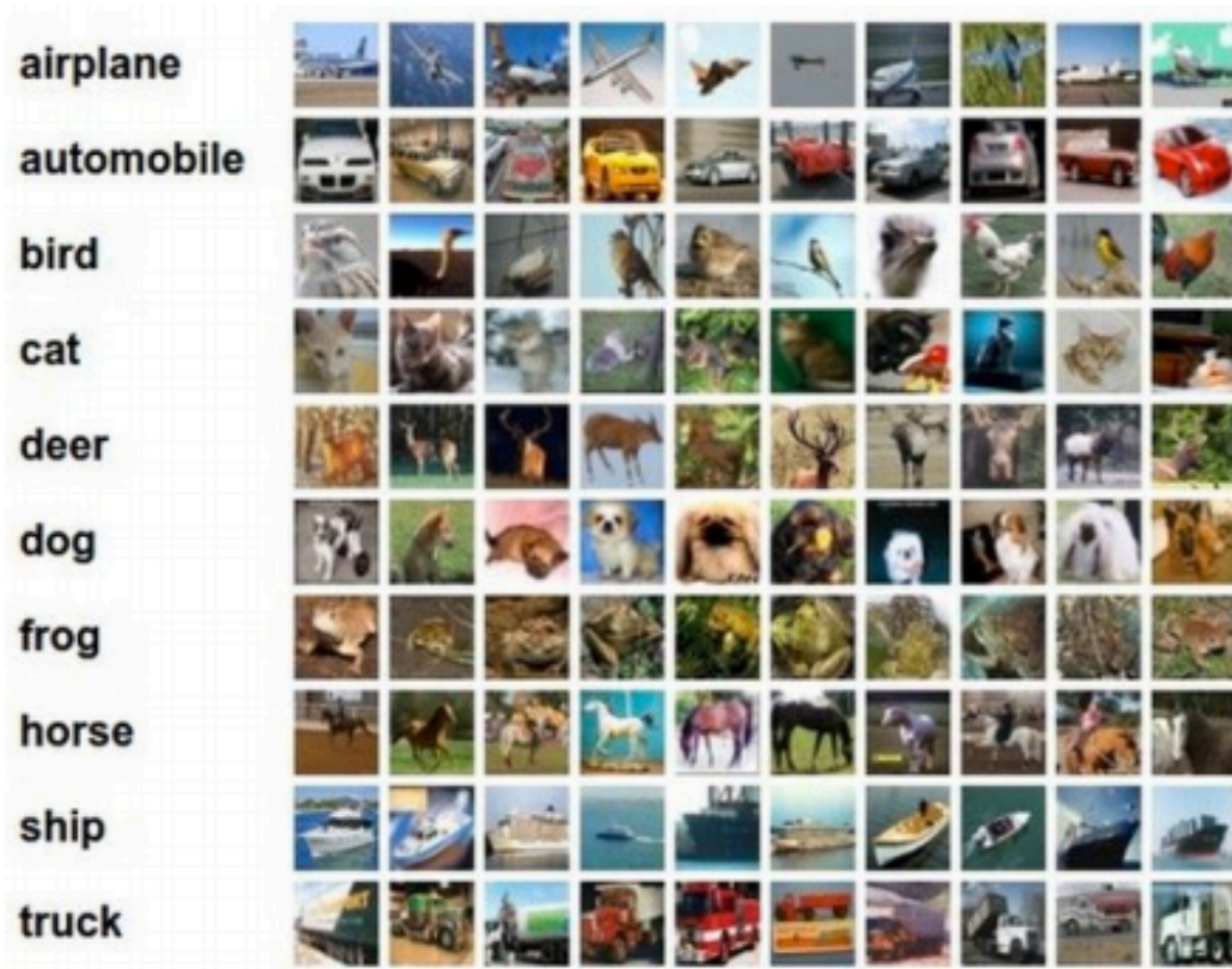
CIFAR-10 and NN results

Example dataset: **CIFAR-10**

10 labels

50,000 training images

10,000 test images.



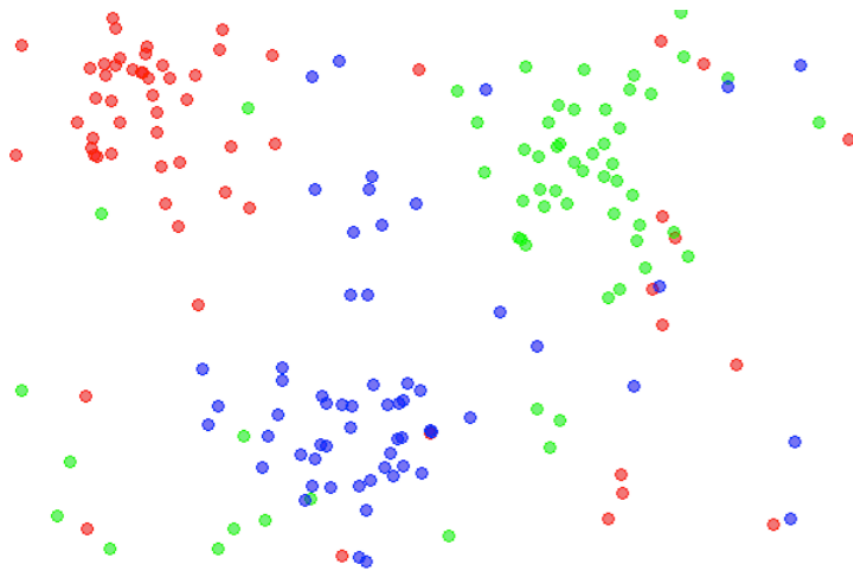
For every test image (first column),
examples of nearest neighbors in rows



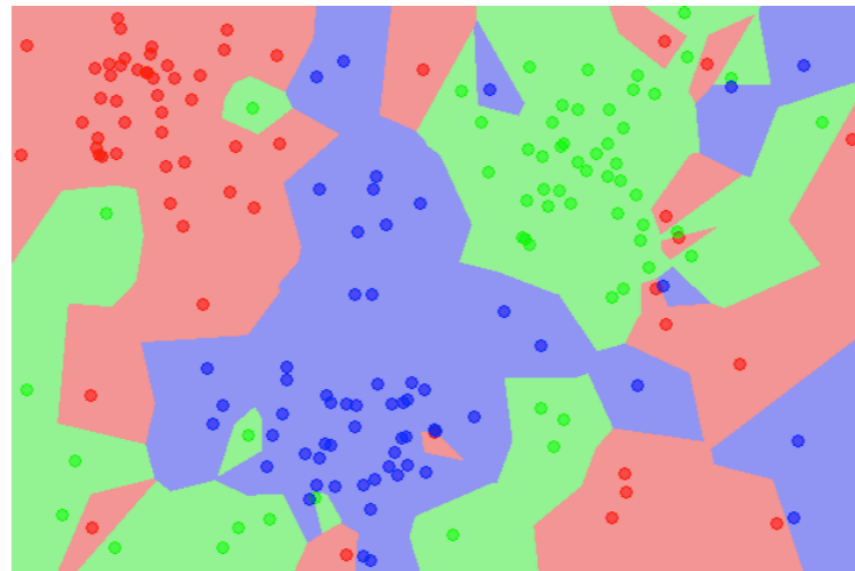
k-nearest neighbor

- Find the k closest points from training data
- Labels of the k points “vote” to classify

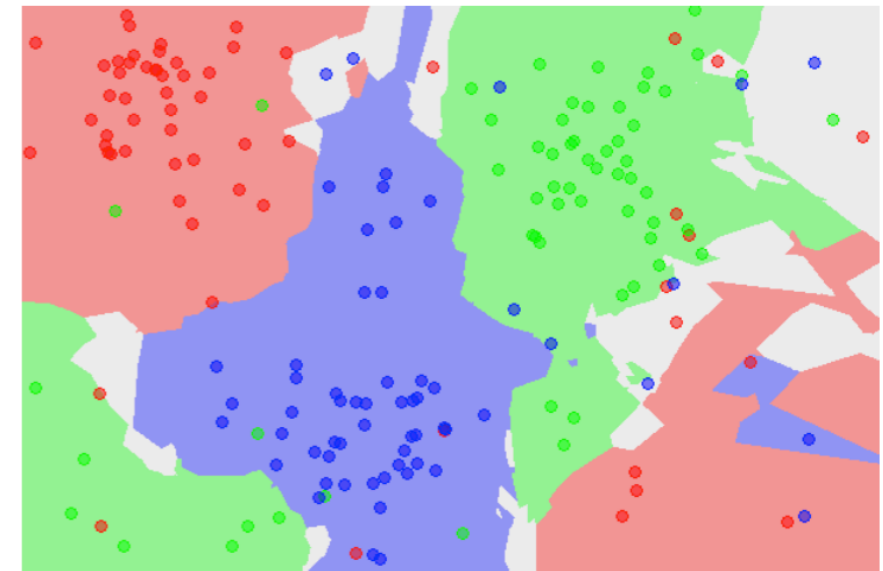
the data



NN classifier



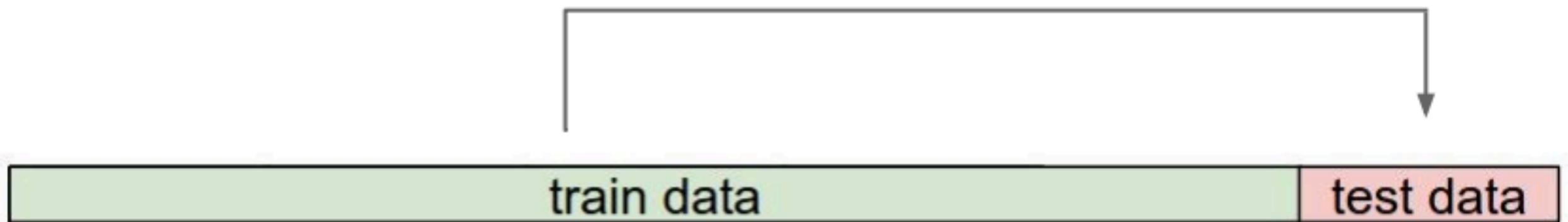
5-NN classifier



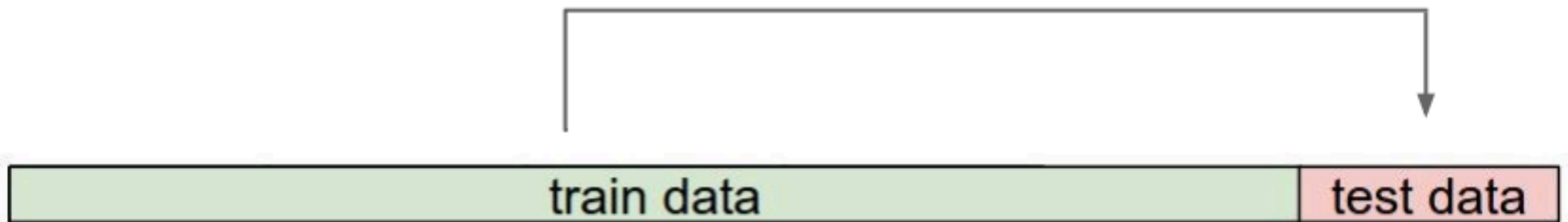
Hyperparameters

- What is the best distance to use?
- What is the best value of k to use?
- i.e., how do we set the hyperparameters?
- Very problem-dependent
- Must try them all and see what works best

Try out what hyperparameters work best on test set.

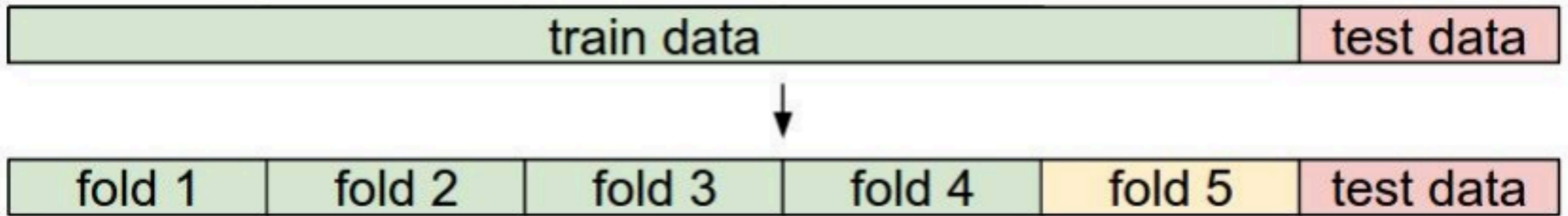


Try out what hyperparameters work best on test set.



VERY BAD IDEA! The test set is a proxy for the generalization performance!
Use only **VERY SPARINGLY**, at the end.

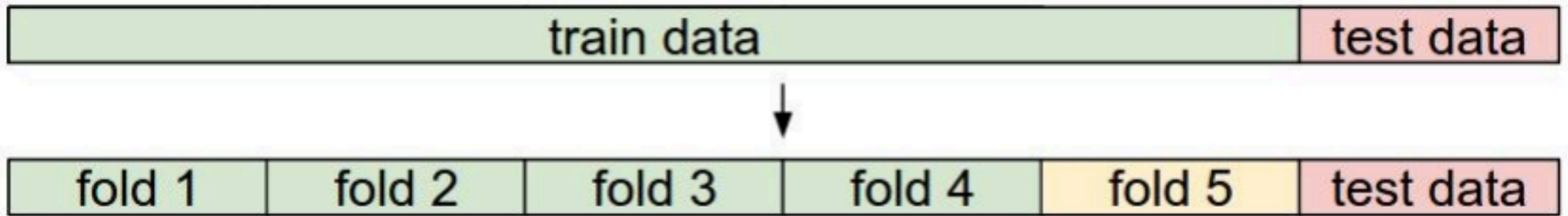
Validation



Validation data

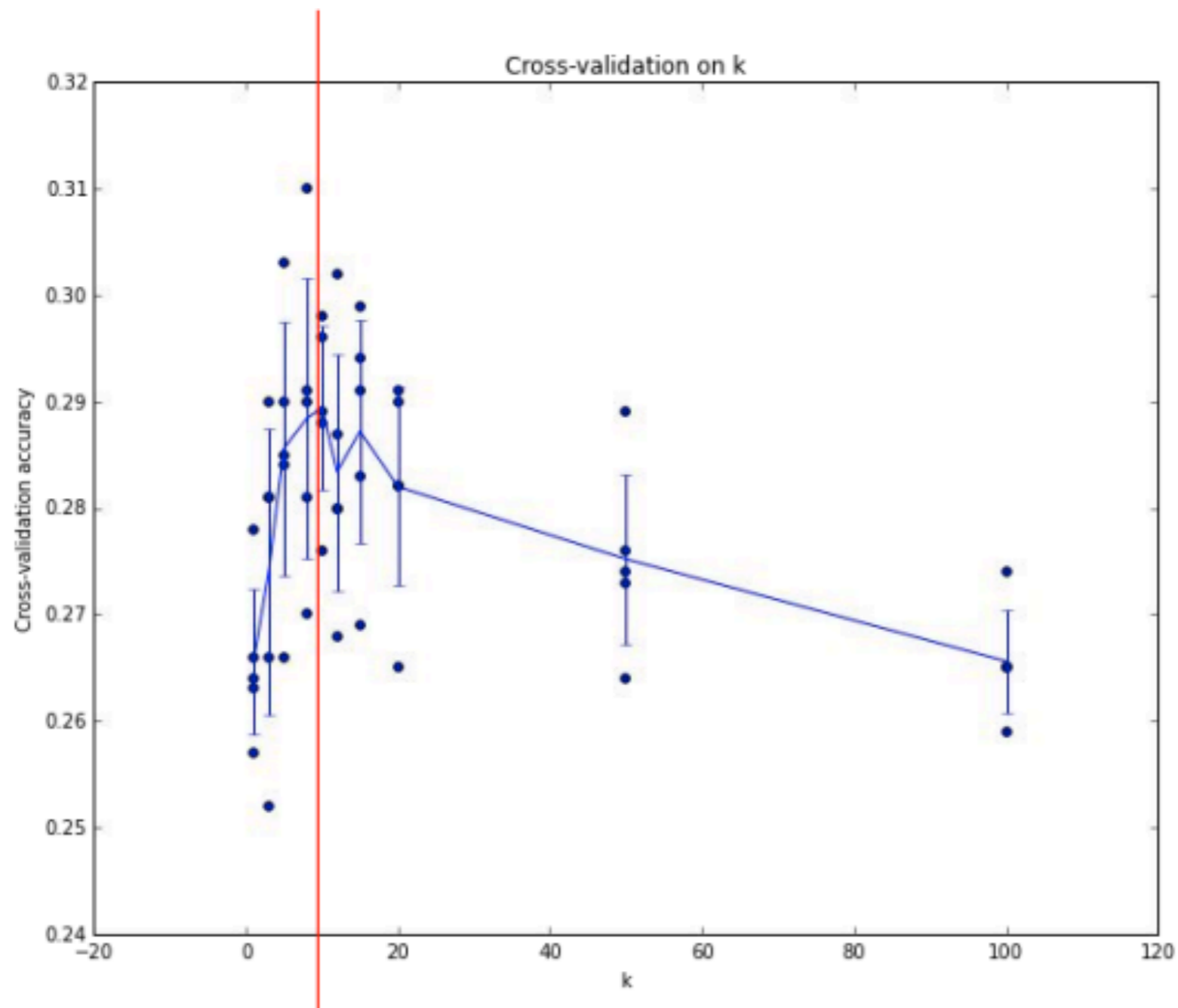
use to tune hyperparameters
evaluate on test set ONCE at the end

Cross-validation



Cross-validation

cycle through the choice of which fold is the validation fold, average results.



Example of
5-fold cross-validation
for the value of k .

Each point: single
outcome.

The line goes
through the mean, bars
indicated standard
deviation

(Seems that $k \approx 7$ works best
for this data)

How to pick hyperparameters?

- Methodology
 - Train, validate, test
- Train for original model
- Validate to find hyperparameters
- Test to understand generalizability

Pros

- simple yet effective

Cons

- search is expensive (can be sped-up)
- storage requirements
- difficulties with high-dimensional data

kNN -- Complexity and Storage

- N training images, M test images
- Training: $O(1)$
- Testing: $O(MN)$
- Hmm...
 - Normally need the opposite
 - Slow training (ok), fast testing (necessary)

k-Nearest Neighbor on images **never used**.

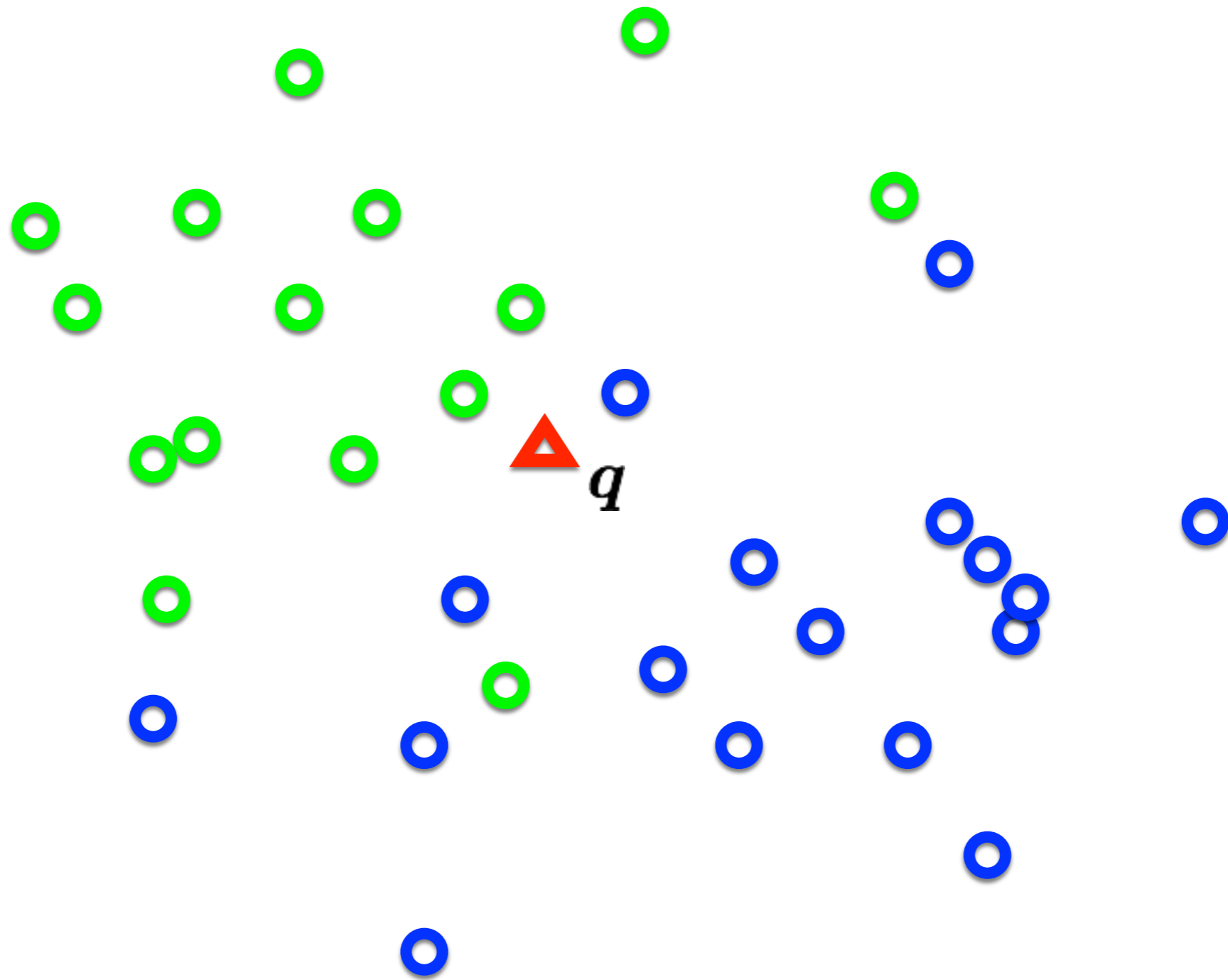
- terrible performance at test time
- distance metrics on level of whole images can be very unintuitive



(all 3 images have same L2 distance to the one on the left)

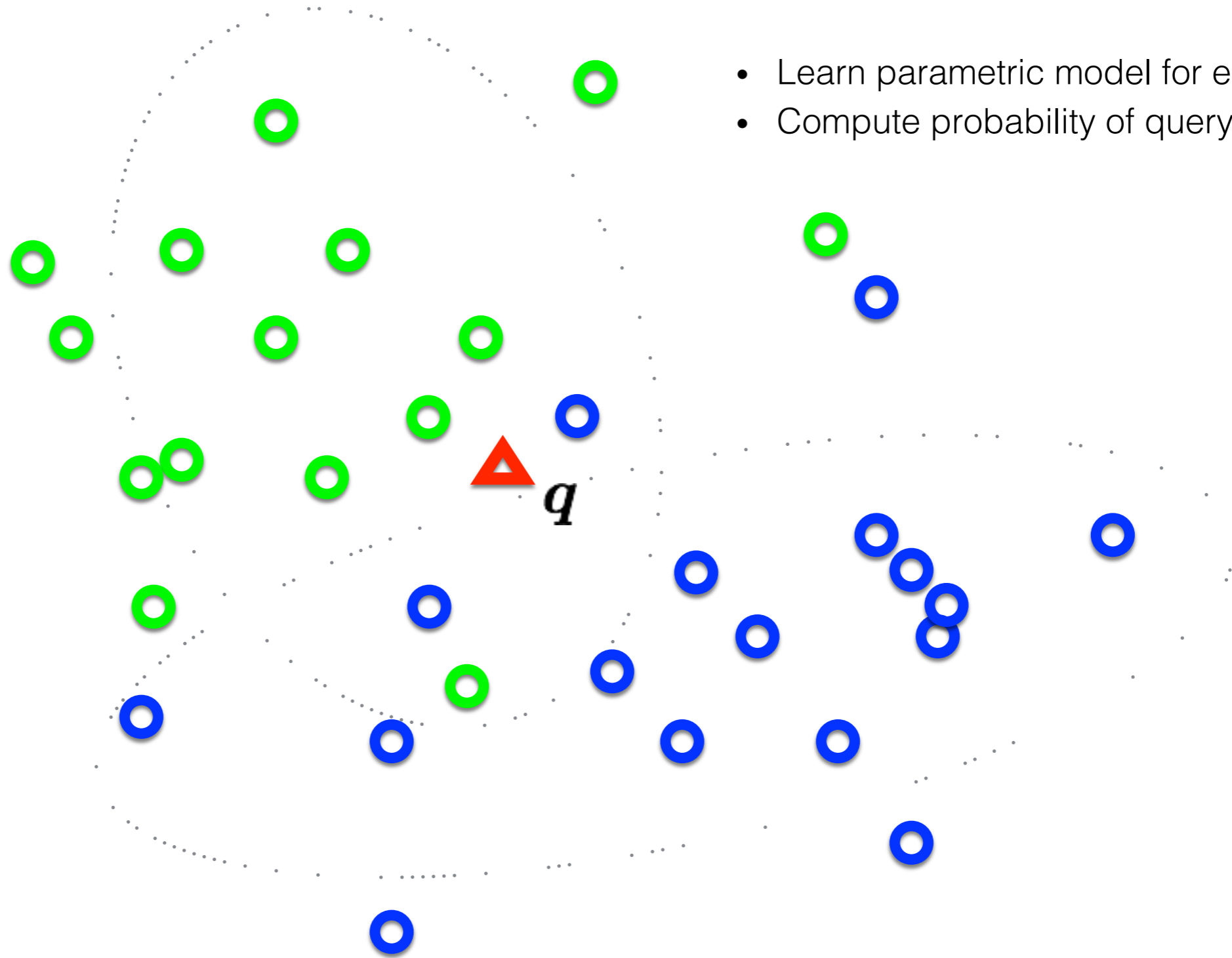
Naïve Bayes

Distribution of data from two classes



Which class does q belong too?

Distribution of data from two classes



- Learn parametric model for each class
- Compute probability of query

This is called the posterior.

the probability of a class z given the observed features X

$$p(z|X)$$



For classification, z is a discrete random variable (e.g., car, person, building)

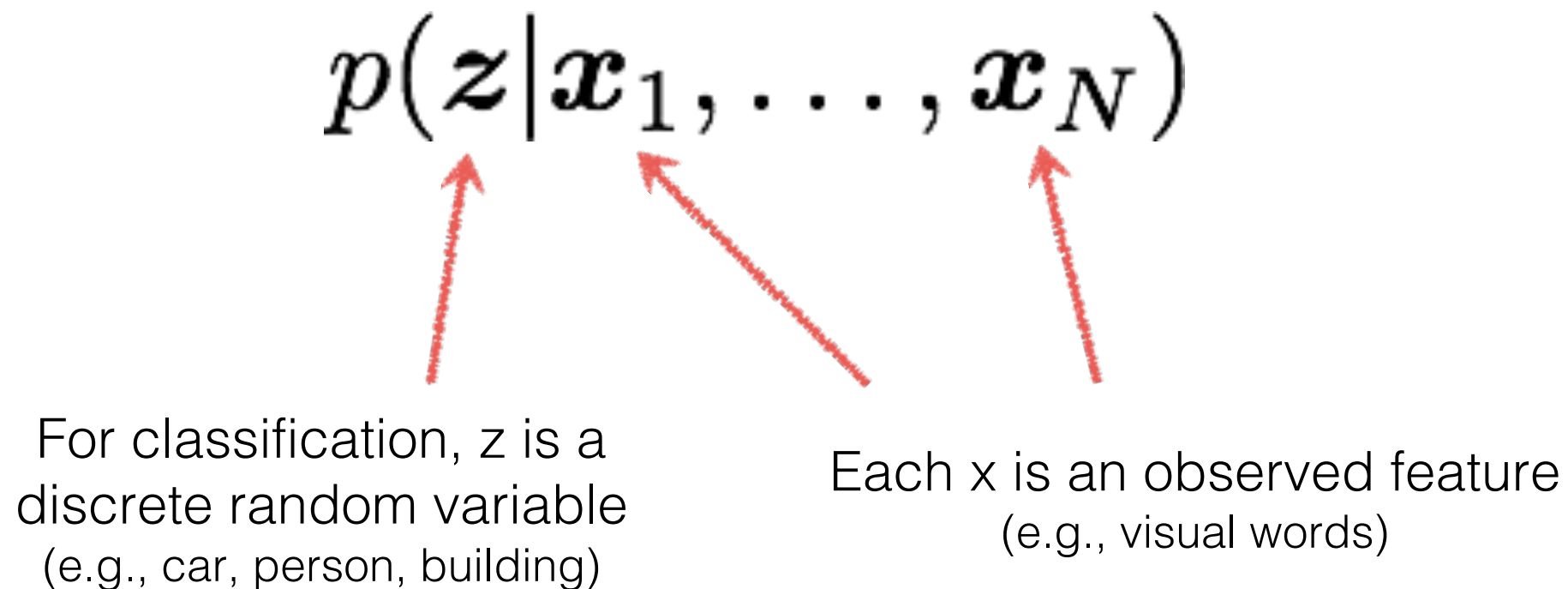
X is a set of observed features (e.g., features from a single image)

(it's a function that returns a single probability value)

This is called the posterior:

the probability of a class z given the observed features X

$$p(\mathbf{z} | \mathbf{x}_1, \dots, \mathbf{x}_N)$$



For classification, z is a discrete random variable (e.g., car, person, building)

Each x is an observed feature (e.g., visual words)

(it's a function that returns a single probability value)

Recall:

The posterior can be decomposed according to
Bayes' Rule

$$p(A|B) = \frac{p(B|A)p(A)}{p(B)}$$

posterior likelihood prior

In our context...

$$p(\mathbf{z}|\mathbf{x}_1, \dots, \mathbf{x}_N) = \frac{p(\mathbf{x}_1, \dots, \mathbf{x}_N|\mathbf{z})p(\mathbf{z})}{p(\mathbf{x}_1, \dots, \mathbf{x}_N)}$$

The naive Bayes' classifier is solving this optimization

$$\hat{z} = \arg \max_{z \in \mathcal{Z}} p(z | \mathbf{X})$$

MAP (maximum a posteriori) estimate

$$\hat{z} = \arg \max_{z \in \mathcal{Z}} \frac{p(\mathbf{X} | z)p(z)}{p(\mathbf{X})}$$

Bayes' Rule

$$\hat{z} = \arg \max_{z \in \mathcal{Z}} p(\mathbf{X} | z)p(z)$$

Remove constants

To optimize this...we need to compute this



Compute the likelihood...

A naive Bayes' classifier assumes all features are ***conditionally independent***

$$\begin{aligned} p(\mathbf{x}_1, \dots, \mathbf{x}_N | \mathbf{z}) &= p(\mathbf{x}_1 | \mathbf{z}) p(\mathbf{x}_2, \dots, \mathbf{x}_N | \mathbf{z}) \\ &= p(\mathbf{x}_1 | \mathbf{z}) p(\mathbf{x}_2 | \mathbf{z}) p(\mathbf{x}_3, \dots, \mathbf{x}_N | \mathbf{z}) \\ &= p(\mathbf{x}_1 | \mathbf{z}) p(\mathbf{x}_2 | \mathbf{z}) \cdots p(\mathbf{x}_N | \mathbf{z}) \end{aligned}$$

To compute the MAP estimate

Given (1) a set of known parameters

(2) observations

$$p(\mathbf{z}) \quad p(\mathbf{x}|\mathbf{z})$$

$$\{x_1, x_2, \dots, x_N\}$$

Compute which z has the largest probability

$$\hat{z} = \arg \max_{z \in \mathcal{Z}} p(z) \prod_n p(x_n | z)$$



count	1	6	2	1	0	0	0	1
word	Tartan	robot	CHIMP	CMU	bio	soft	ankle	sensor
p(x z)	0.09	0.55	0.18	0.09	0.0	0.0	0.0	0.09

$$\begin{aligned}
 p(X|z) &= \prod_v p(x_v|z)^{c(w_v)} \\
 &= (0.09)^1 (0.55)^6 \dots (0.09)^1
 \end{aligned}$$

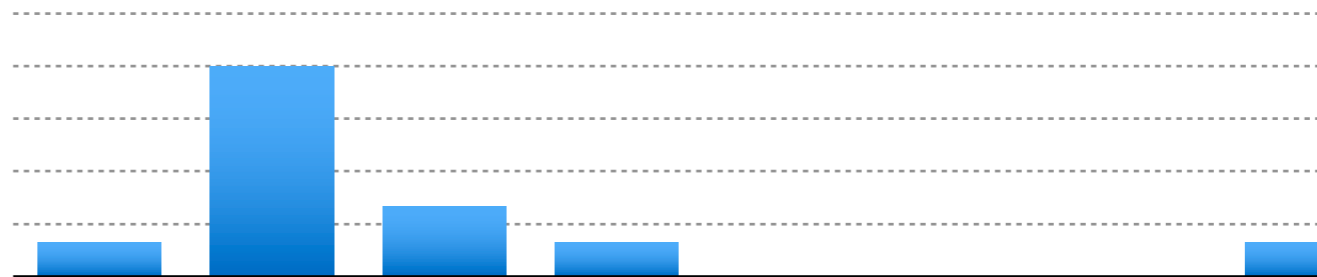
Numbers get really small so use log probabilities

$$\log p(X|z = \text{'grandchallenge'}) = -2.42 - 3.68 - 3.43 - 2.42 - 0.07 - 0.07 - 0.07 - 2.42 = -14.58$$

$$\log p(X|z = \text{'softrobot'}) = -7.63 - 9.37 - 15.18 - 2.97 - 0.02 - 0.01 - 0.02 - 2.27 = -37.48$$

* typically add pseudo-counts (0.001)

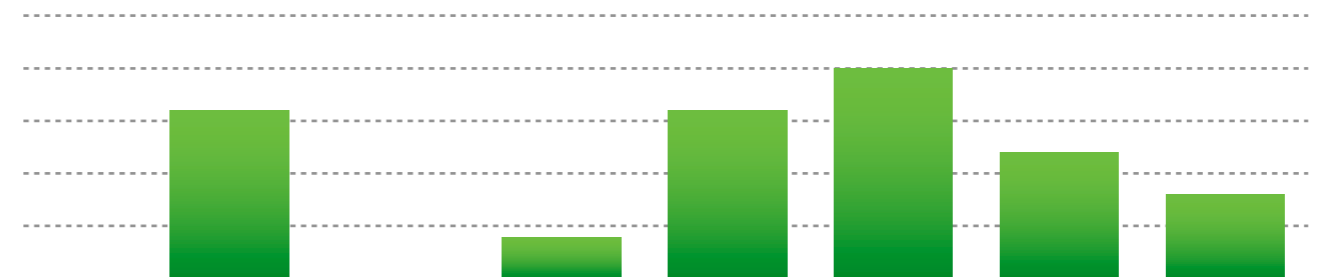
** this is an example for computing the likelihood, need to multiply times **prior** to get posterior



count	1	6	2	1	0	0	0	1
word	Tartan	robot	CHIMP	CMU	bio	soft	ankle	sensor
p(x z)	0.09	0.55	0.18	0.09	0.0	0.0	0.0	0.09

$$\log p(X|z=\text{grand challenge}) = - \mathbf{14.58}$$

$$\log p(X|z=\text{bio inspired}) = - 37.48$$



count	0	4	0	1	4	5	3	2
word	Tartan	robot	CHIMP	CMU	bio	soft	ankle	sensor
p(x z)	0.0	0.21	0.0	0.05	0.21	0.26	0.16	0.11

$$\log p(X|z=\text{grand challenge}) = - 94.06$$

$$\log p(X|z=\text{bio inspired}) = - \mathbf{32.41}$$

* typically add pseudo-counts (0.001)

** this is an example for computing the likelihood, need to multiply times prior to get posterior

Support Vector Machine

Image Classification



(assume given set of discrete labels)
{dog, cat, truck, plane, ...}



cat

Score function



class scores

Linear Classifier

define a **score function**

data (histogram)

$$f(x_i, W, b) = Wx_i + b$$

class scores

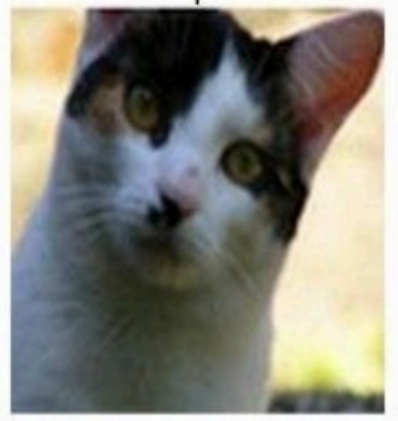
“weights”

“bias vector”

“parameters”

Example with an image with 4 pixels, and 3 classes (cat/dog/ship)

Convert image to histogram representation



input image

0.2	-0.5	0.1	2.0
1.5	1.3	2.1	0.0
0	0.25	0.2	-0.3

W

56
231
24
2

x_i

+

1.1
3.2
-1.2

b

→

-96.8
437.9
61.95

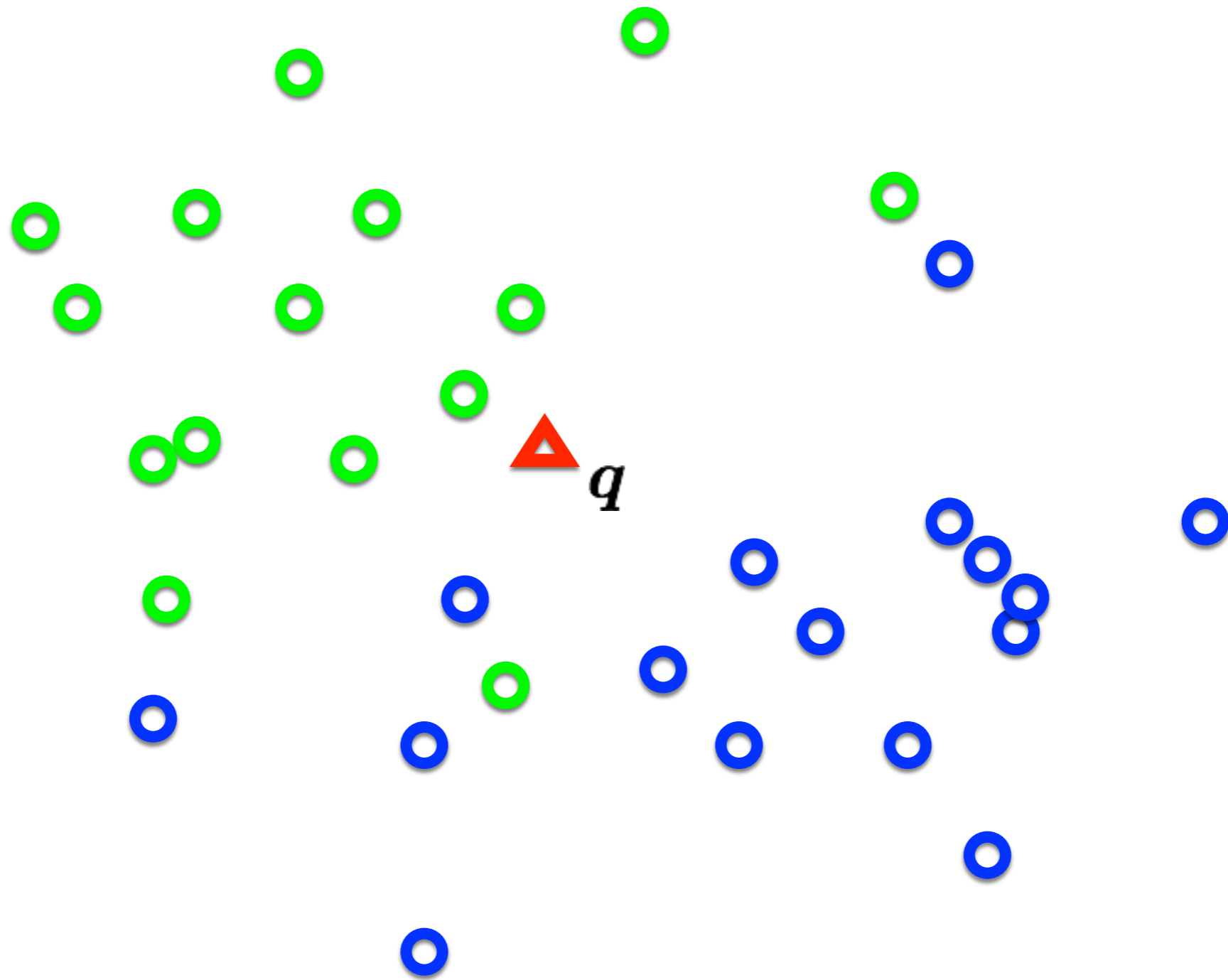
$f(x_i; W, b)$

cat score

dog score

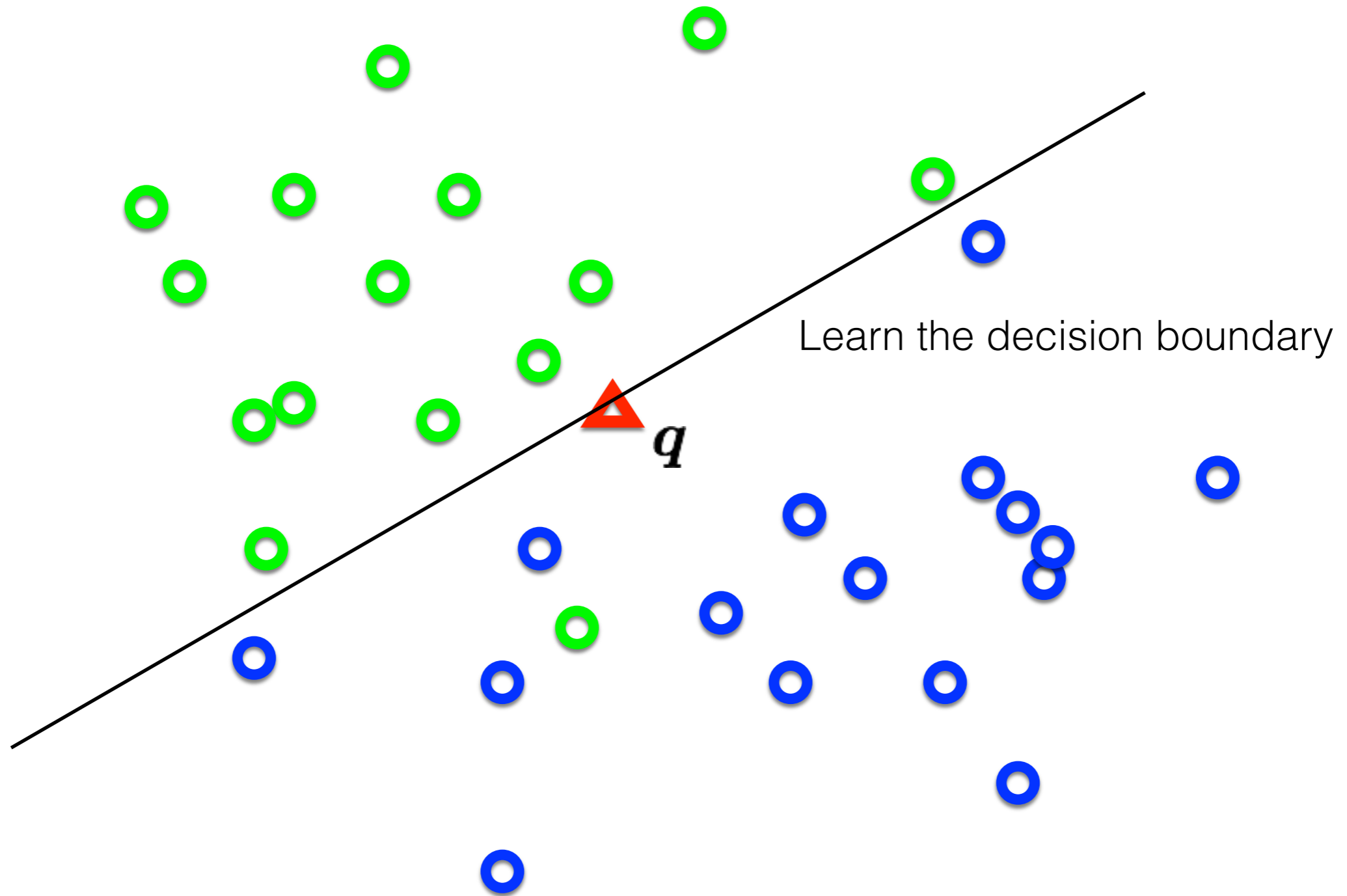
ship score

Distribution of data from two classes



Which class does q belong too?

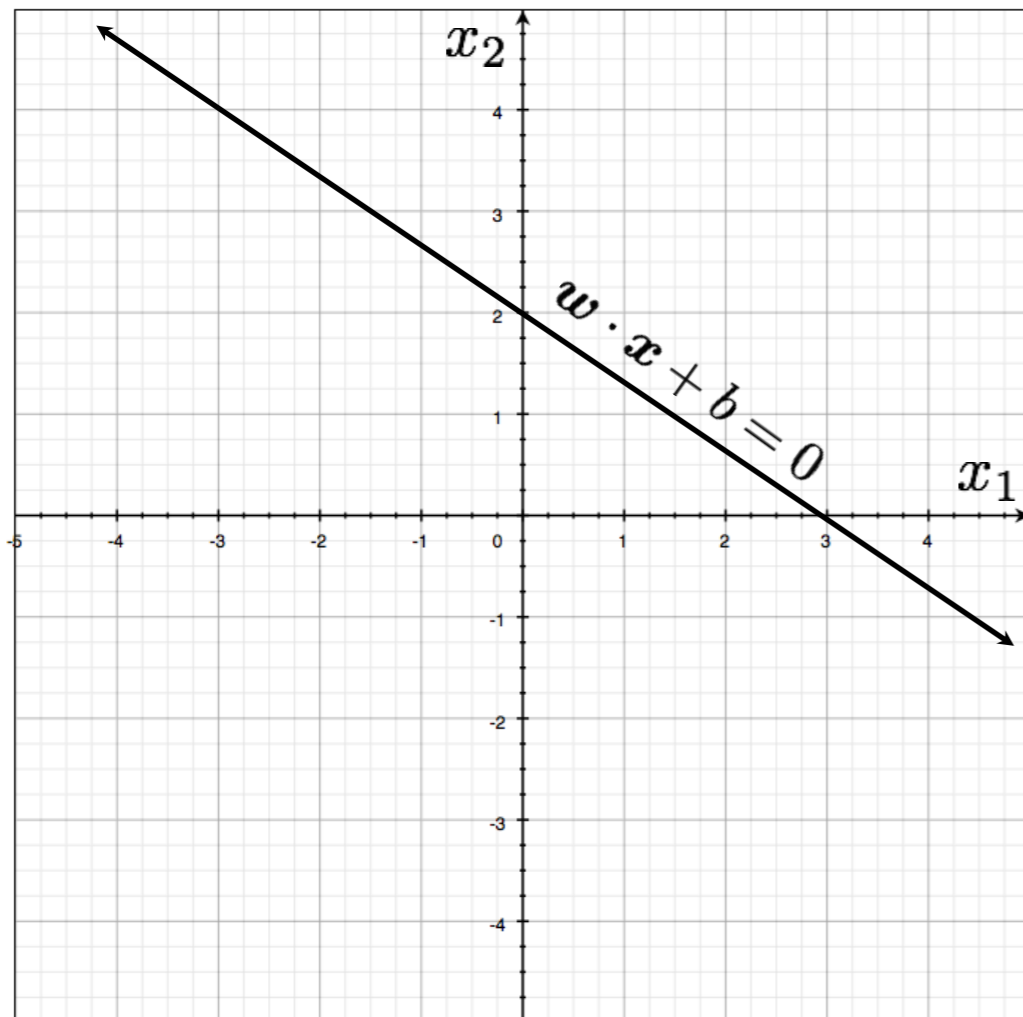
Distribution of data from two classes



First we need to understand hyperplanes...

Hyperplanes (lines) in 2D

$$w_1x_1 + w_2x_2 + b = 0$$



a line can be written as
dot product plus a bias

$$w \cdot x + b = 0$$

$$w \in \mathcal{R}^2$$

another version, add a weight 1
and push the bias inside

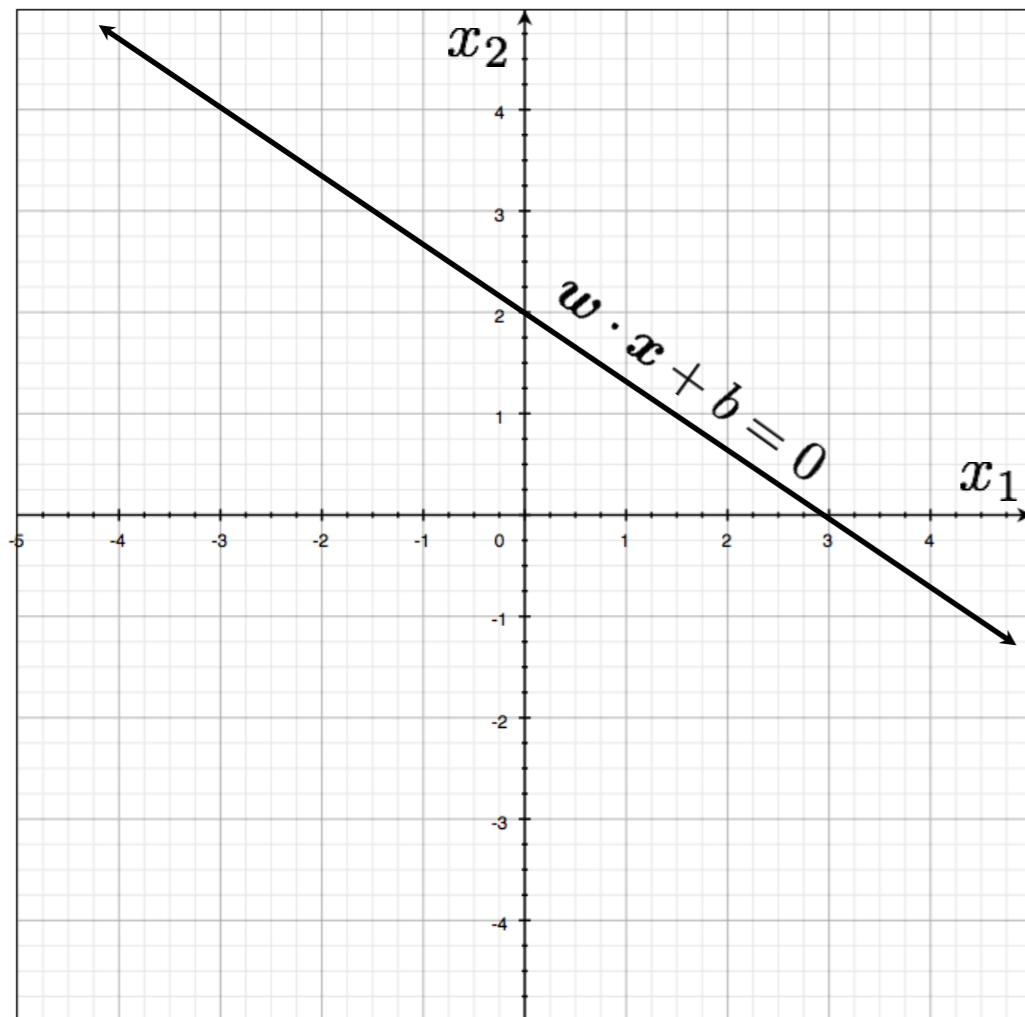
$$w \cdot x = 0$$

$$w \in \mathcal{R}^3$$

Hyperplanes (lines) in 2D

$$\boldsymbol{w} \cdot \boldsymbol{x} + b = 0 \quad (\text{offset/bias outside}) \quad \boldsymbol{w} \cdot \boldsymbol{x} = 0 \quad (\text{offset/bias inside})$$

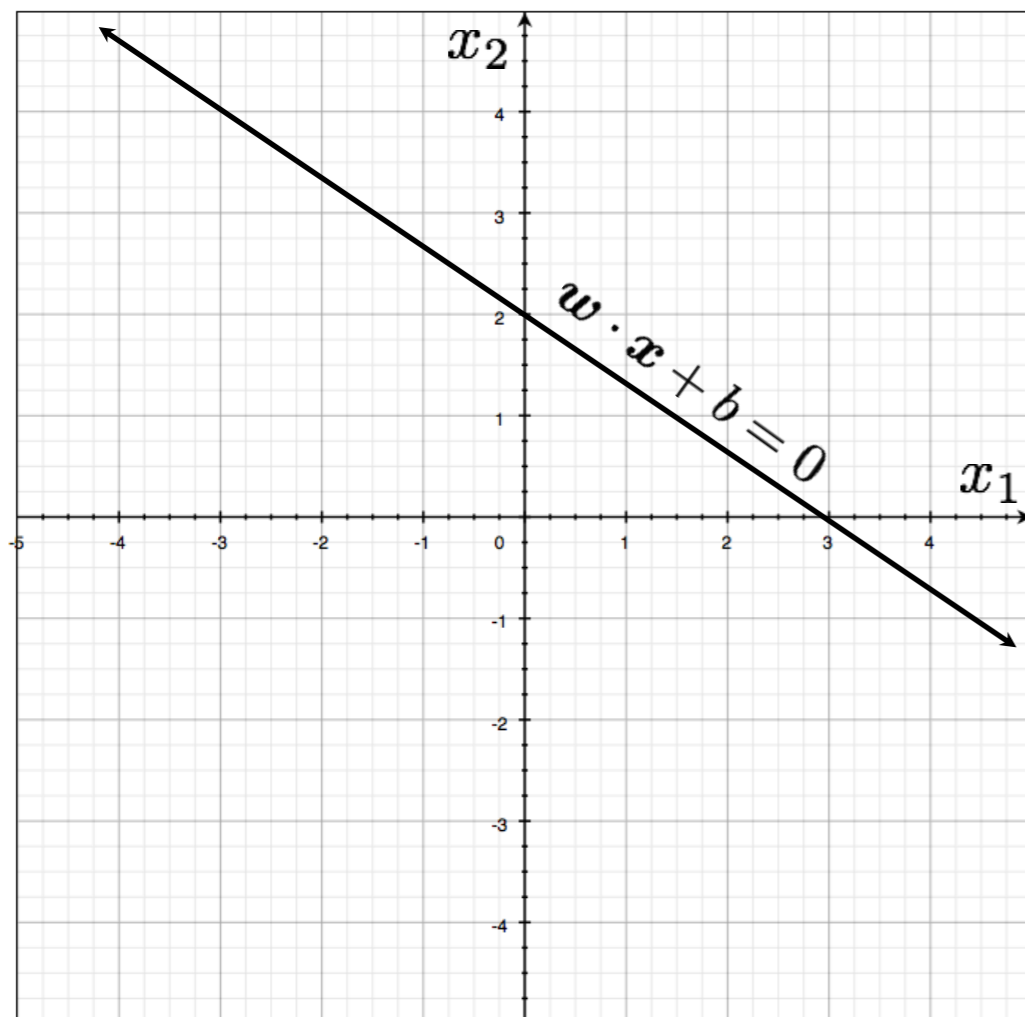
$$w_1 x_1 + w_2 x_2 + b = 0$$



Hyperplanes (lines) in 2D

$$\boldsymbol{w} \cdot \boldsymbol{x} + b = 0 \quad (\text{offset/bias outside}) \quad \boldsymbol{w} \cdot \boldsymbol{x} = 0 \quad (\text{offset/bias inside})$$

$$w_1x_1 + w_2x_2 + b = 0$$



Important property:
Free to choose any normalization of w

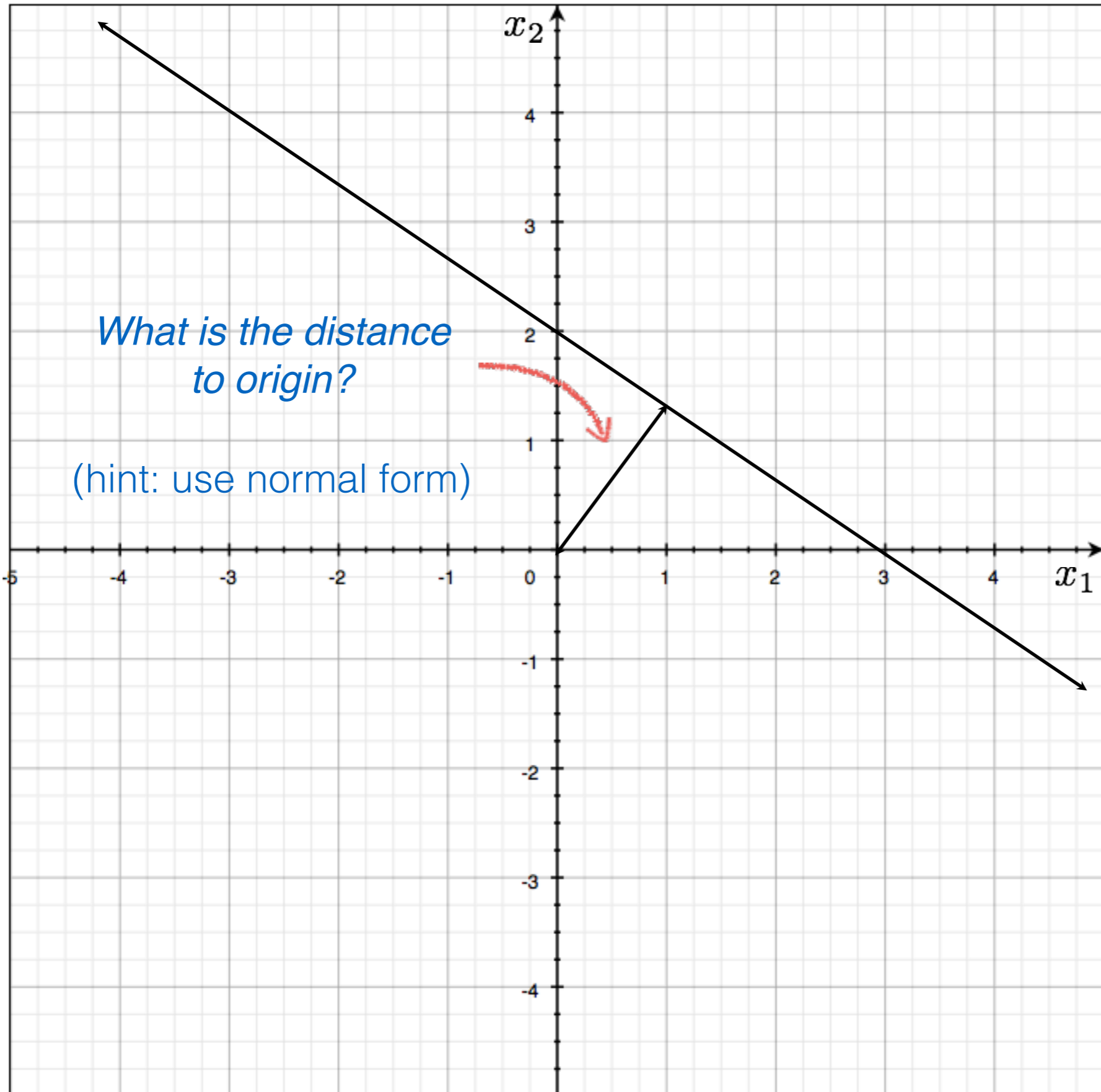
The line

$$w_1x_1 + w_2x_2 + b = 0$$

and the line

$$\lambda(w_1x_1 + w_2x_2 + b) = 0$$

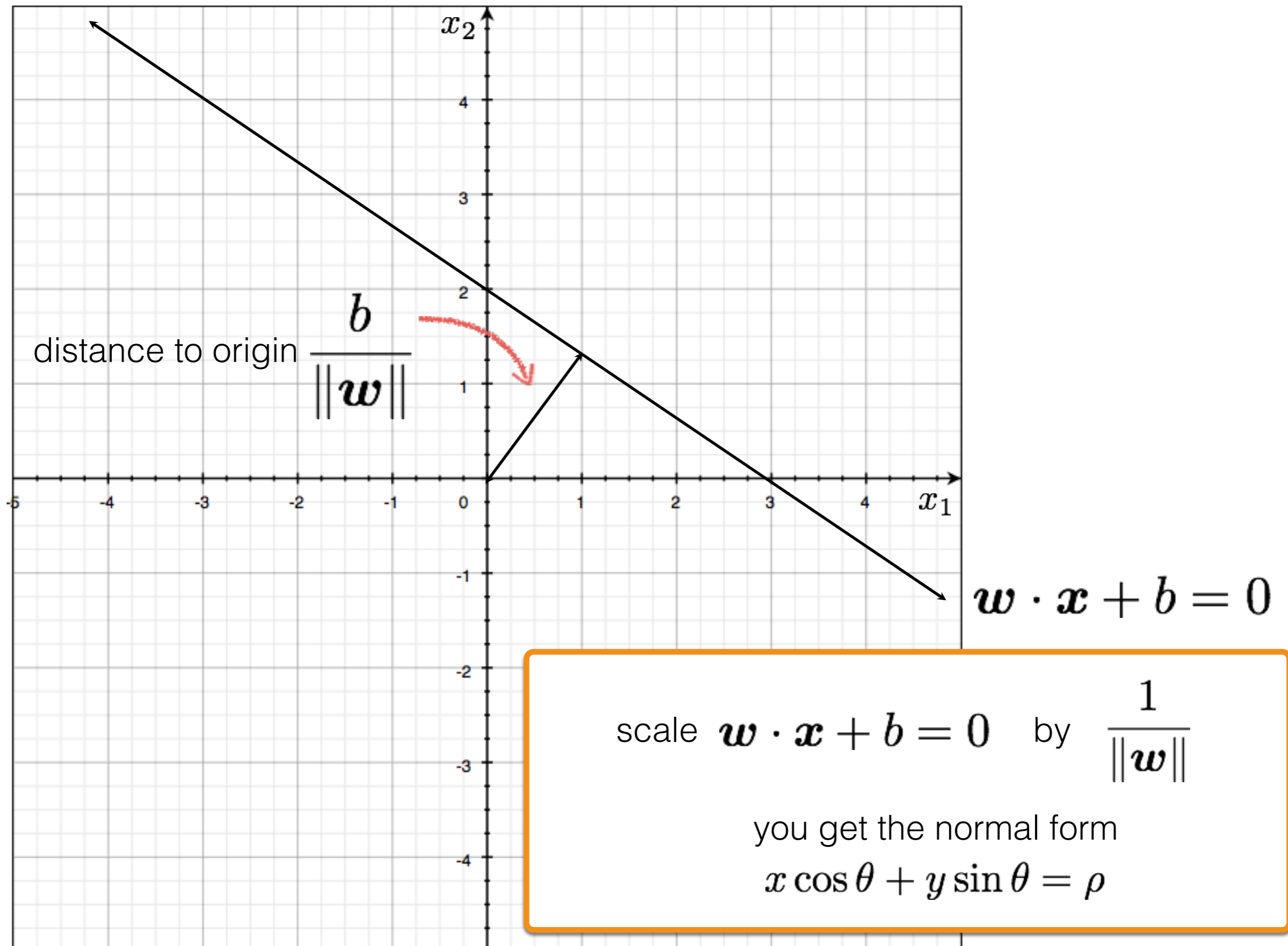
define the same line

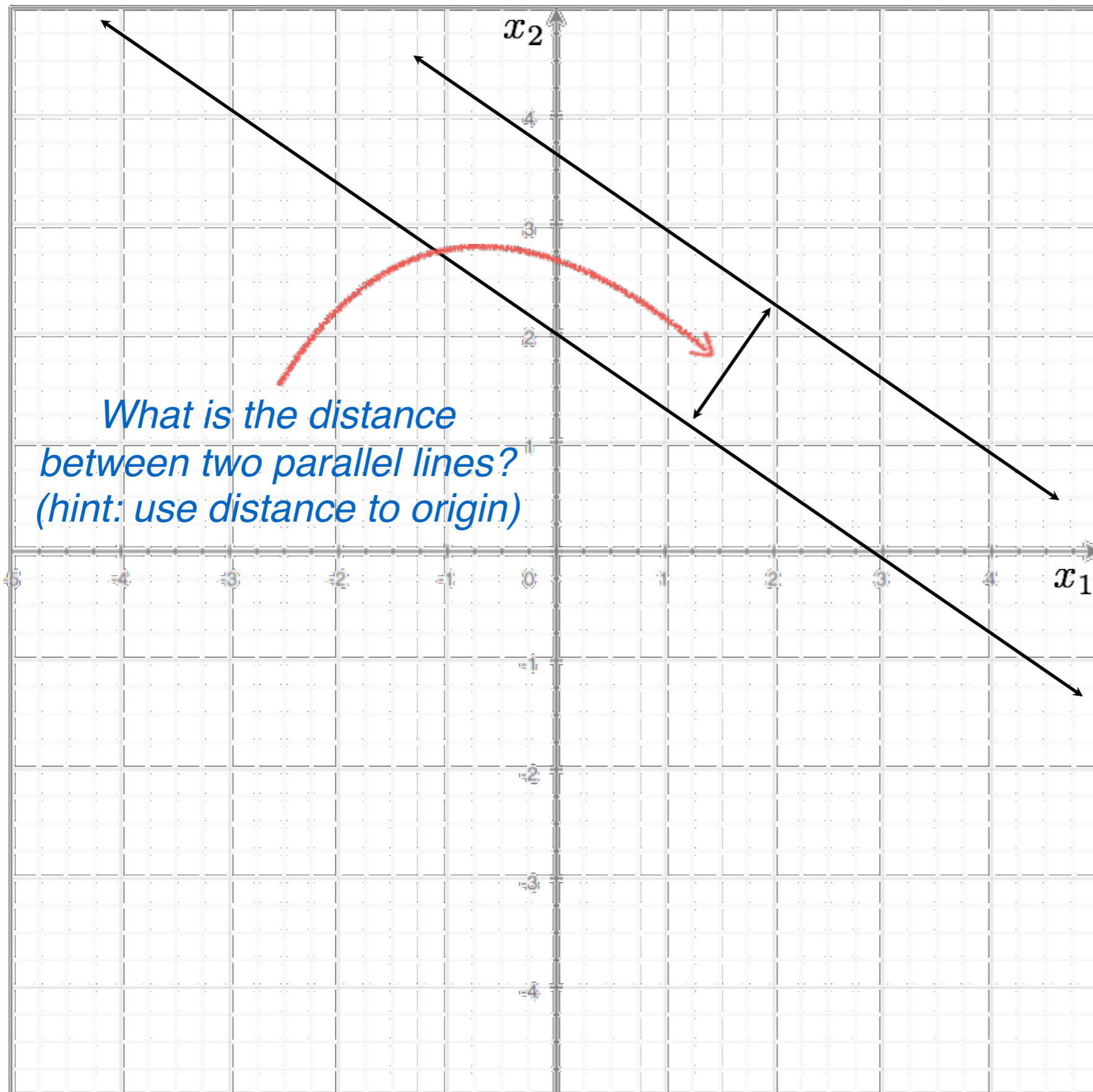


*What is the distance
to origin?*

(hint: use normal form)

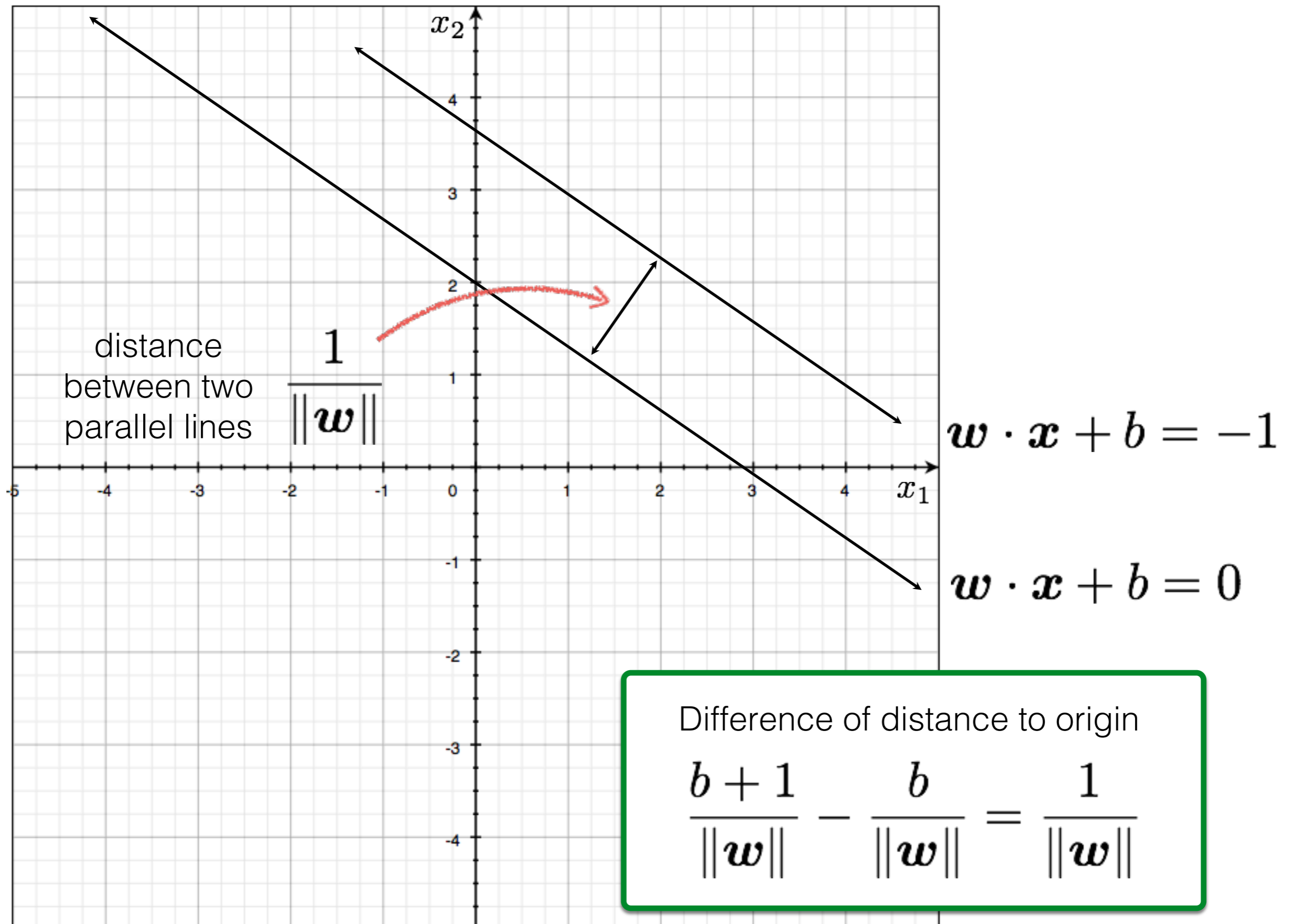
$$w \cdot x + b = 0$$





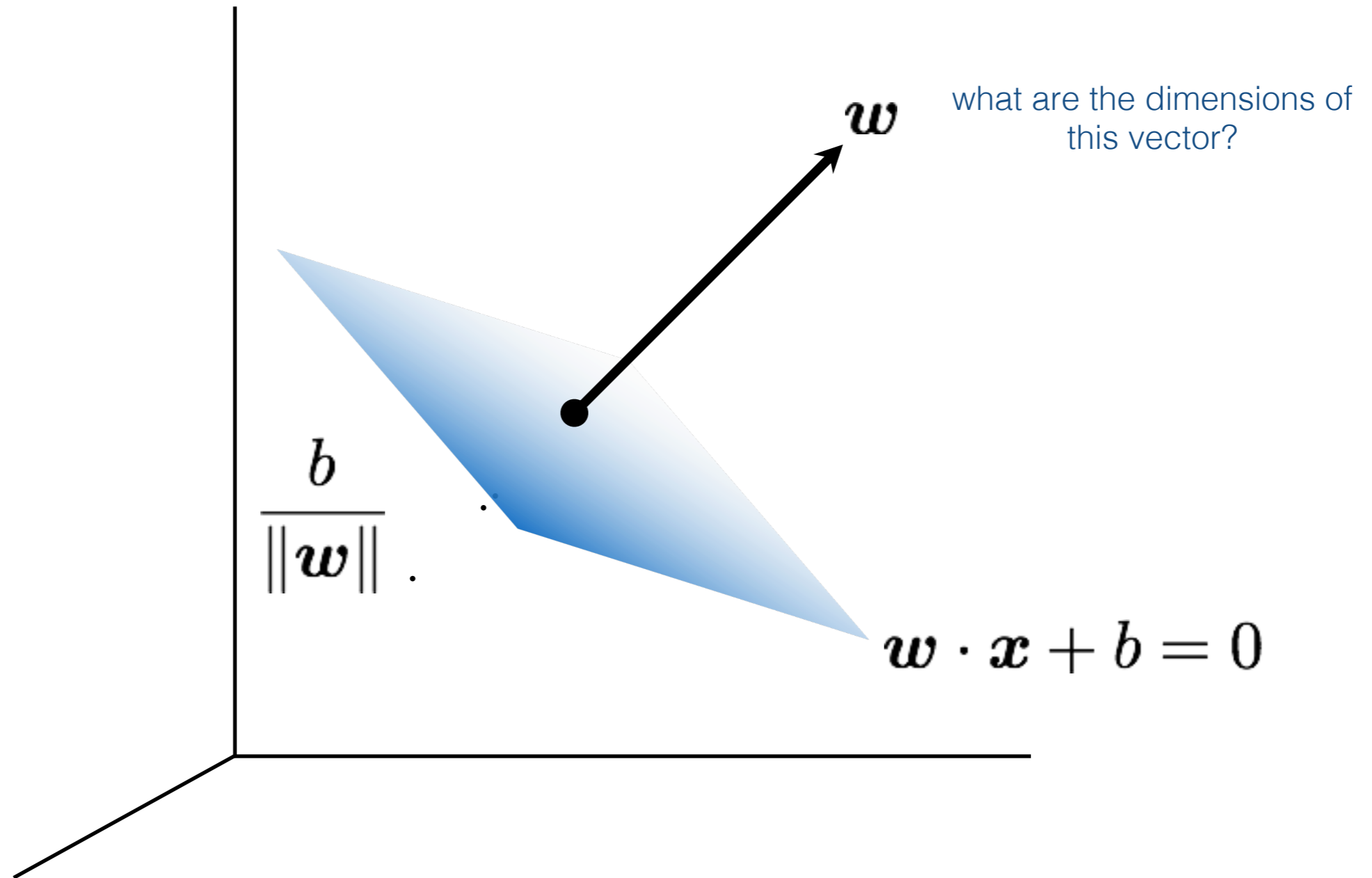
$$w \cdot x + b = -1$$

$$w \cdot x + b = 0$$



Now we can go to 3D ...

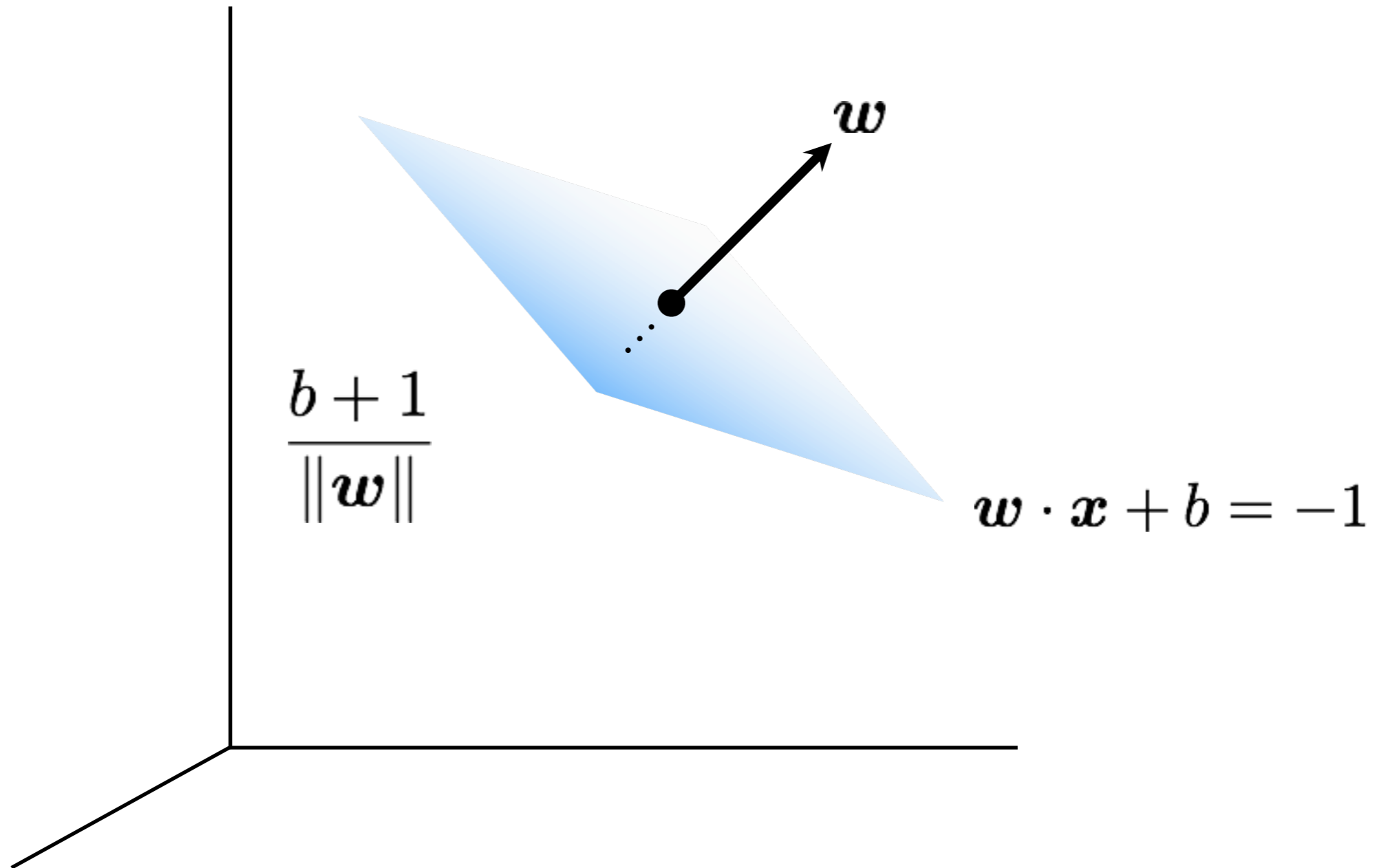
Hyperplanes (planes) in 3D



what are the dimensions of this vector?

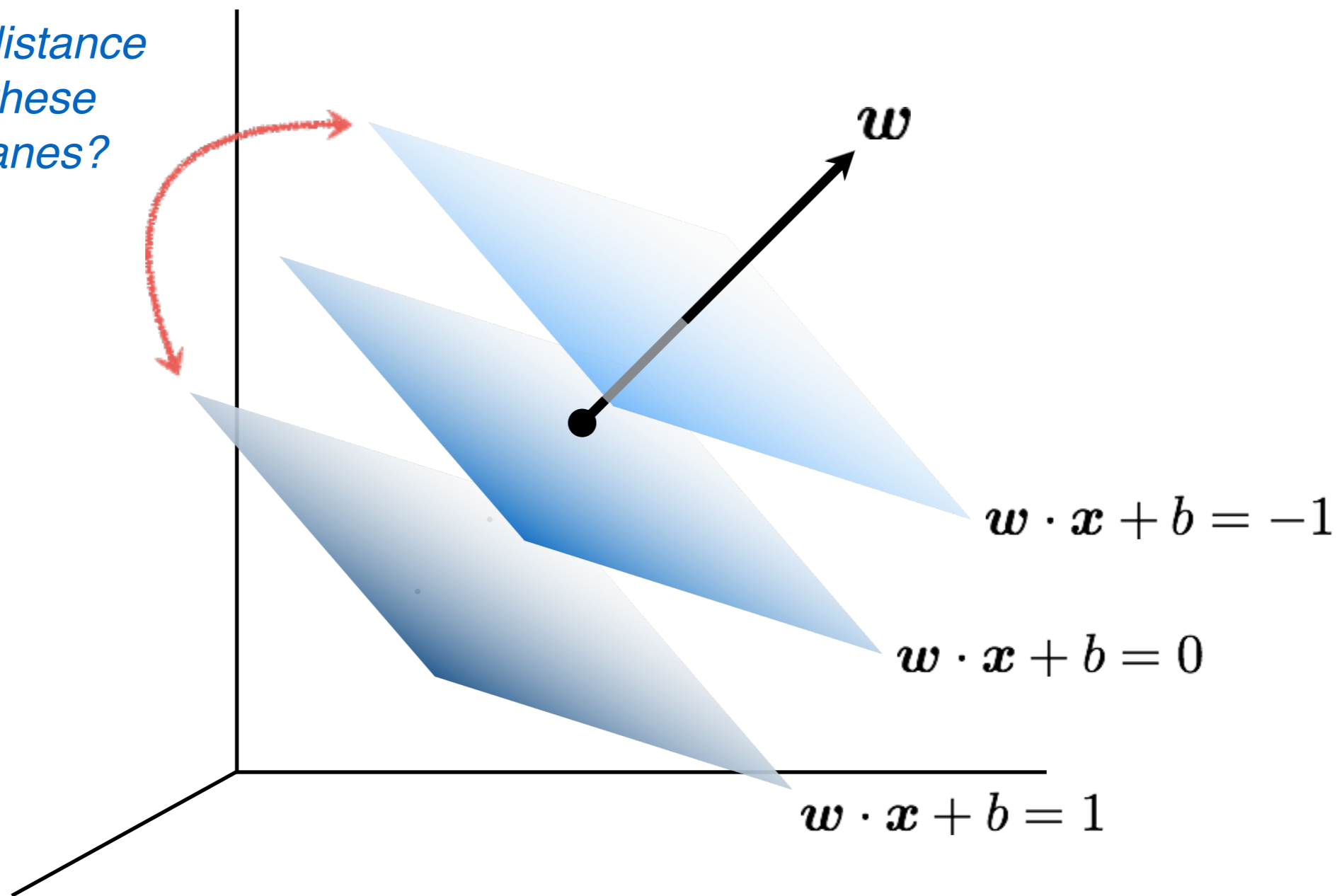
What happens if you change b ?

Hyperplanes (planes) in 3D

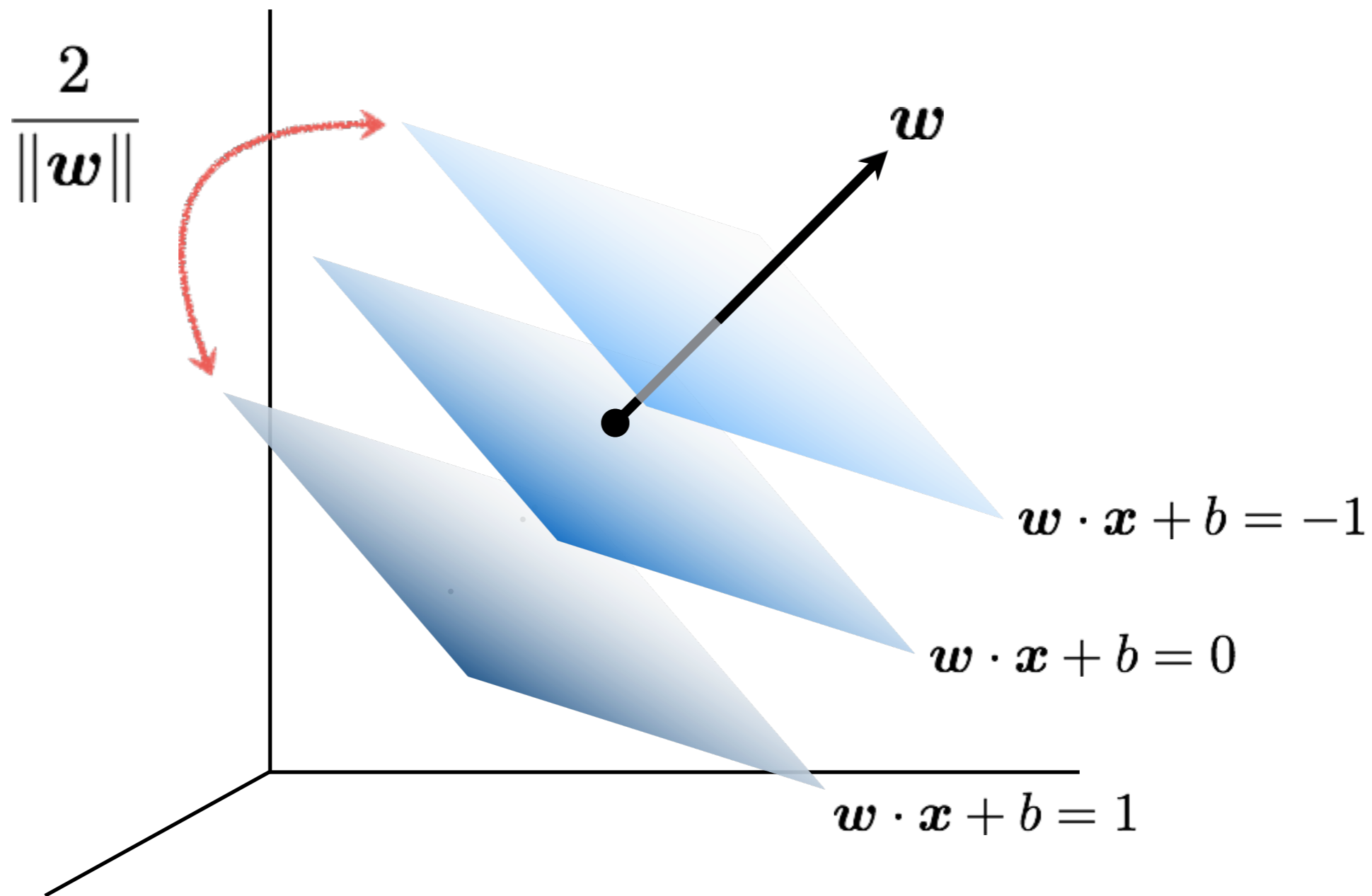


Hyperplanes (planes) in 3D

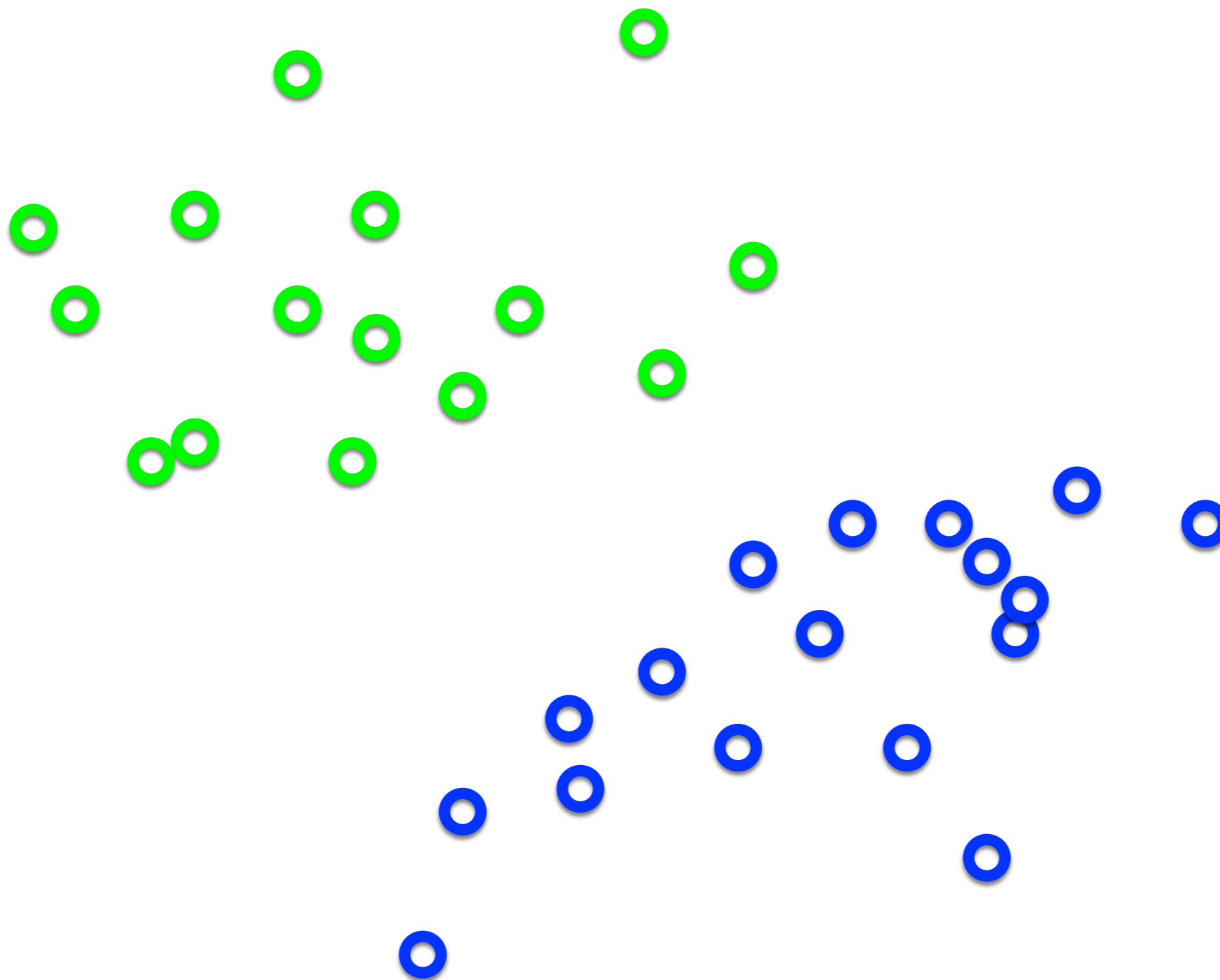
*What's the distance
between these
parallel planes?*



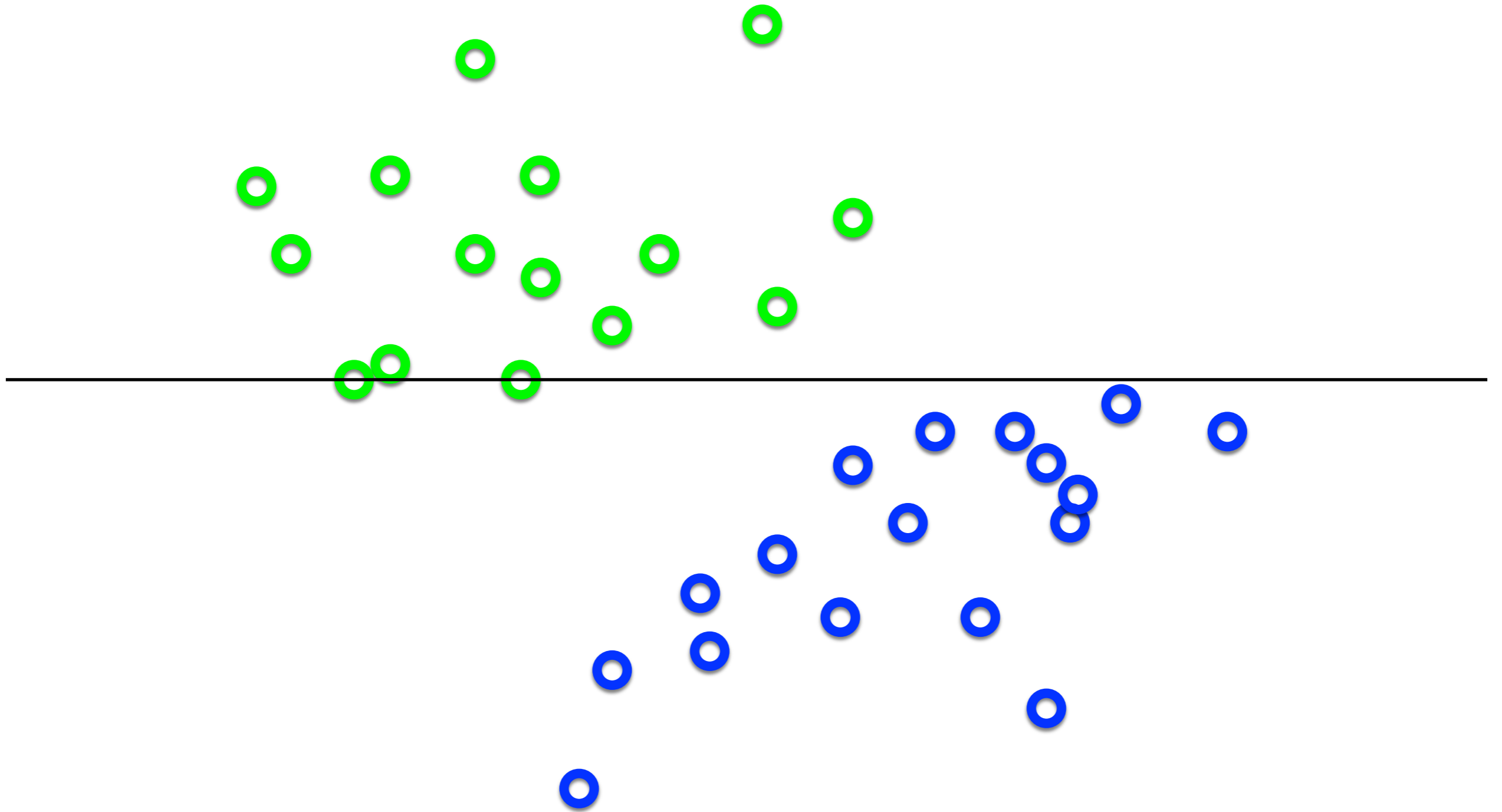
Hyperplanes (planes) in 3D



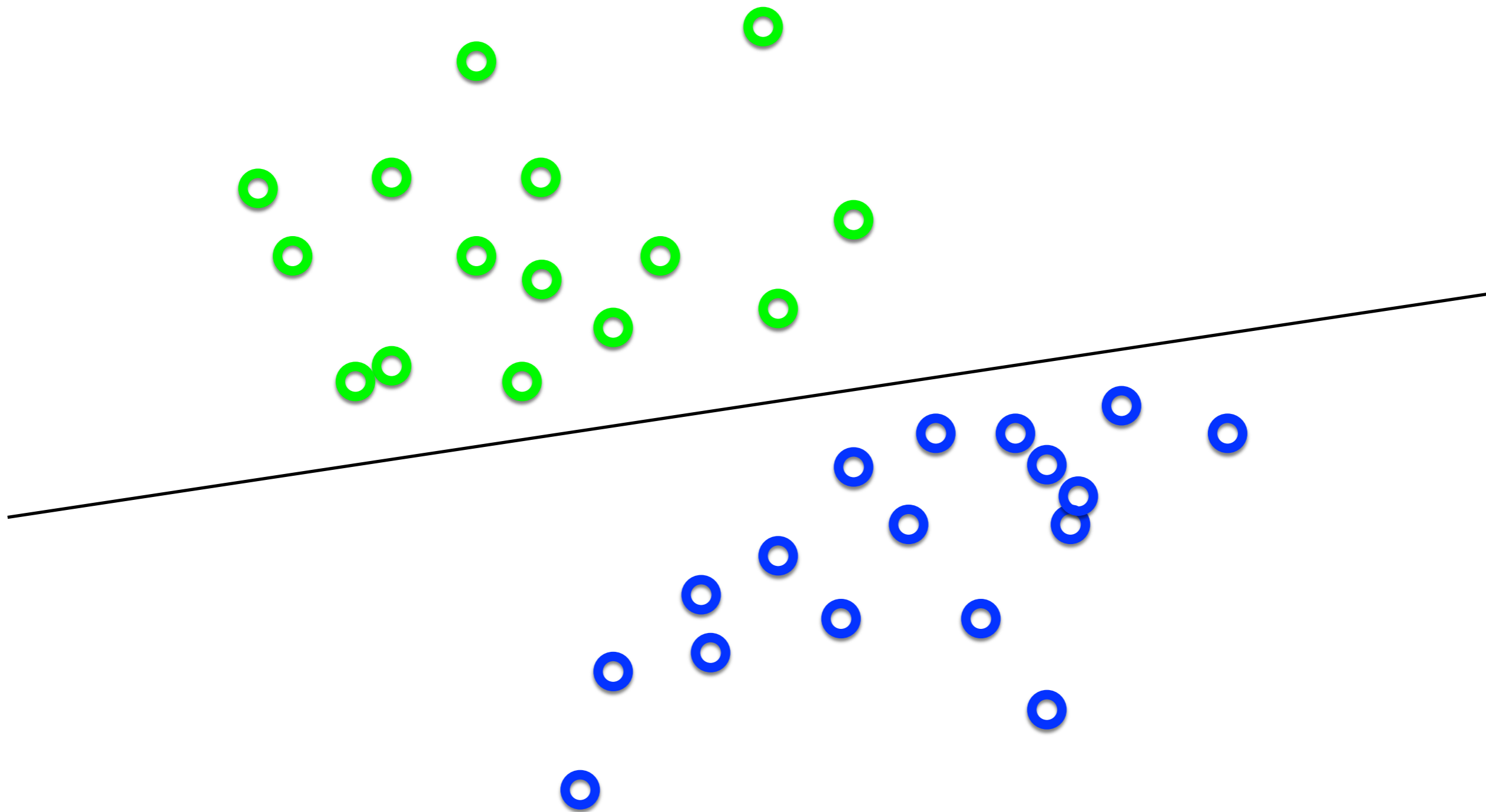
What's the best \mathbf{w} ?



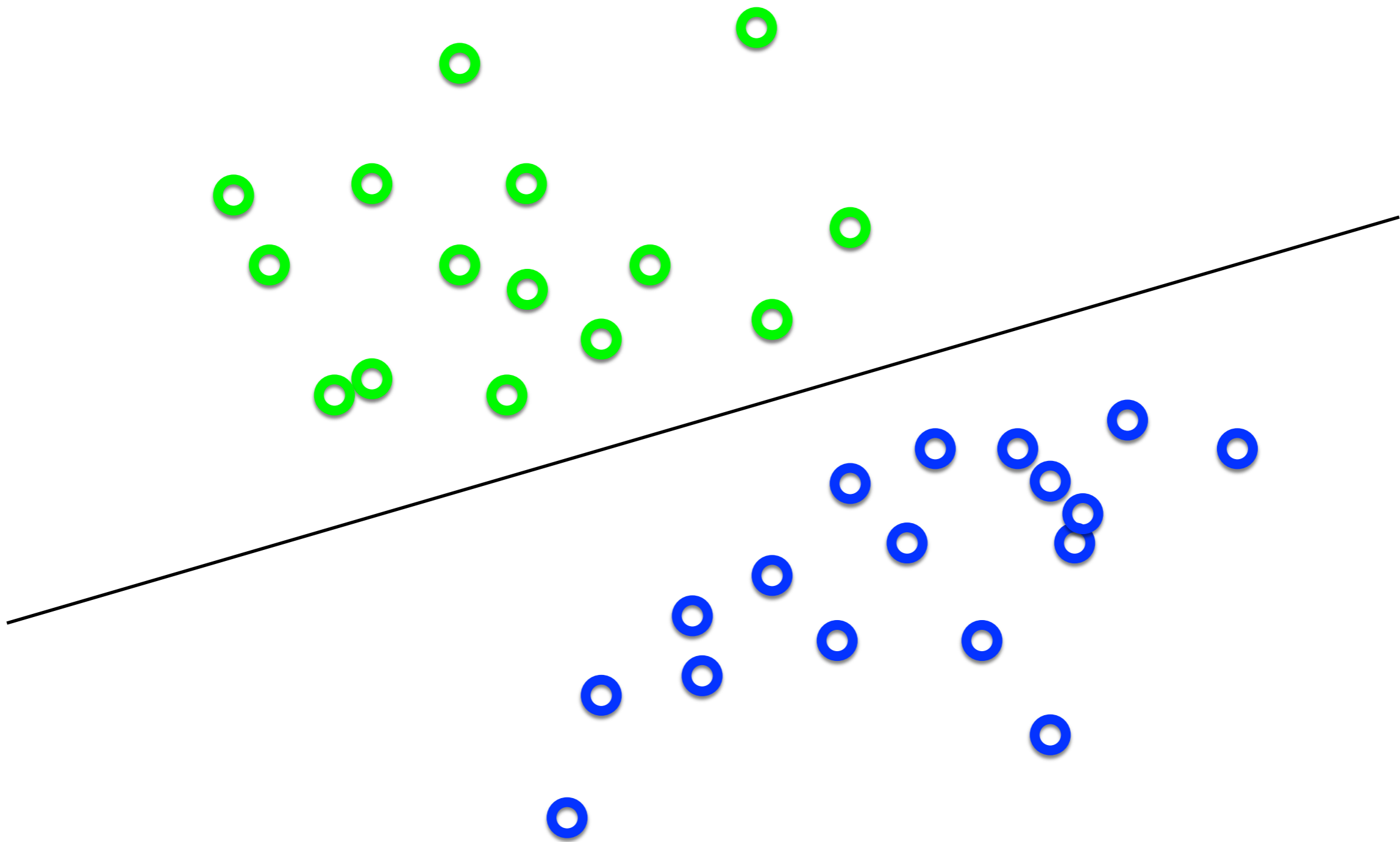
What's the best \mathbf{w} ?



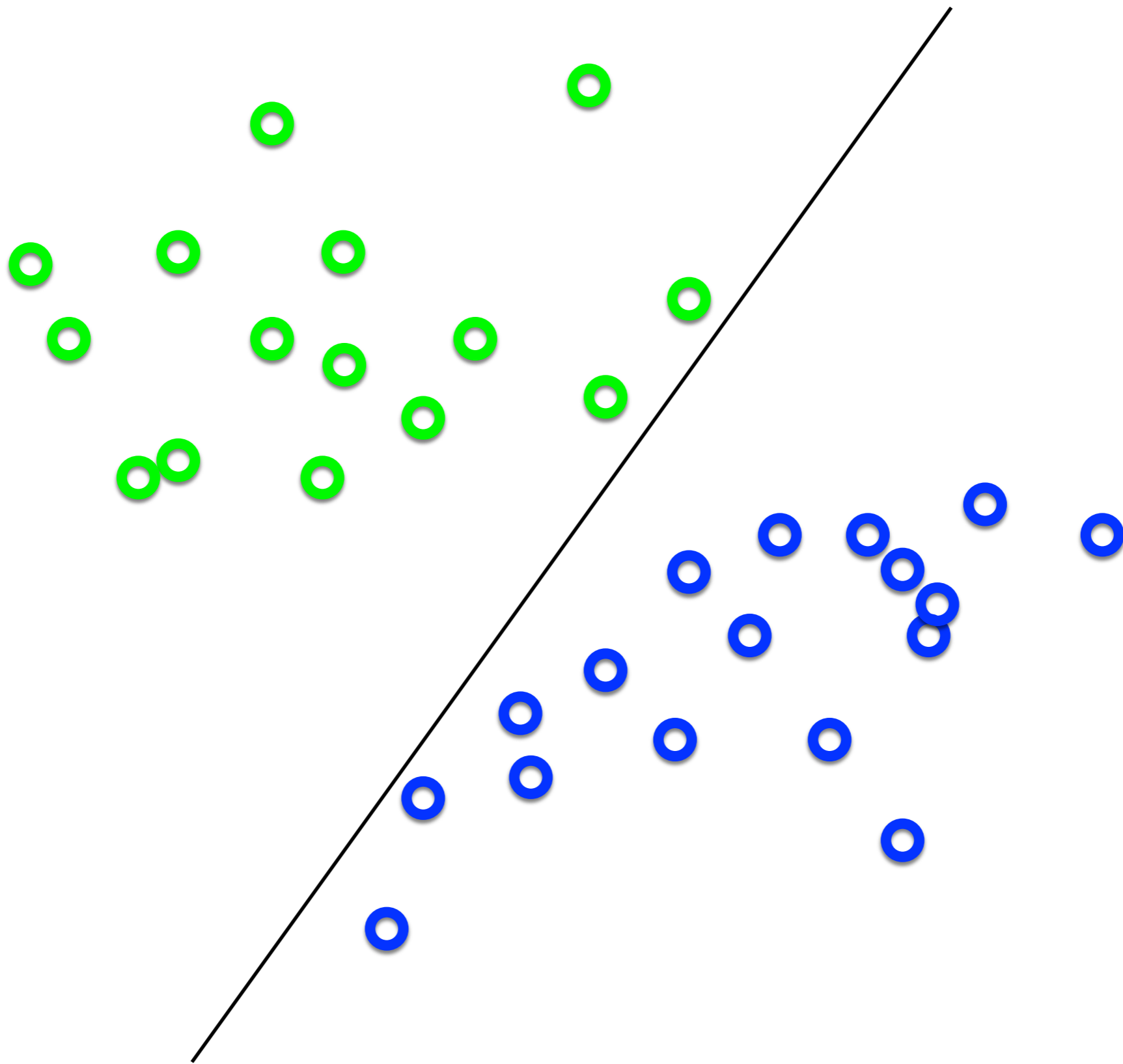
What's the best \mathbf{w} ?



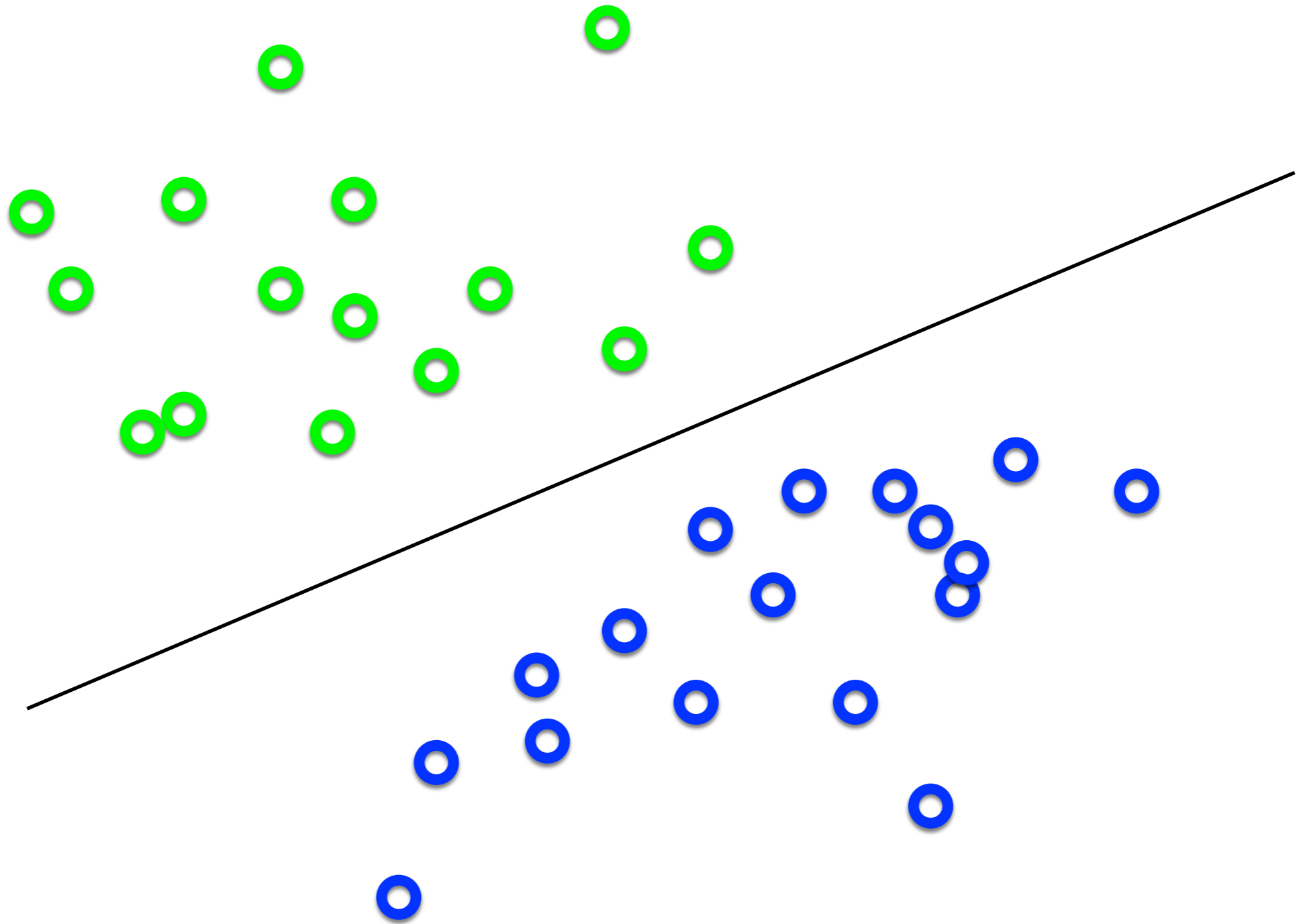
What's the best \mathbf{w} ?



What's the best \mathbf{w} ?

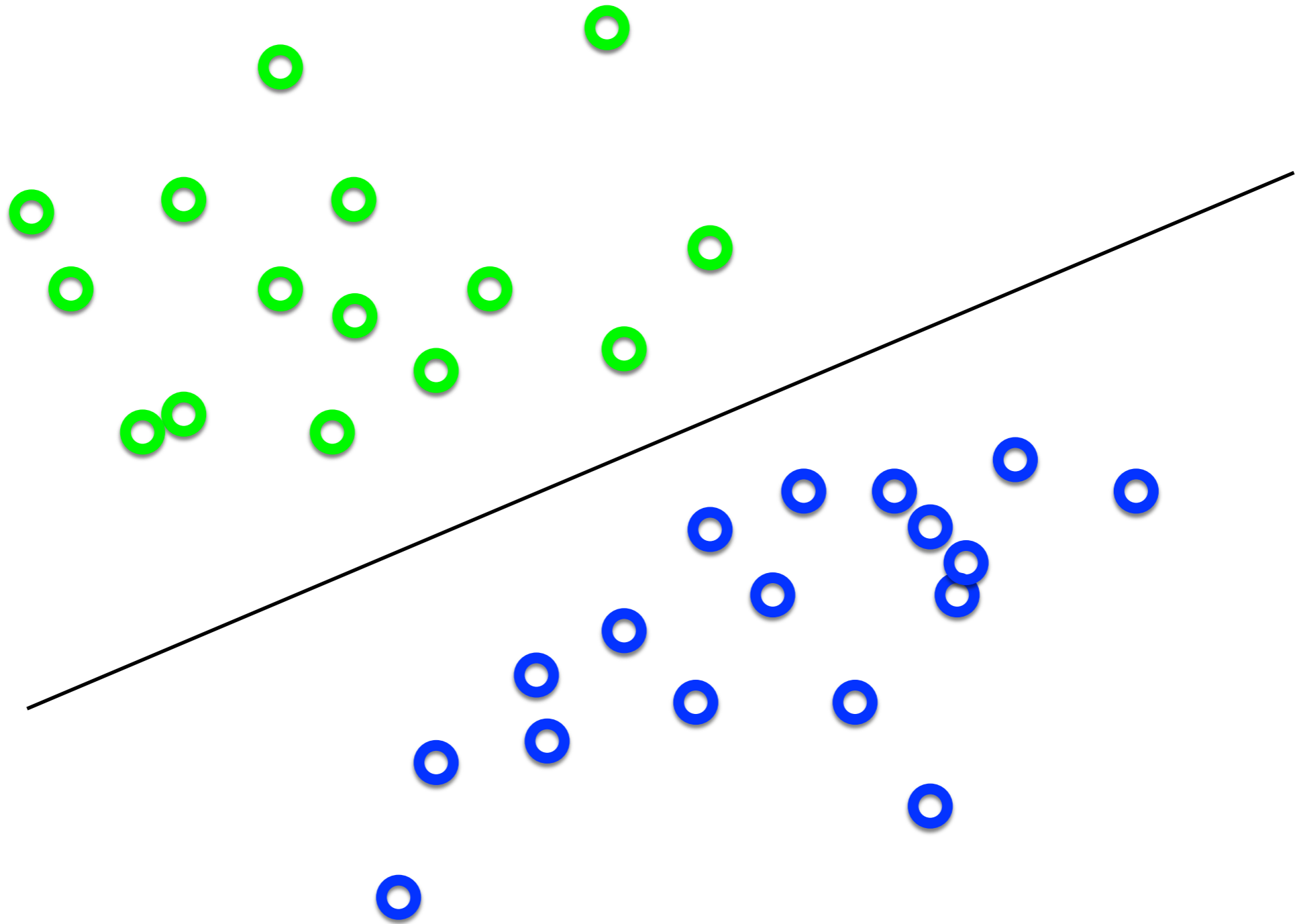


What's the best \mathbf{w} ?



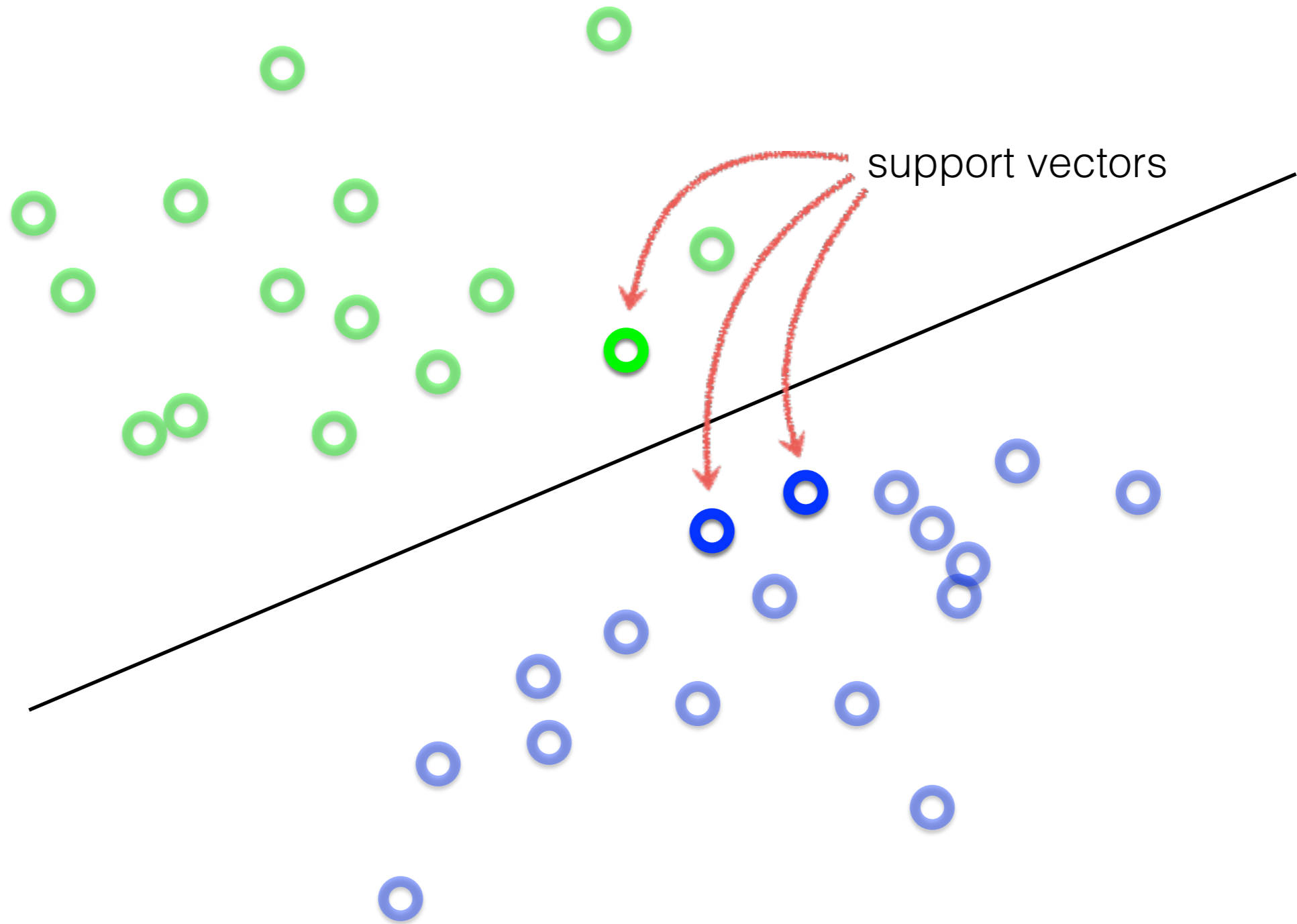
Intuitively, the line that is the farthest from all interior points

What's the best \mathbf{w} ?



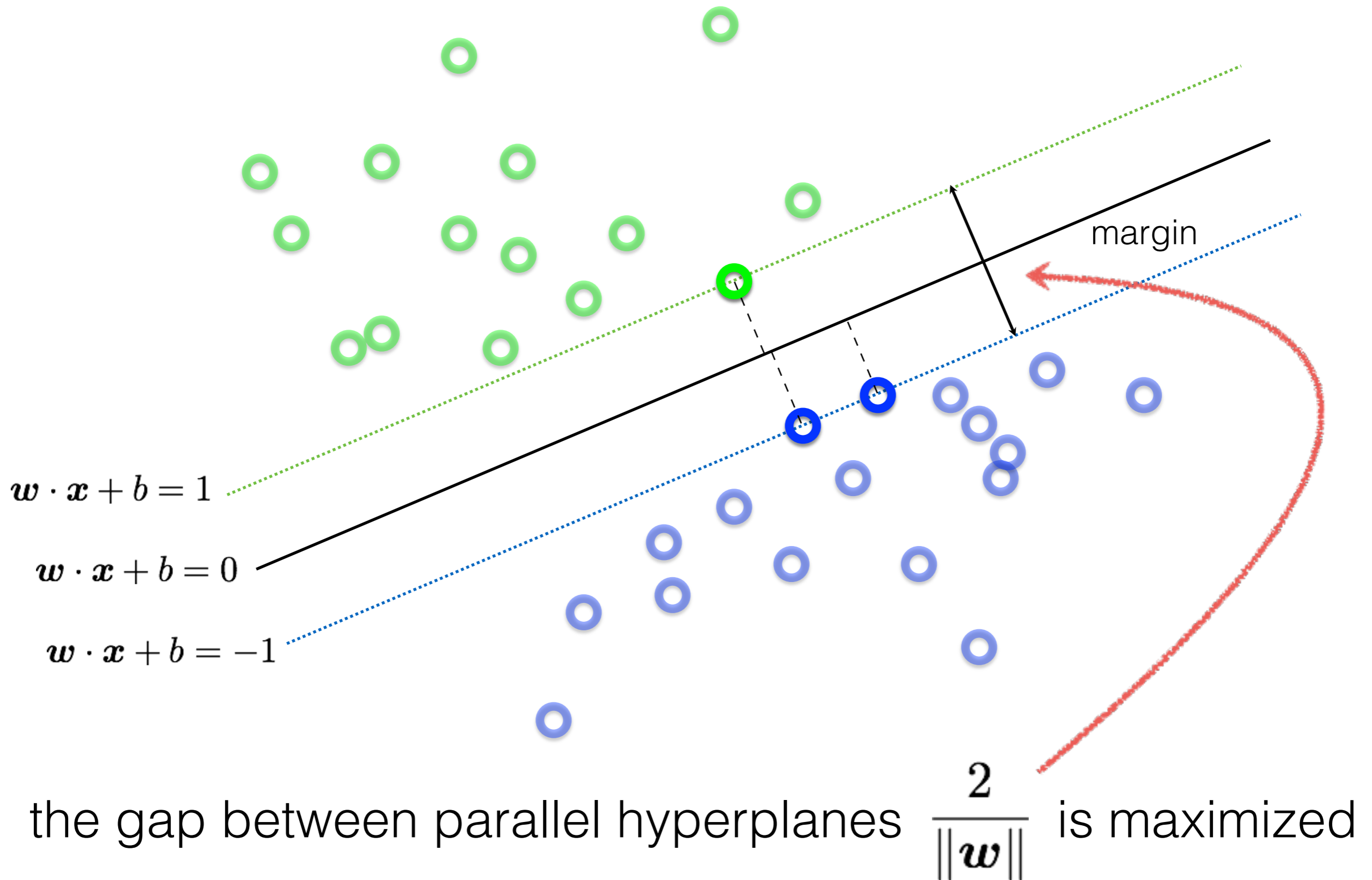
Maximum Margin solution:
most stable to perturbations of data

What's the best \mathbf{w} ?



Want a hyperplane that is far away from 'inner points'

Find hyperplane \mathbf{w} such that ...

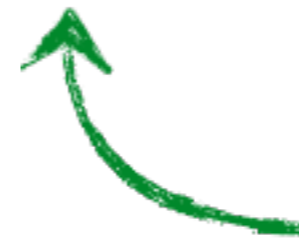


Can be formulated as a maximization problem

$$\max_{\mathbf{w}} \frac{2}{\|\mathbf{w}\|}$$

$$\text{subject to } \mathbf{w} \cdot \mathbf{x}_i + b \begin{cases} \geq +1 & \text{if } y_i = +1 \\ \leq -1 & \text{if } y_i = -1 \end{cases} \text{ for } i = 1, \dots, N$$

What does this constraint mean?



label of the data point

Why is it +1 and -1?

Can be formulated as a maximization problem

$$\max_{\mathbf{w}} \frac{2}{\|\mathbf{w}\|}$$

$$\text{subject to } \mathbf{w} \cdot \mathbf{x}_i + b \begin{cases} \geq +1 & \text{if } y_i = +1 \\ \leq -1 & \text{if } y_i = -1 \end{cases} \text{ for } i = 1, \dots, N$$

Equivalently,

Where did the 2 go?

$$\min_{\mathbf{w}} \|\mathbf{w}\|$$

$$\text{subject to } y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1 \text{ for } i = 1, \dots, N$$

What happened to the labels?

'Primal formulation' of a linear SVM

$$\min_{\mathbf{w}} \|\mathbf{w}\|$$

Objective Function

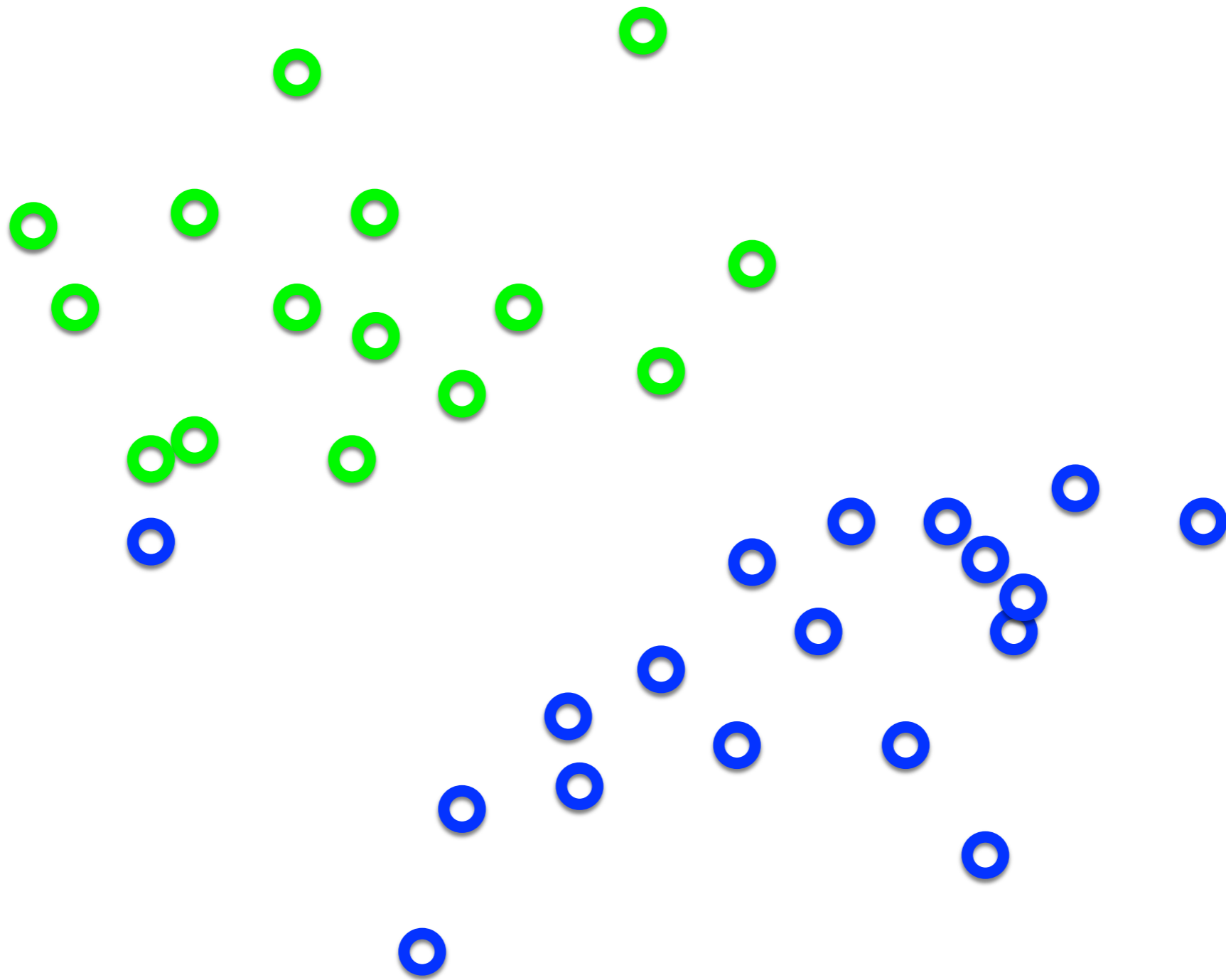
subject to $y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1$ for $i = 1, \dots, N$

Constraints

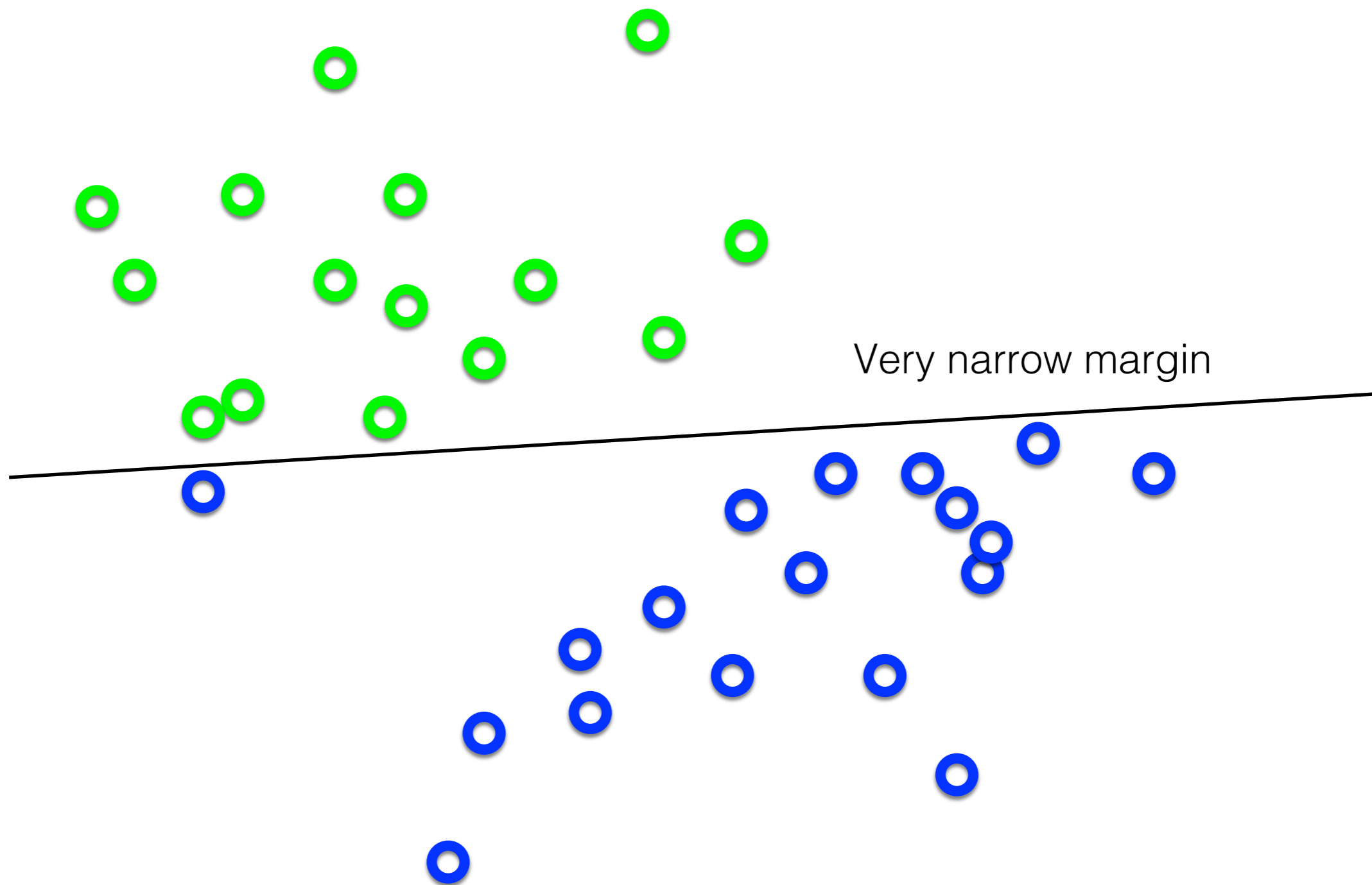
This is a convex quadratic programming (QP) problem
(a unique solution exists)

‘soft’ margin

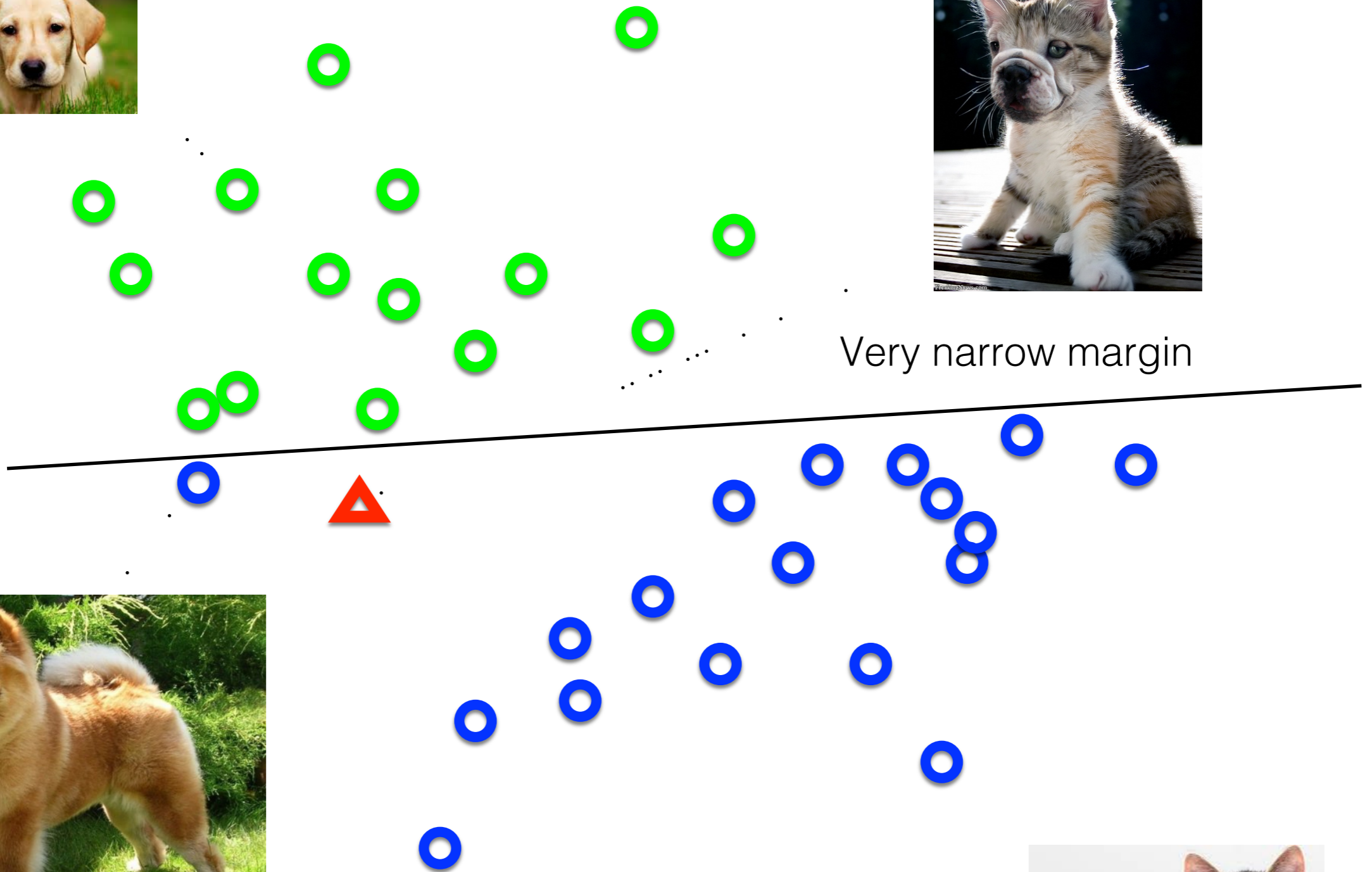
What's the best \mathbf{w} ?



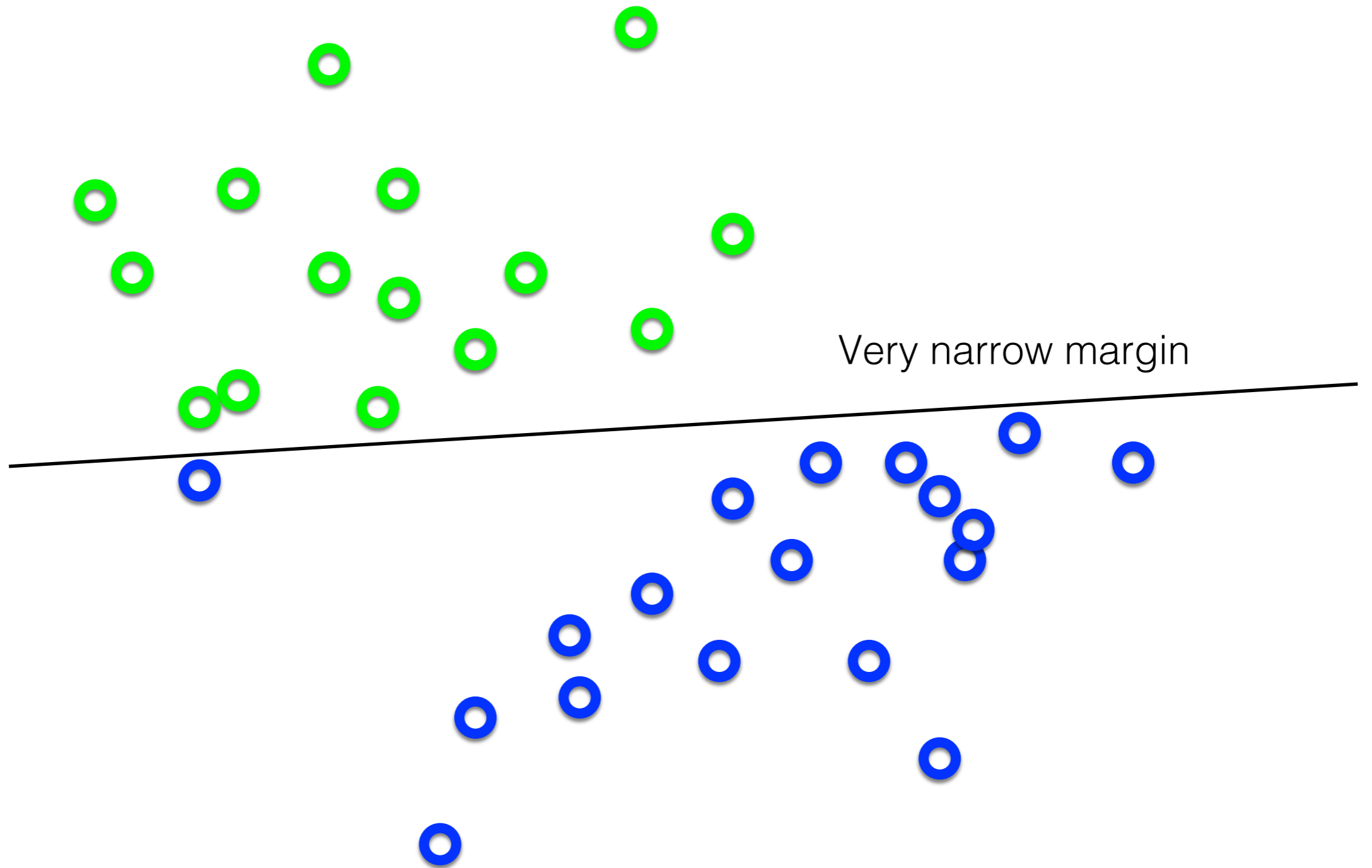
What's the best \mathbf{w} ?



Separating cats and dogs

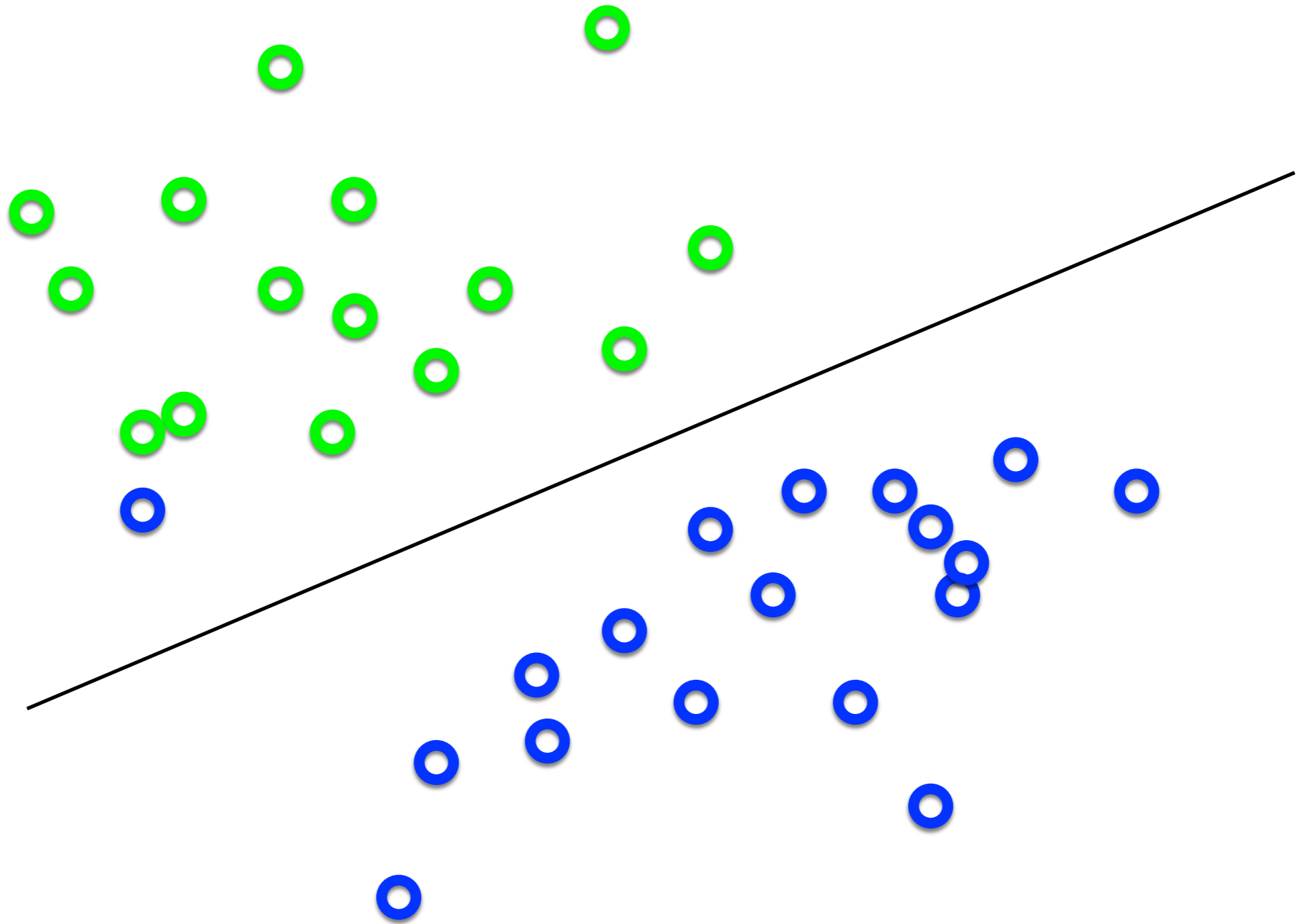


What's the best \mathbf{w} ?



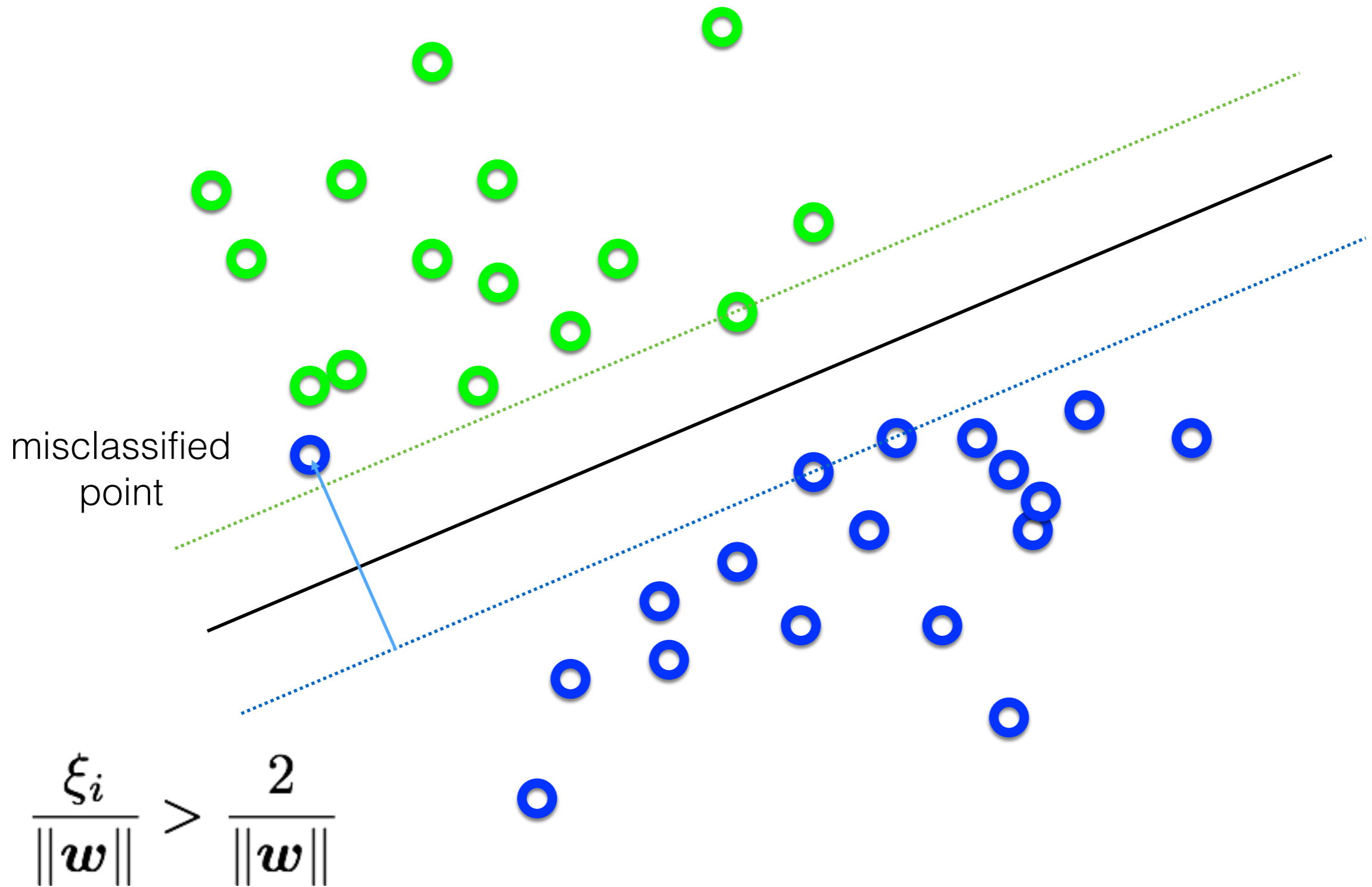
Intuitively, we should allow for some misclassification if we can get more robust classification

What's the best \mathbf{w} ?



Trade-off between the MARGIN and the MISTAKES
(might be a better solution)

Adding slack variables $\xi_i \geq 0$



'soft' margin

objective

$$\min_{\mathbf{w}, \boldsymbol{\xi}} \|\mathbf{w}\|^2 + C \sum_i \xi_i$$

subject to

$$y_i(\mathbf{w}^\top \mathbf{x}_i + b) \geq 1 - \xi_i$$

for $i = 1, \dots, N$

'soft' margin

objective

$$\min_{\mathbf{w}, \xi} \|\mathbf{w}\|^2 + C \sum_i \xi_i$$

subject to

$$y_i(\mathbf{w}^\top \mathbf{x}_i + b) \geq 1 - \xi_i$$

for $i = 1, \dots, N$

The slack variable allows for mistakes, as long as the inverse margin is minimized.

'soft' margin

objective

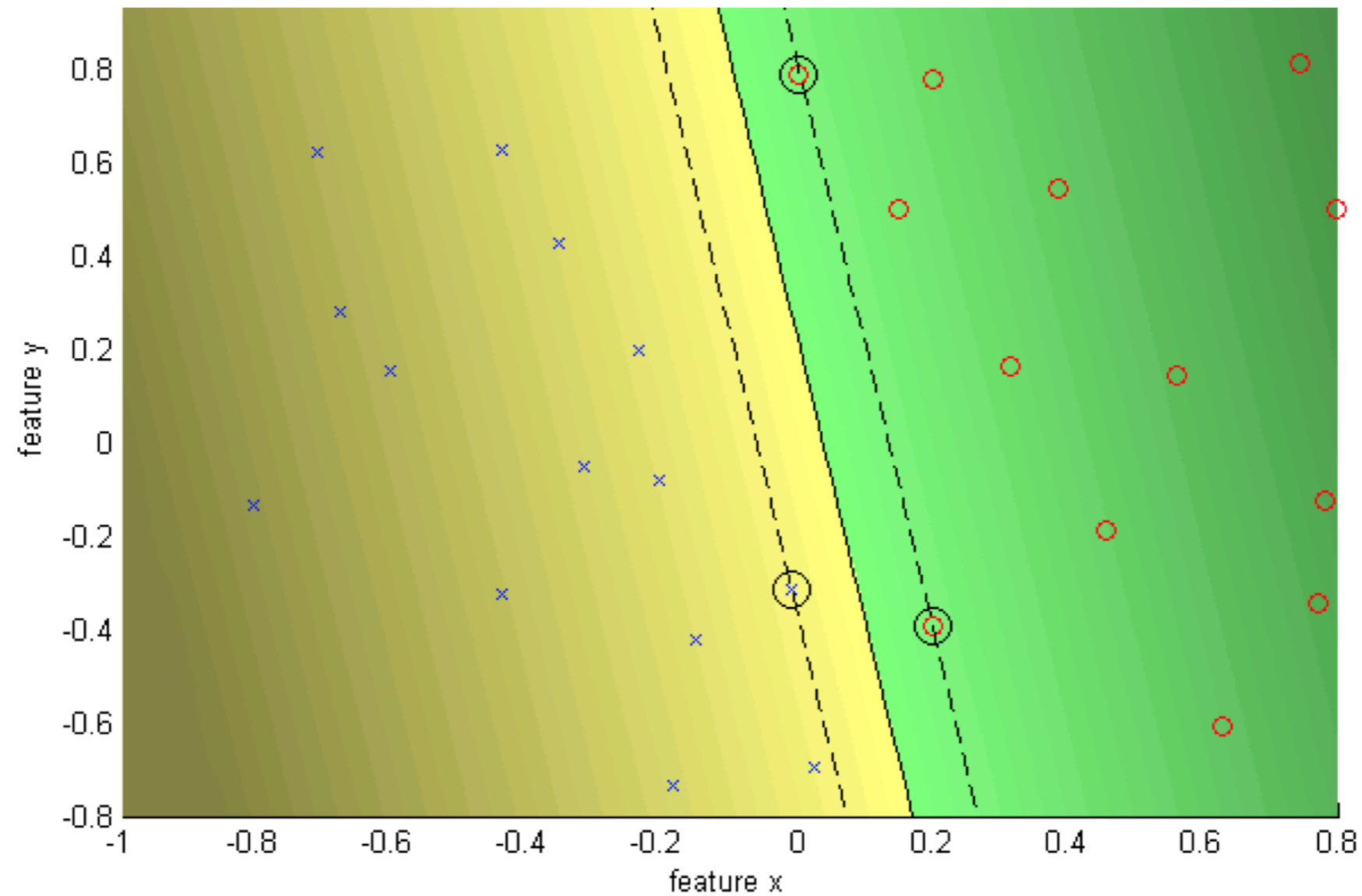
$$\min_{\mathbf{w}, \boldsymbol{\xi}} \|\mathbf{w}\|^2 + C \sum_i \xi_i$$

subject to

$$y_i(\mathbf{w}^\top \mathbf{x}_i + b) \geq 1 - \xi_i \\ \text{for } i = 1, \dots, N$$

- Every constraint can be satisfied if slack is large
- C is a regularization parameter
 - Small C: ignore constraints (larger margin)
 - Big C: constraints (small margin)
- Still QP problem (unique solution)

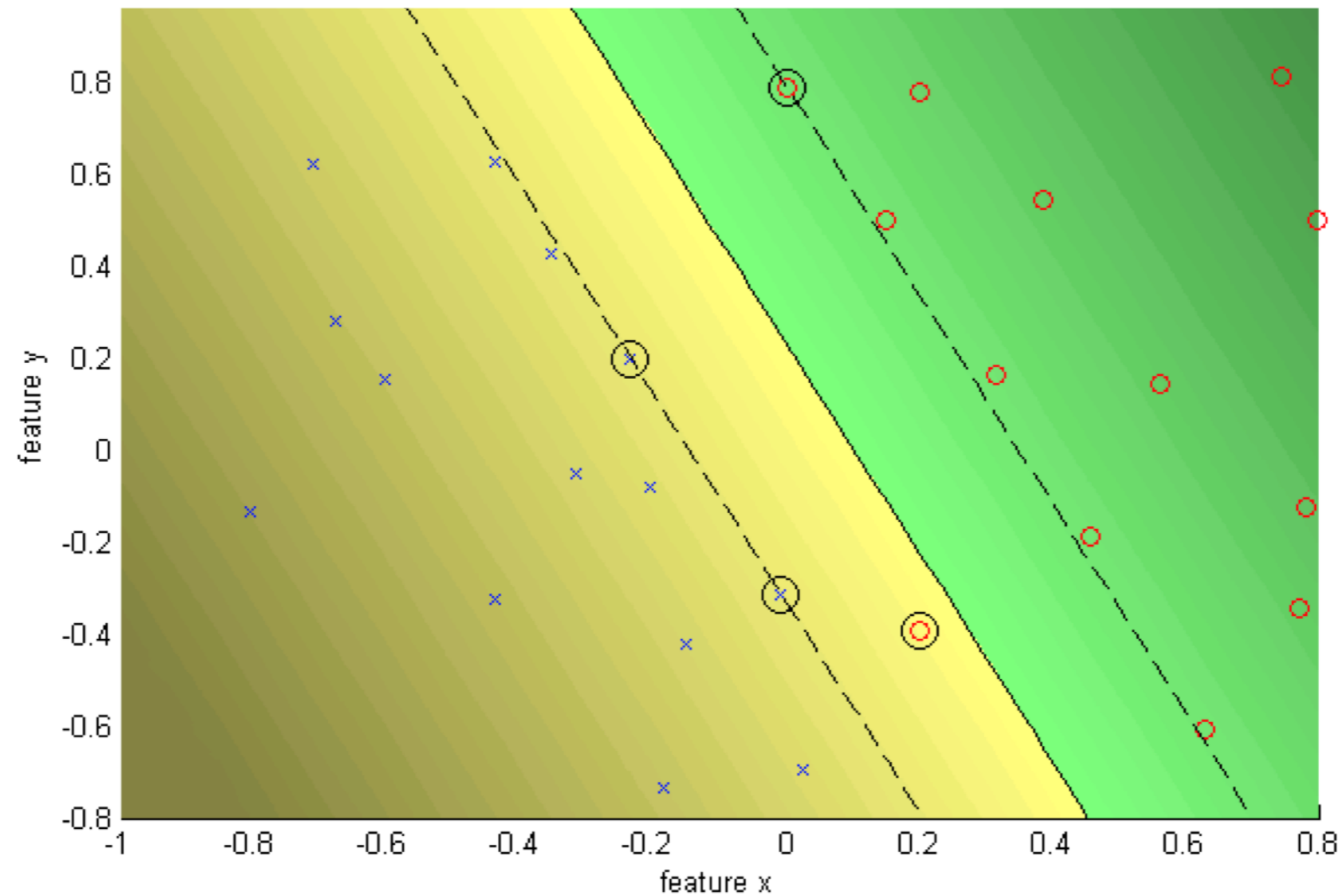
C = Infinity hard margin



Comment Window

SVM (L1) by Sequential Minimal Optimizer
Kernel: linear (-), C: Inf
Kernel evaluations: 971
Number of Support Vectors: 3
Margin: 0.0966
Training error: 0.00%

C = 10 soft margin



Comment Window

SVM (L1) by Sequential Minimal Optimizer
Kernel: linear (-), C: 10.0000
Kernel evaluations: 2645
Number of Support Vectors: 4
Margin: 0.2265
Training error: 3.70%