

# Linear Classifiers: Expressiveness

Machine Learning



# Lecture outline

- Linear models: Introduction
- What functions do linear classifiers express?

# Where are we?

- Linear models: Introduction
- What functions do linear classifiers express?
  - Conjunctions and disjunctions
  - m-of-n functions
  - Not all functions are linearly separable
  - Feature space transformations
  - Exercises

# Which Boolean functions can linear classifiers represent?

- Linear classifiers are an expressive hypothesis class
- Many Boolean functions are **linearly separable**
  - Not all though
  - **Recall:** In comparison, decision trees can represent any Boolean function

# Conjunctions and disjunctions

Consider this truth table of a conjunction

$x_1$	$x_2$	$x_3$	$y$
0	0	0	0
0	0	1	0
0	1	0	0
0	1	1	0
1	0	0	0
1	0	1	0
1	1	0	0
1	1	1	1

$y = 1$  if and only if *all* the  $x$ 's are 1

# Conjunctions and disjunctions

$y = x_1 \wedge x_2 \wedge x_3$  is equivalent to “ $y = 1$  whenever  $x_1 + x_2 + x_3 \geq 3$ ”

$x_1$	$x_2$	$x_3$	$y$
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Negations are okay too.

In general, use  $1 - x$  in the linear threshold unit if  $x$  is negated

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Questions?

# m-of-n functions

## m-of-n rules

- There is a fixed set of  $n$  variables
- $y = \text{true}$  if, and only if, at least  $m$  of them are `true`
- All other variables are ignored

Suppose there are five Boolean variables:  $x_1, x_2, x_3, x_4, x_5$

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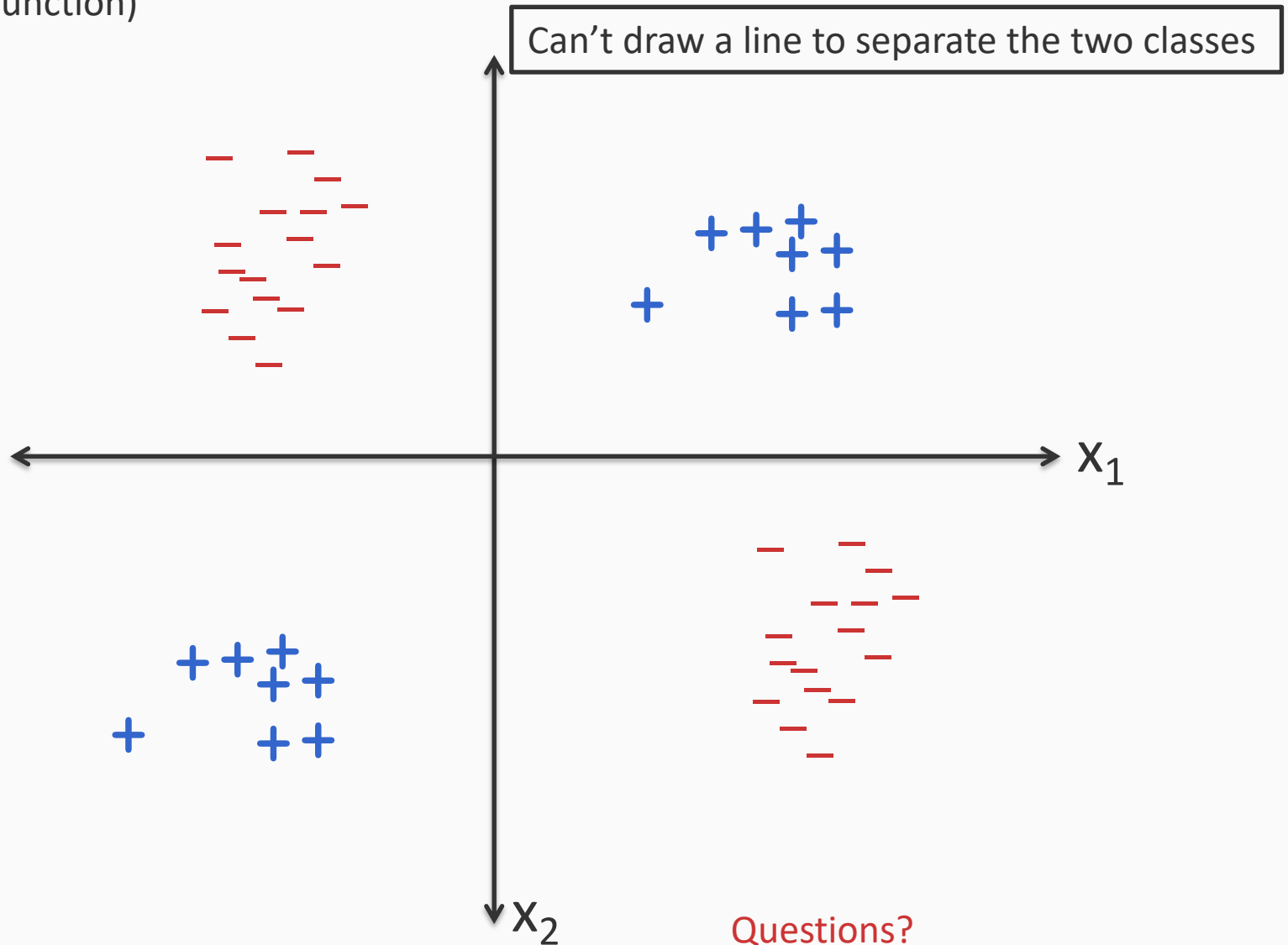
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Questions?

*Not all functions are linearly separable*

# Parity is not linearly separable

(The XOR function)



# Not all functions are linearly separable

- XOR is not linear
  - $y = x \text{ XOR } y = (x \wedge \neg y) \vee (\neg x \wedge y)$
  - *Parity* cannot be represented as a linear classifier
    - $f(\mathbf{x}) = 1$  if the number of 1's is even
- Many non-trivial Boolean functions
  - Example:  $y = (x_1 \wedge x_2) \vee (x_3 \wedge \neg x_4)$
  - The function is not linear in the four variables

# Even these functions can be *made* linear

These points are not separable in 1-dimension by a line

What is a one-dimensional line, by the way?





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The trick: Change the representation

# The blown up feature space

The trick: Use feature *conjunctions*

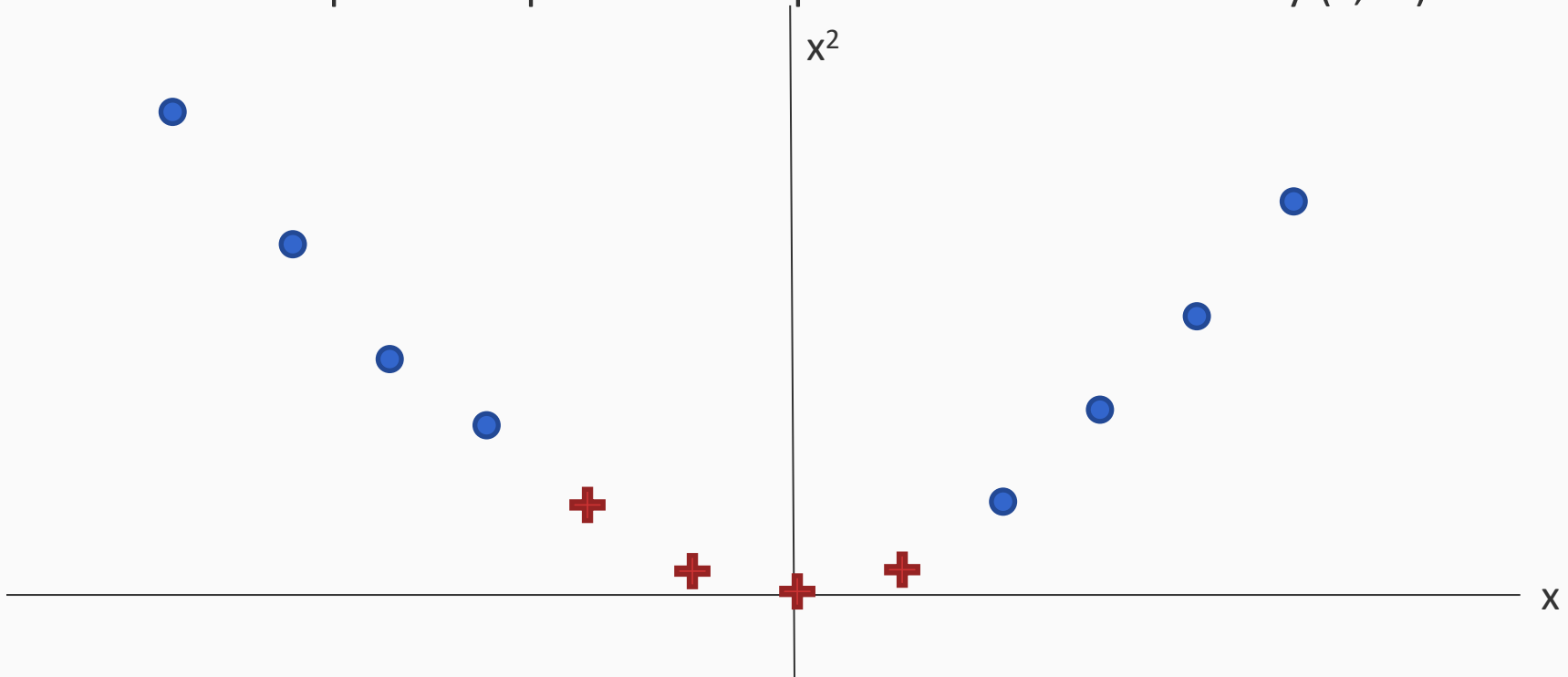
Transform points: Represent each point  $x$  in 2 dimensions by  $(x, x^2)$



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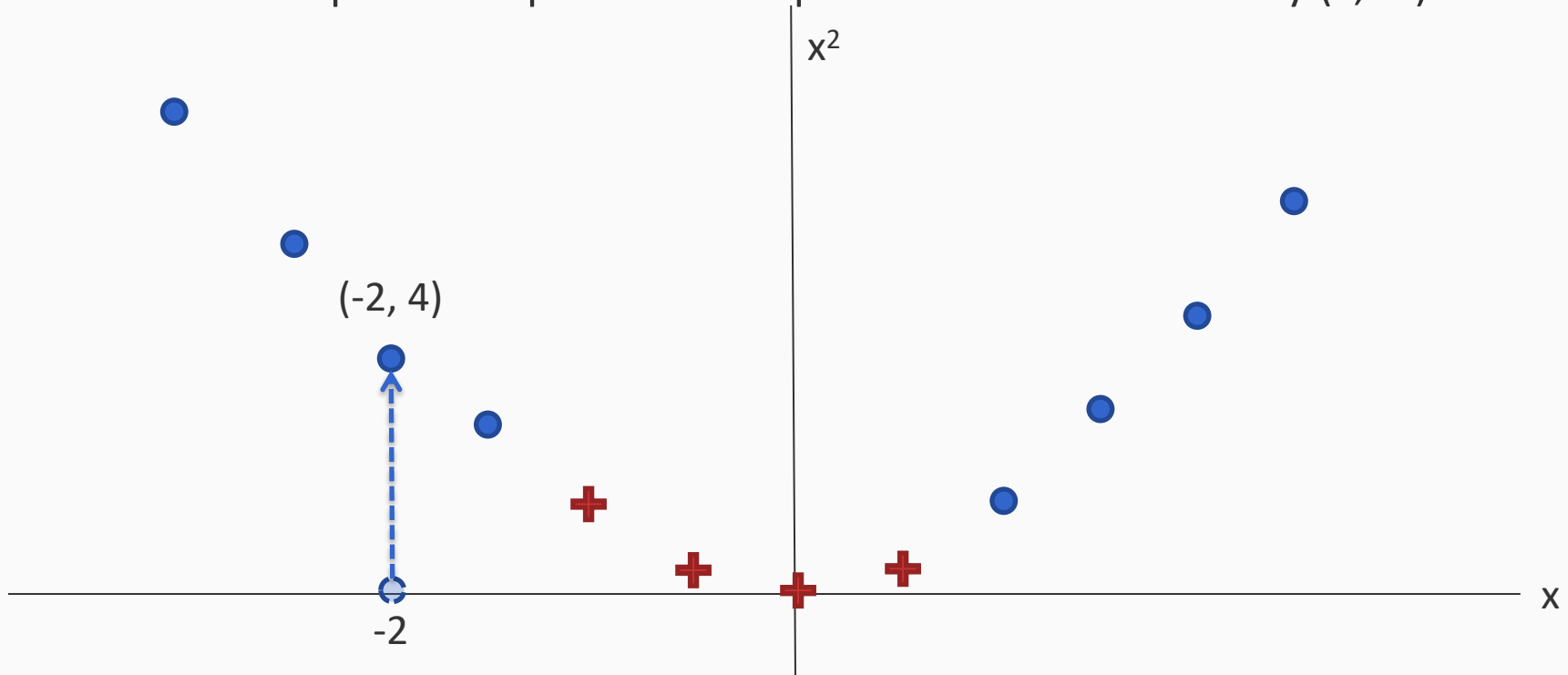
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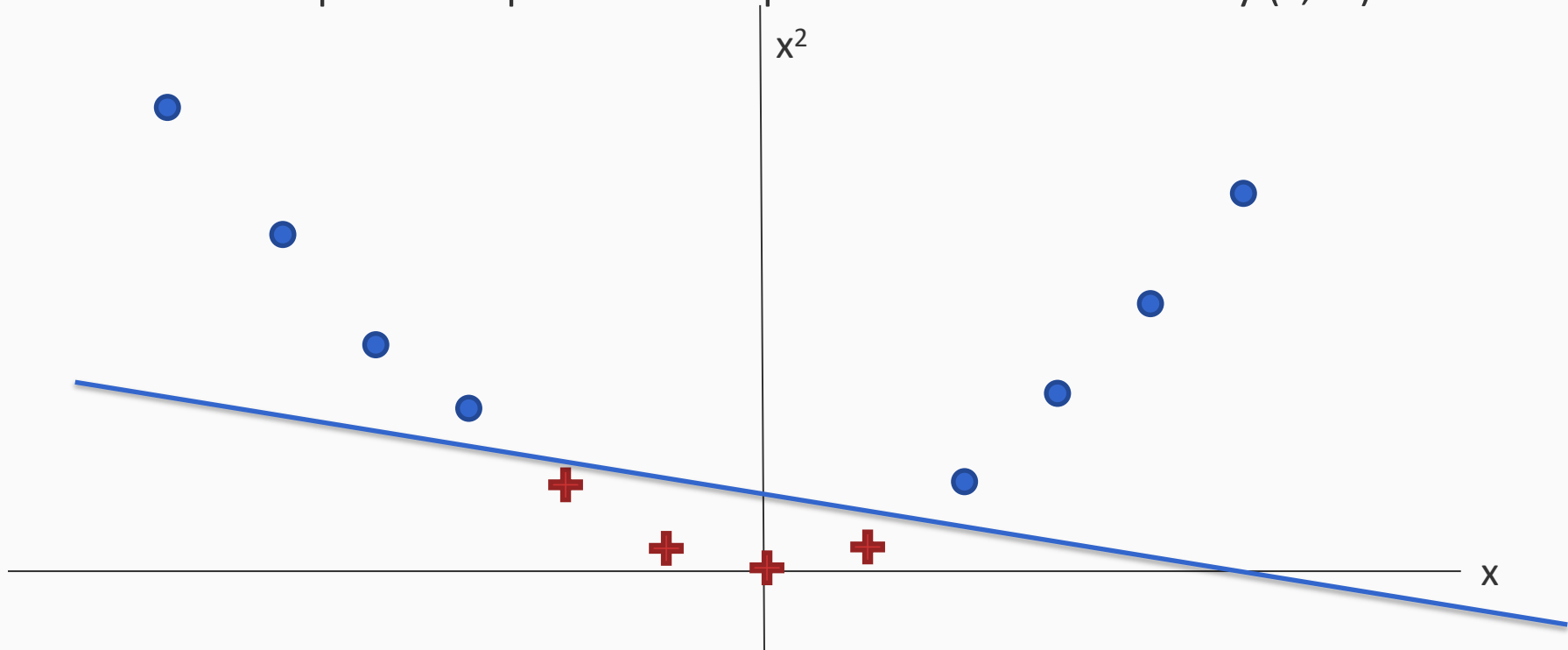
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Now the data is linearly separable in this space!

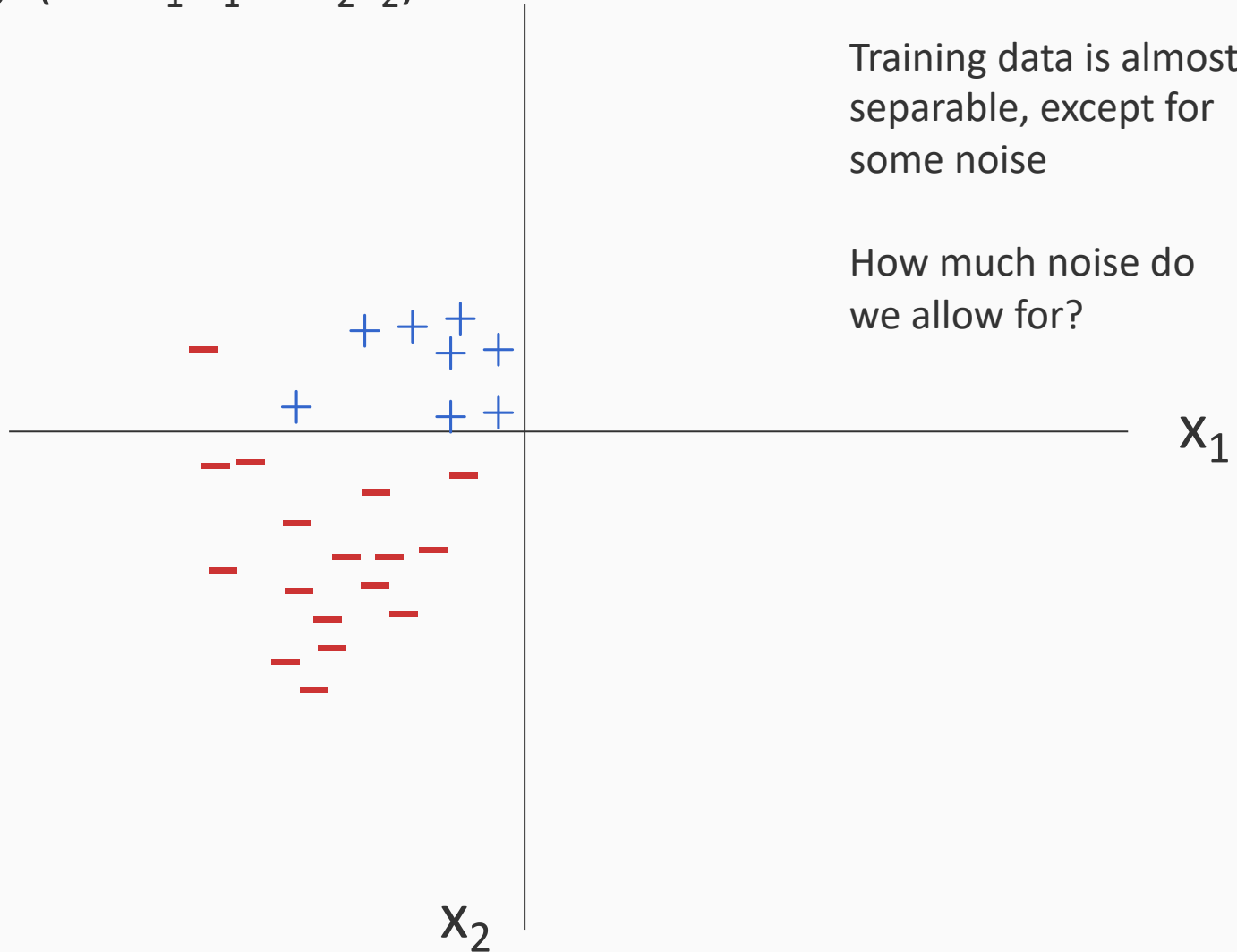
# Exercise

How would you use the feature transformation idea to make XOR in two dimensions linearly separable in a new space?

To answer this question, you need to think about a function that maps examples from two dimensional space to a higher dimensional space.

# Almost linearly separable data

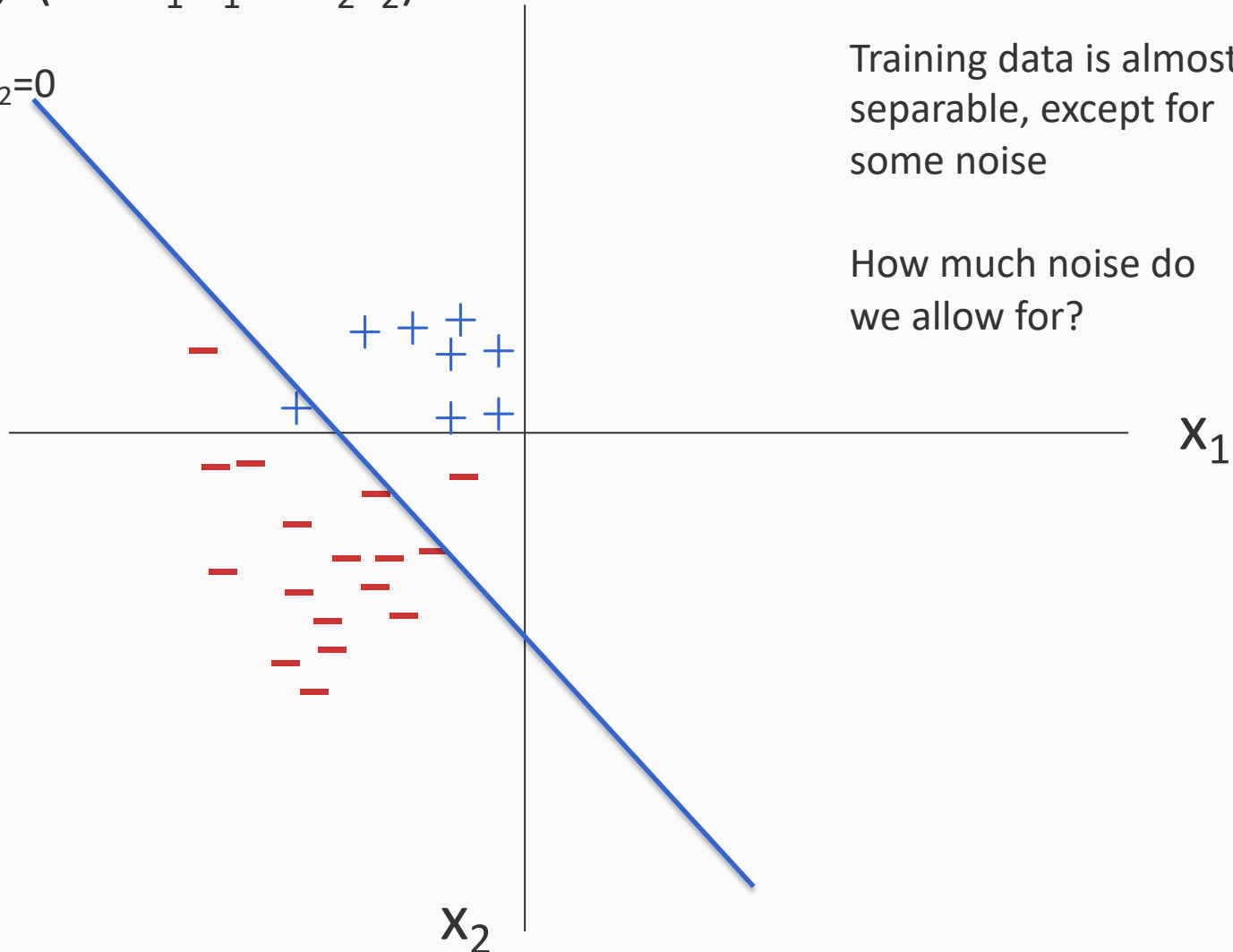
$$\text{sgn}(b + w_1 x_1 + w_2 x_2)$$



# Almost linearly separable data

$$\text{sgn}(b + w_1 x_1 + w_2 x_2)$$

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

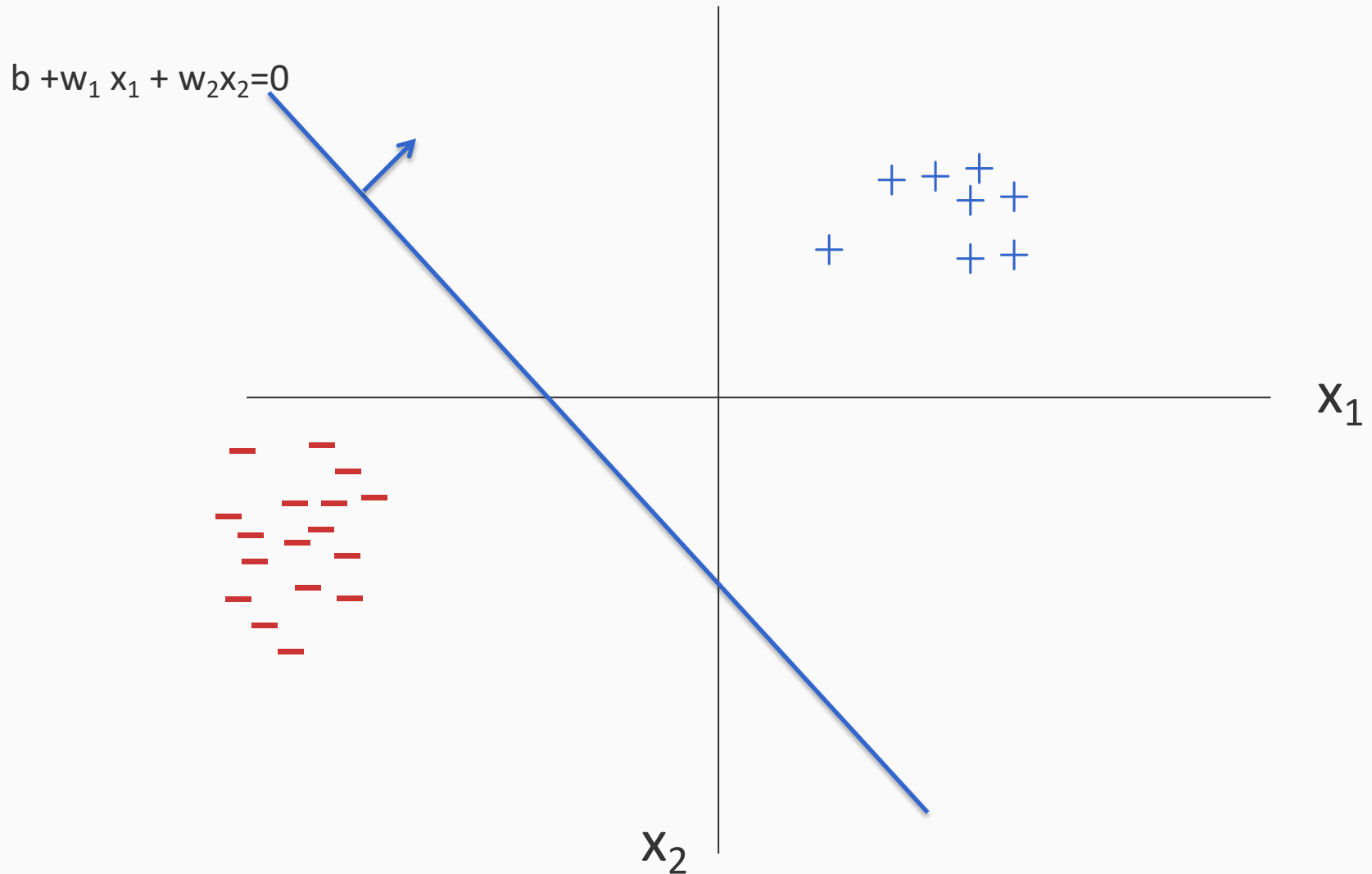




# Linear classifiers: An expressive hypothesis class

- Many functions are linear
- Often a good <sup>first</sup> guess for a hypothesis space
- Some functions are not linear
  - The XOR function
  - Non-trivial Boolean functions
- But there are ways of making them linear in a higher dimensional feature space

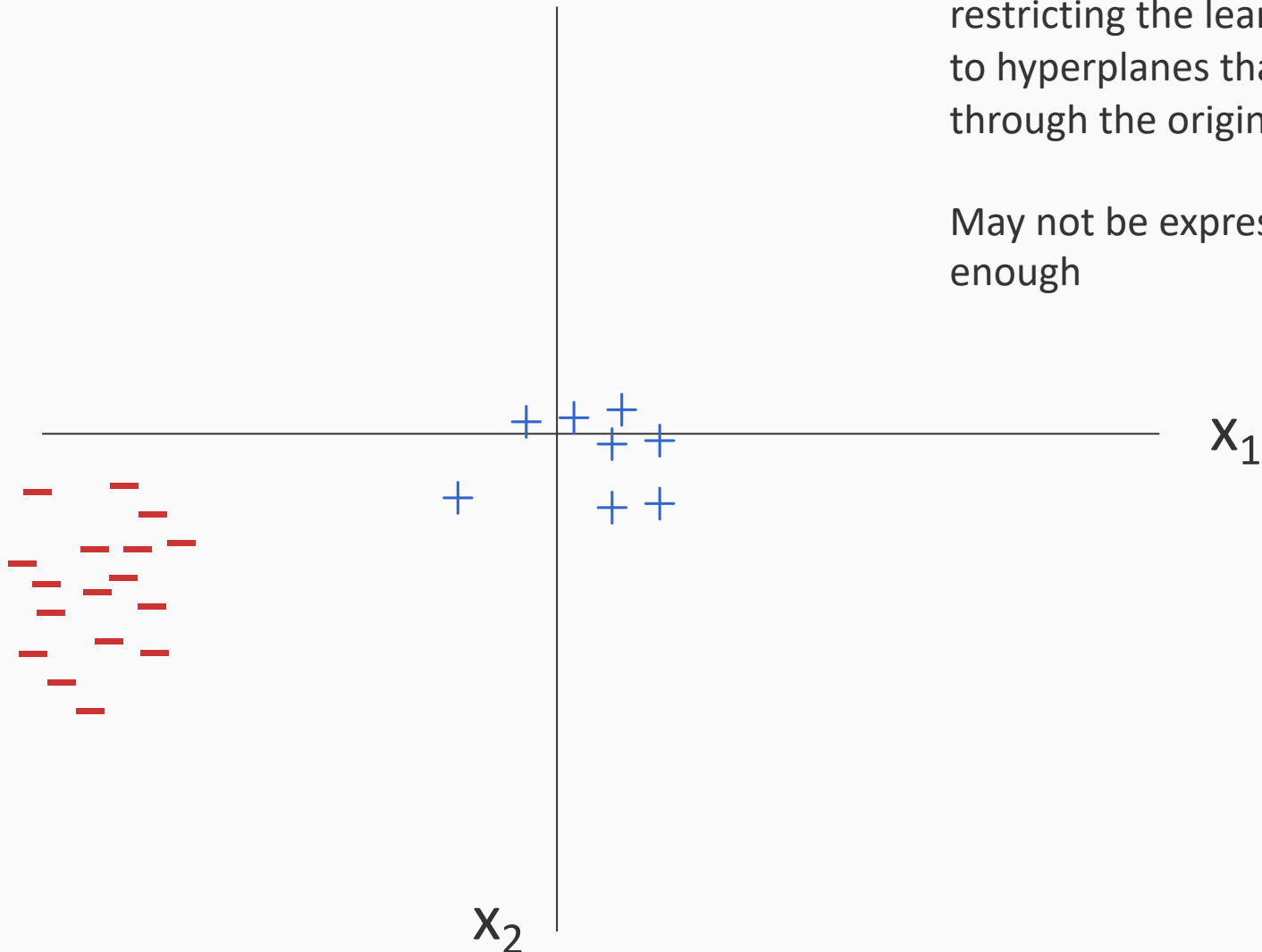
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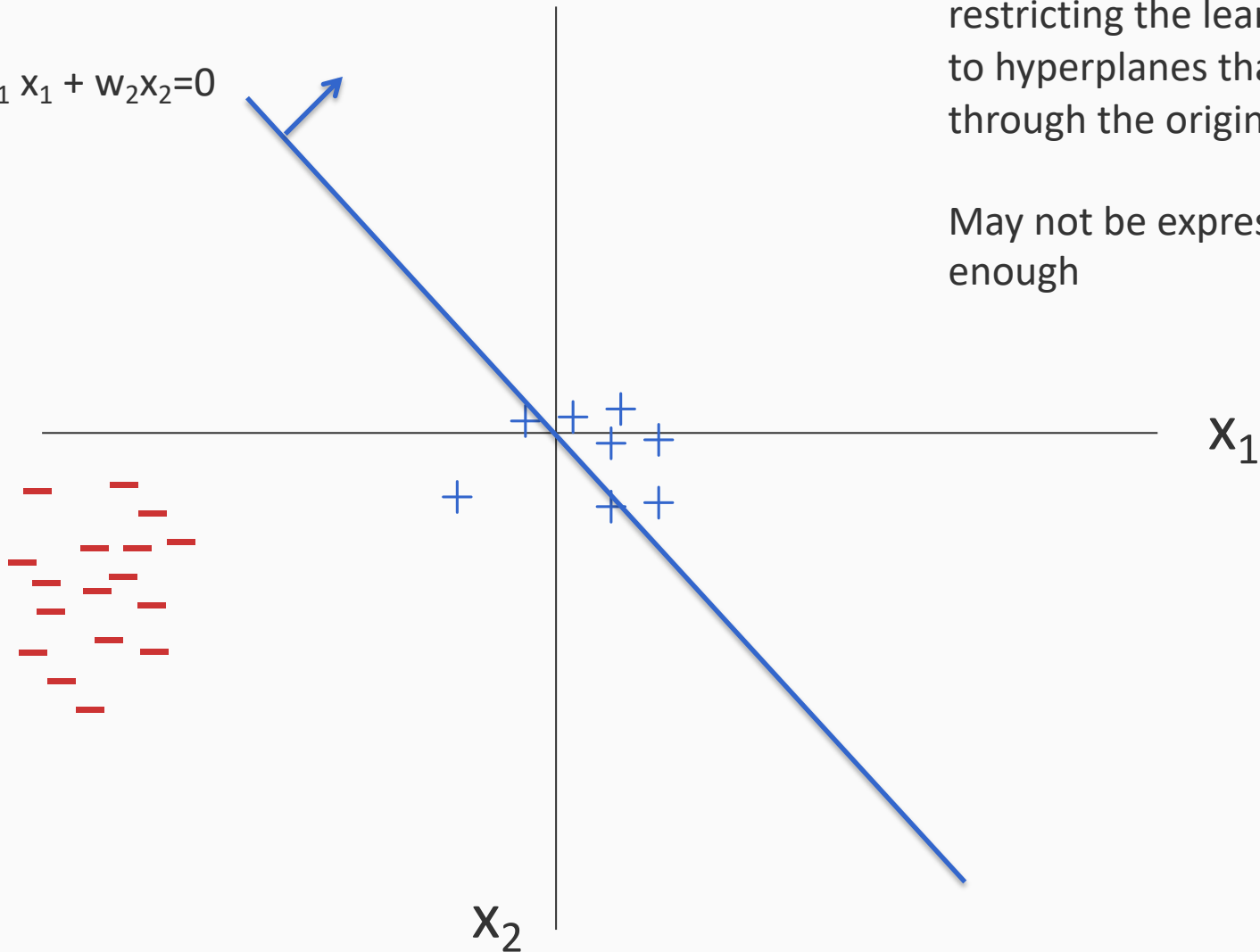
If  $b$  is zero, then we are restricting the learner only to hyperplanes that go through the origin

May not be expressive enough



# Why is the bias term needed?

$$w_1 x_1 + w_2 x_2 = 0$$



If  $b$  is zero, then we are restricting the learner only to hyperplanes that go through the origin

May not be expressive enough

# Exercises

1. Represent the simple disjunction as a linear classifier.
2. How would you apply the feature space expansion idea for the XOR function?