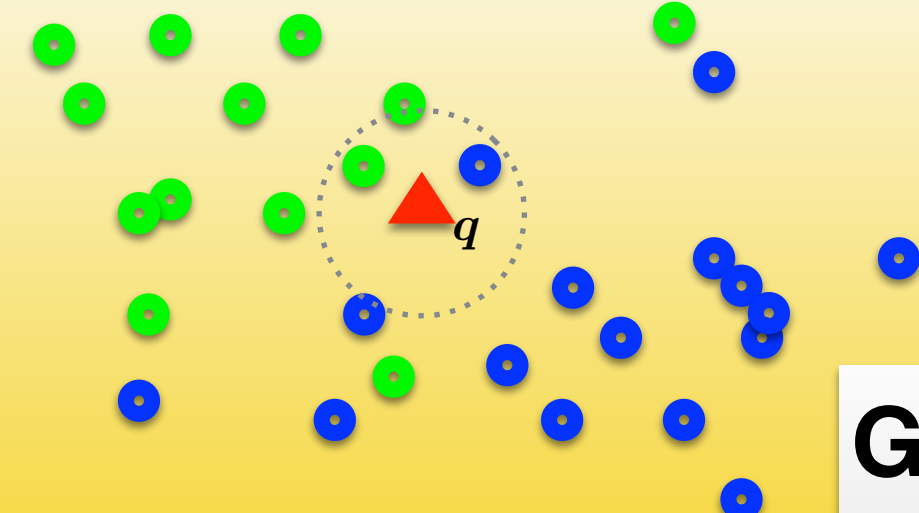


Support Vector Machine

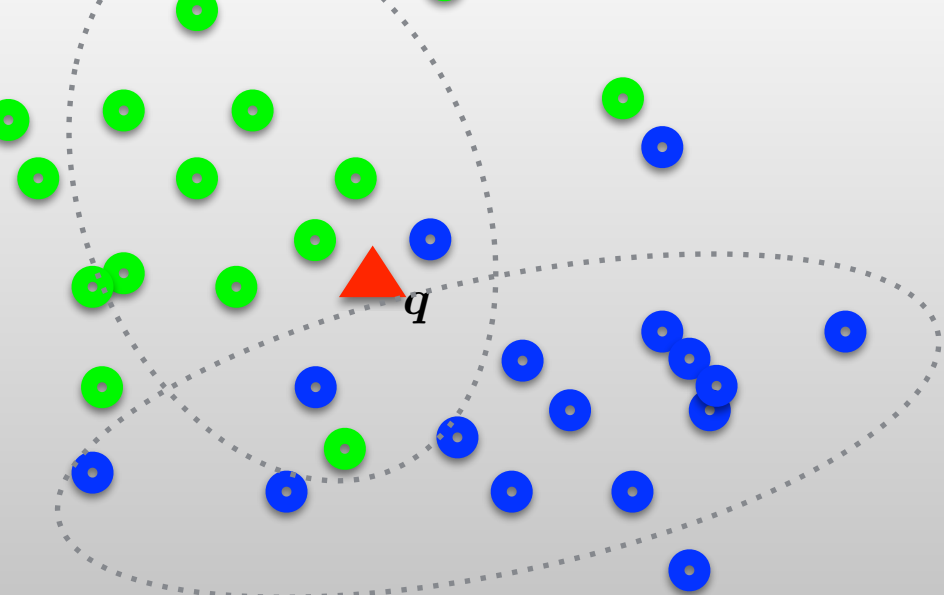
Non-parametric



Nearest Neighbor

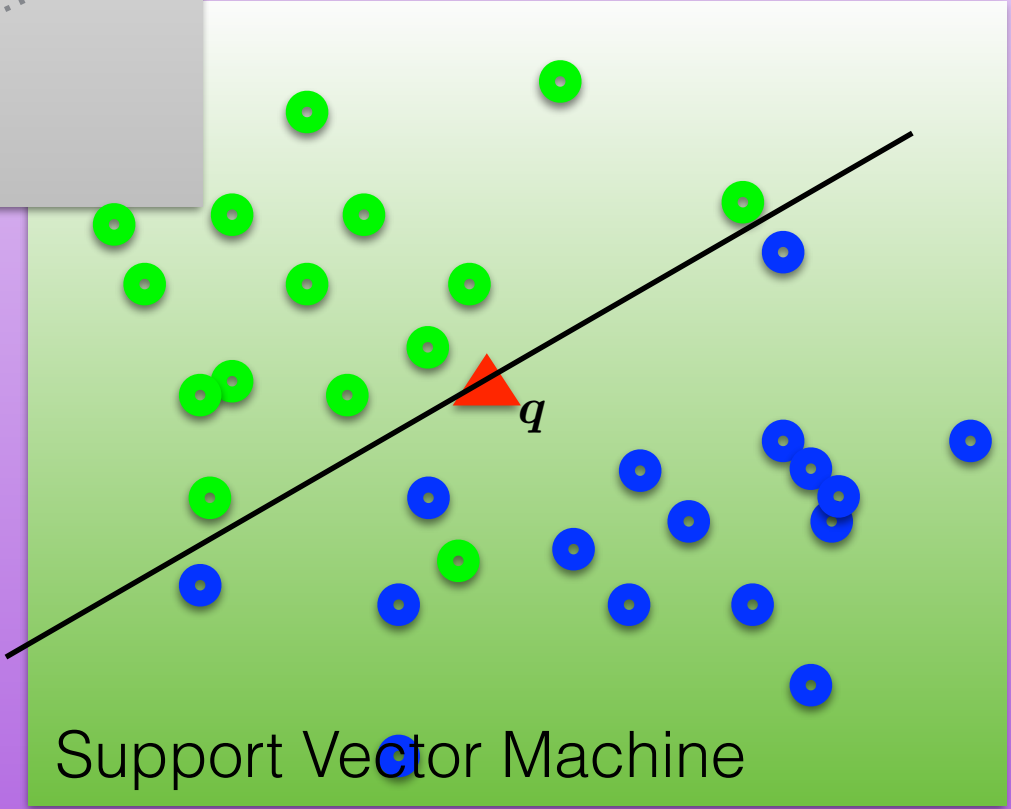
Parametric

Generative



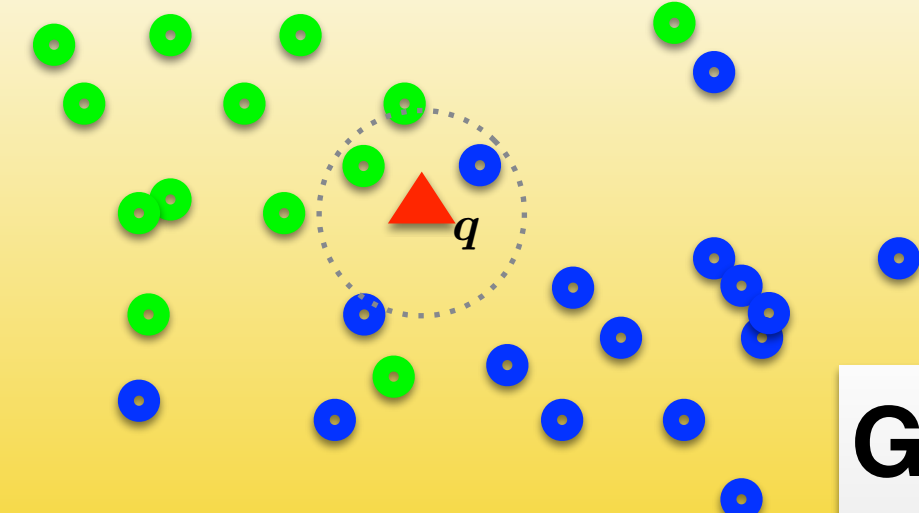
Naive Bayes

Discriminative



Support Vector Machine

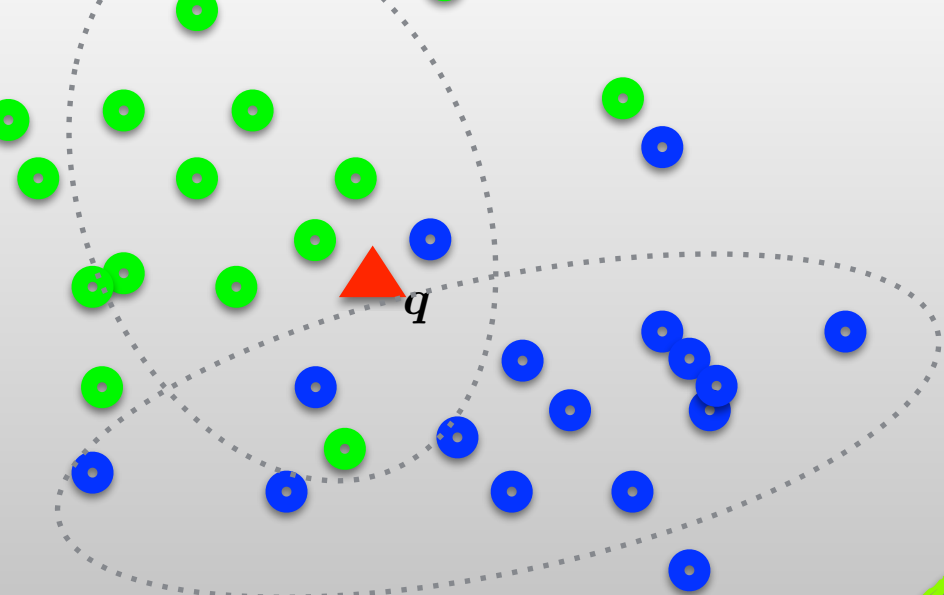
Non-parametric



Nearest Neighbor

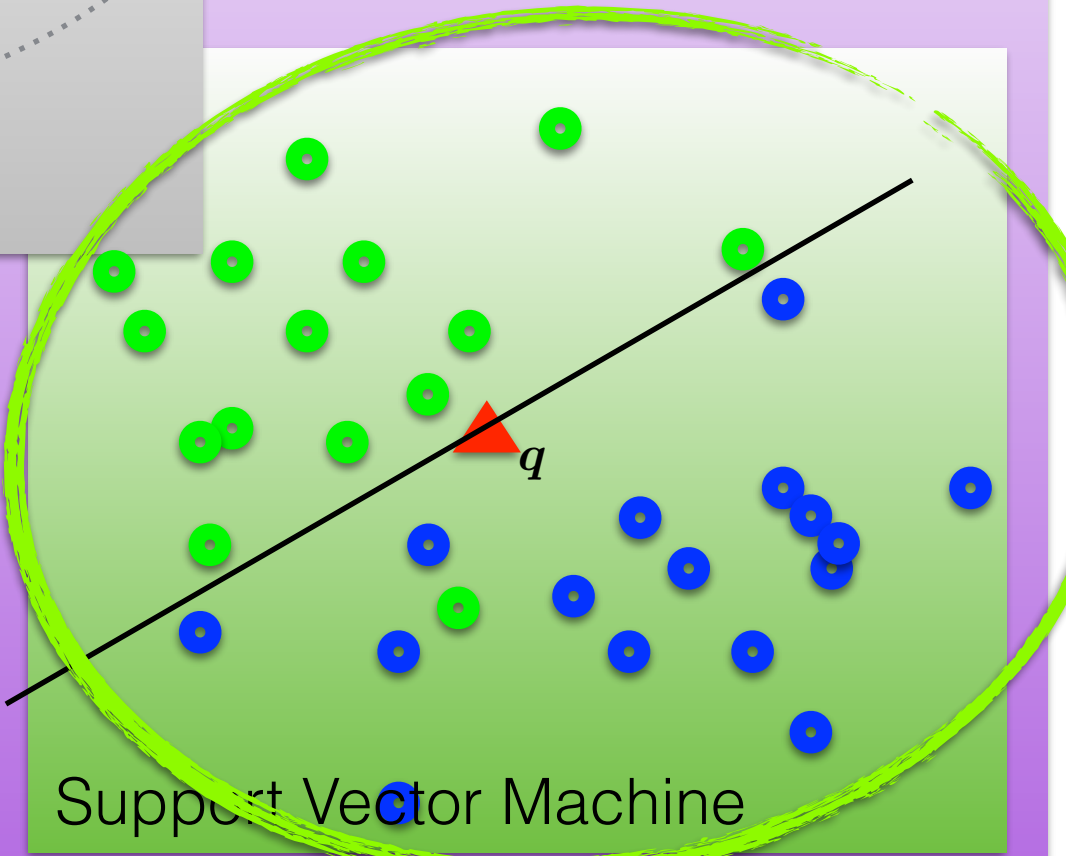
Parametric

Generative



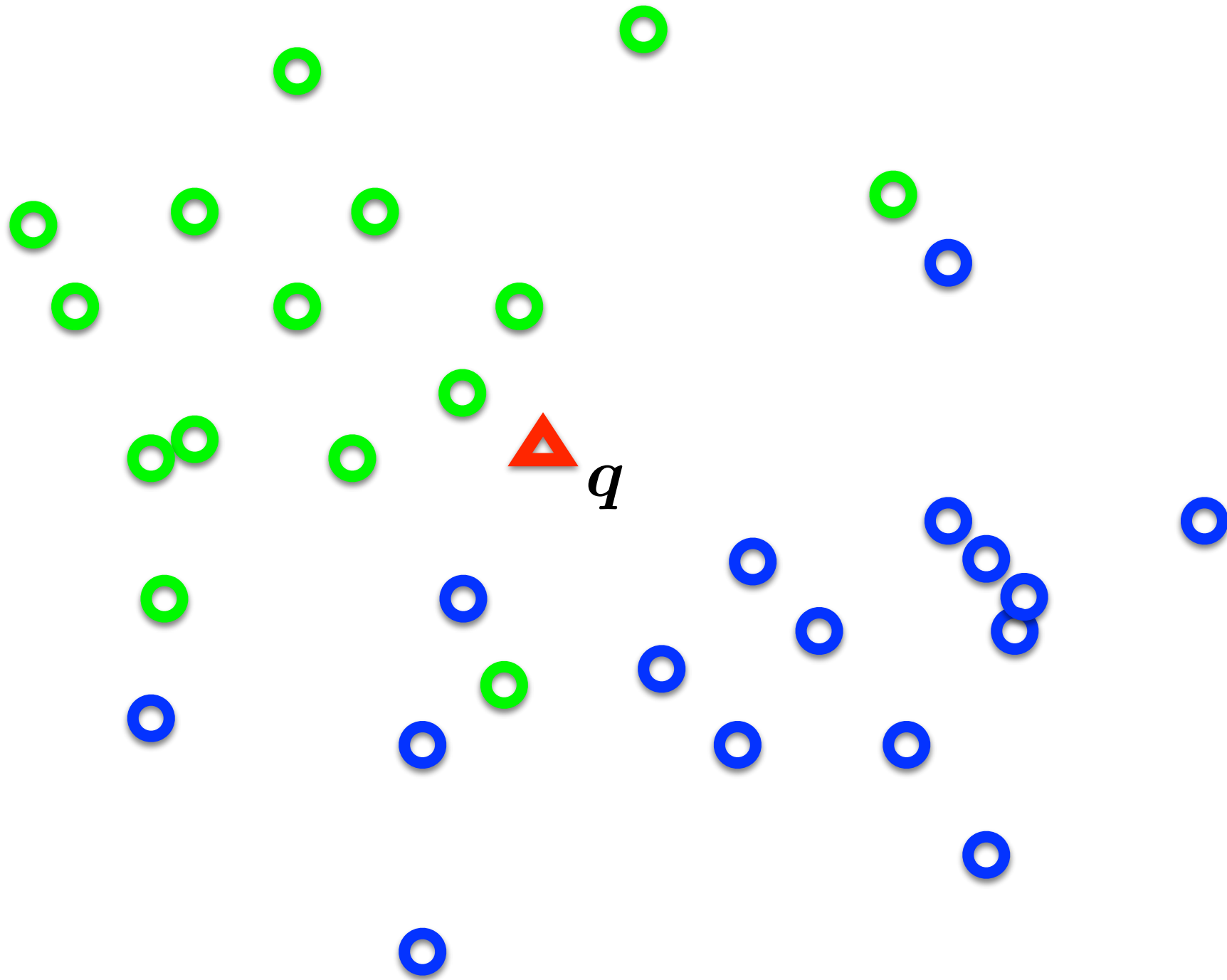
Naive Bayes

Discriminative



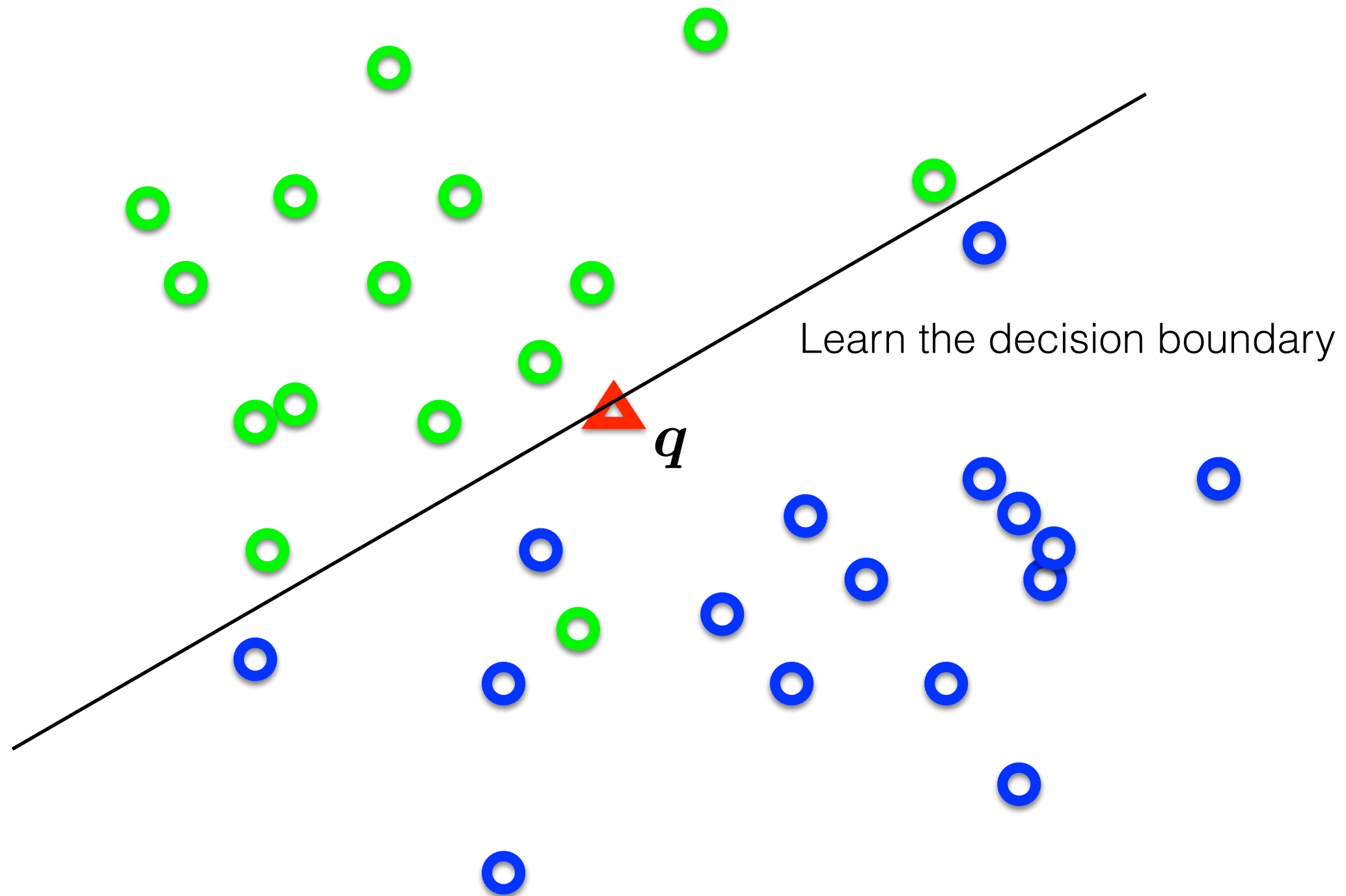
Support Vector Machine

Distribution of data from two classes

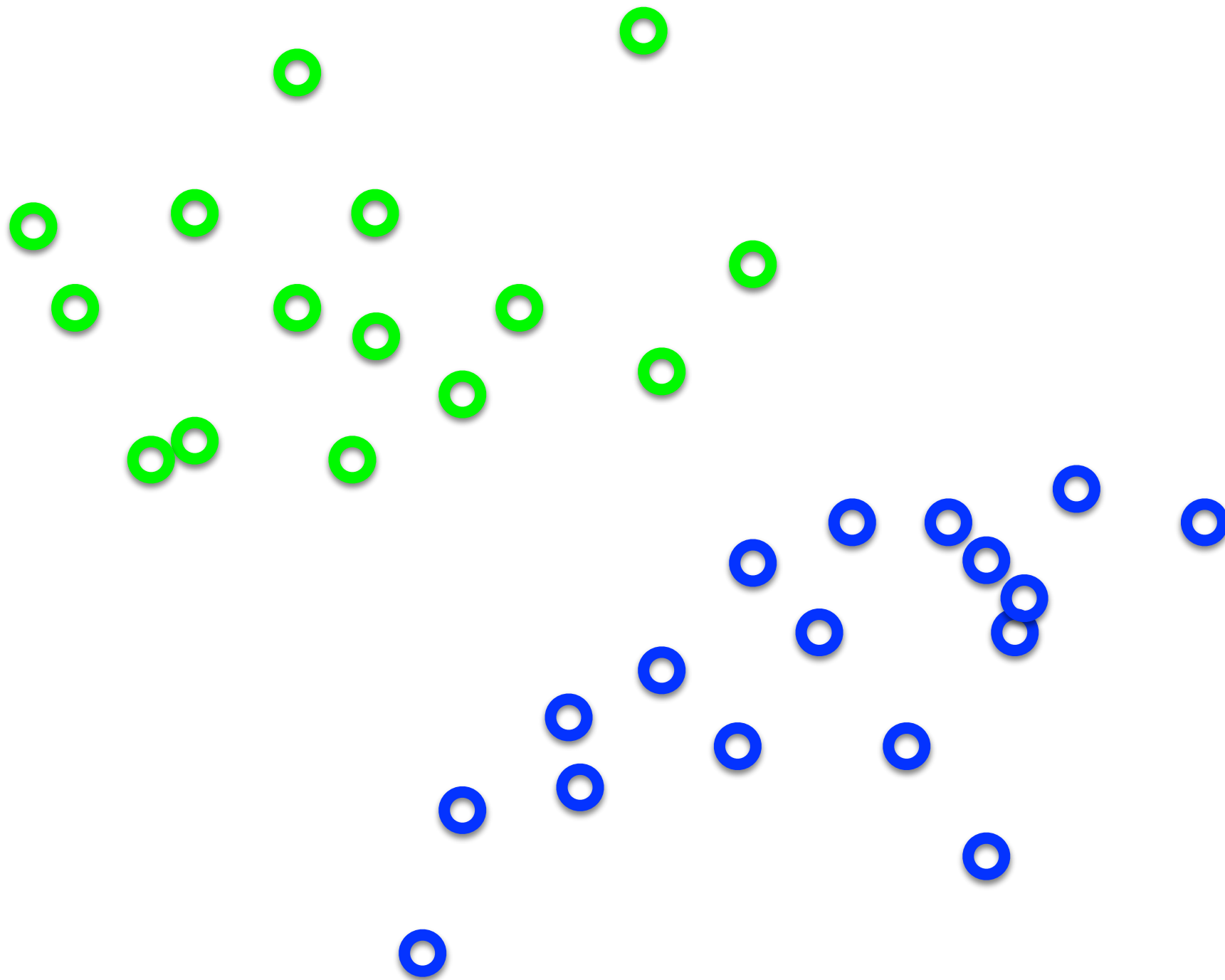


Which class does q belong too?

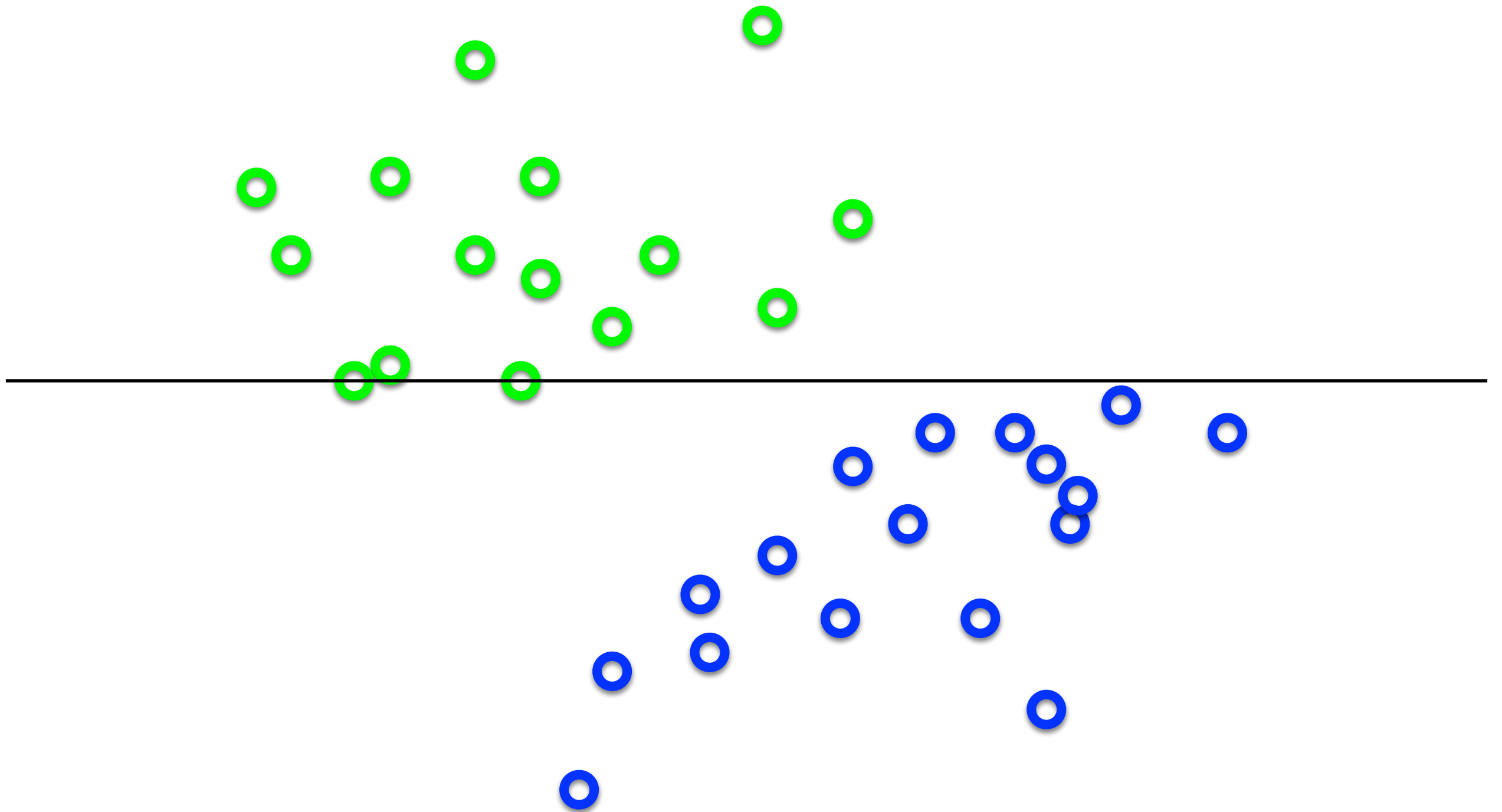
Distribution of data from two classes



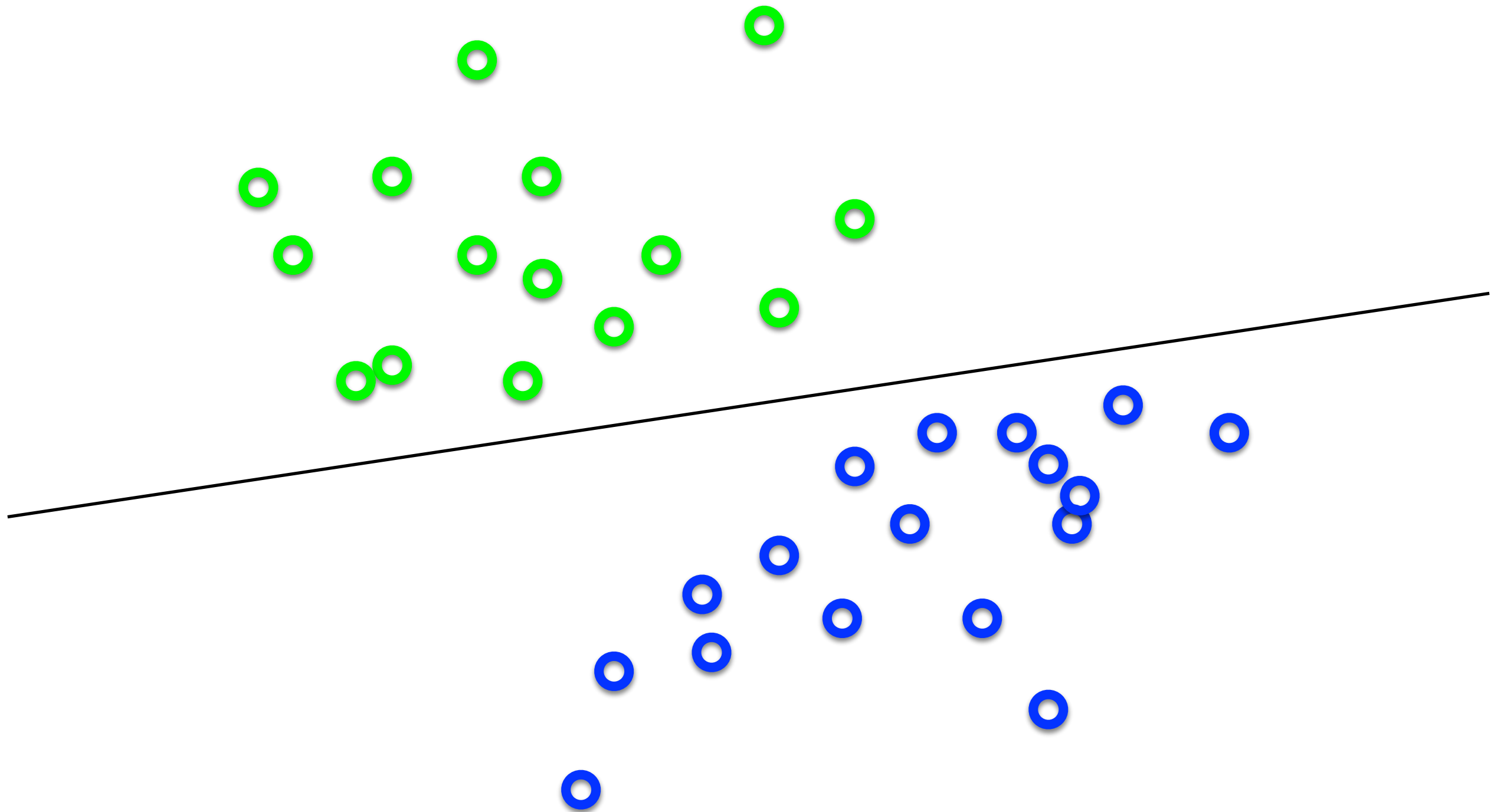
What's the best \mathbf{w} ?



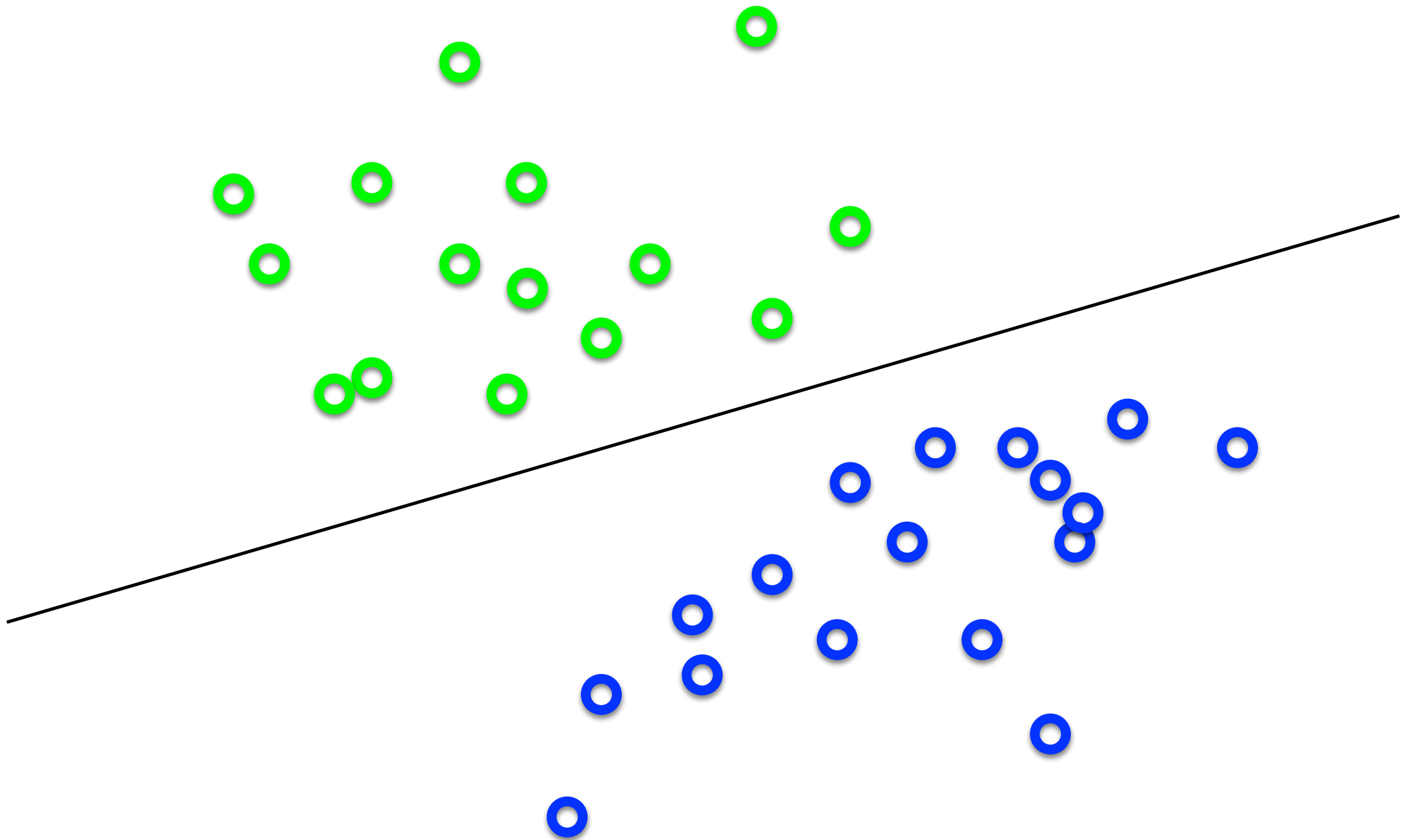
What's the best \mathbf{w} ?



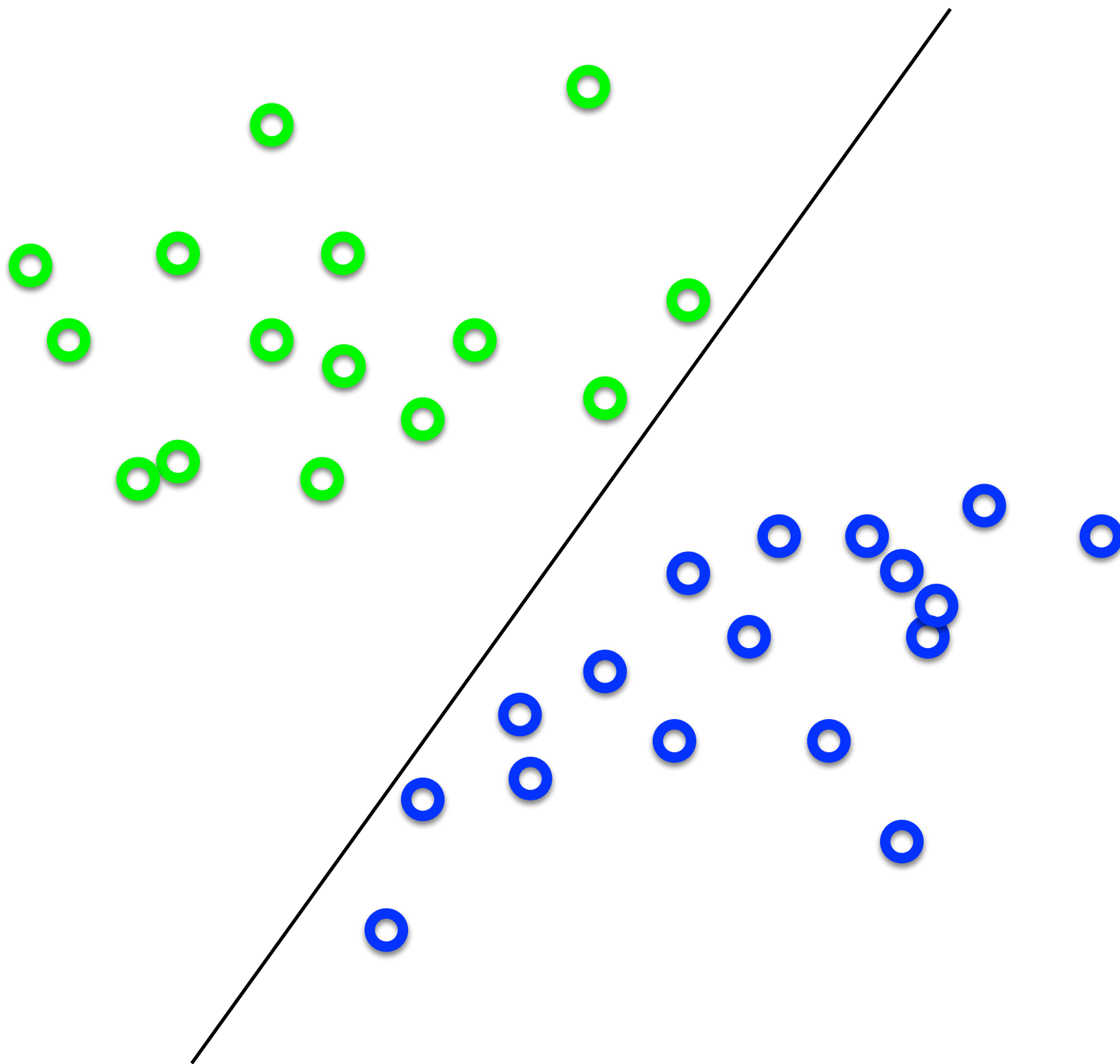
What's the best \mathbf{w} ?



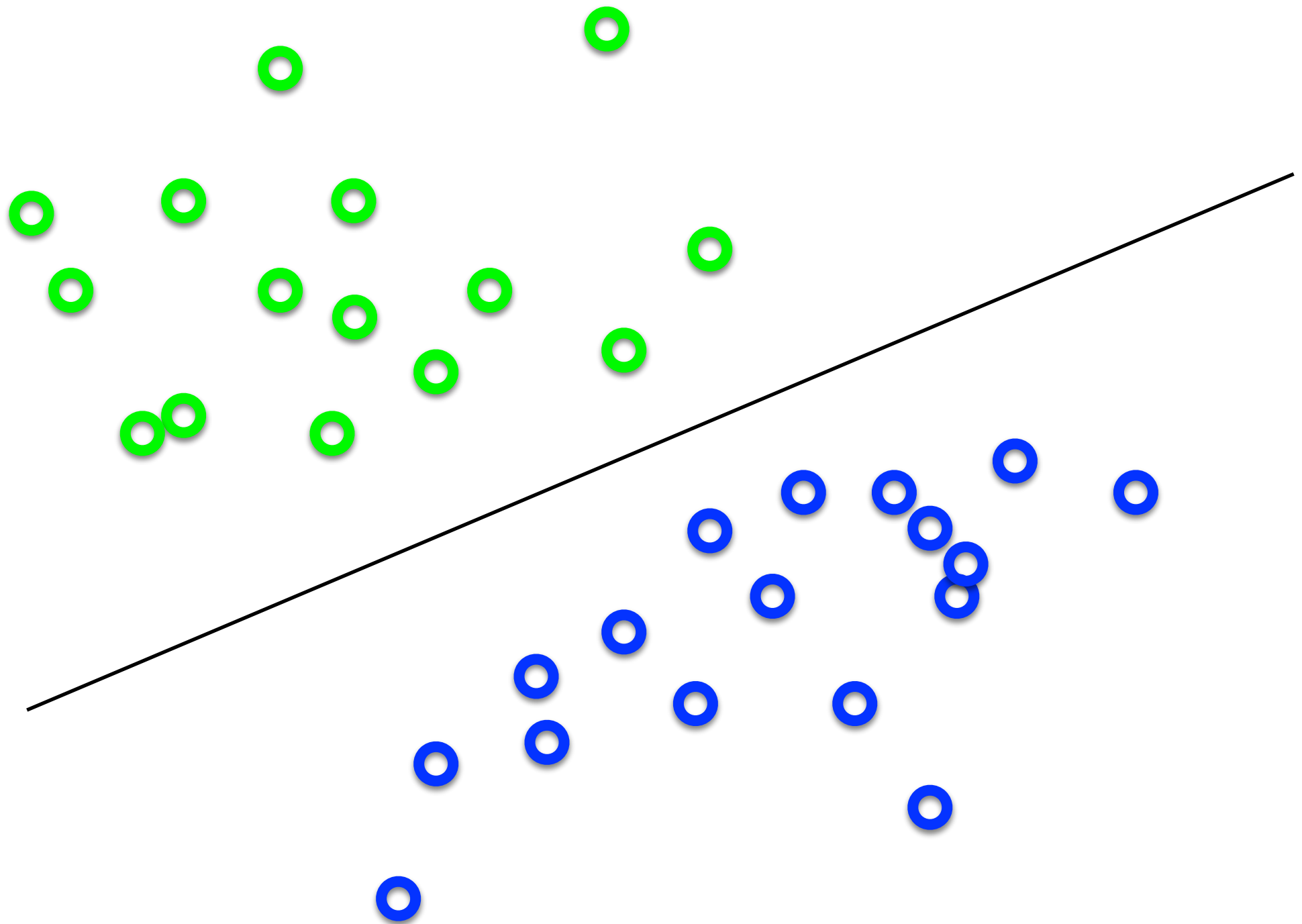
What's the best \mathbf{w} ?



What's the best \mathbf{w} ?

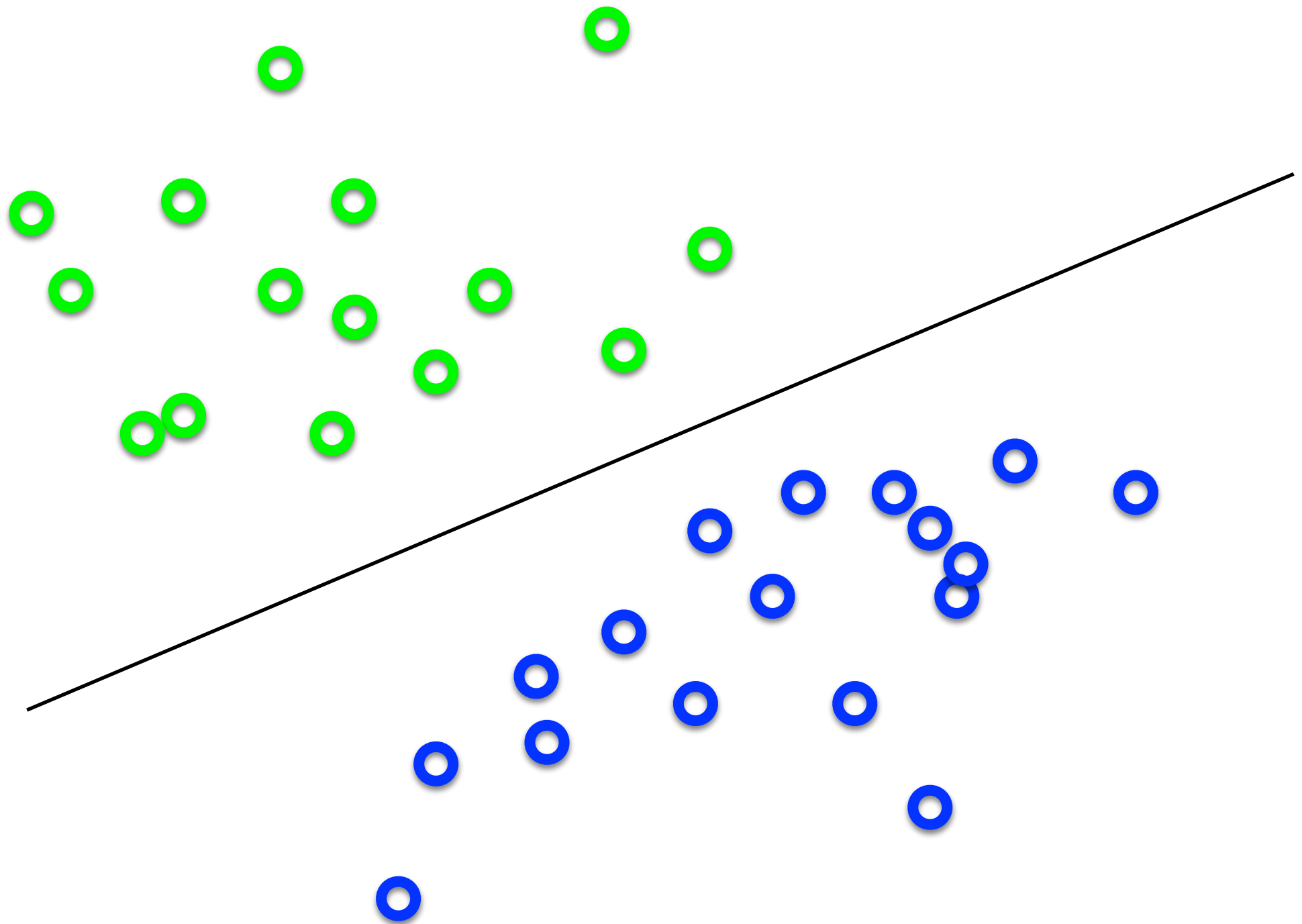


What's the best \mathbf{w} ?



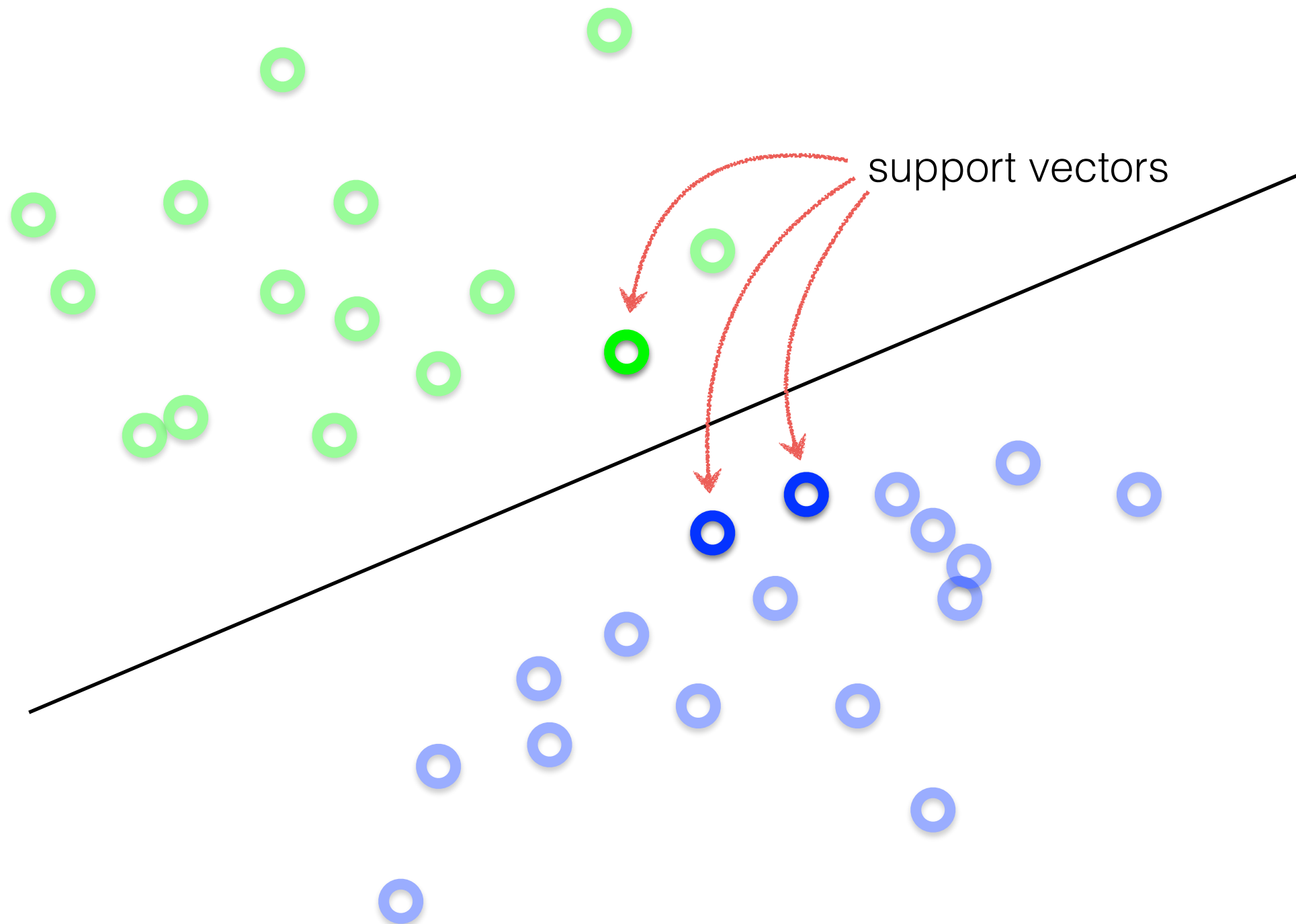
Intuitively, the line that is the farthest from all interior points

What's the best \mathbf{w} ?



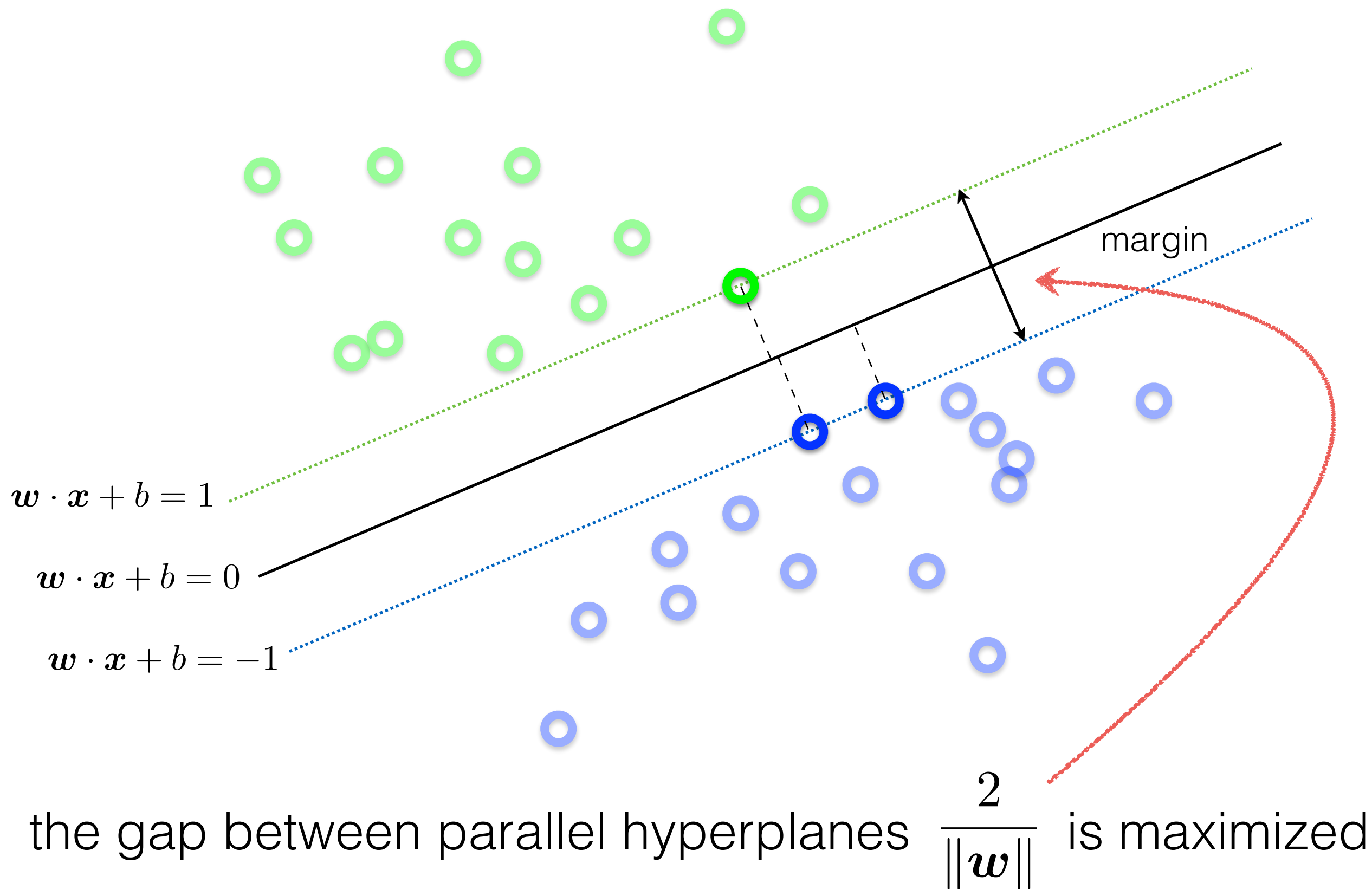
Maximum Margin solution:
most stable to perturbations of data

What's the best \mathbf{w} ?



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

Find hyperplane **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 $i = 1, \dots, N$

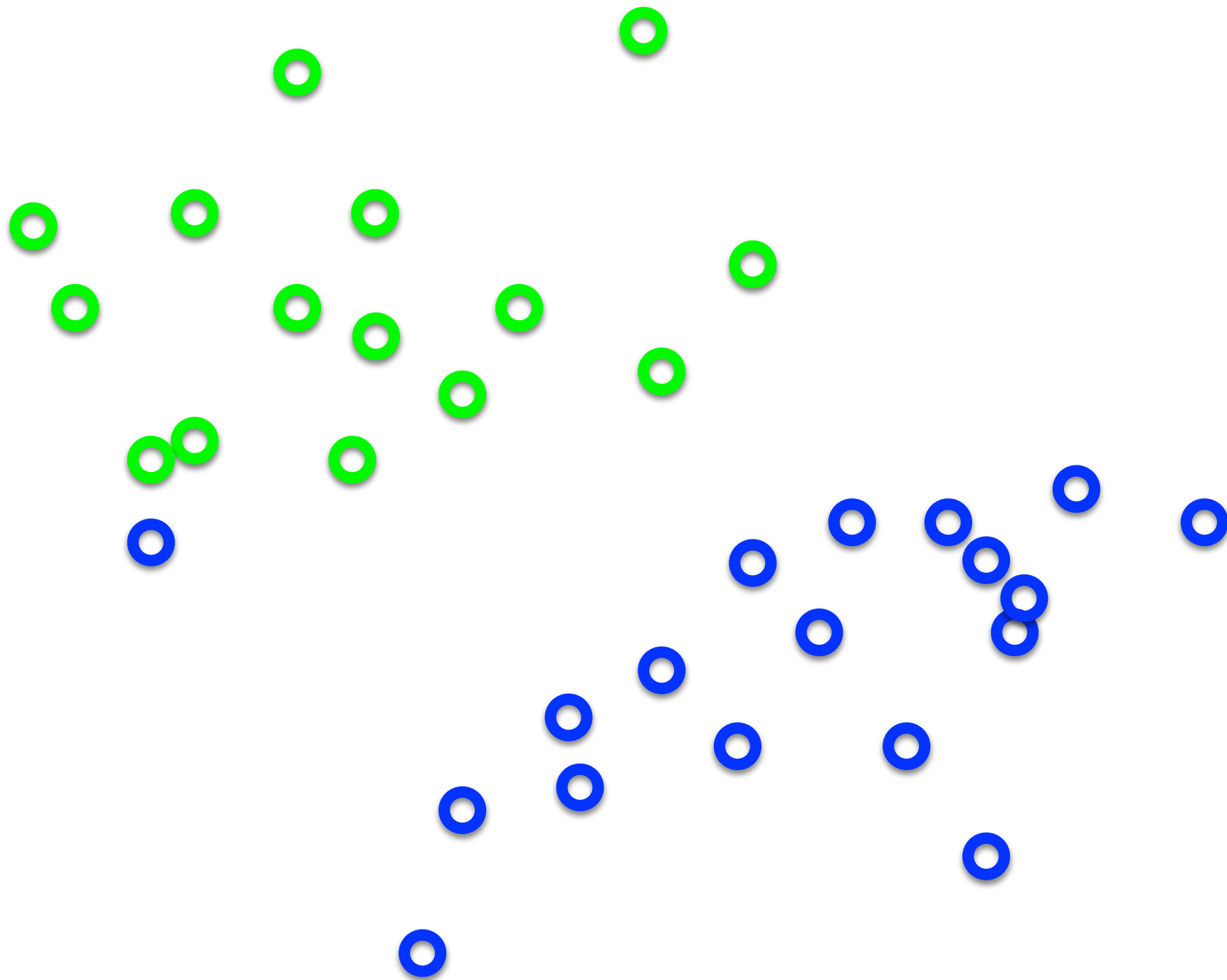
Constraints

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

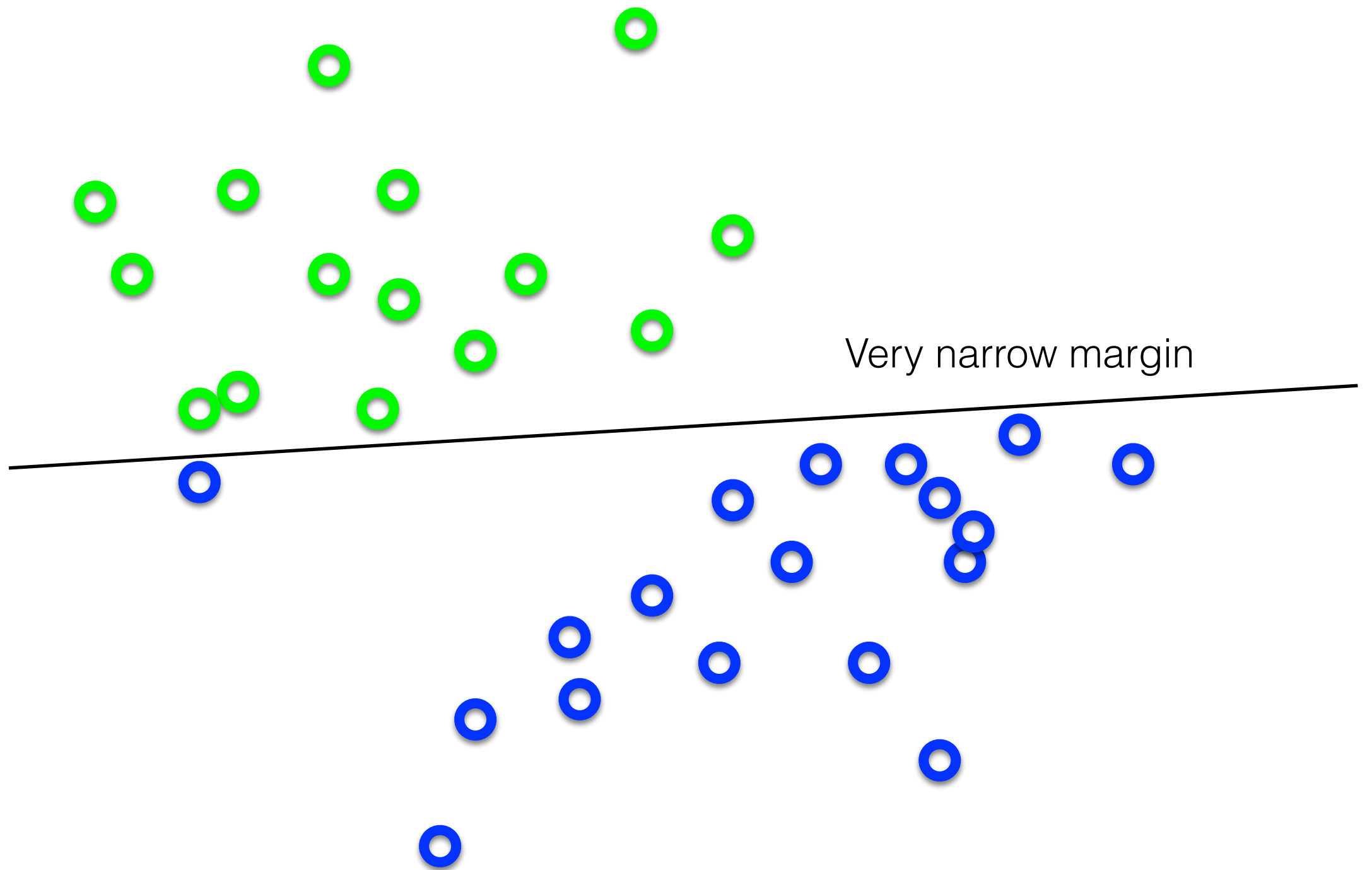
(you can learn more about this in convex optimization)

‘soft’ margin

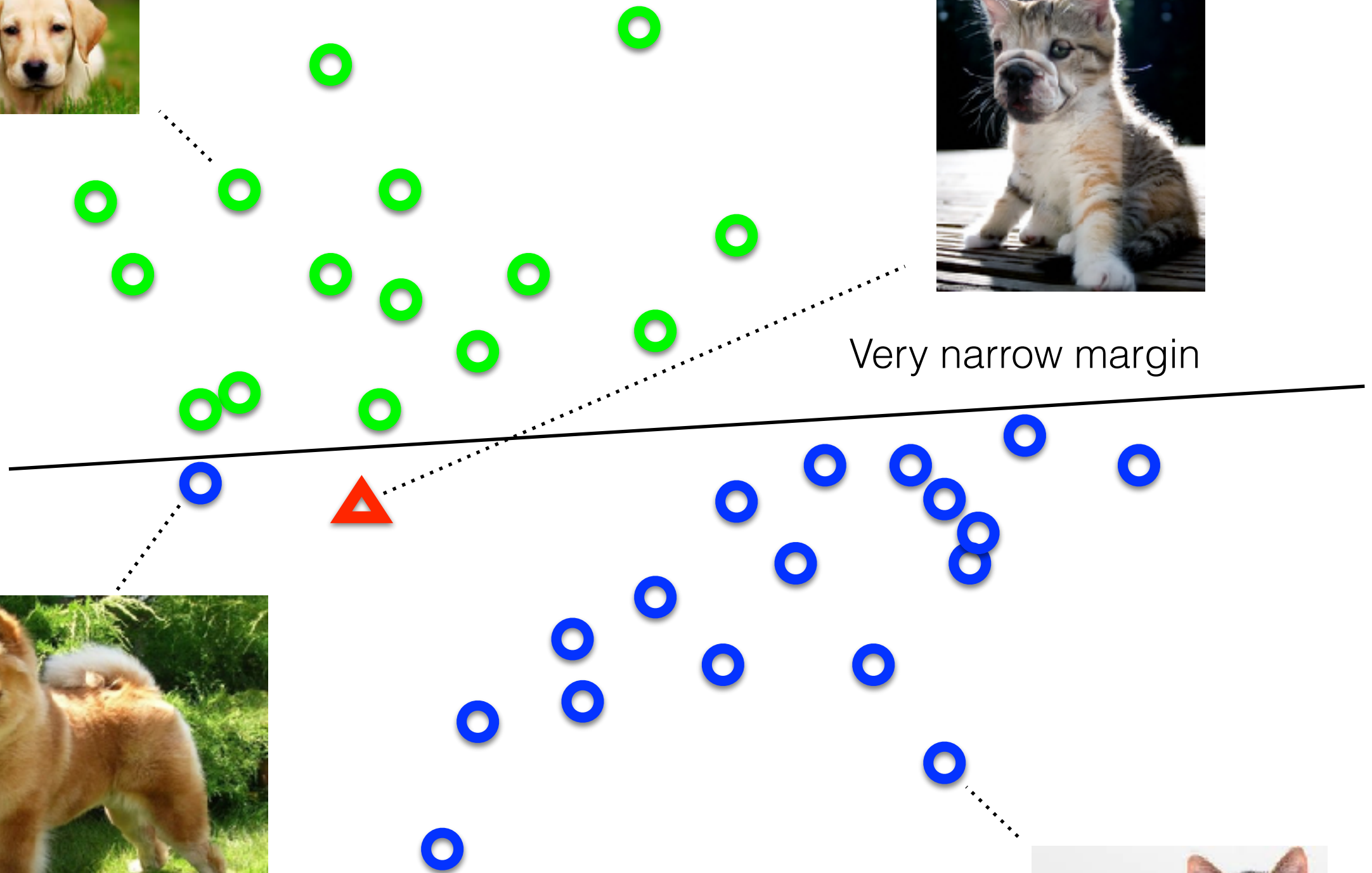
What's the best \mathbf{w} ?



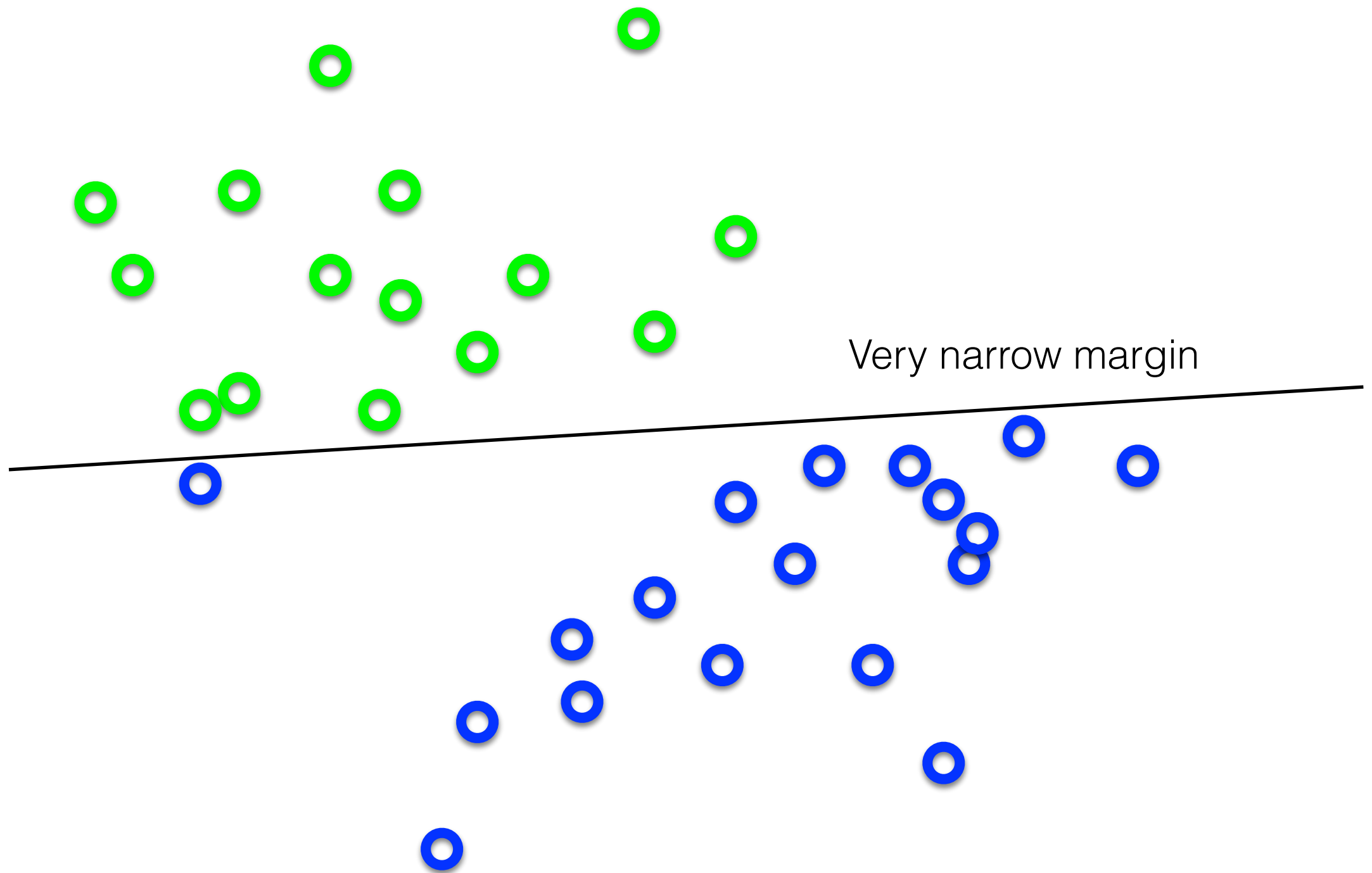
What's the best \mathbf{w} ?



Separating cats and dogs

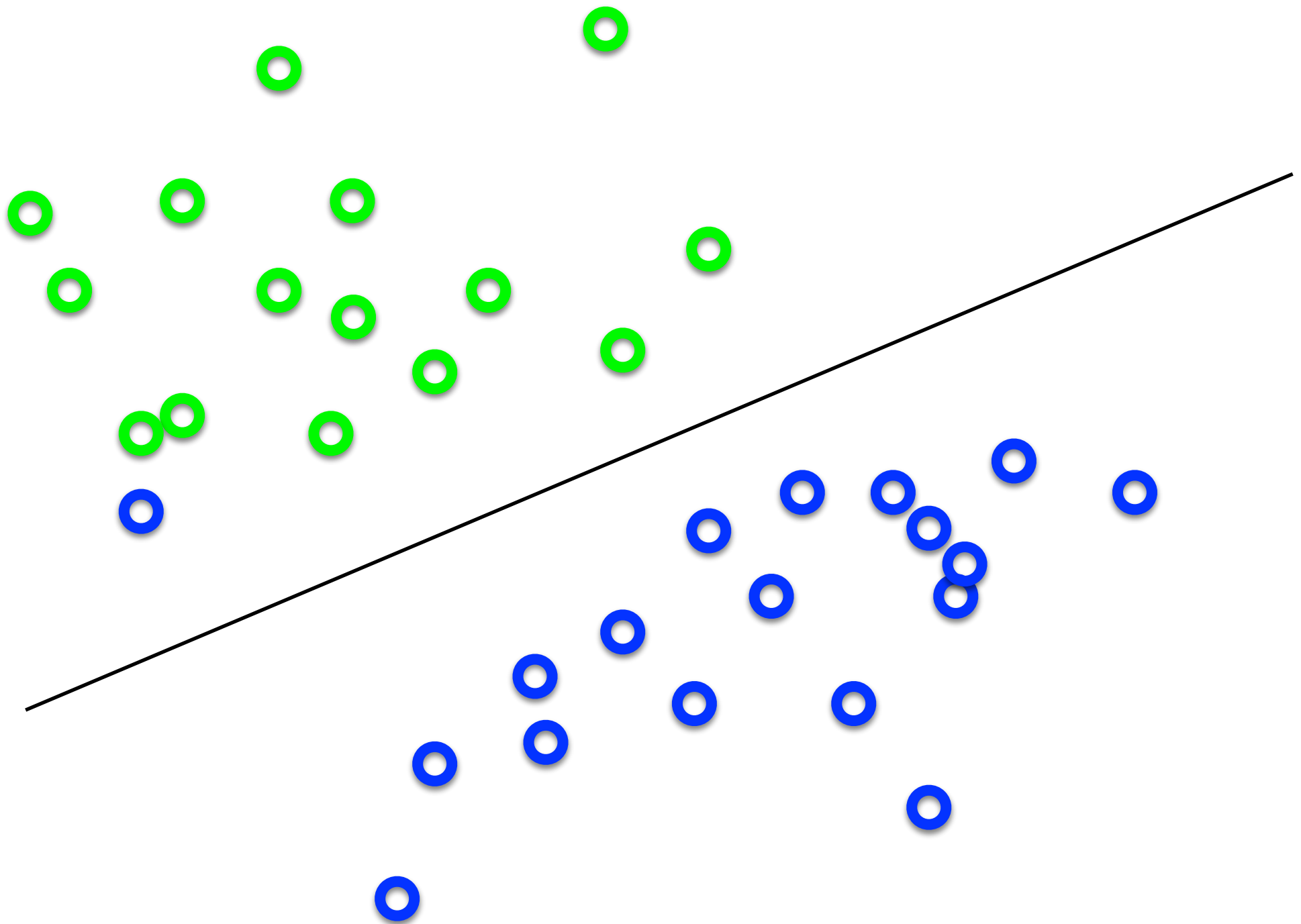


What's the best \mathbf{w} ?



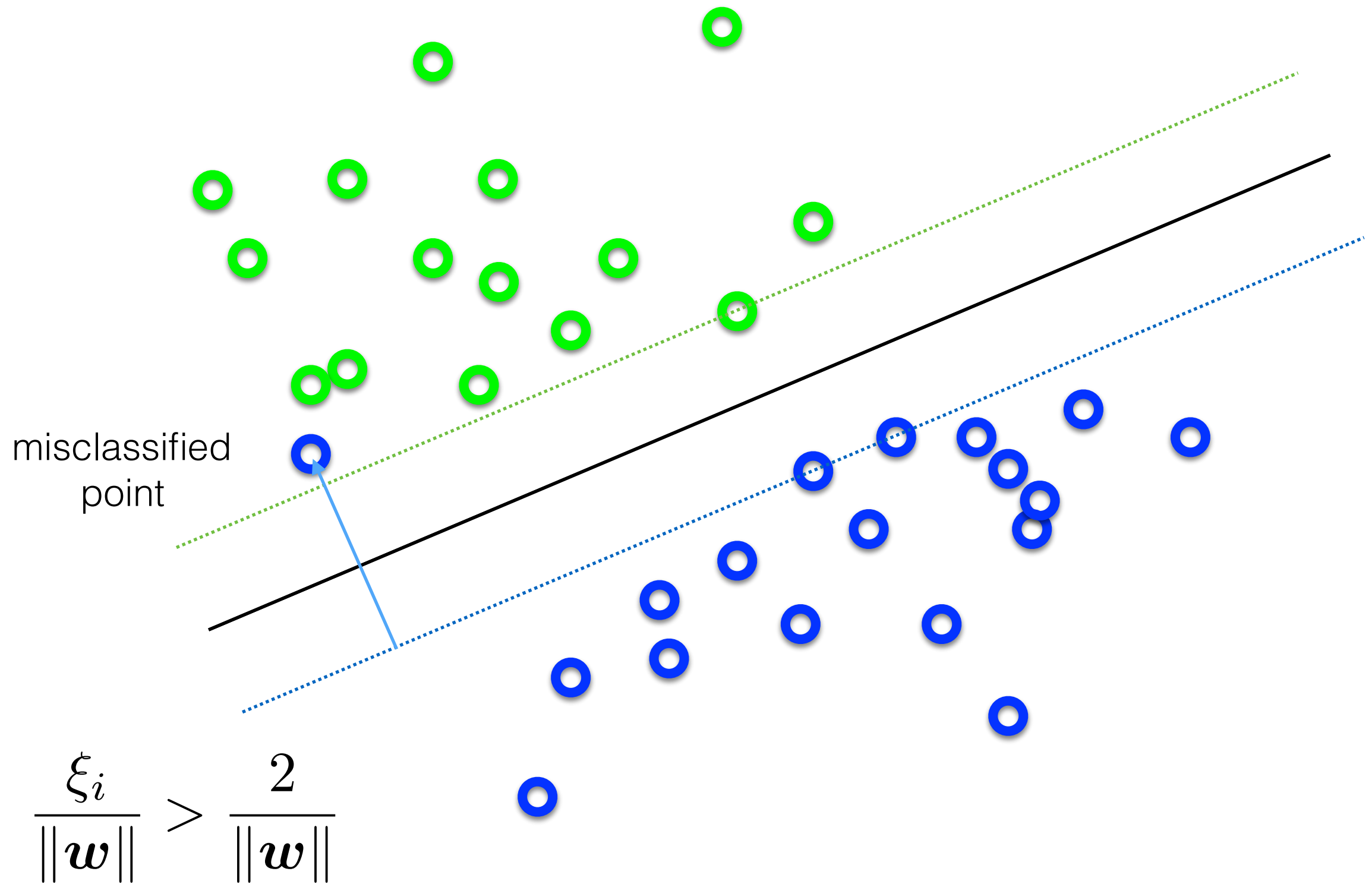
Intuitively, we should allow for some misclassification if we can get more robust classification

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

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

subject to

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

'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

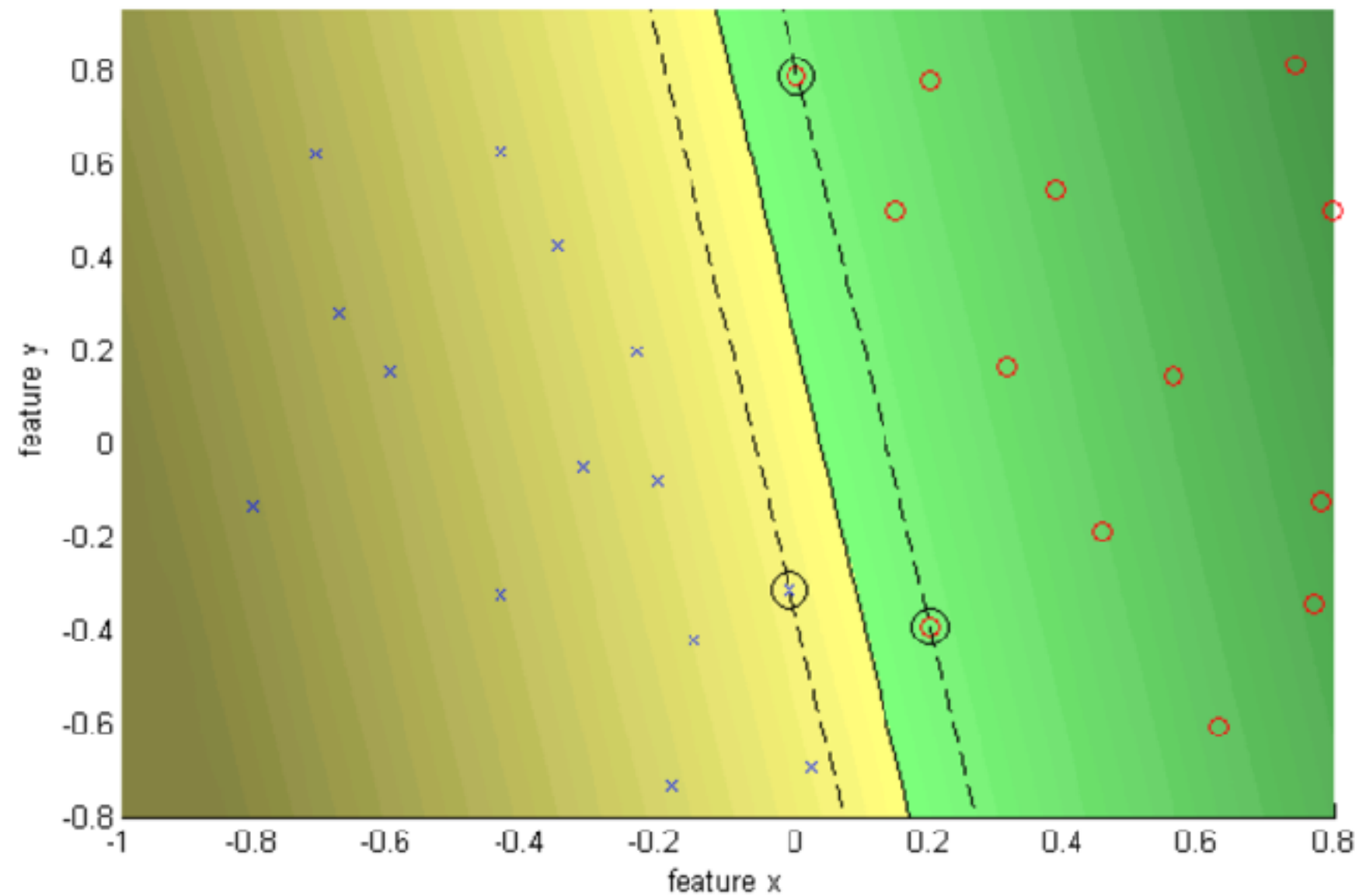
$$\min_{\mathbf{w}, \xi} \|\mathbf{w}\|^2 + C \sum_i \xi_i$$

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)

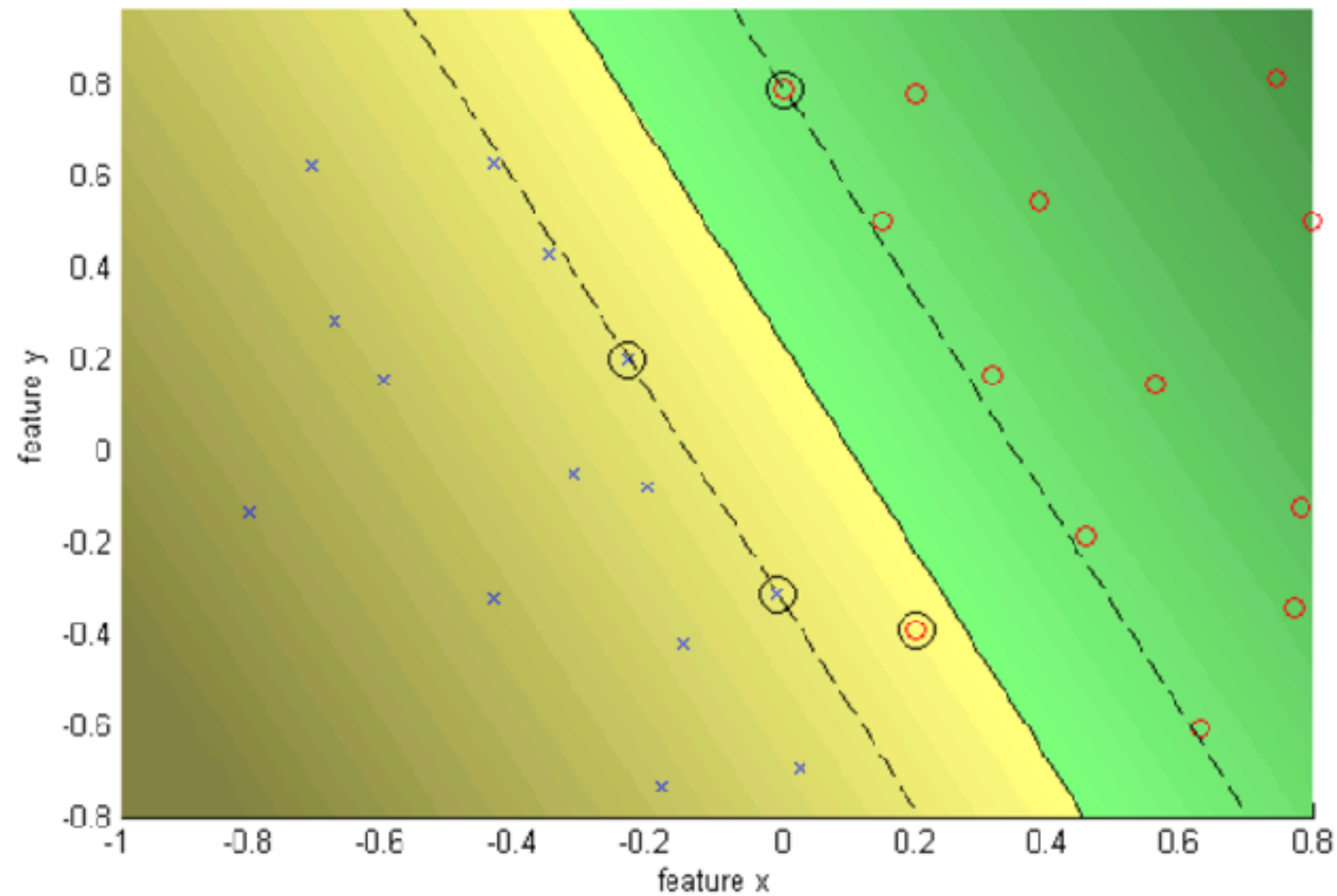
$C = \text{Infinity}$ hard margin



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%

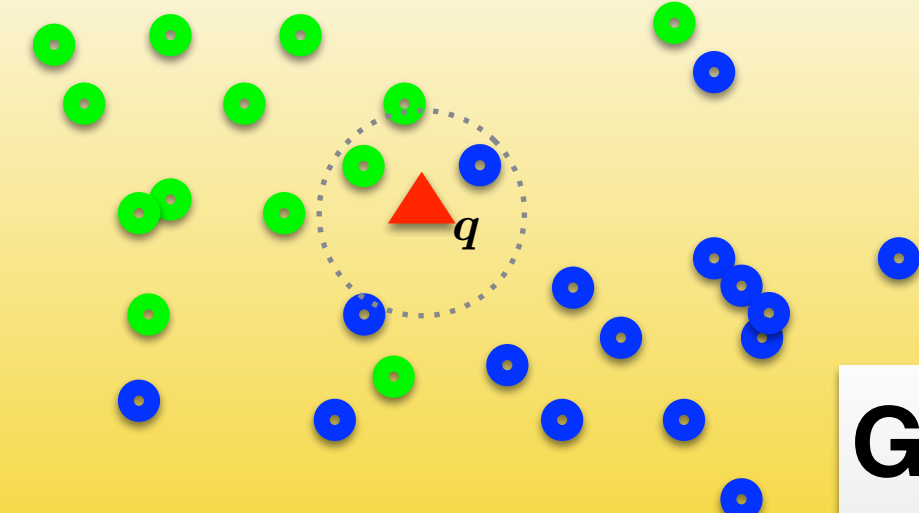
$C = 10$ soft margin



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%

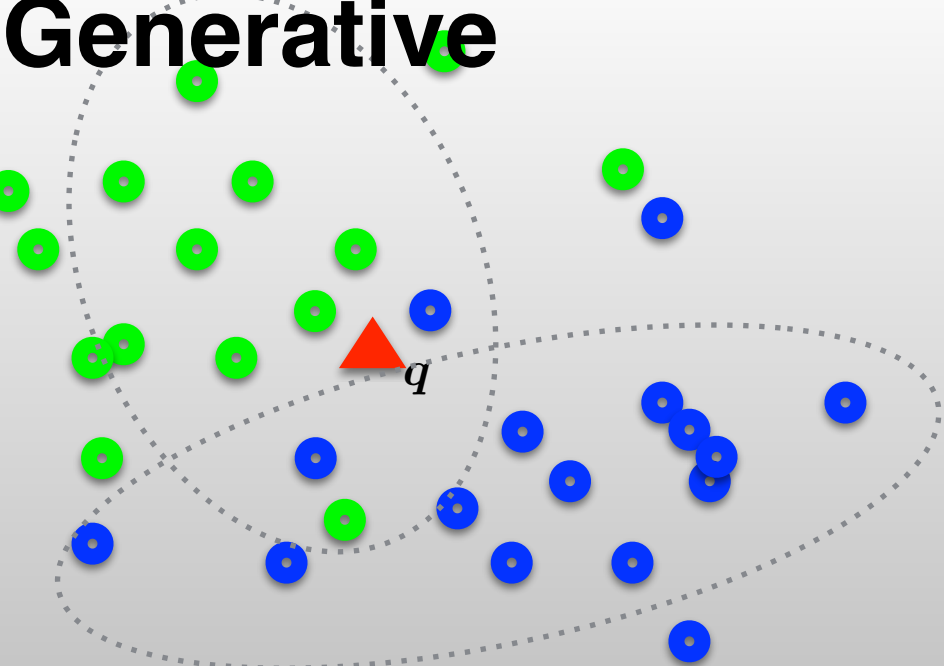
Non-parametric



Nearest Neighbor

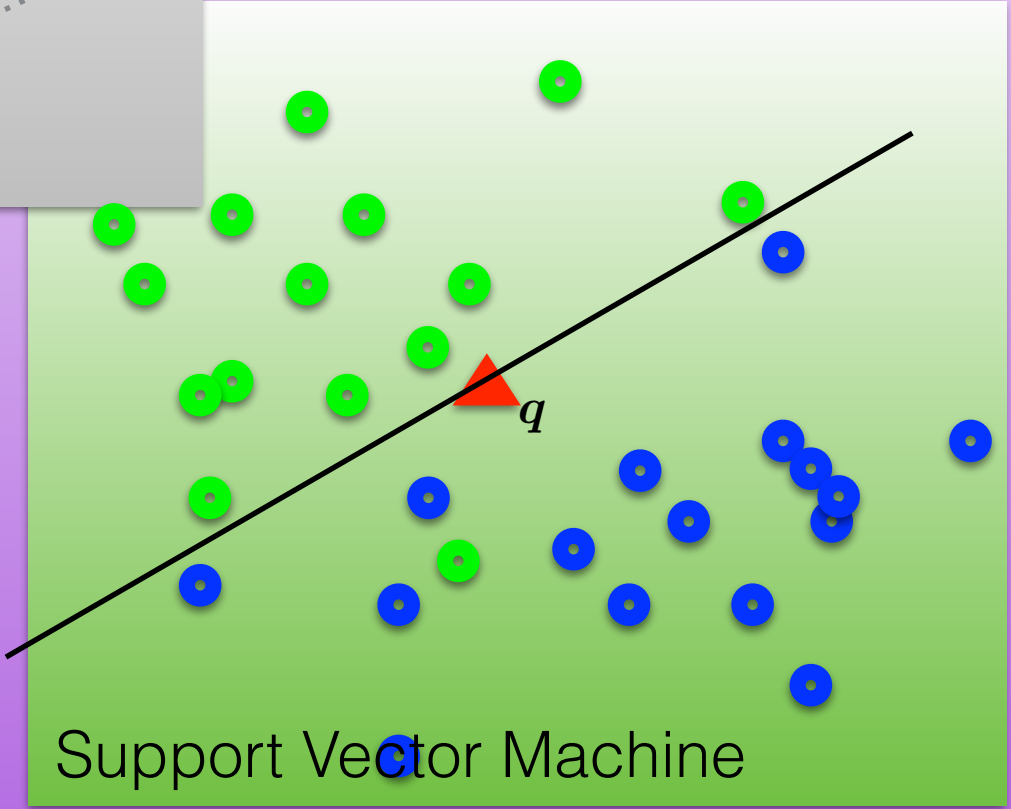
Parametric

Generative



Naive Bayes

Discriminative



Support Vector Machine

‘Classical’

Image Classification Pipeline

