MIT · 6.036 | Introduction to Machine Learning (2020)

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6.036/6.862: Introduction to Machine Learning

Lecture: starts Tuesdays 9:35am (Boston time zone)

Course website: introml.odl.mit.edu

Who's talking? Prof. Tamara Broderick

Questions? discourse.odl.mit.edu ("Lecture 2" category)

Materials: Will all be available at course website

Last Time

I. Machine learning setup
II. Linear classifiers
III. Learning algorithms

Today's Plan

I. Perceptron algorithm
II. Harder and easier linear classification
III. Perceptron theorem

Recall: Classifiers

Recall: Classifiers

- A linear classifier:

$h(x; \theta, \theta_0)$

Recall: Classifiers

- A linear classifier:

$$h(x; \theta, \theta_0) = \text{sign}(\theta^\top x + \theta_0)$$

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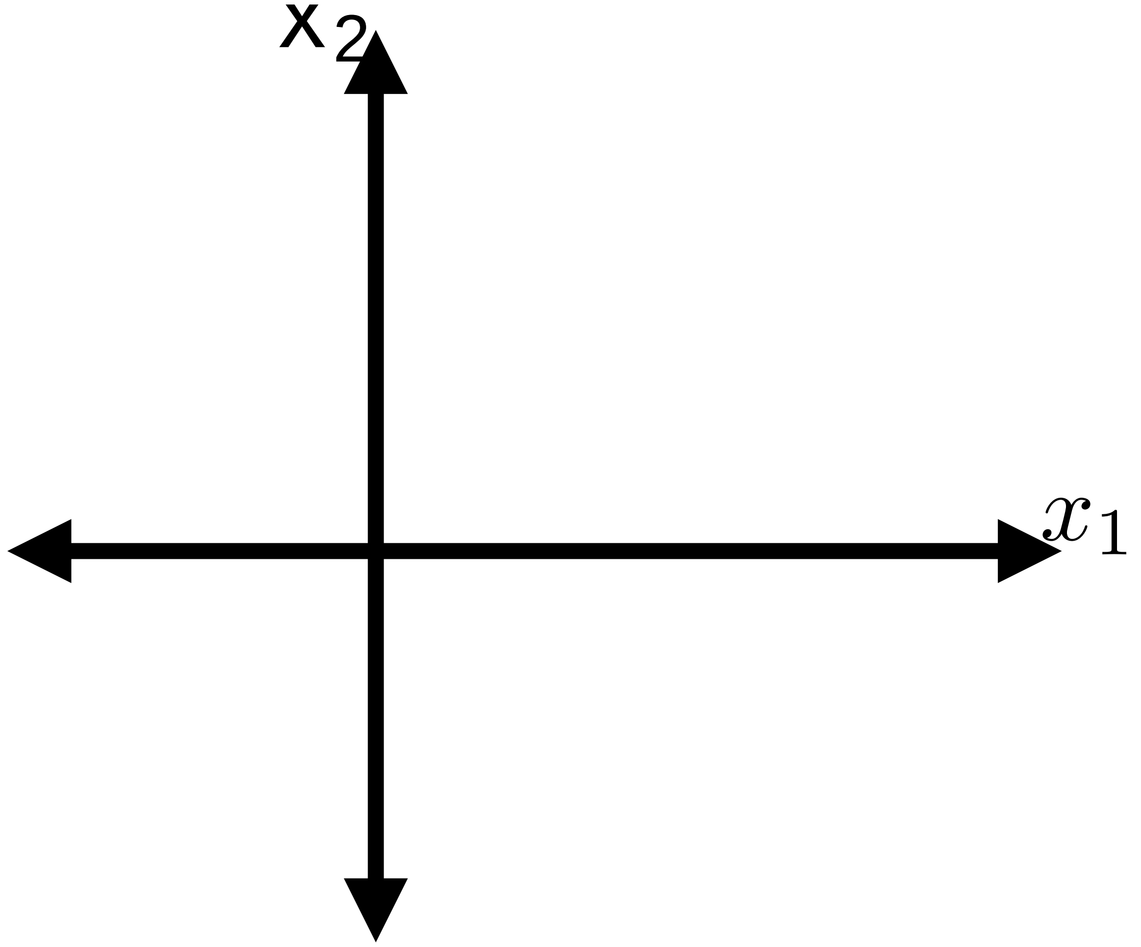

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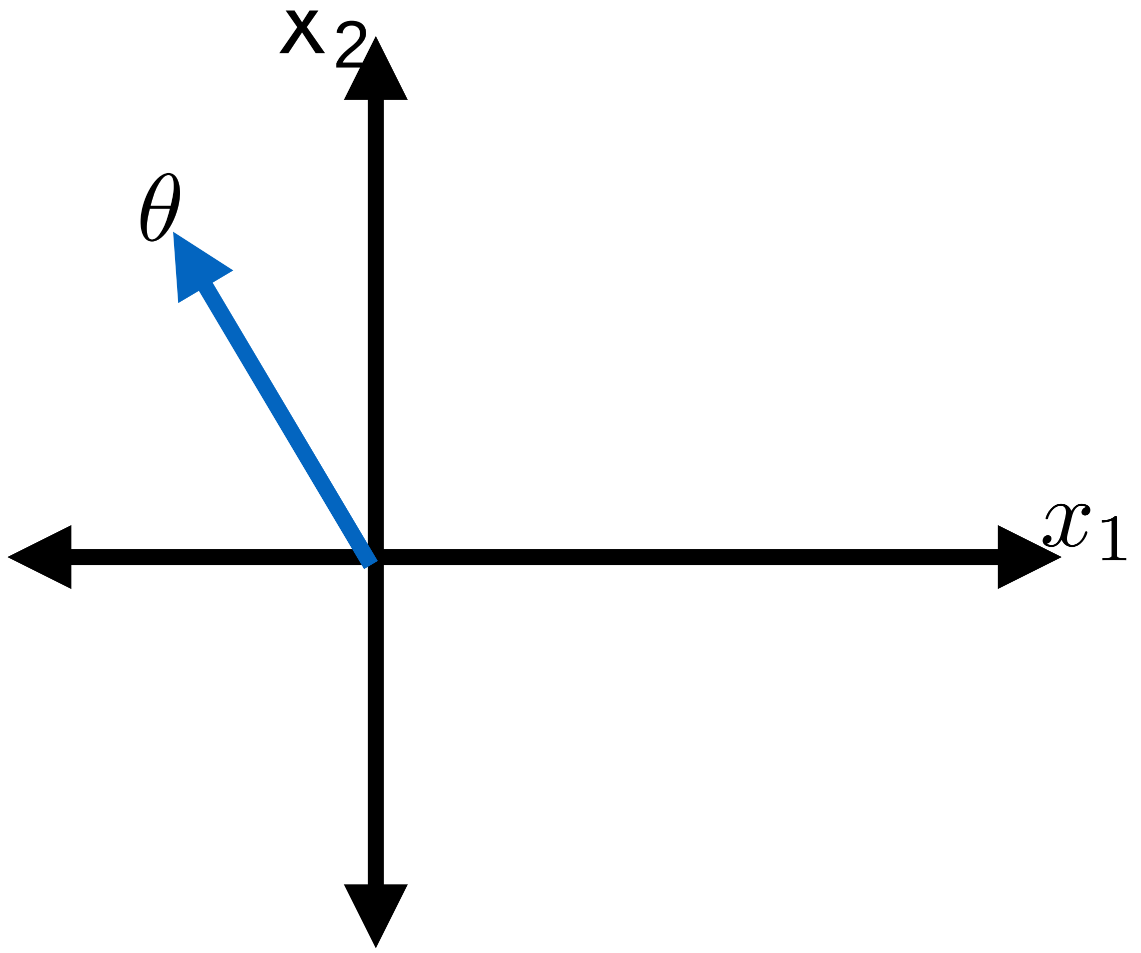

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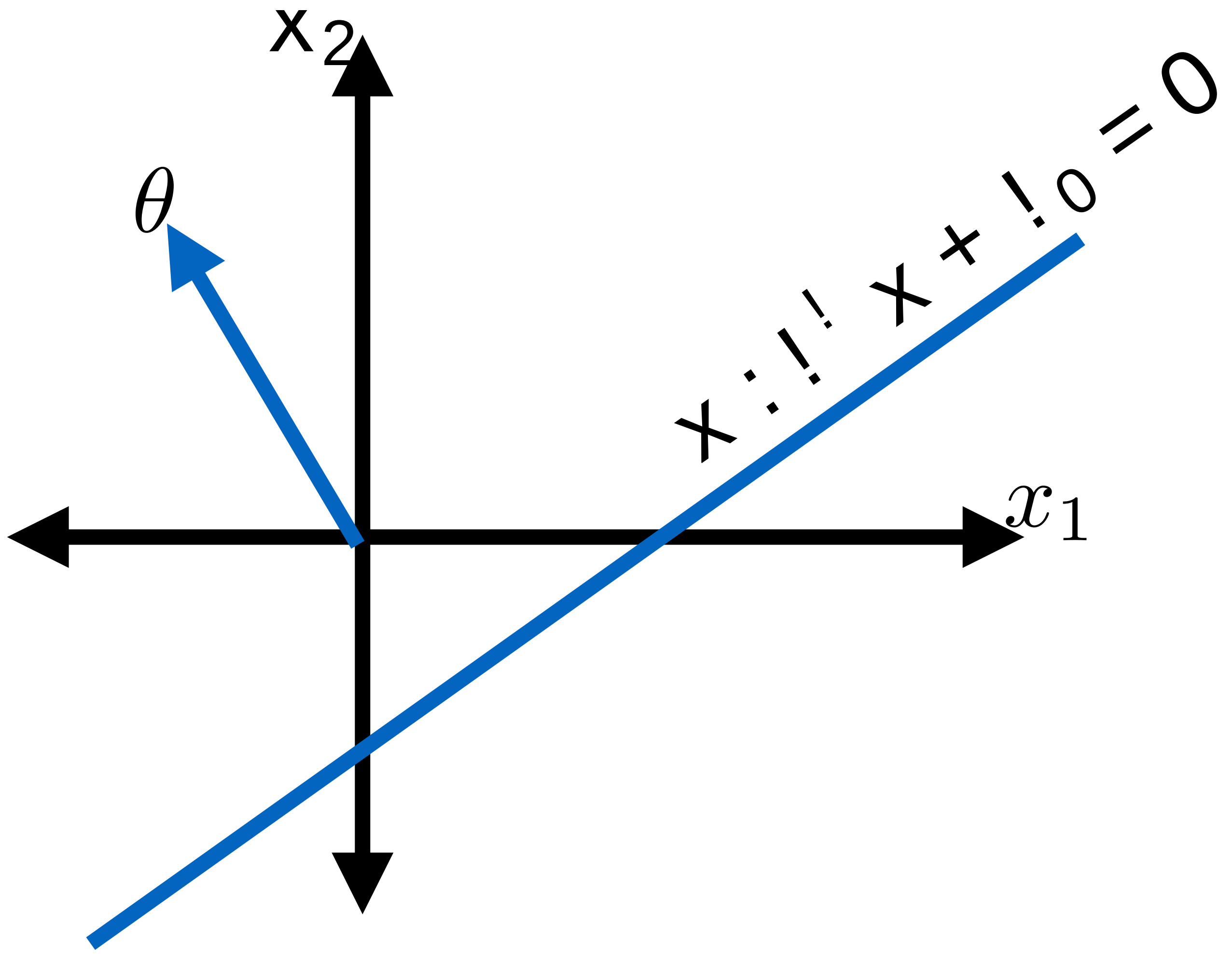

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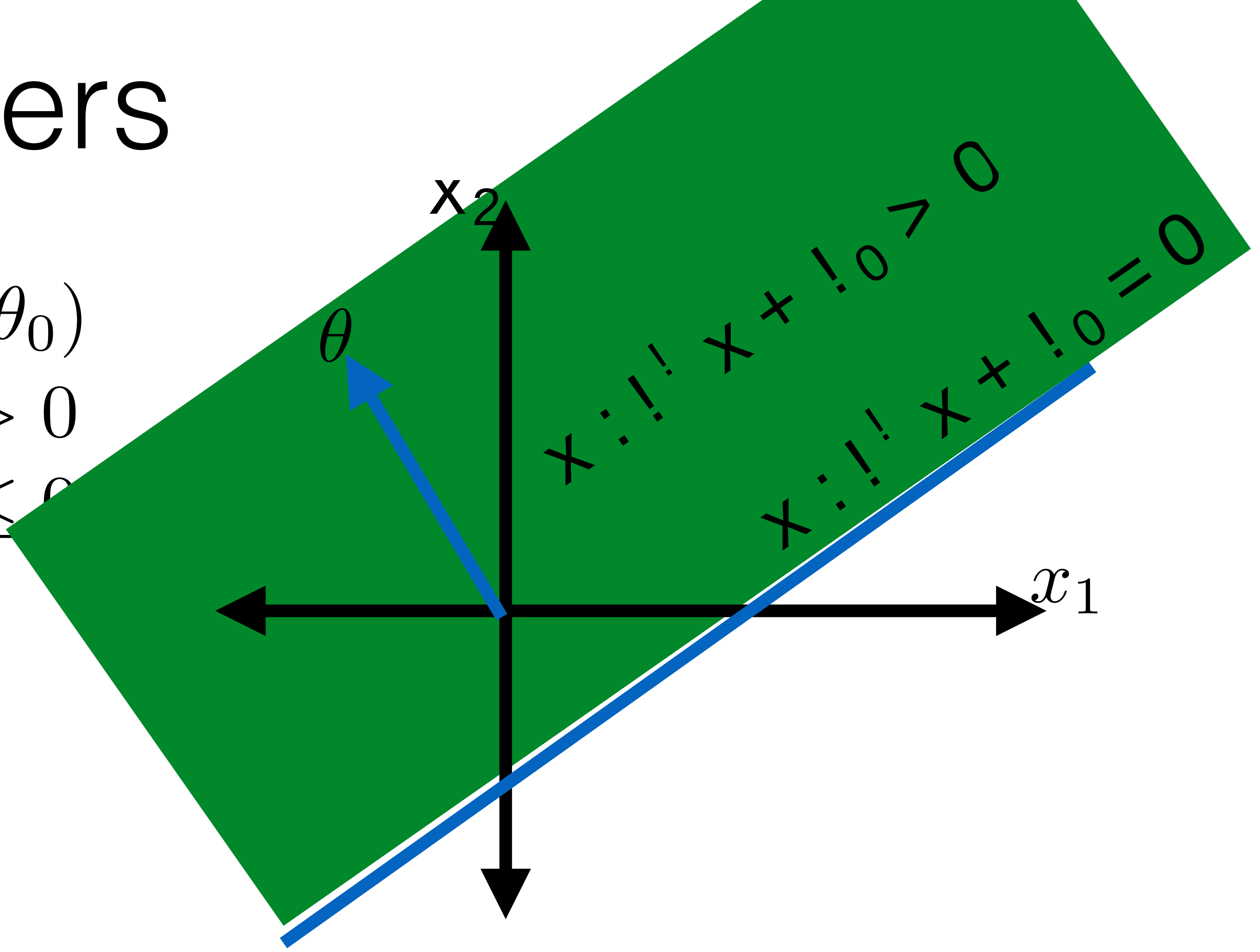

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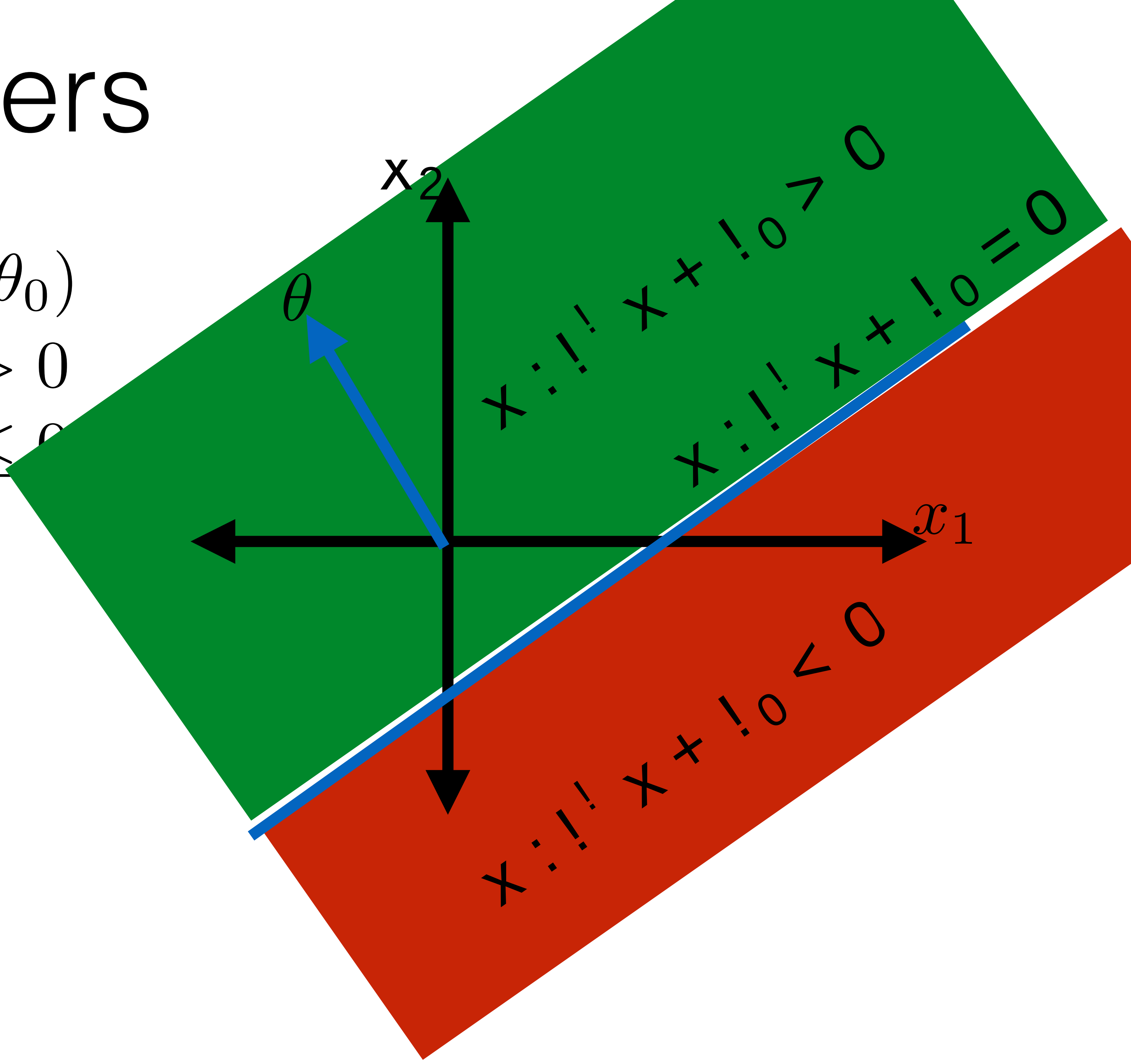

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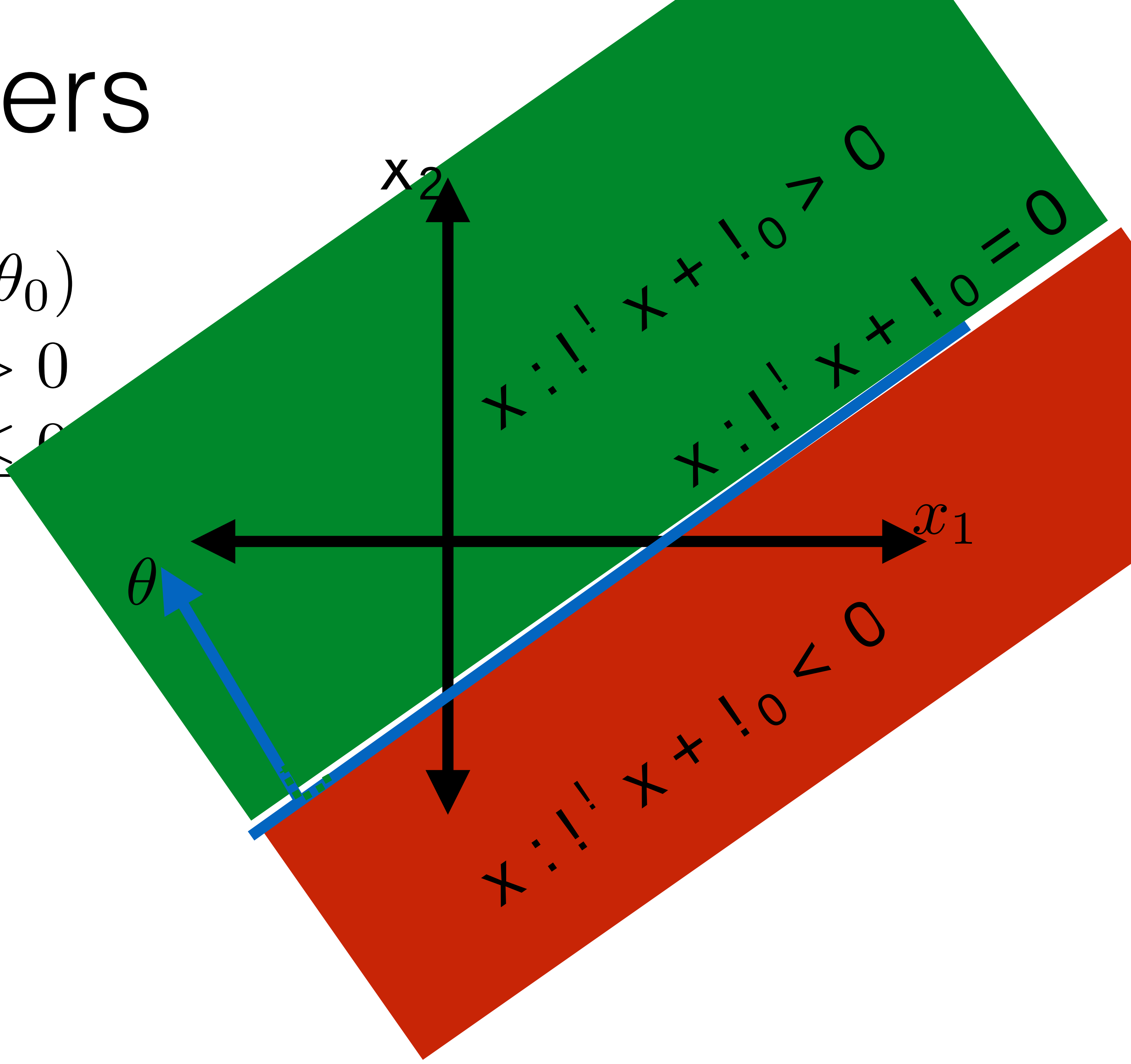

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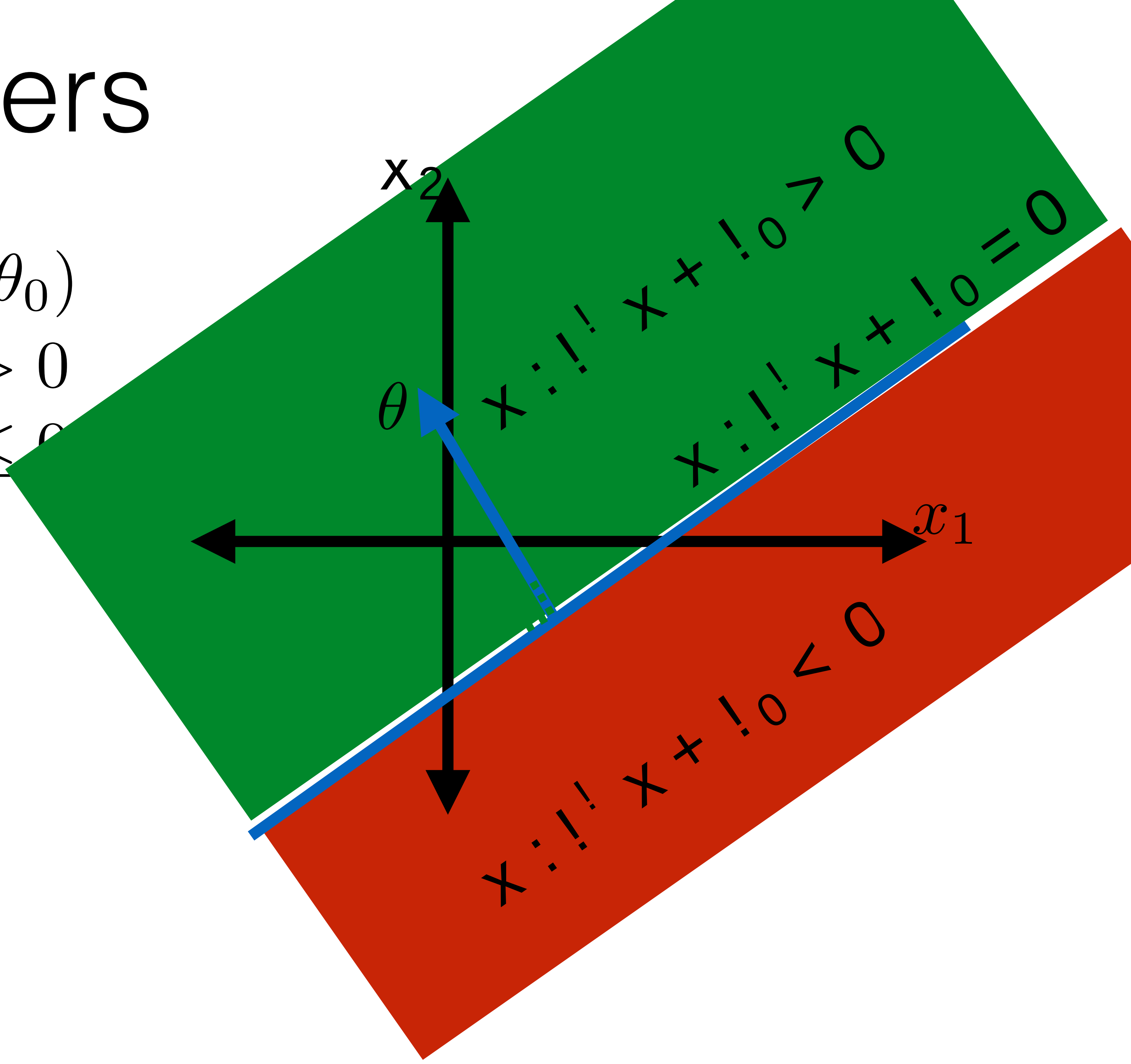

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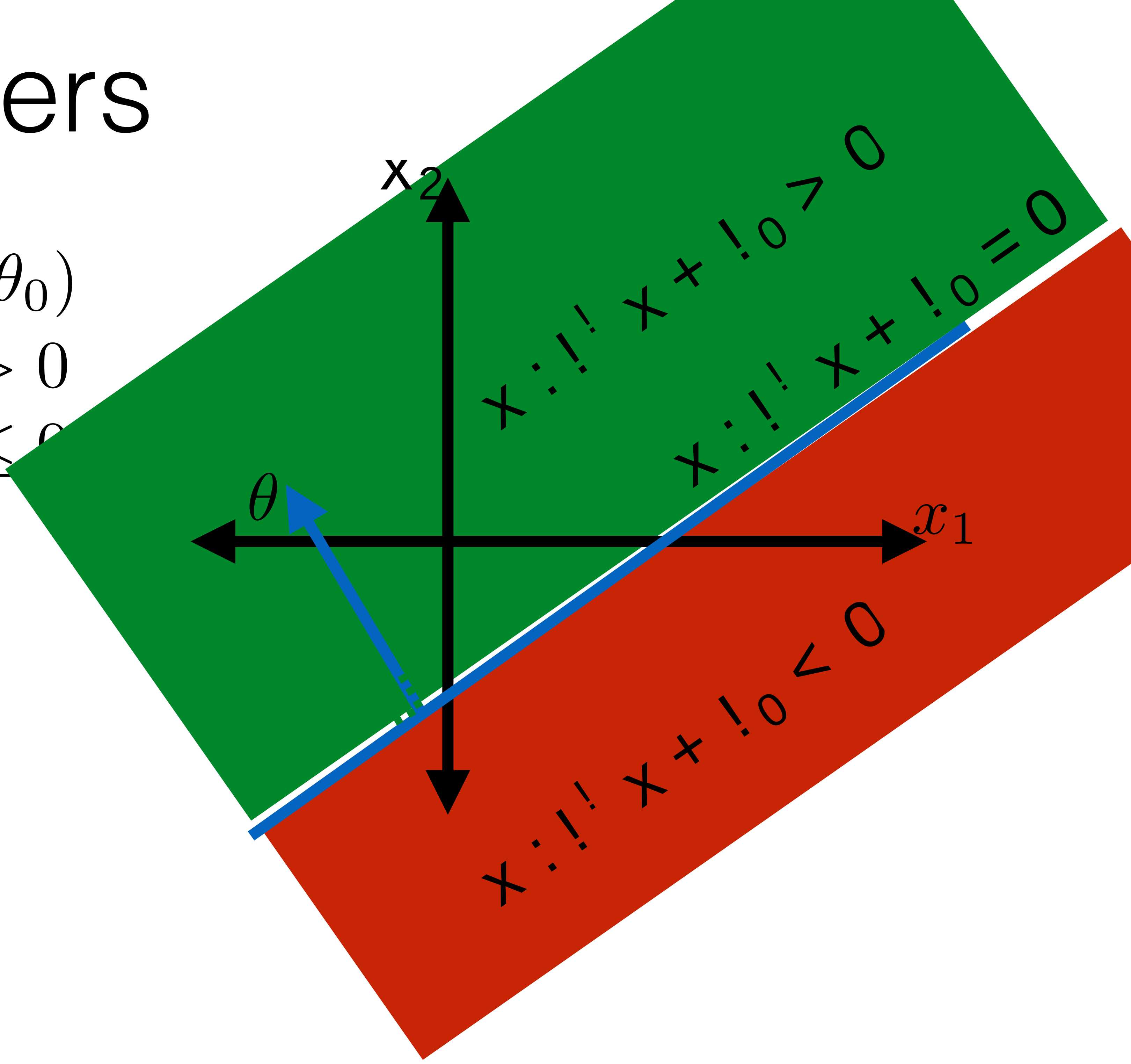

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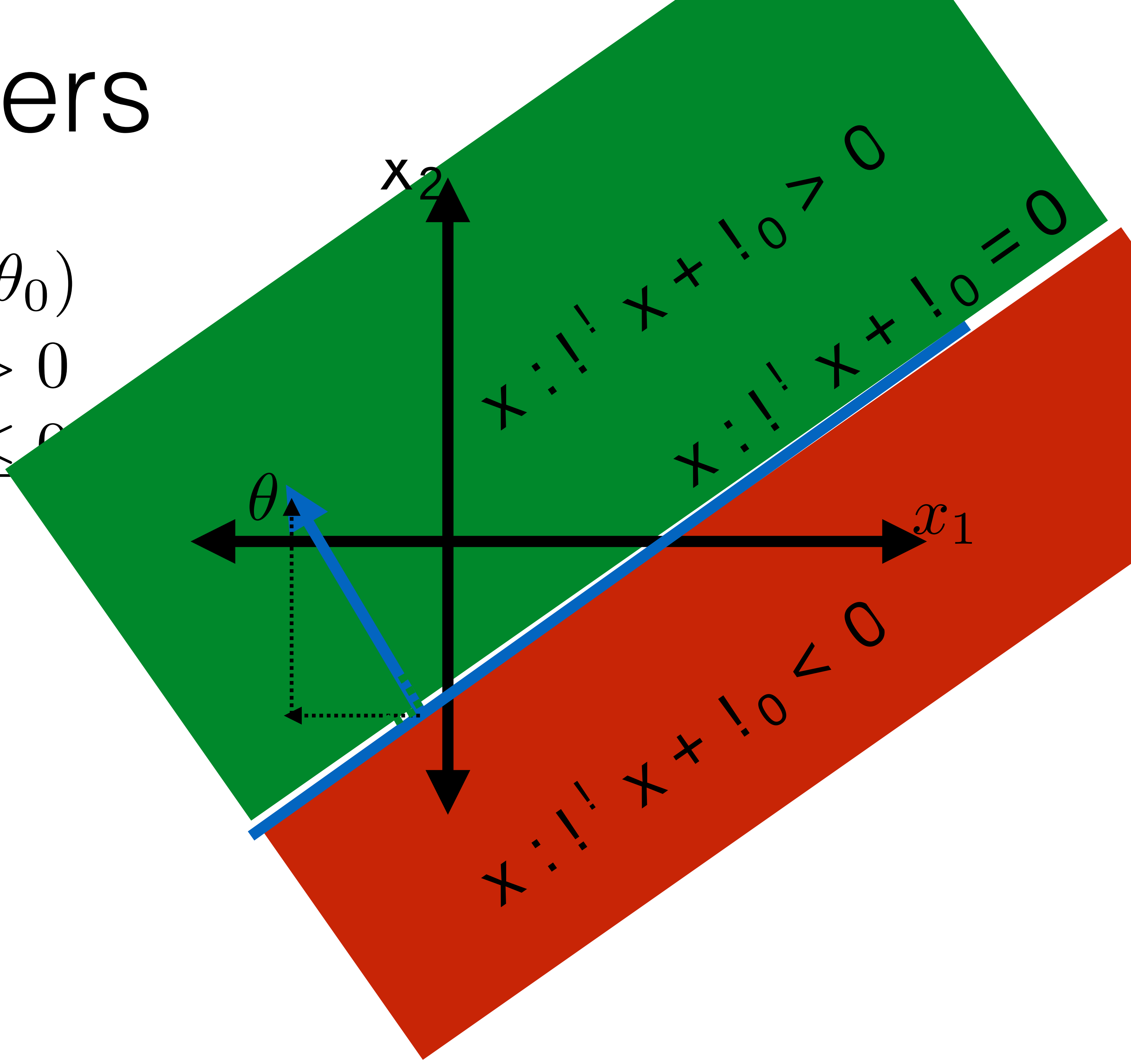

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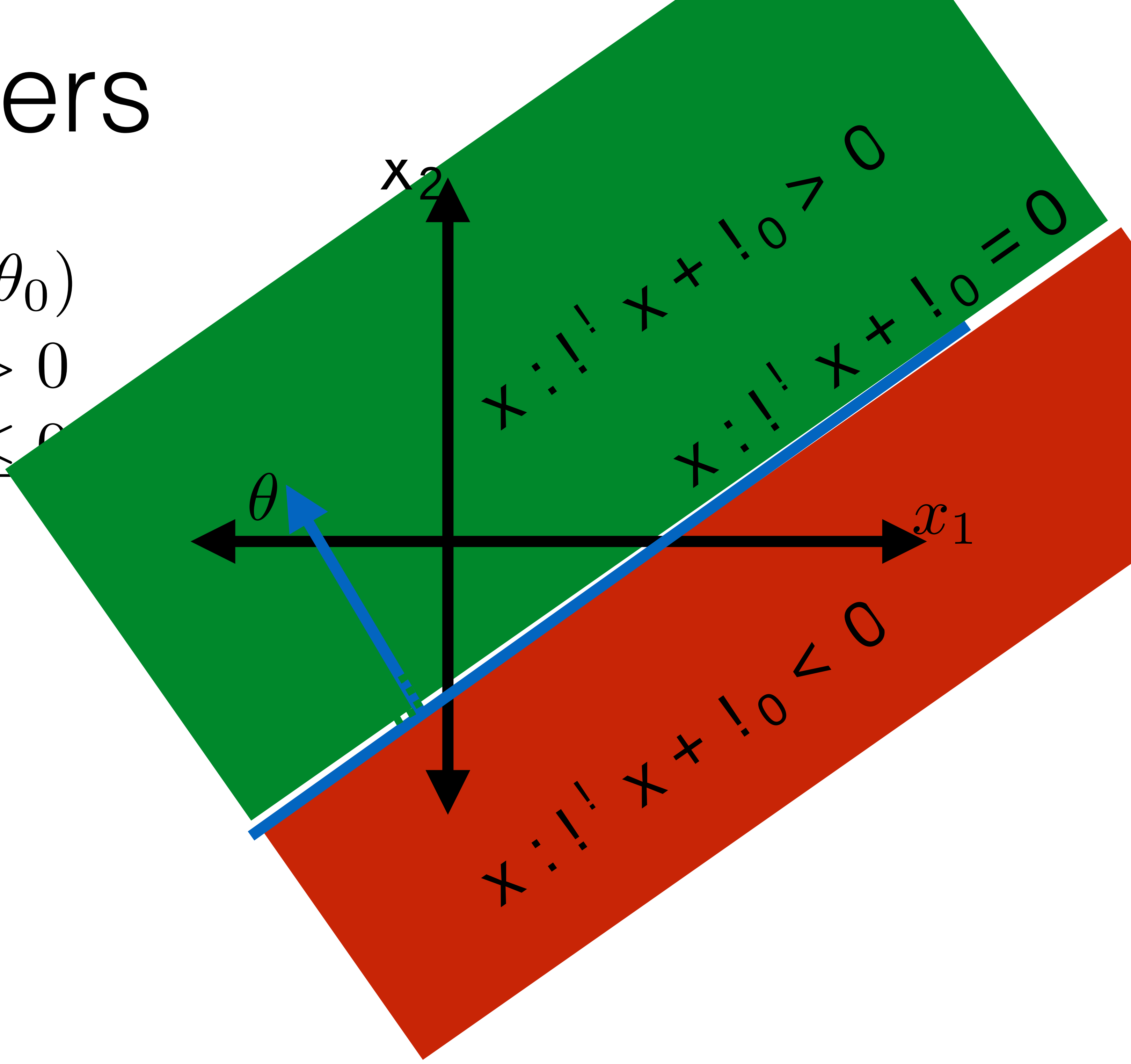

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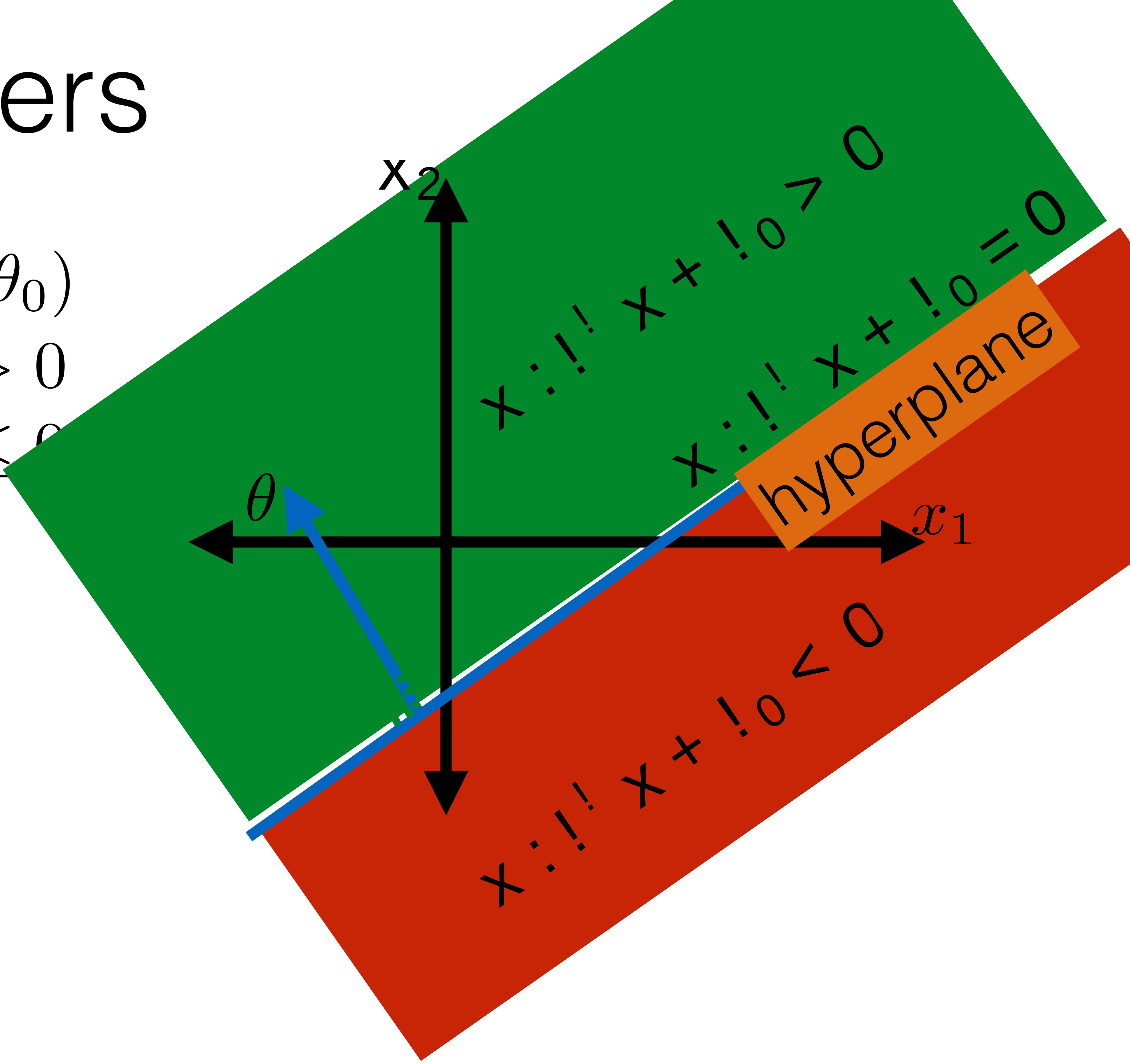

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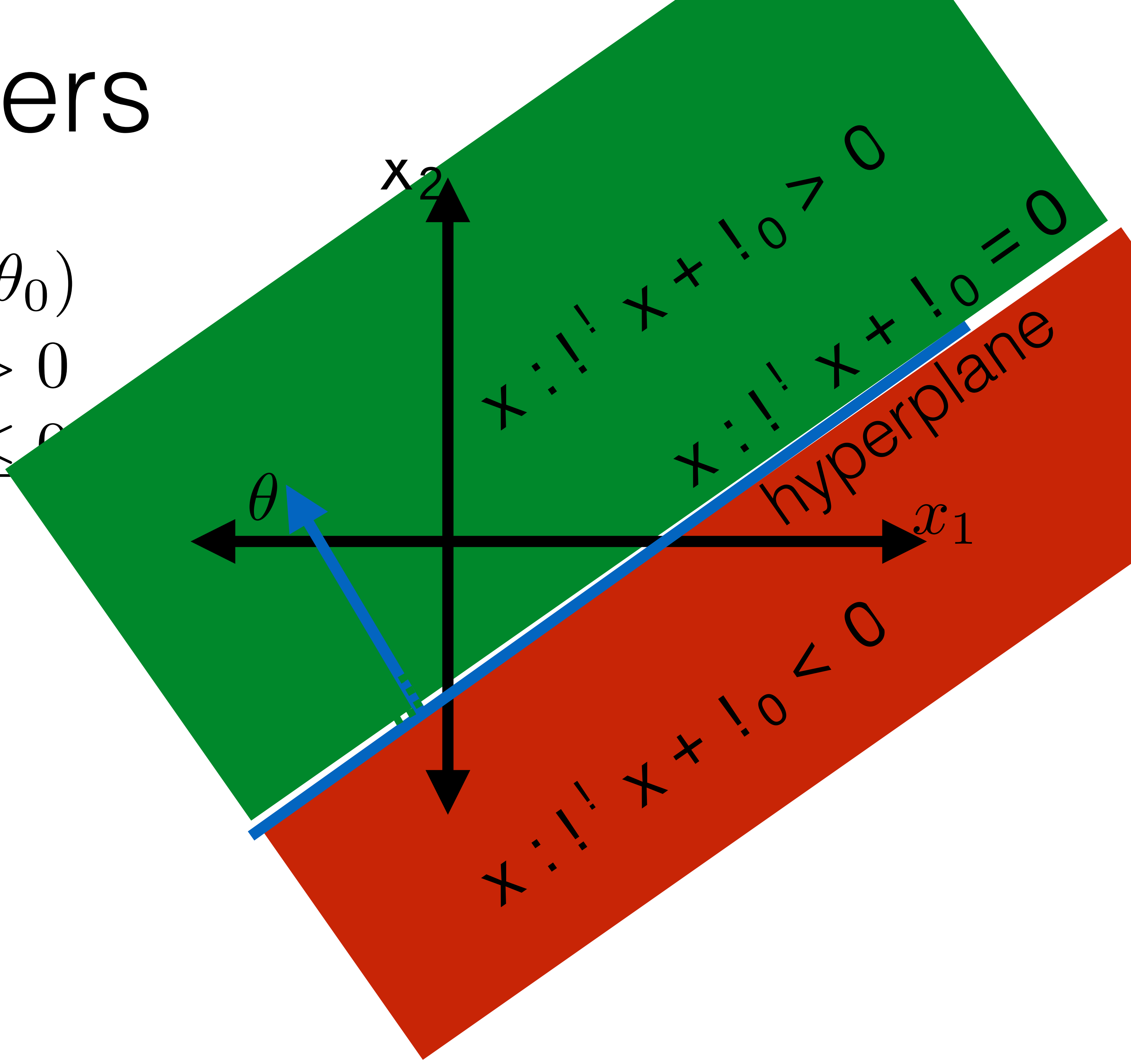

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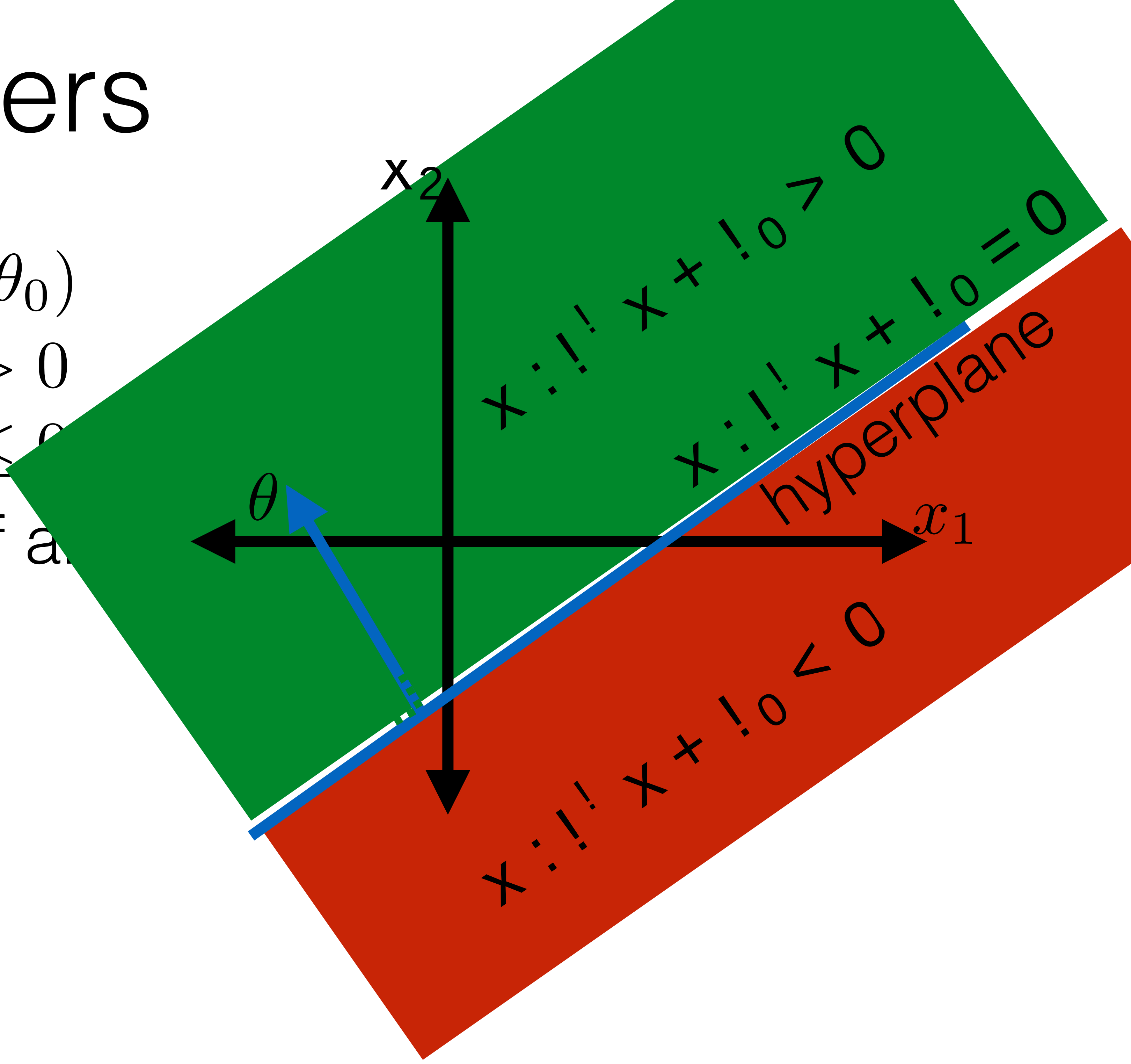

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L(g, a) = 0 if g = a
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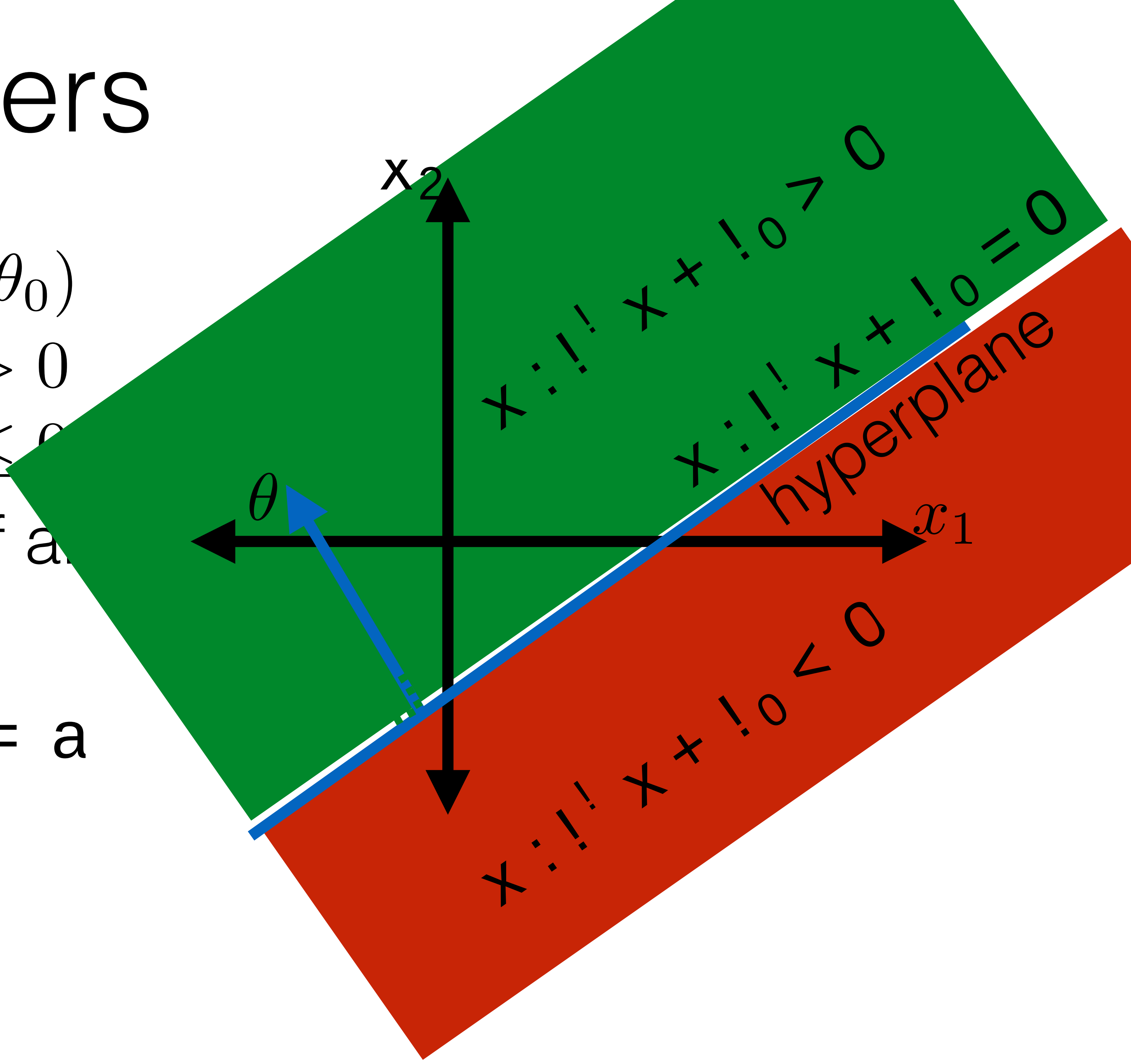

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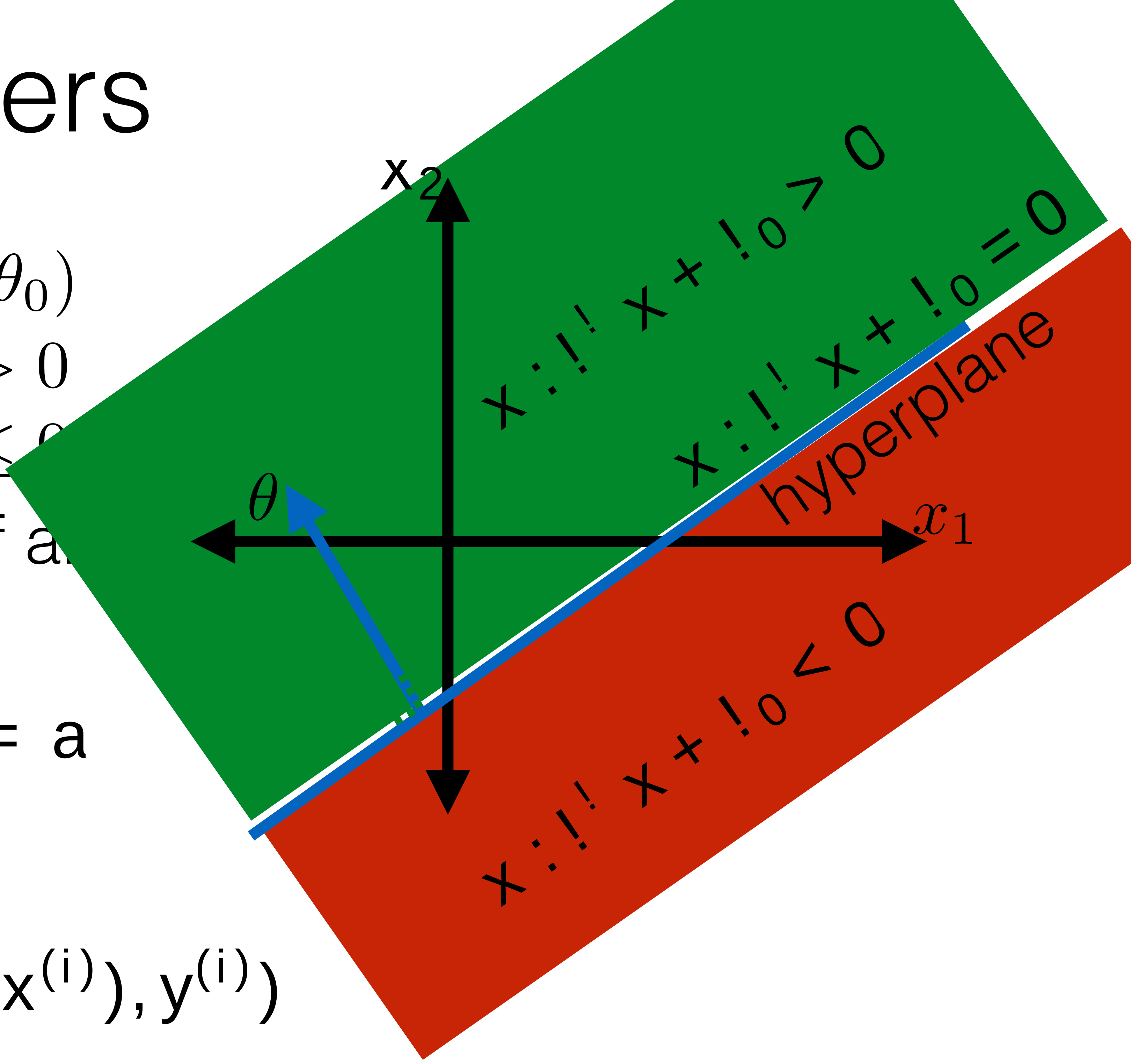

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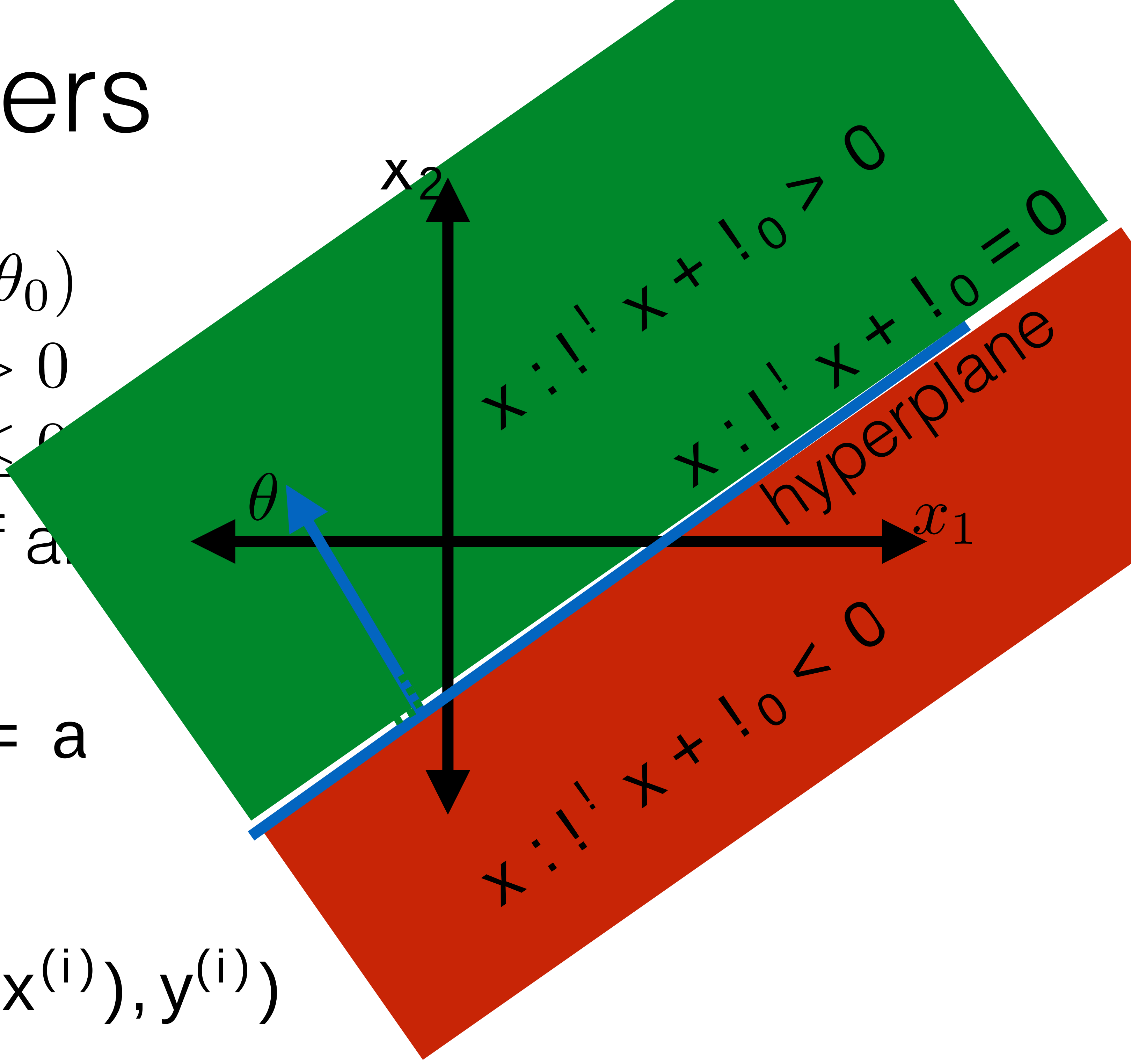

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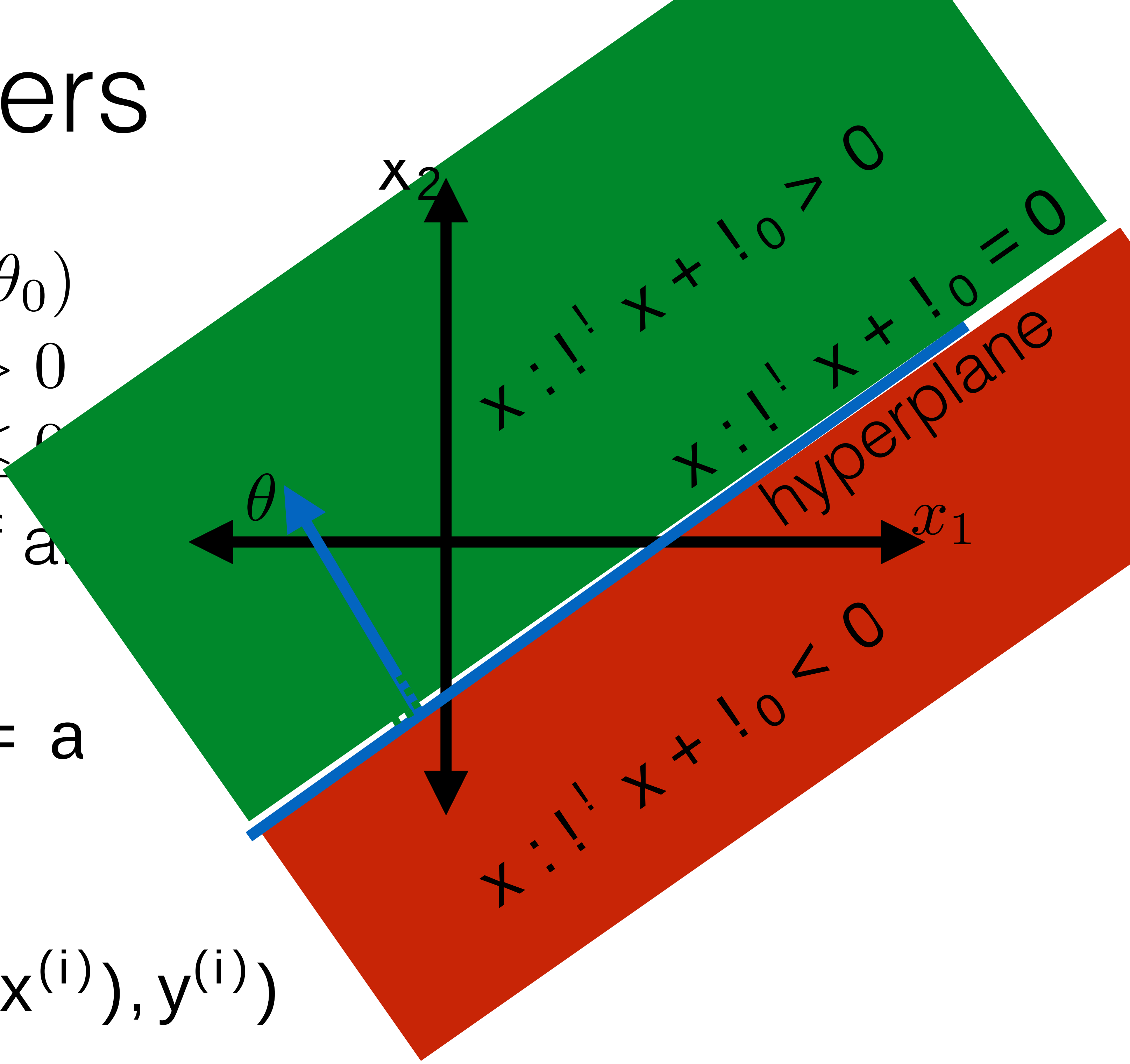
```
Ex_learning_alg( $\mathcal{D}_n$ ; k )
    Set $j^* = \text{argmin}_{j \in \{1,\ldots,k\}} E_n(h^{(j)})$
    Return $h^{(j^*)}$
```



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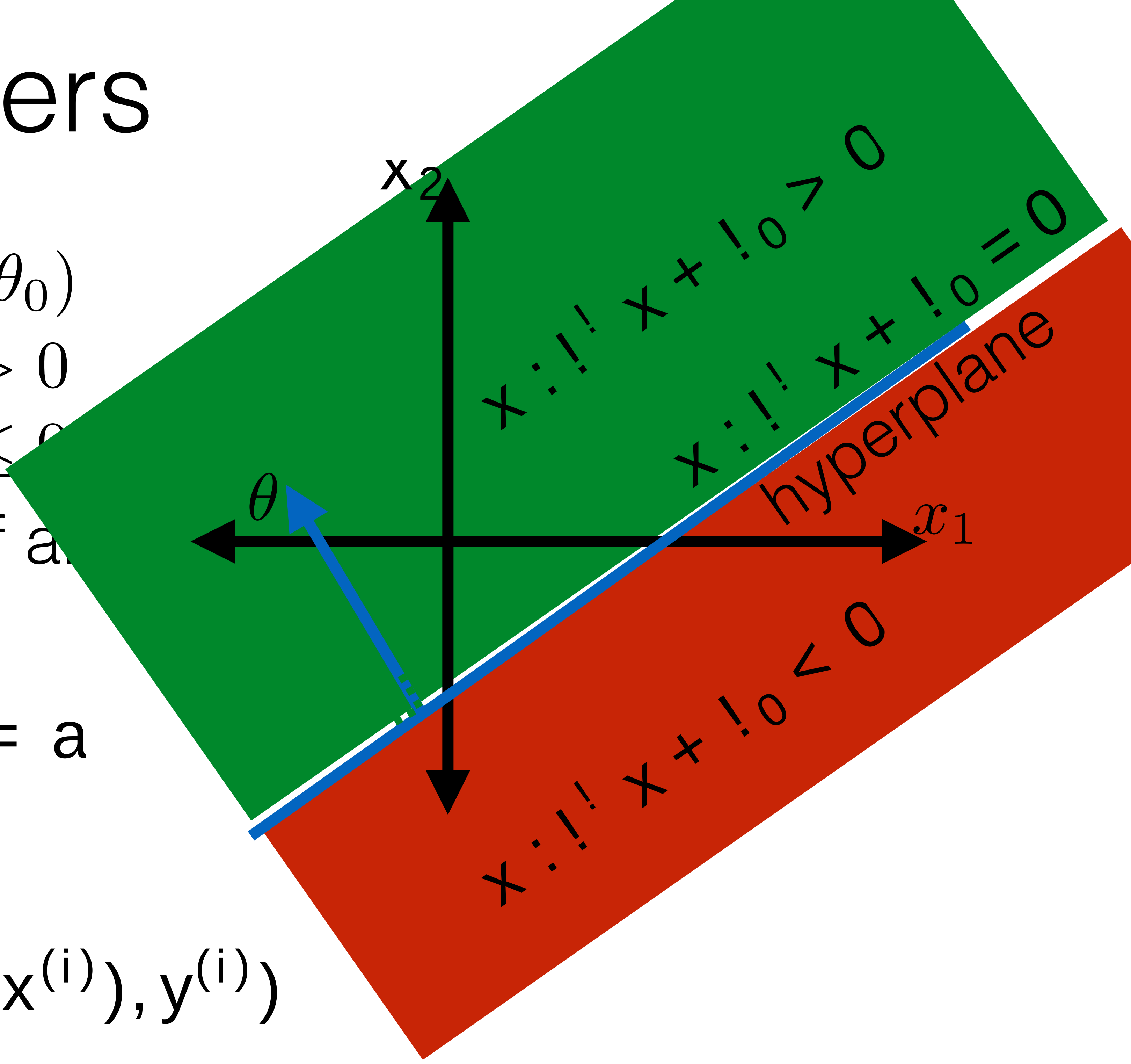

[demo]

Perceptron Algorithm

Perceptron Algorithm

```
Perceptron
```

Perceptron Algorithm

```
Perceptron( $\mathcal{D}_n$ ; ! )
```

Perceptron Algorithm

```
Perceptron( $\mathcal{D}_n$ ; ! )
    Initialize ! = [0  0  …  0]$^{!}$
    Initialize $!_0$ = 0
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Perceptron Algorithm

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Perceptron( $\mathcal{D}_n$ ; ! )
  Initialize  ! = [0  0  …  0]$^!$        [How many 0s?]
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  **for** t = 1 to !
```

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```

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[How many 0s?]

[i.e. True if either:

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```

[How many 0s?]

[i.e. True if either:

A. point is not on the line & prediction is wrong

Perceptron Algorithm

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```

[How many 0s?]

[i.e. True if either:

A. point is not on the line & prediction is wrong
B. point is on the line

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      if $y^{(i)}(!^! x^{(i)} + !_0) !\ 0$
        Set $! = ! + y^{(i)}x^{(i)}$
        Set $!_0 = !_0 + y^{(i)}$
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        changed = True
    if not changed
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  Return $!, !_0$
```

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Let’s Talk About Classifier Quality

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- *Definition*: A training set $\mathcal{D}_n$ is **linearly separable** if there exist $!, !_0$ such that, for every point index $i \; ! \; \{1, \ldots, n\}$, we have

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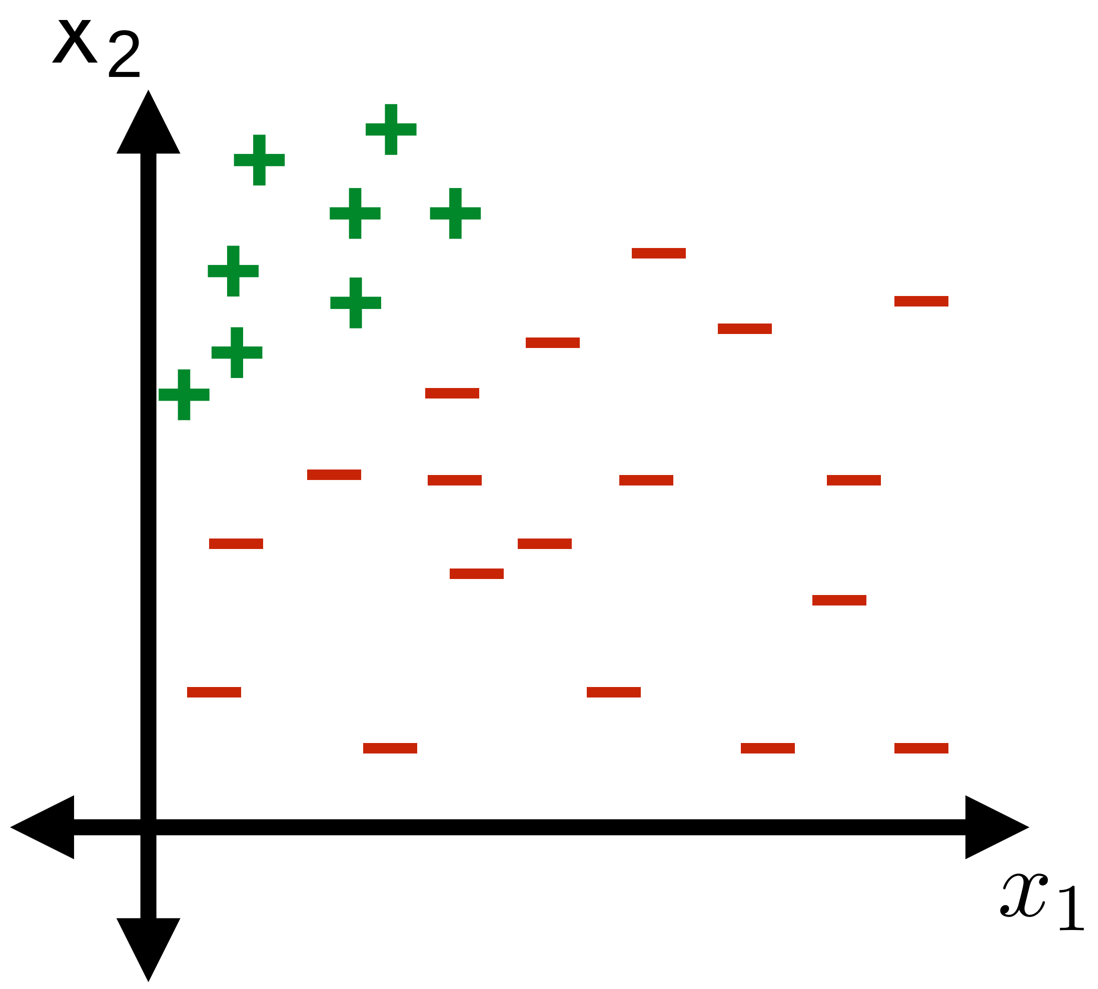

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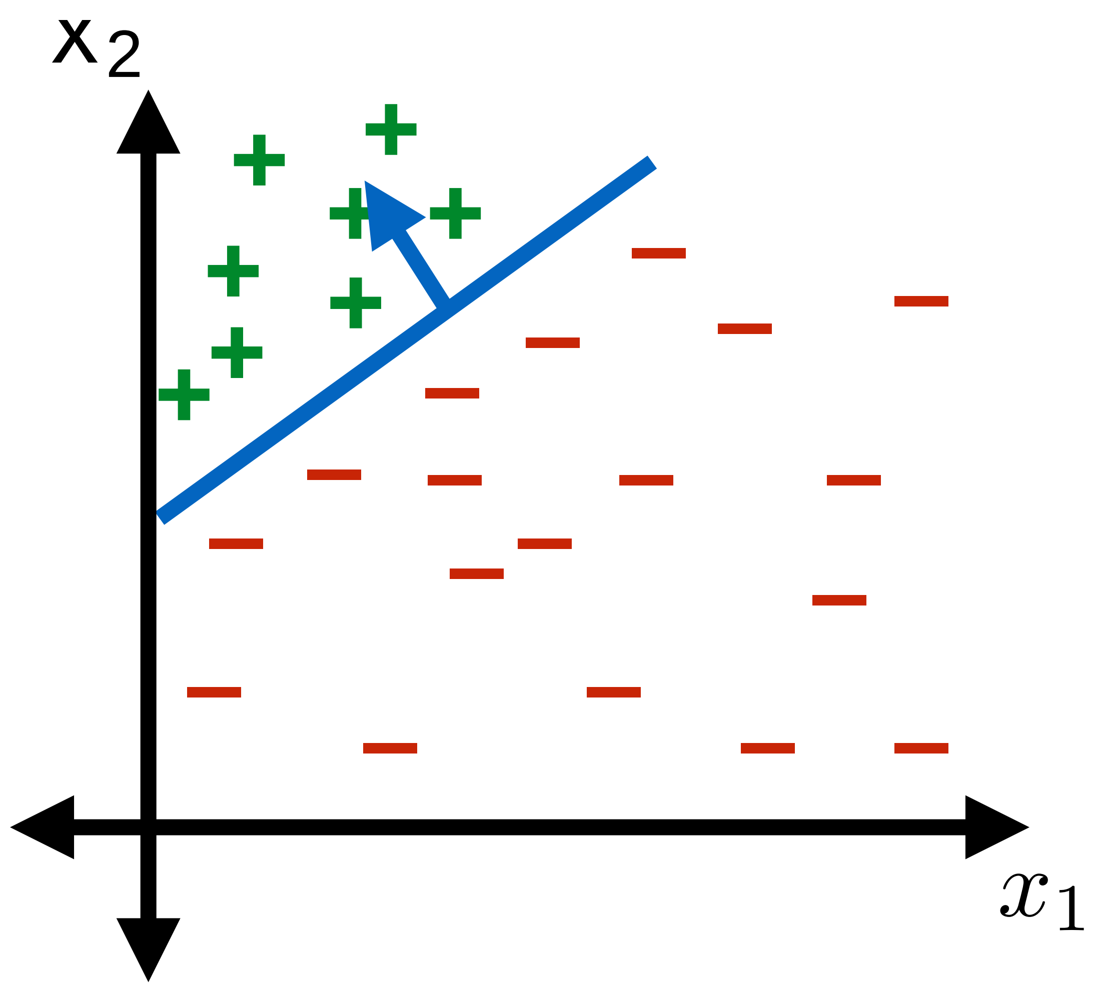

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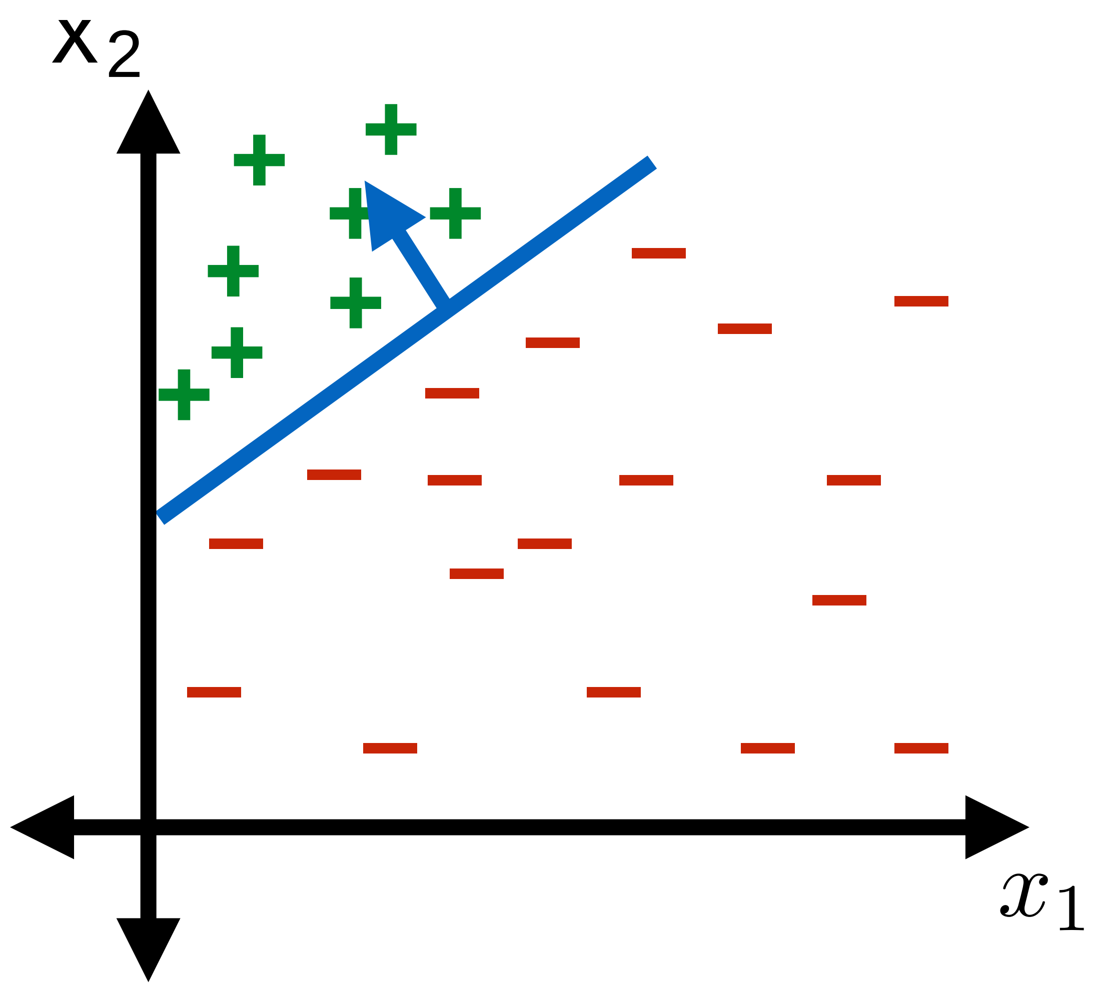

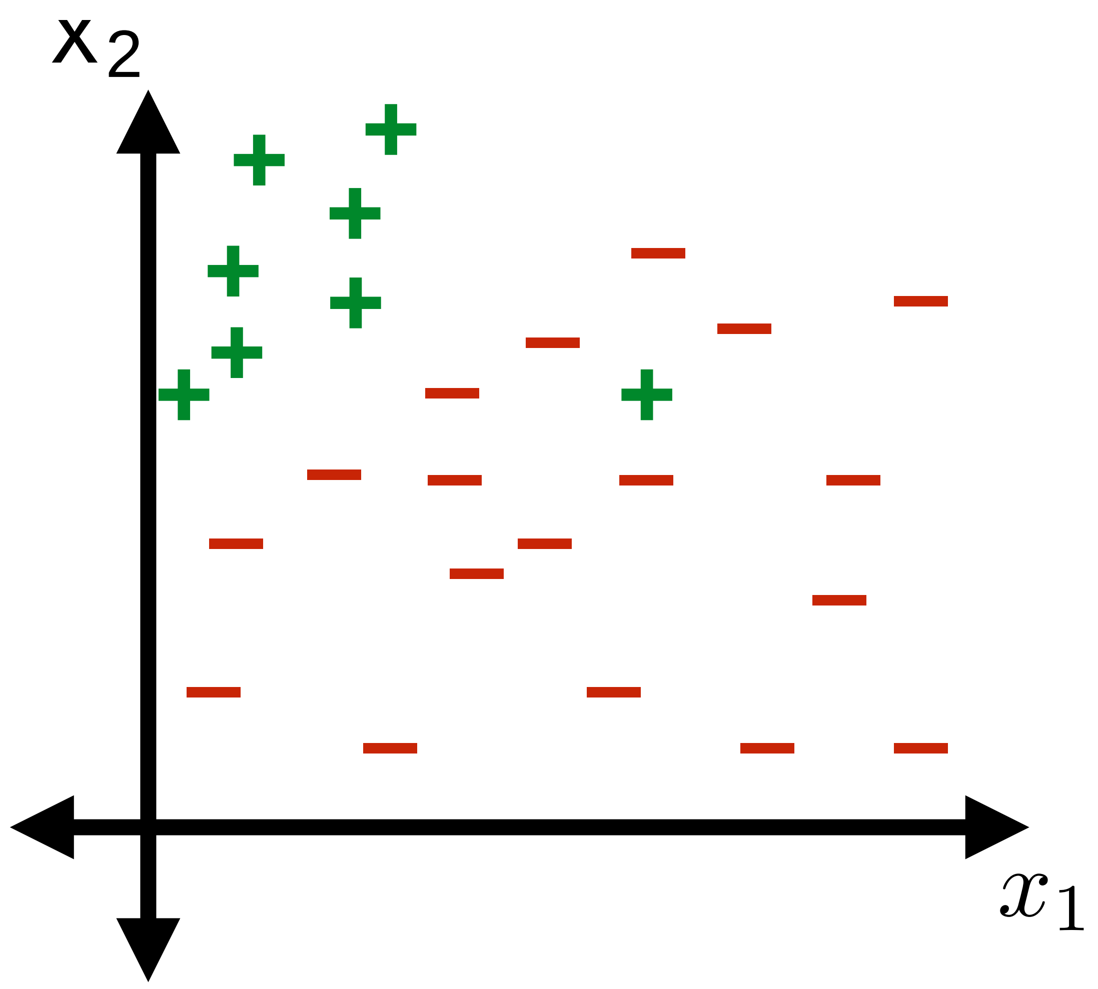

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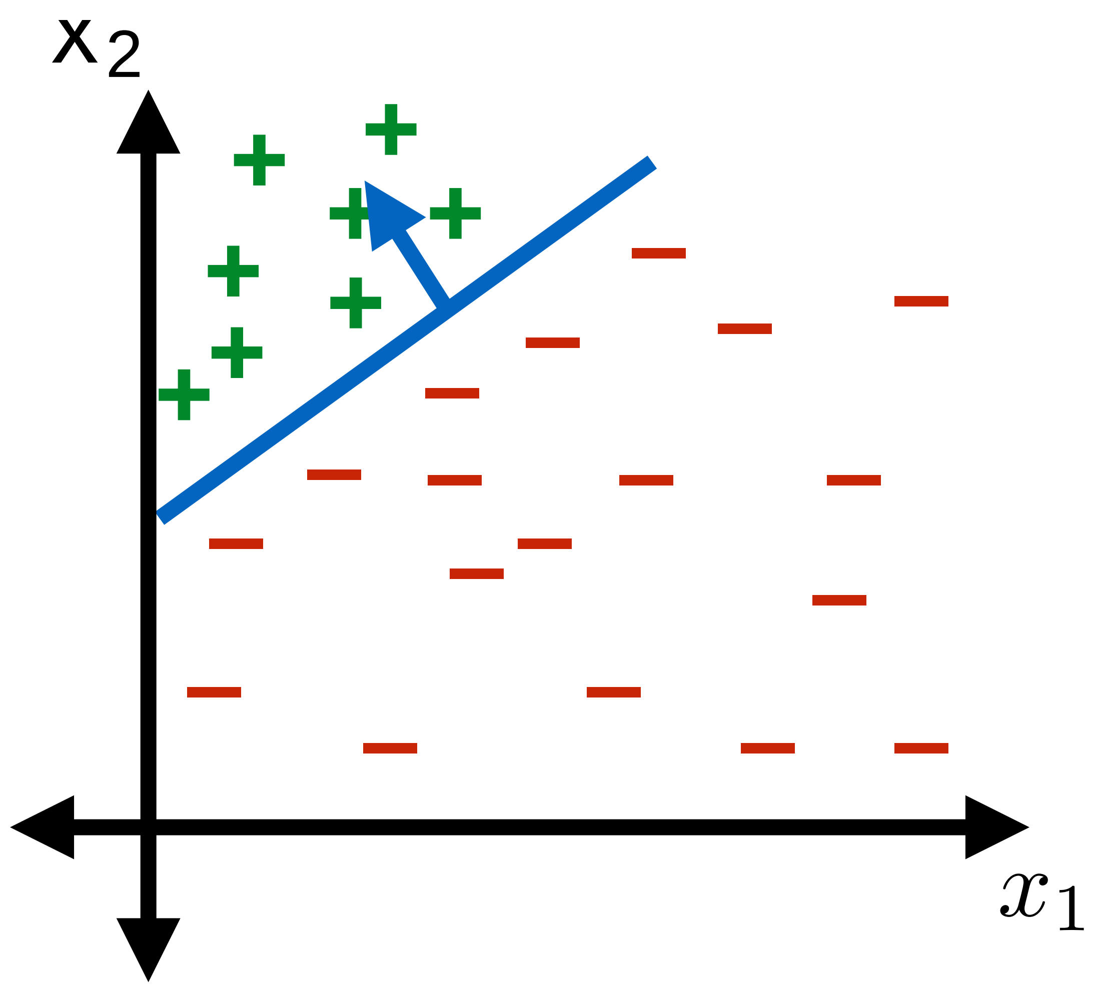

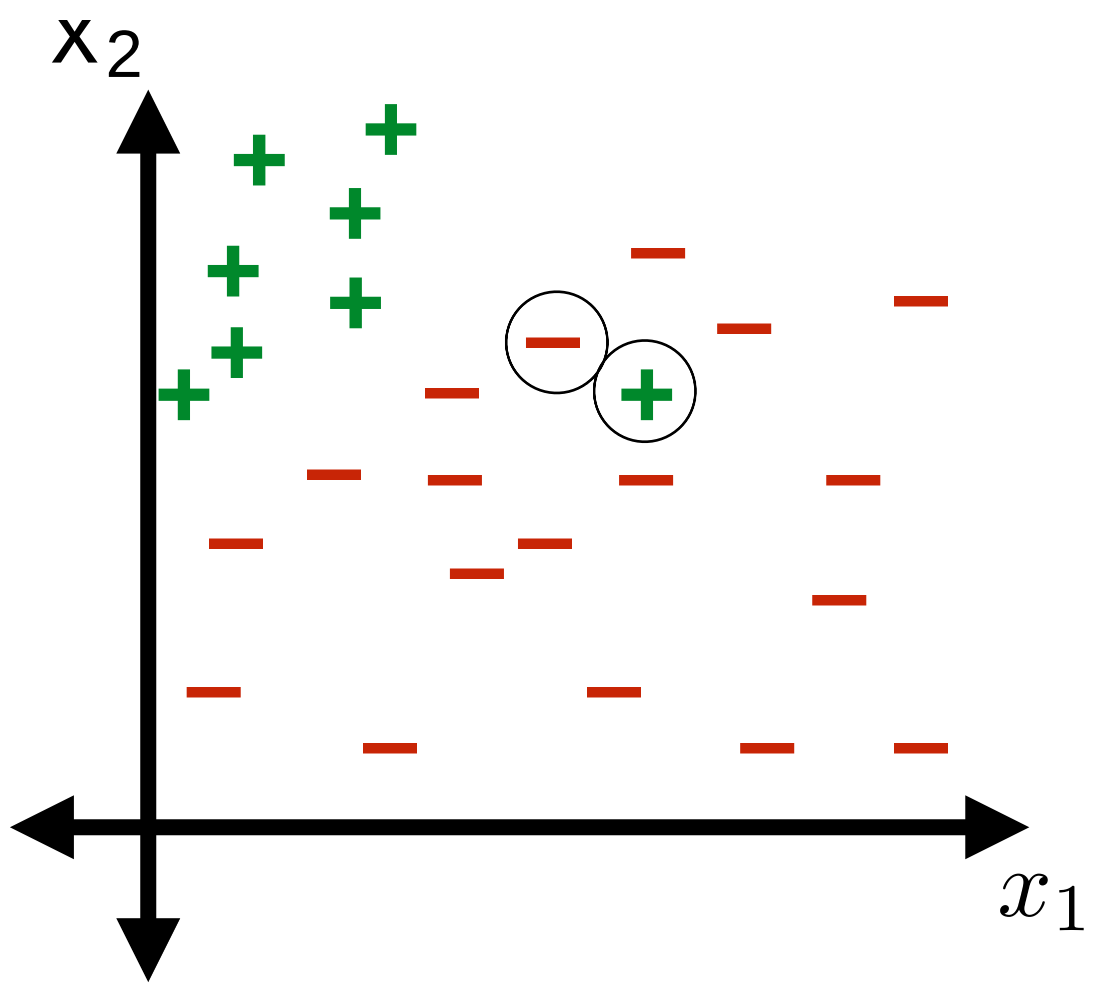

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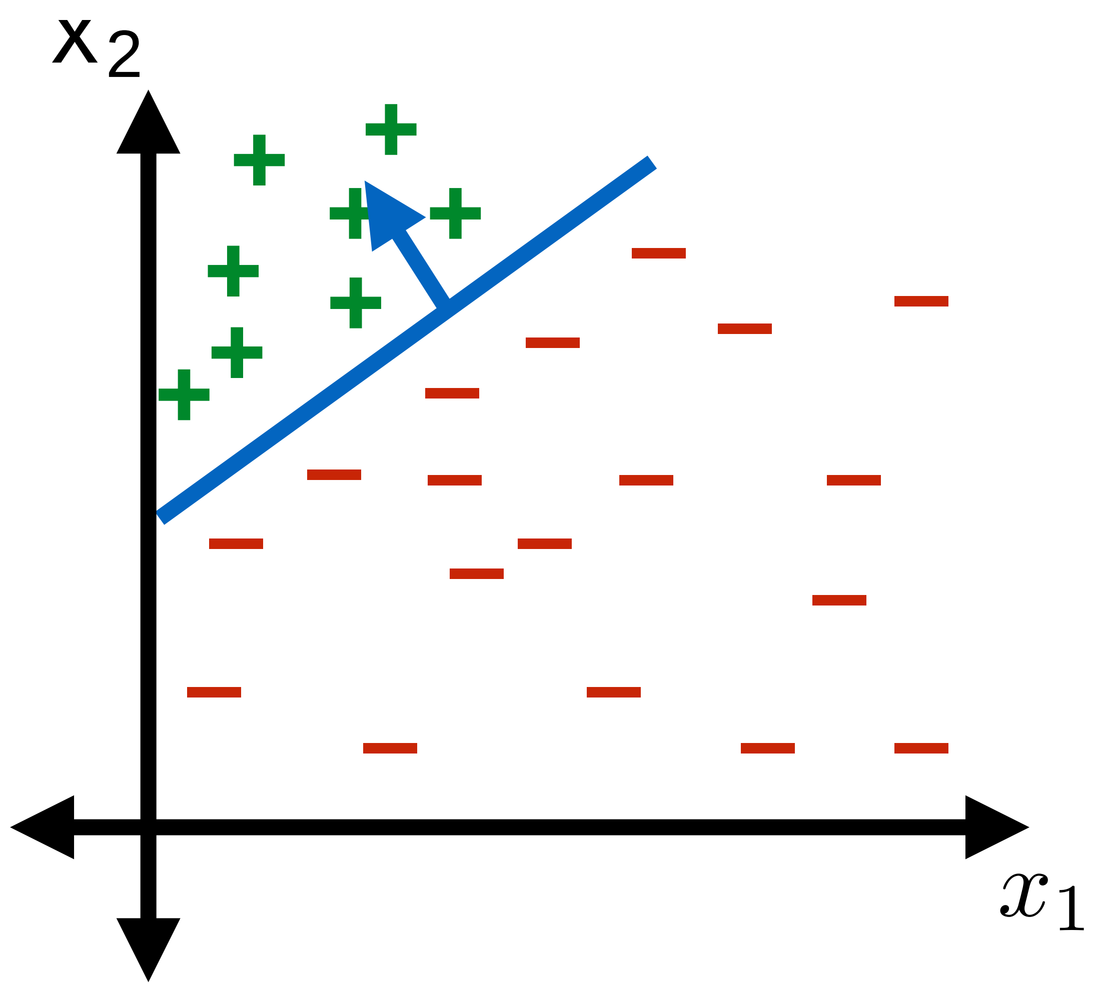

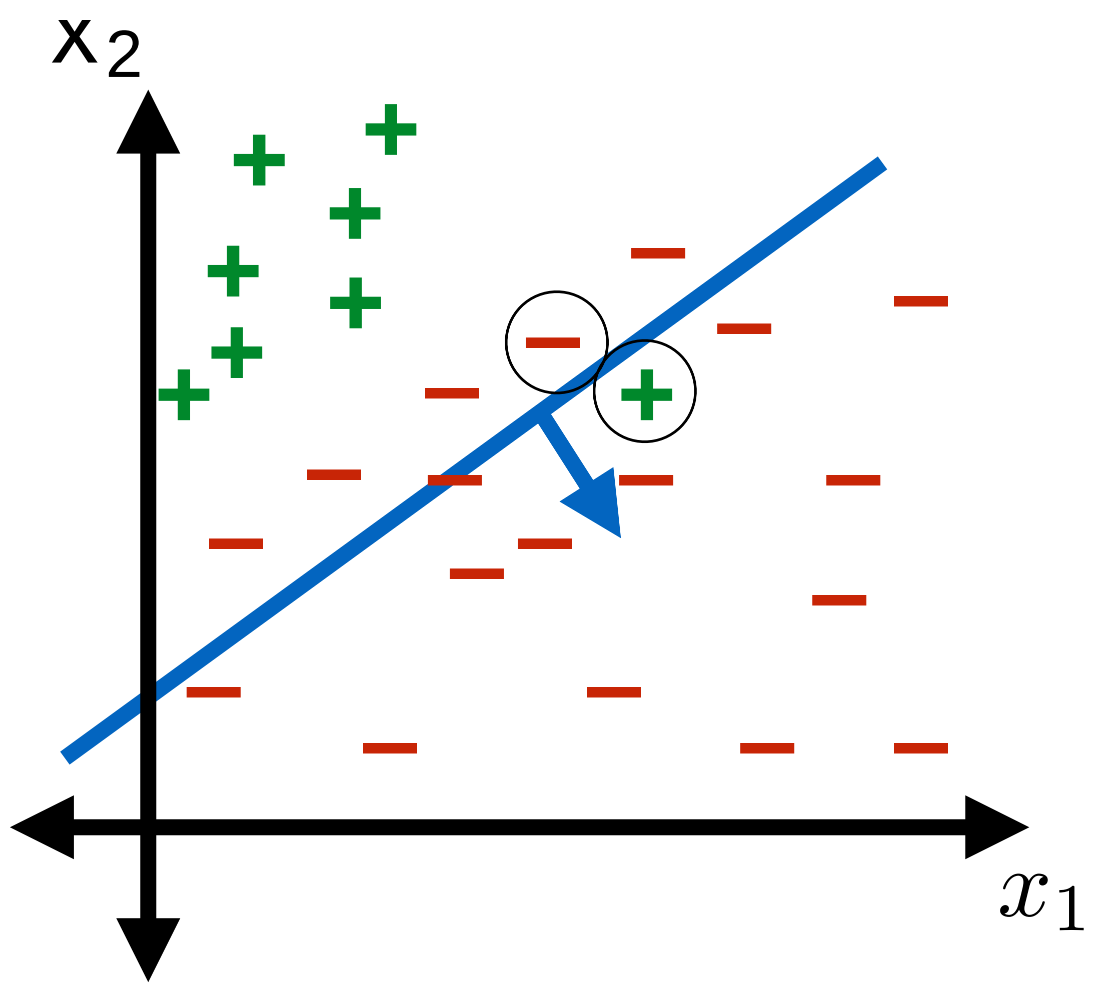

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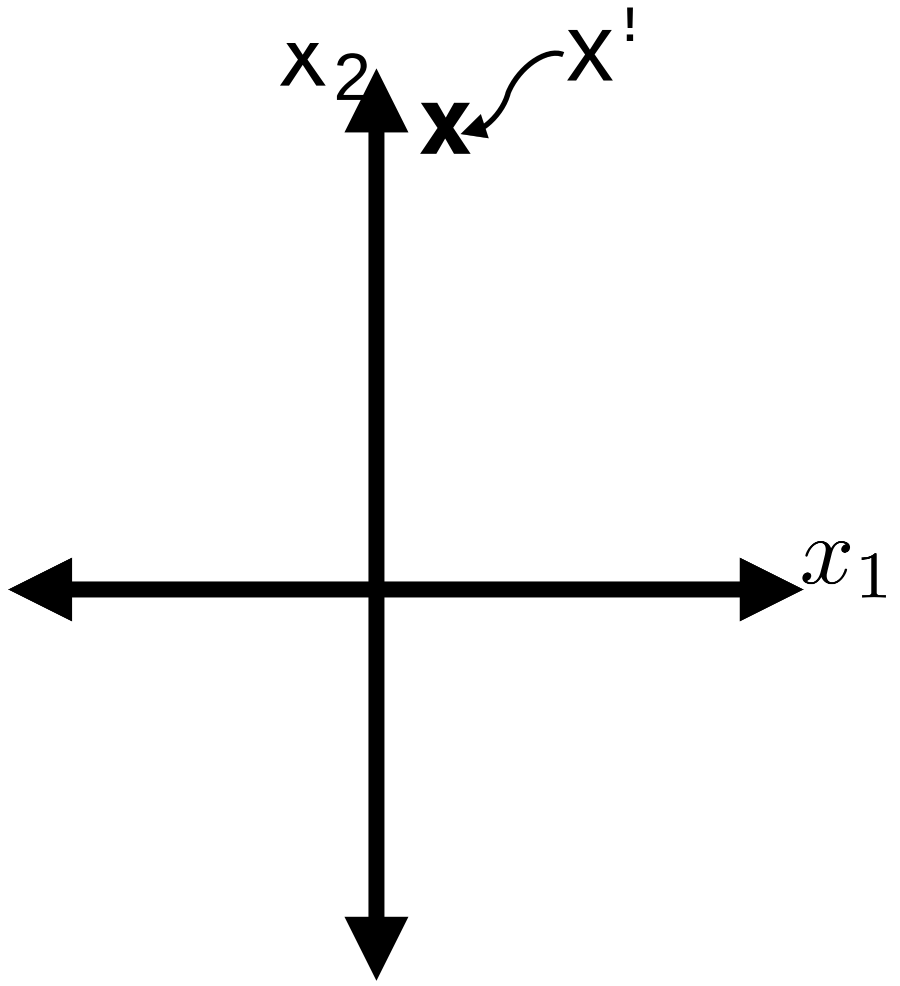

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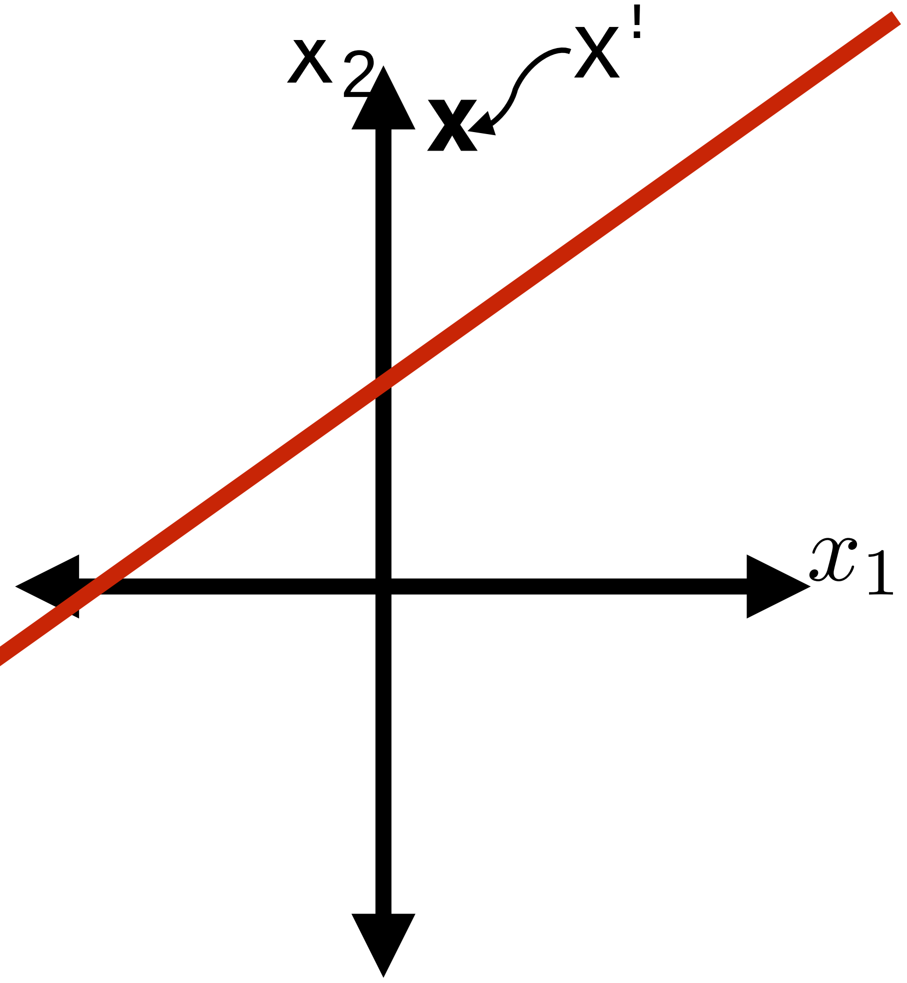

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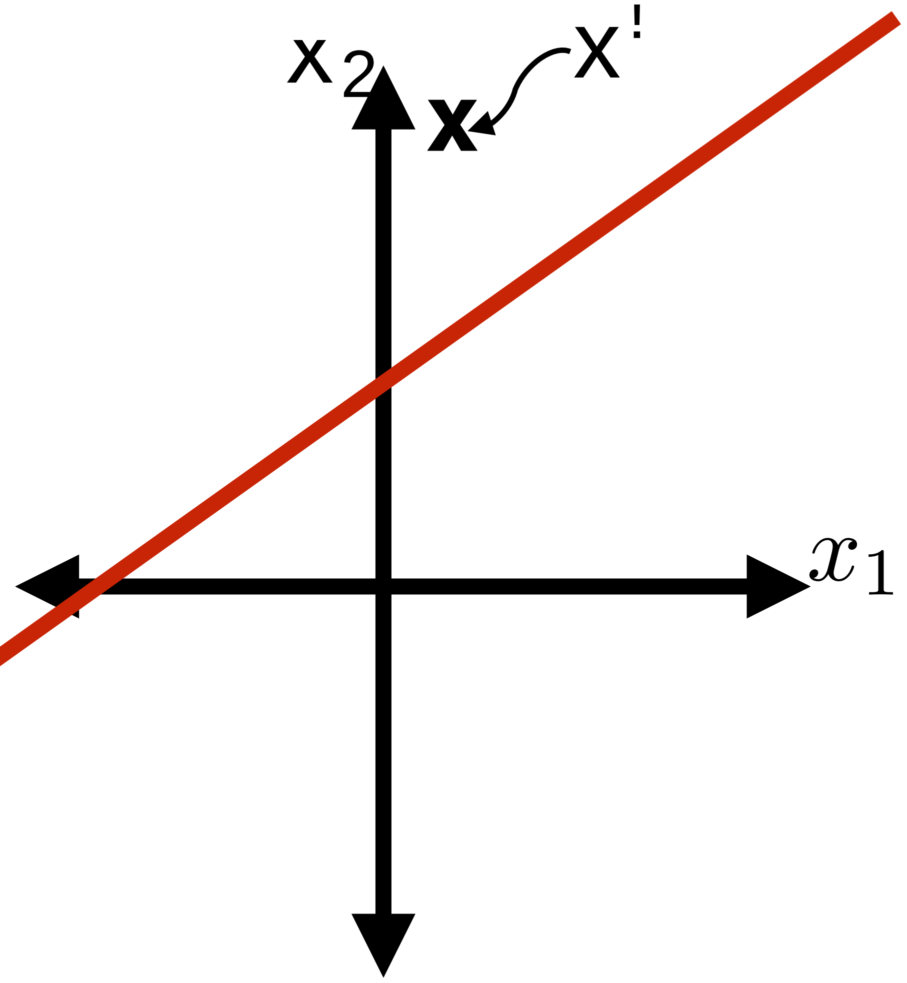

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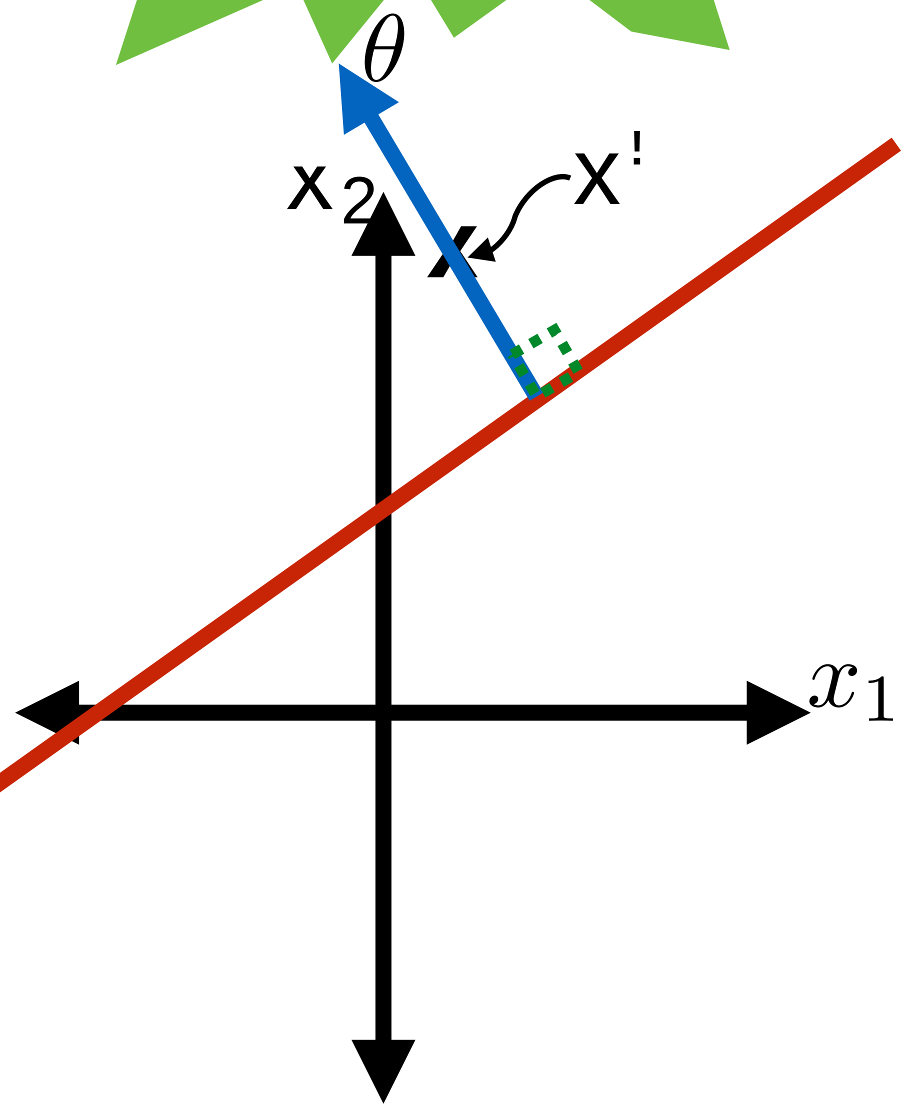

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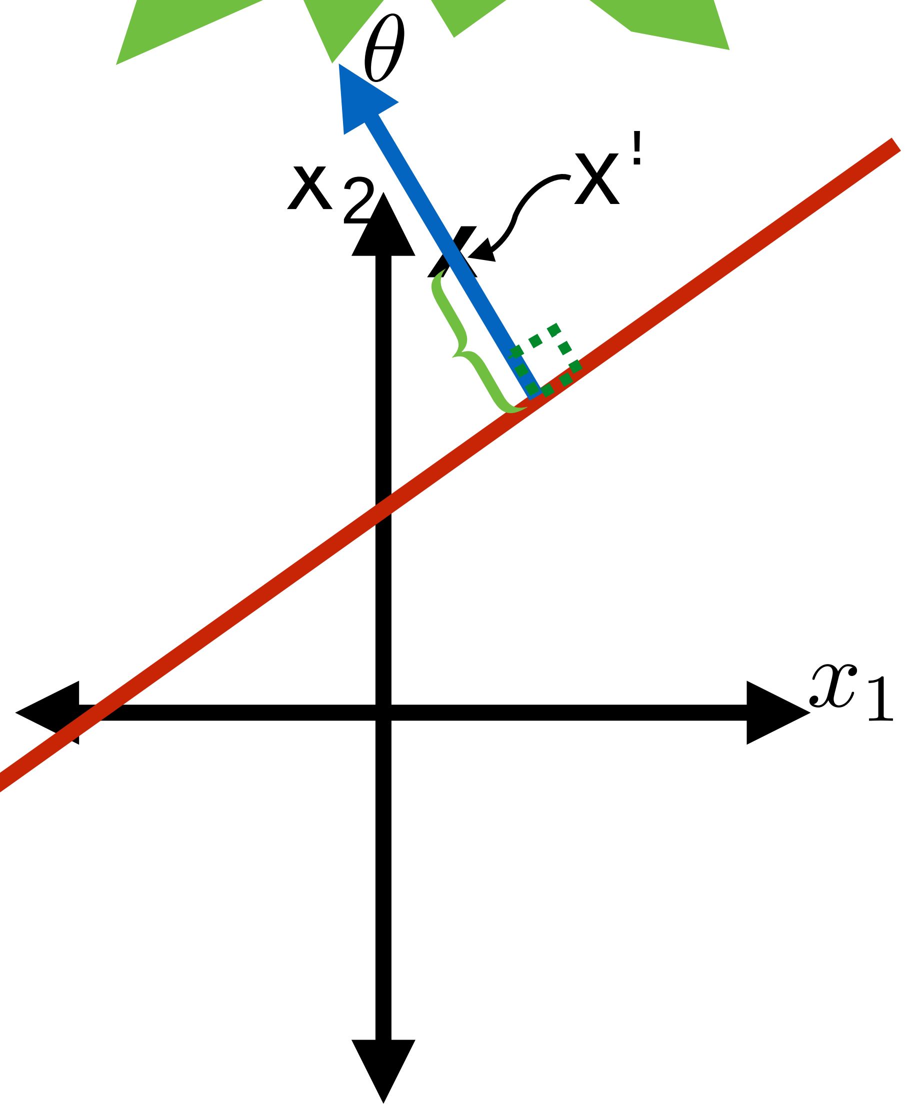

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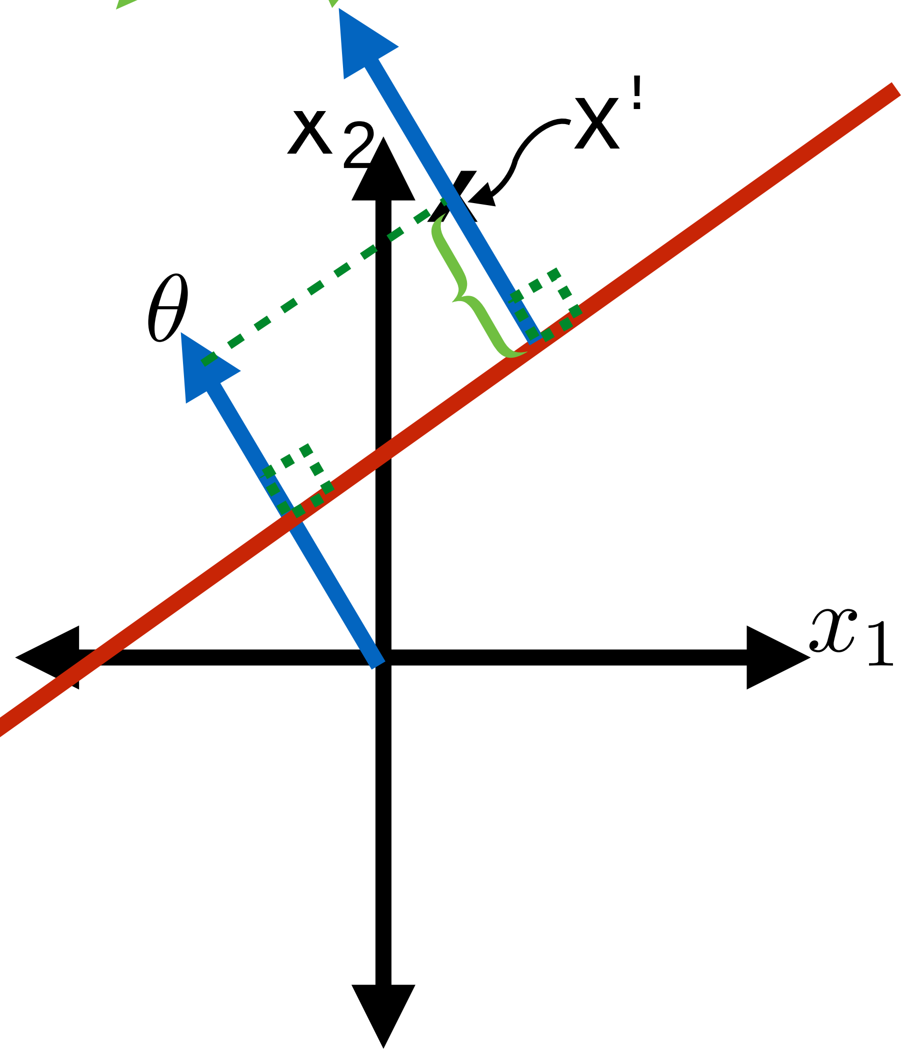

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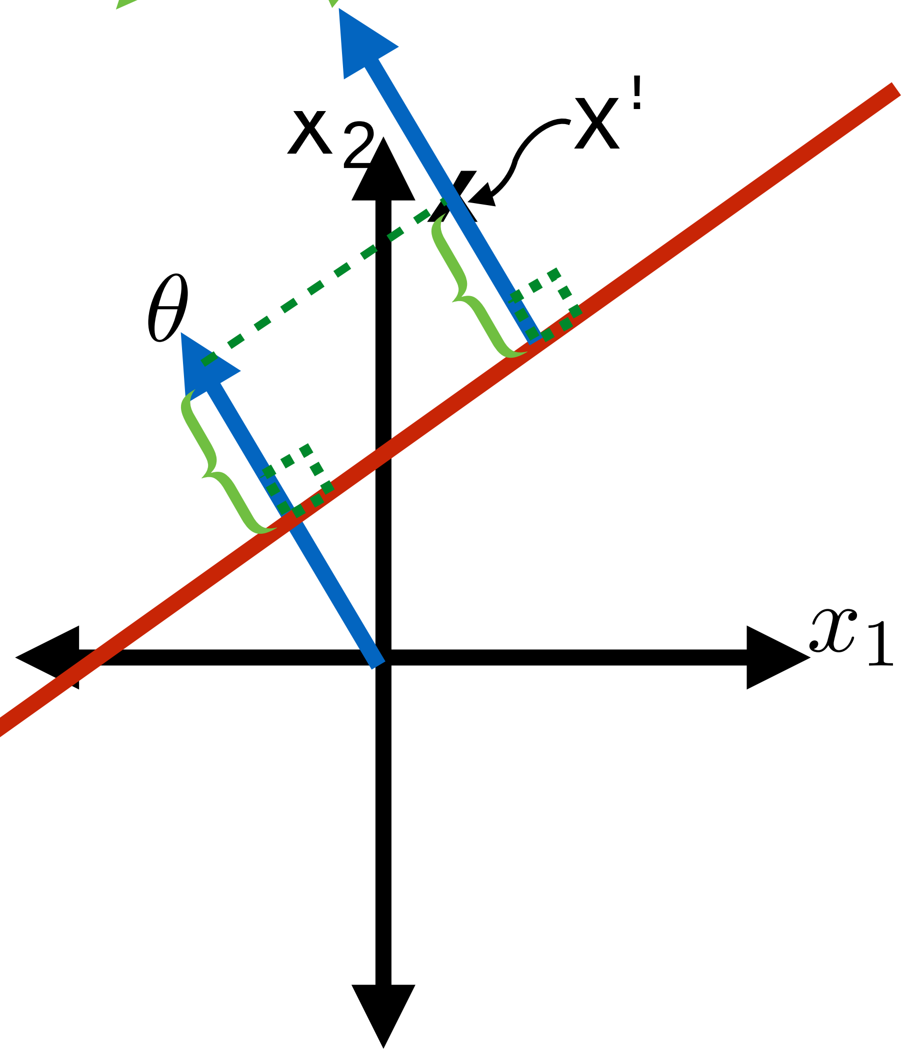

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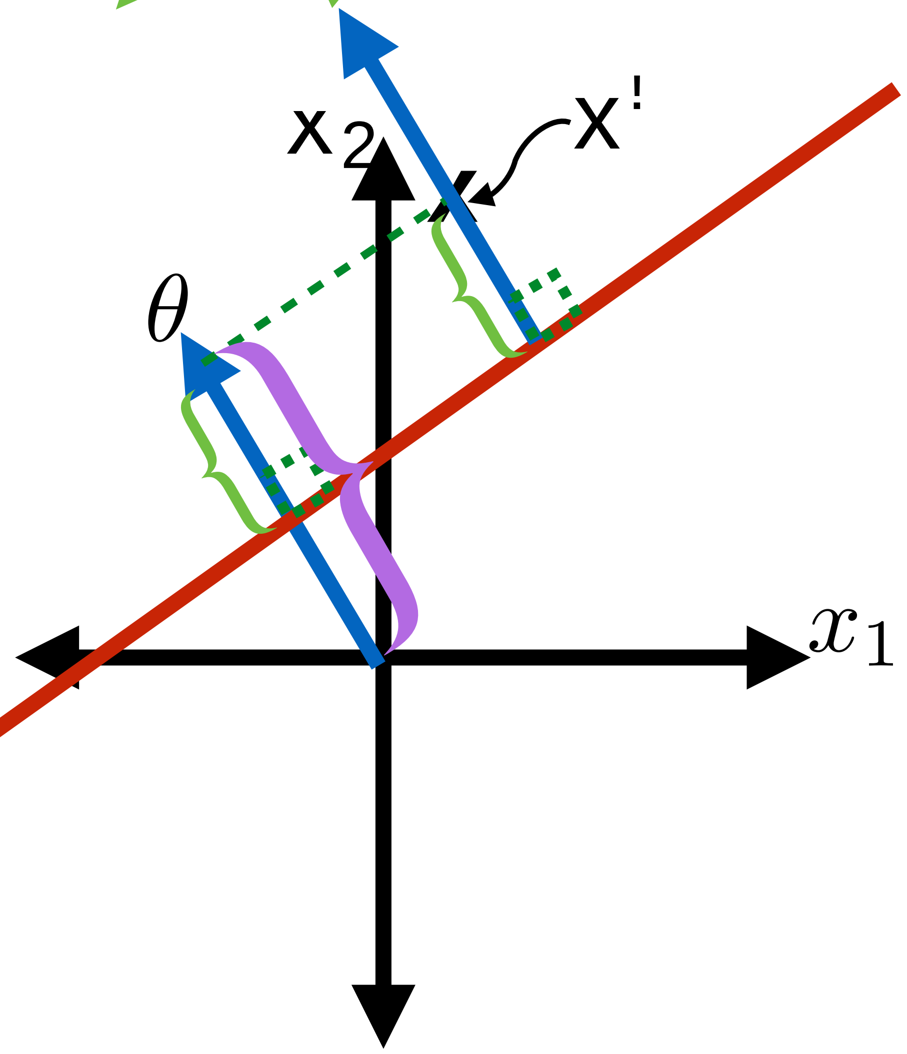

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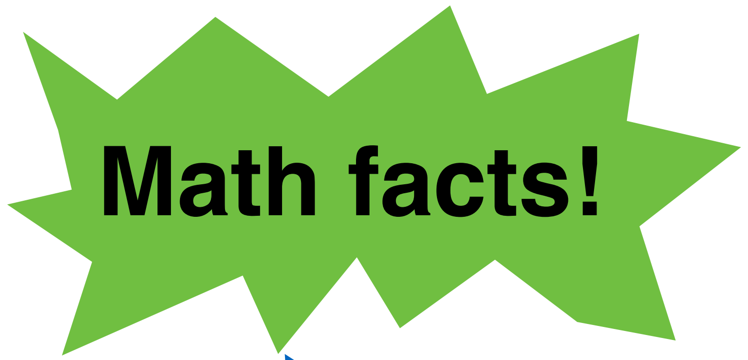

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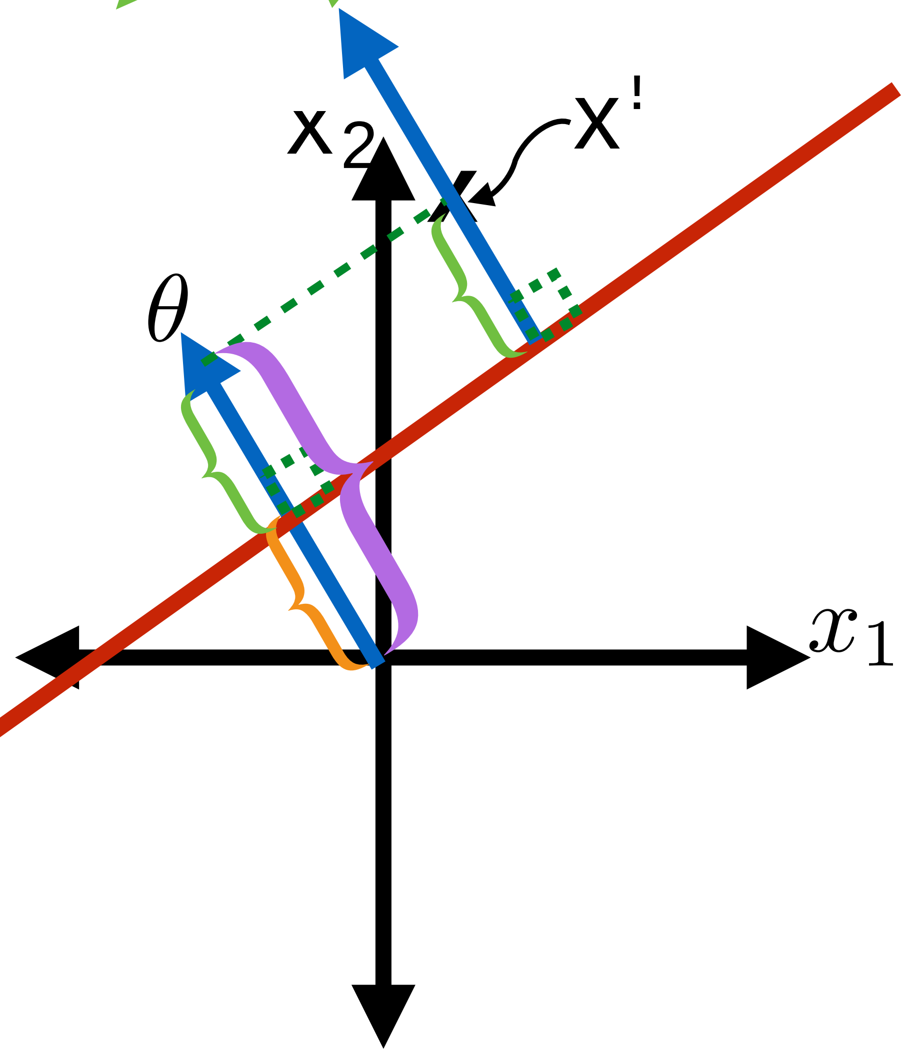

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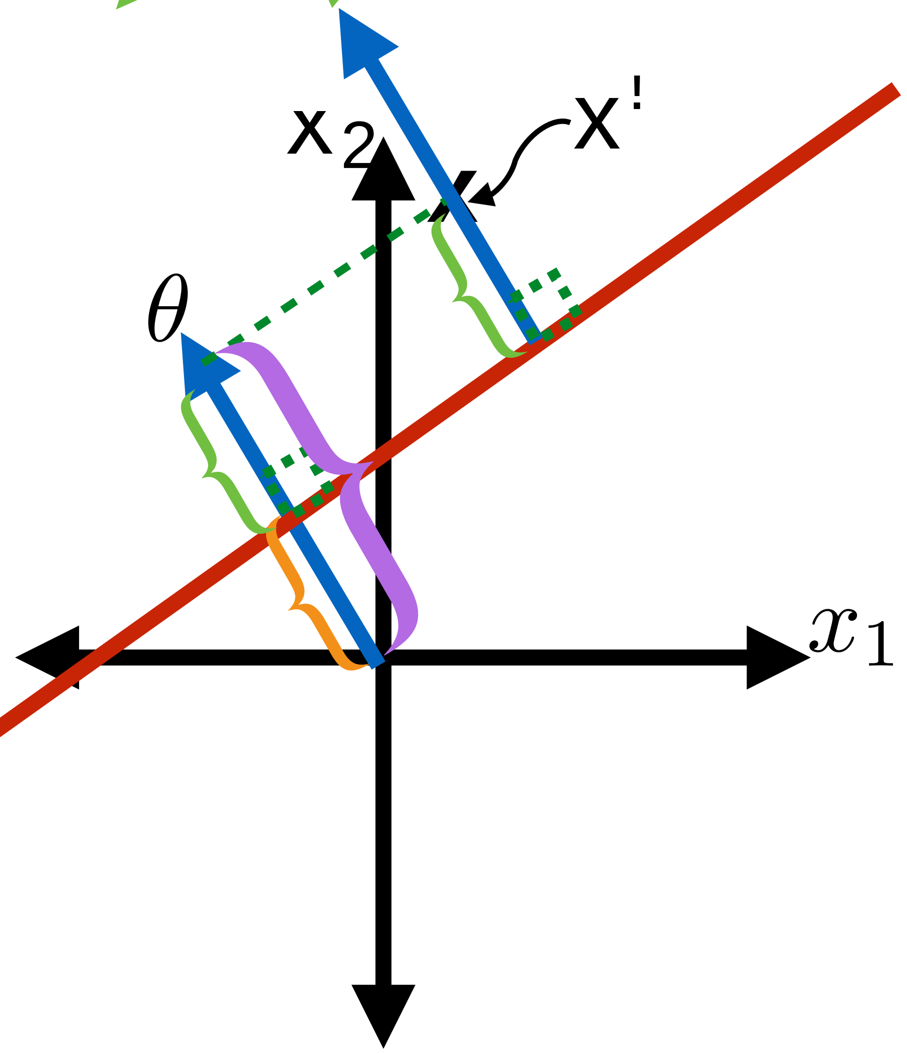

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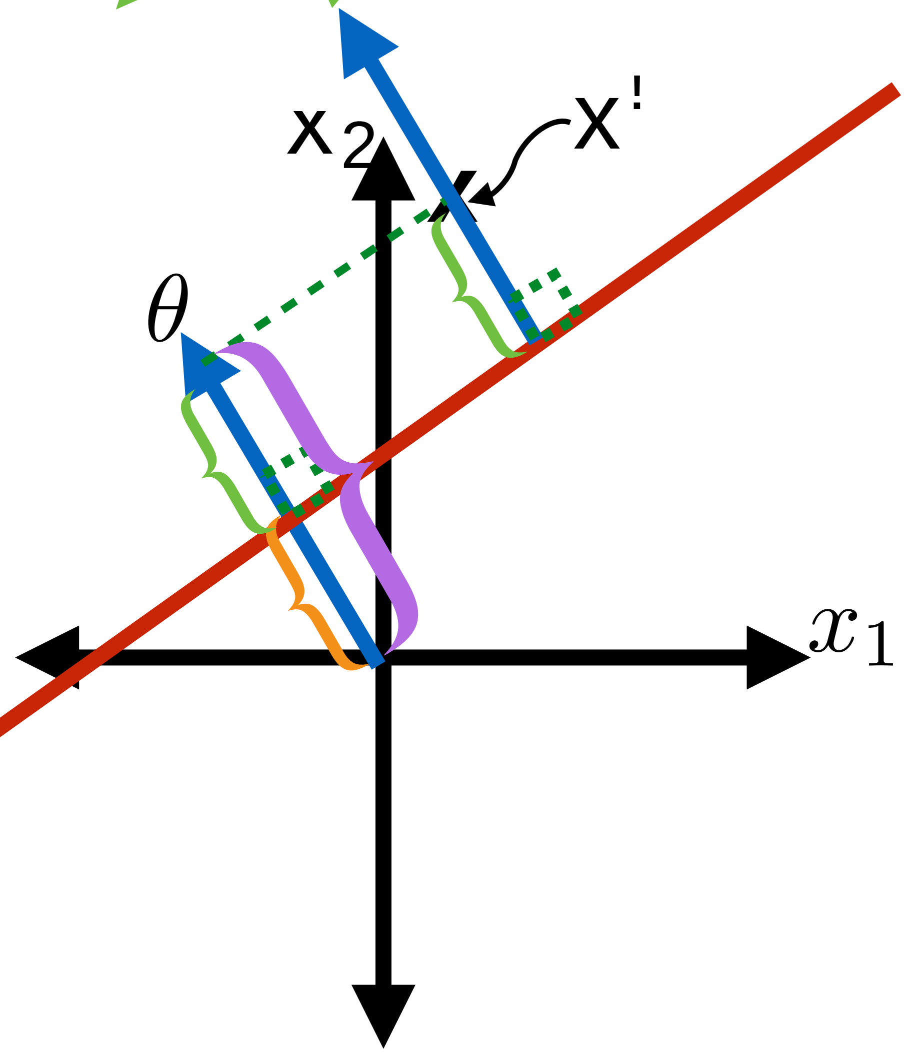

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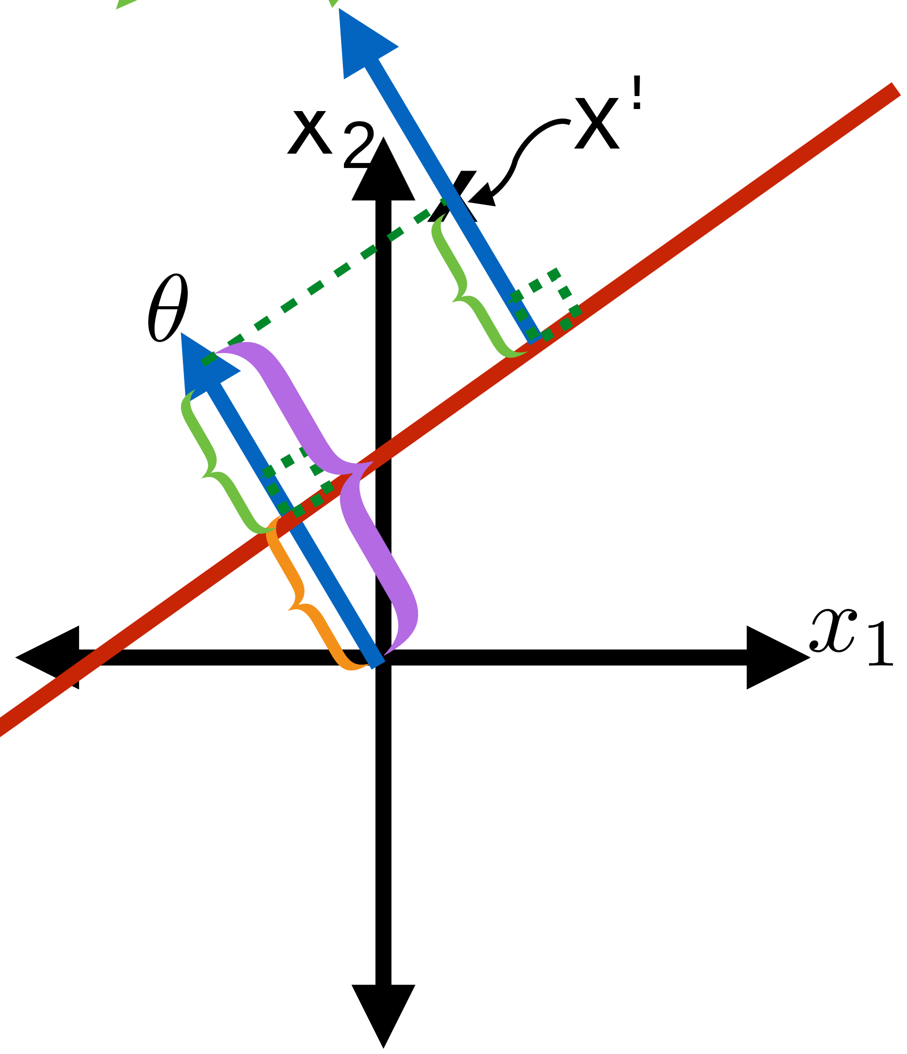

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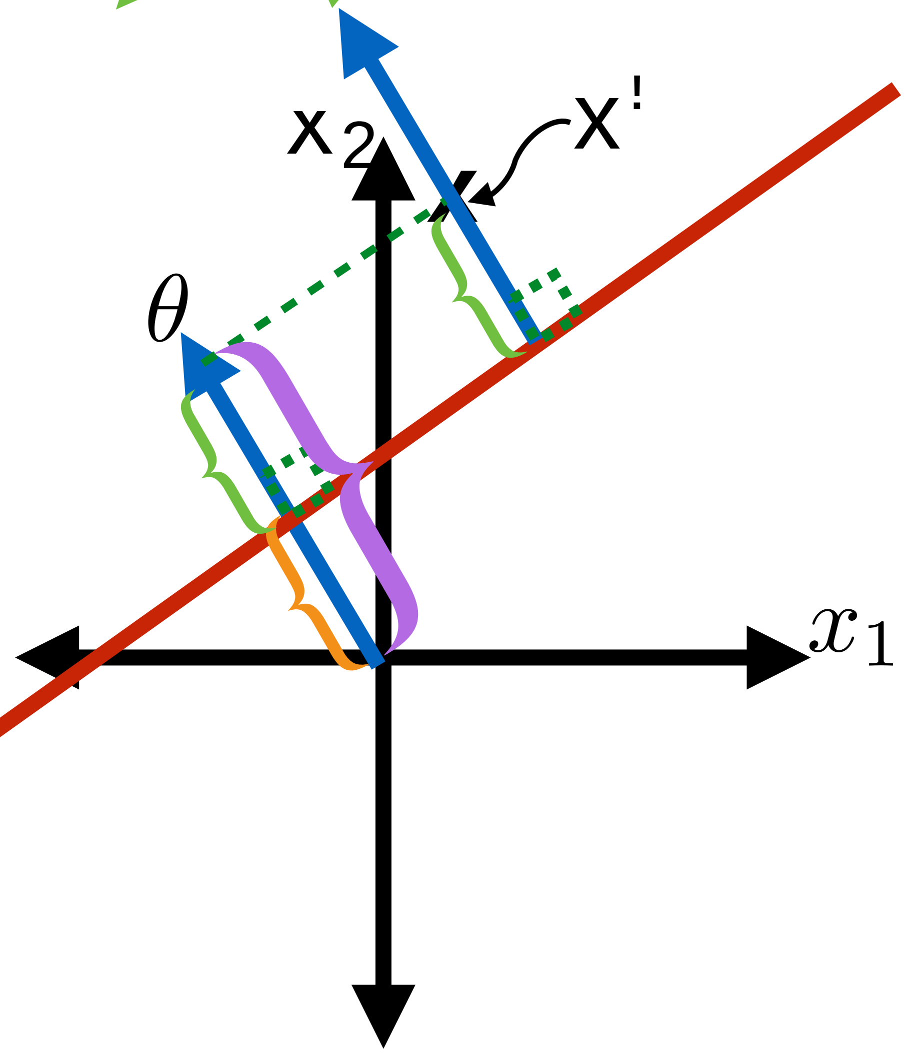

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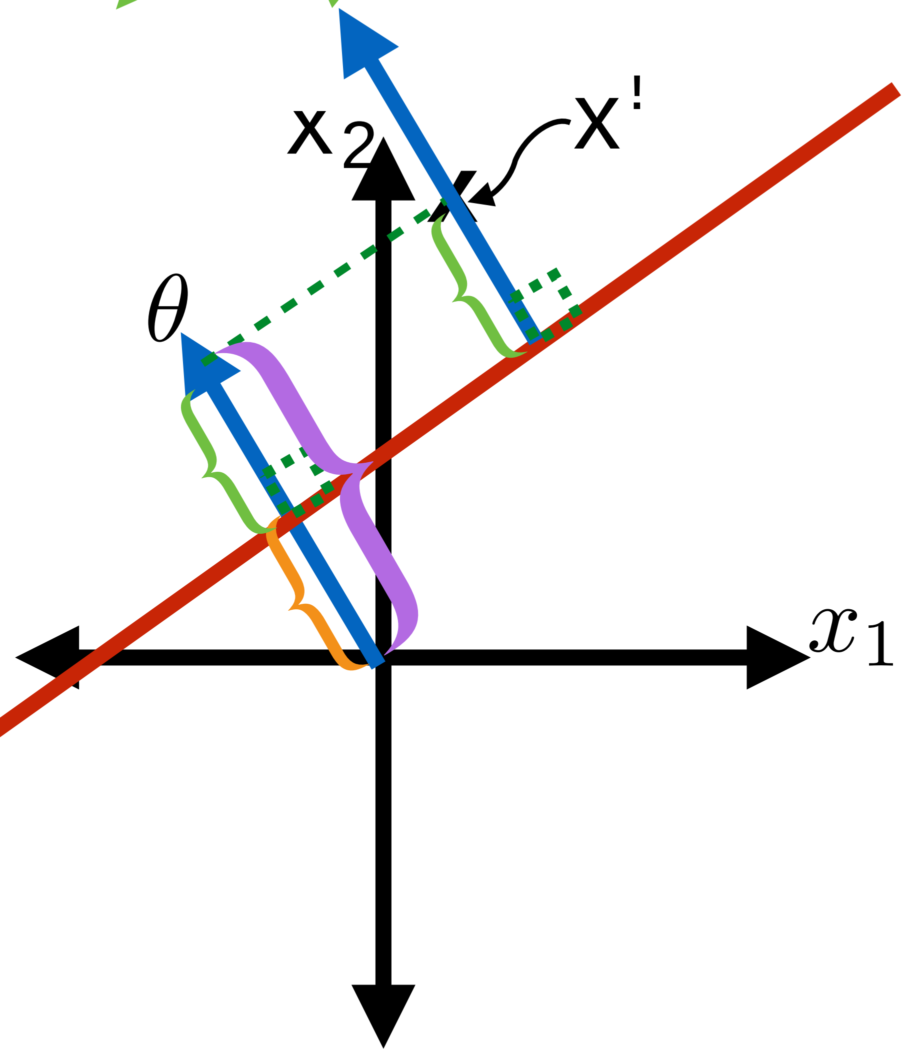

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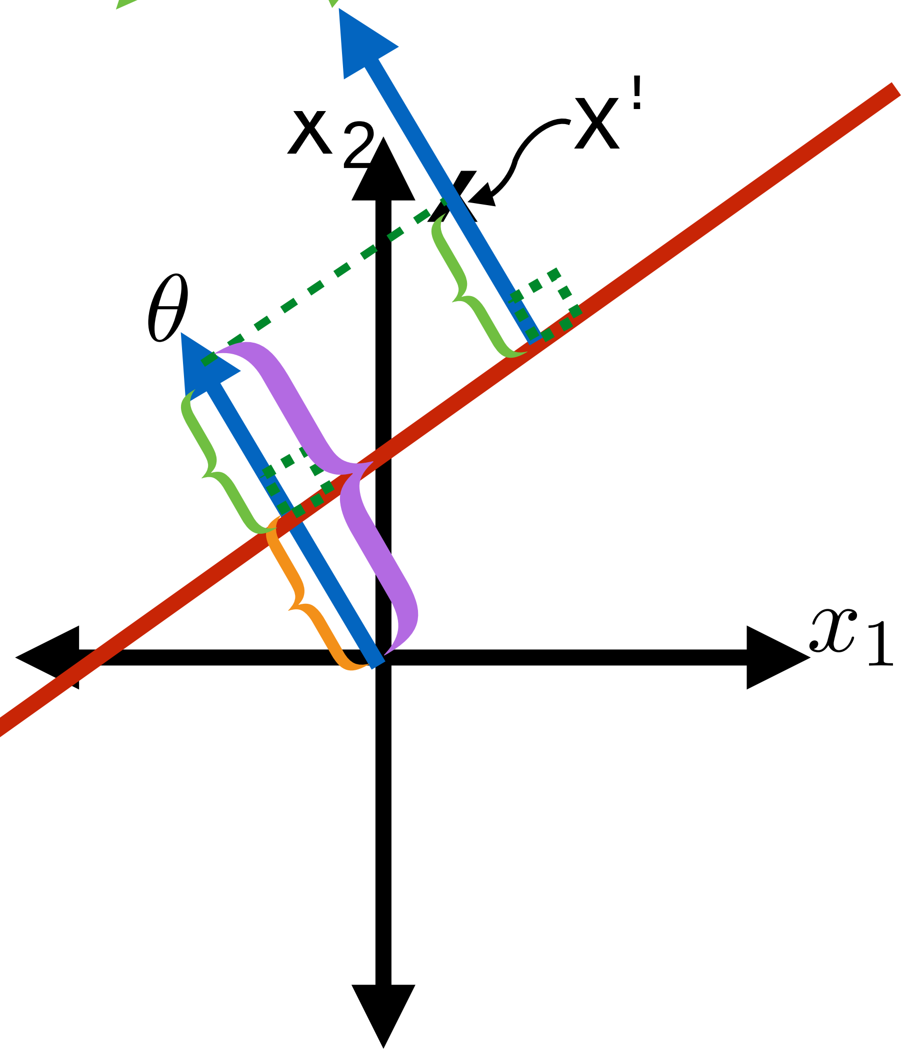

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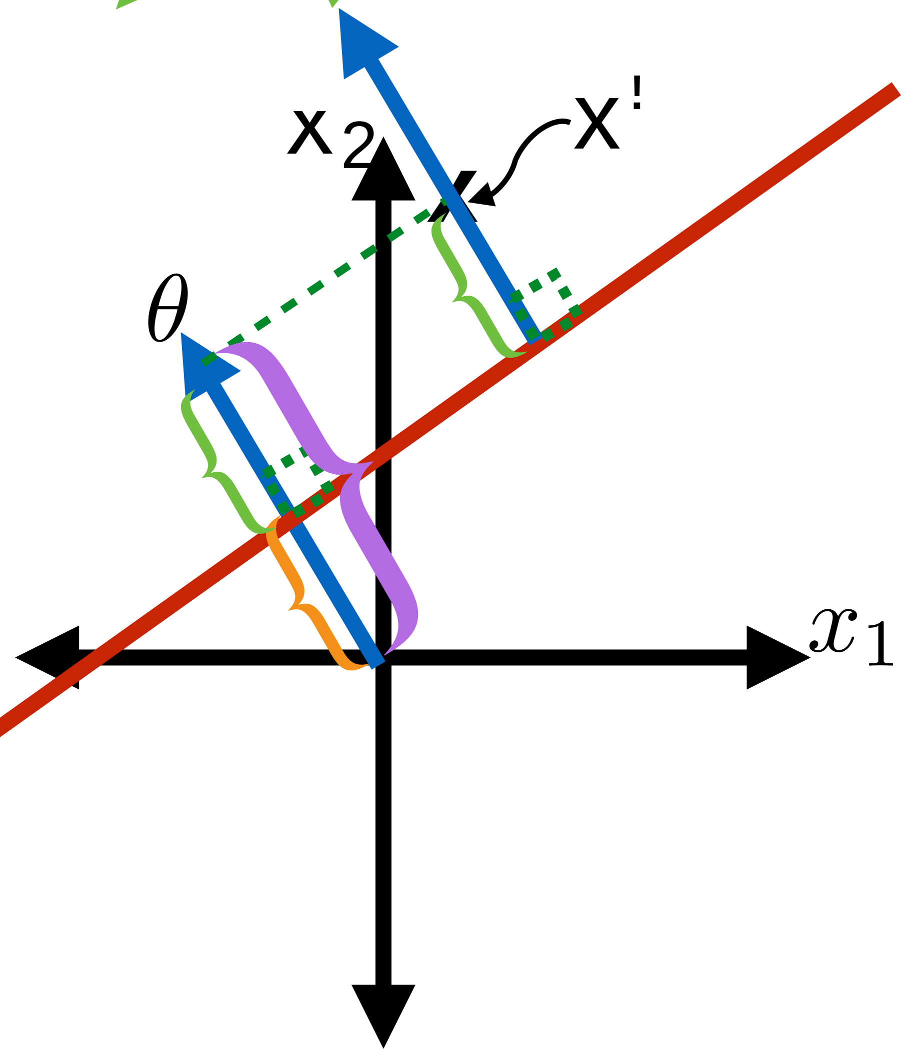

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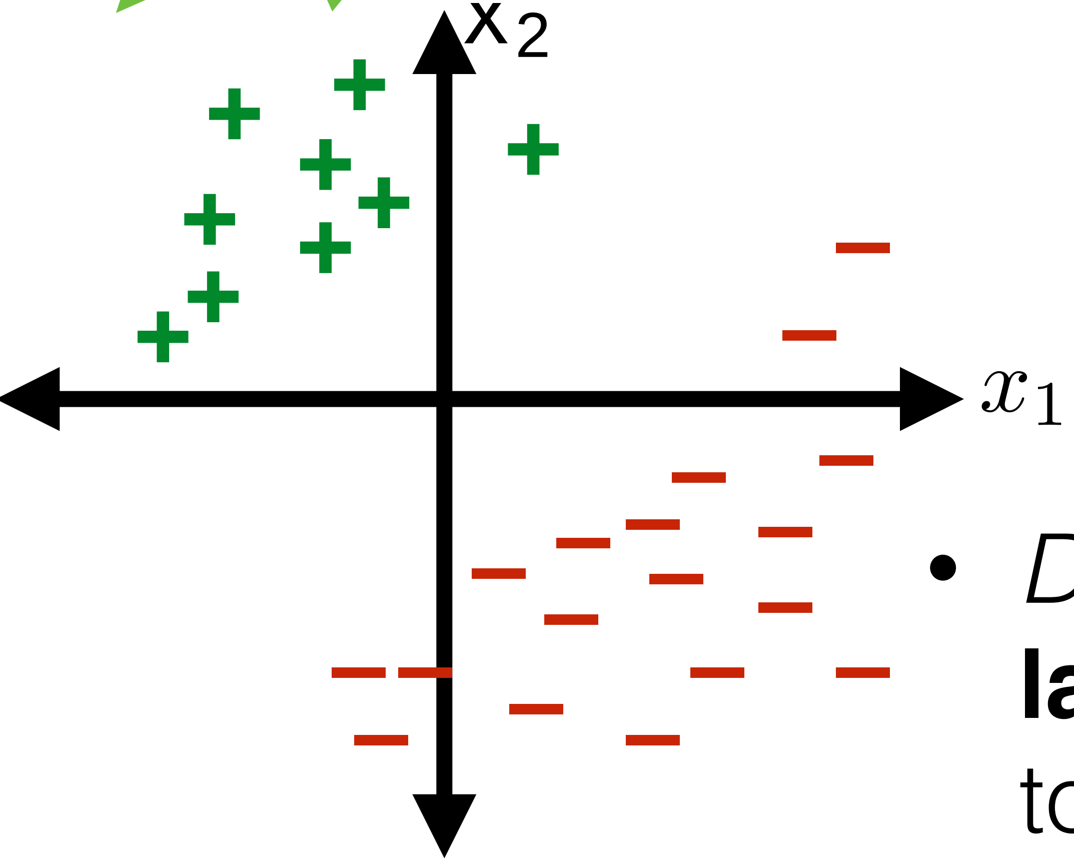

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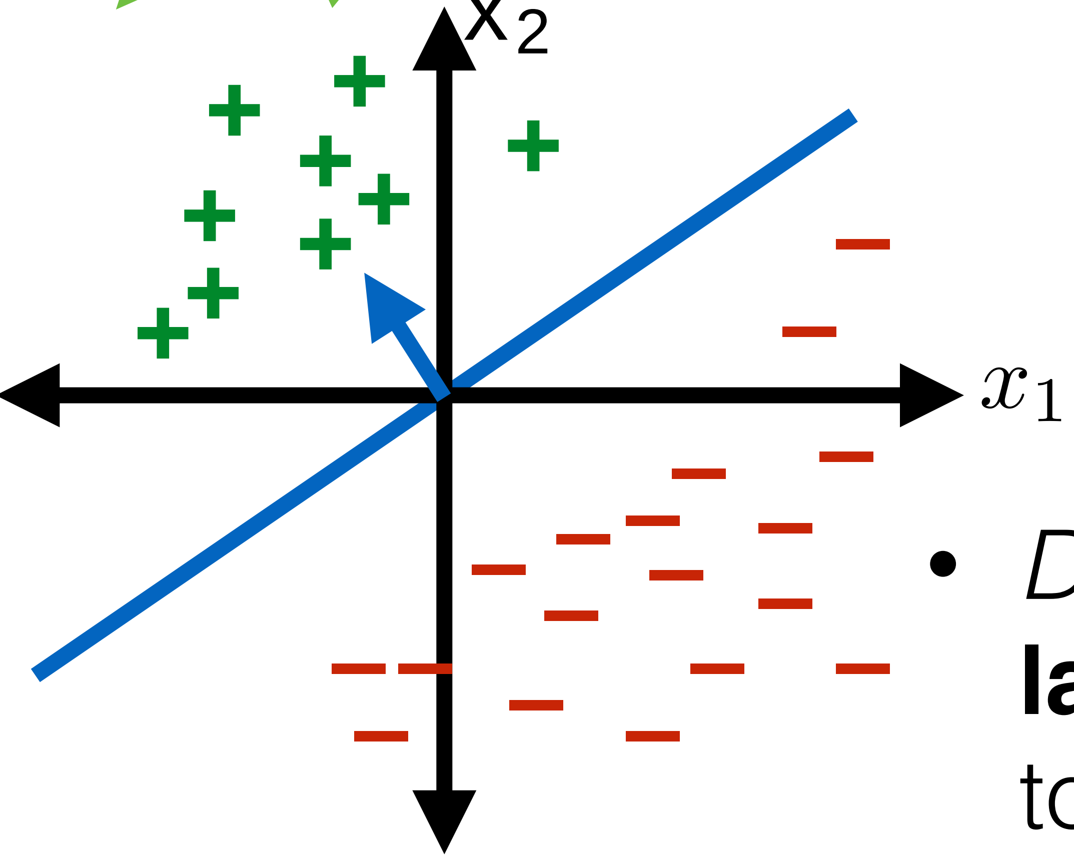

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5

Let's Talk About Classifier Quality

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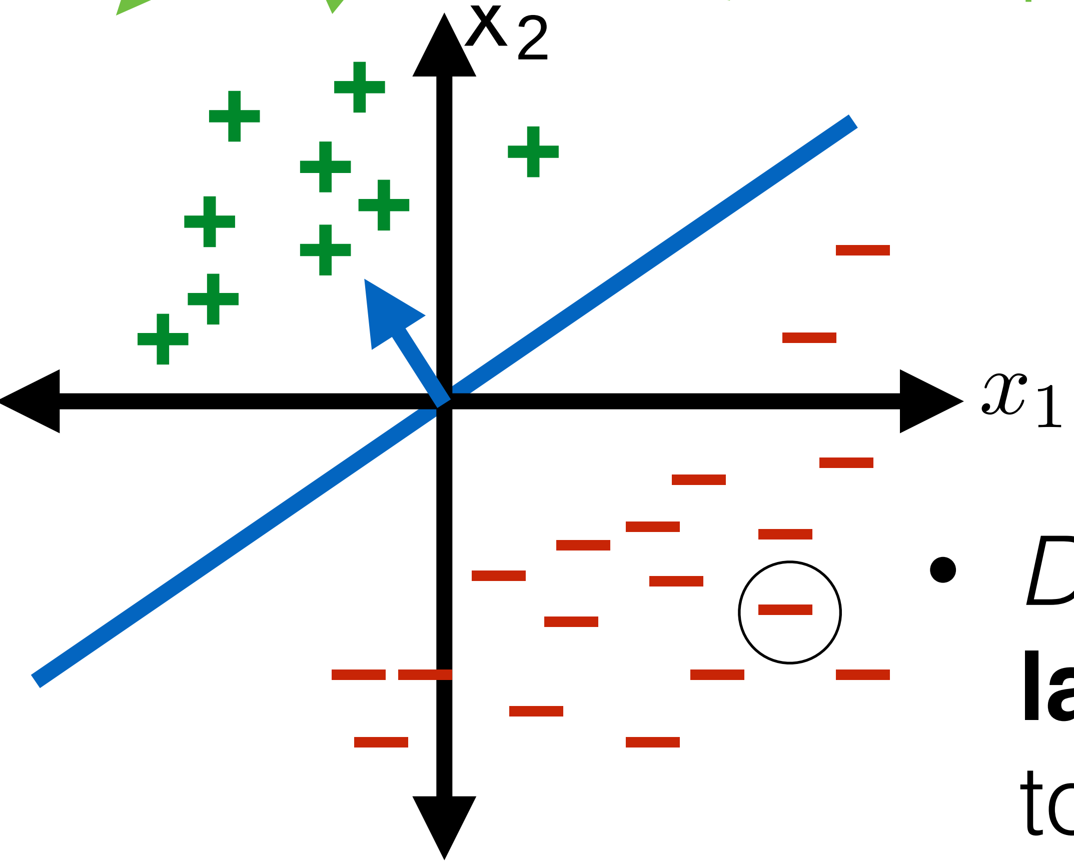

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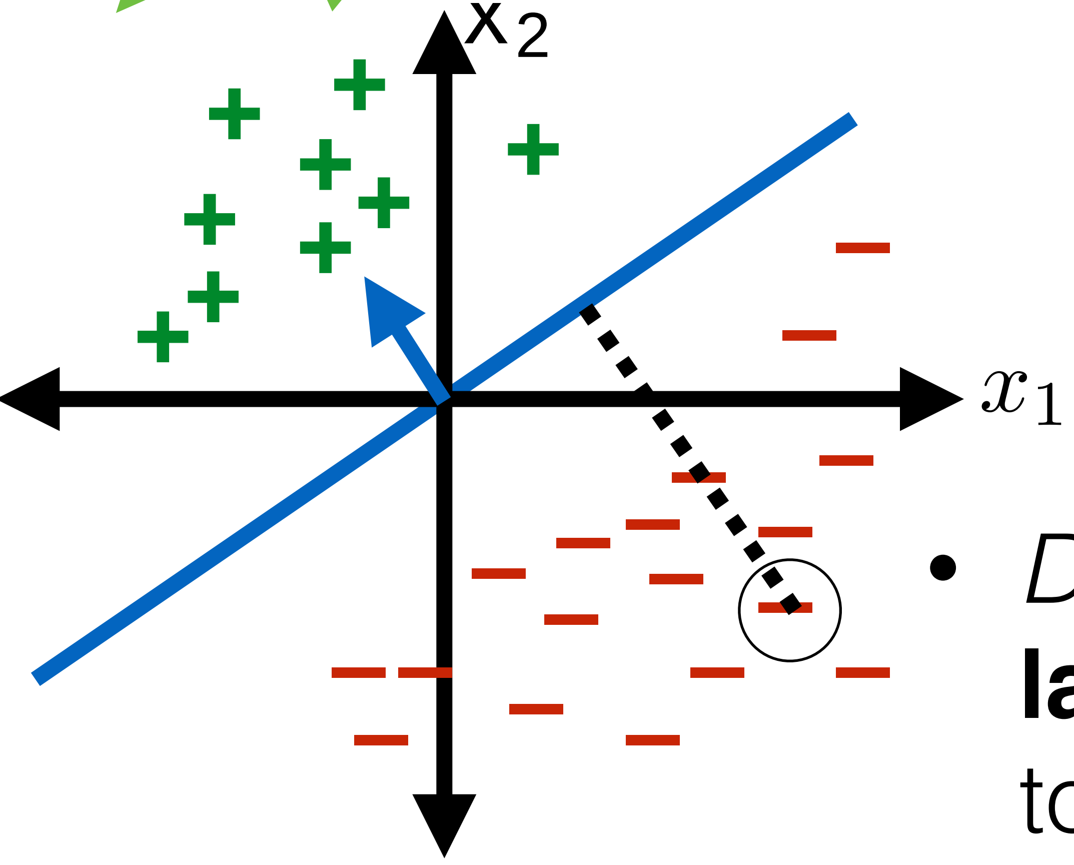

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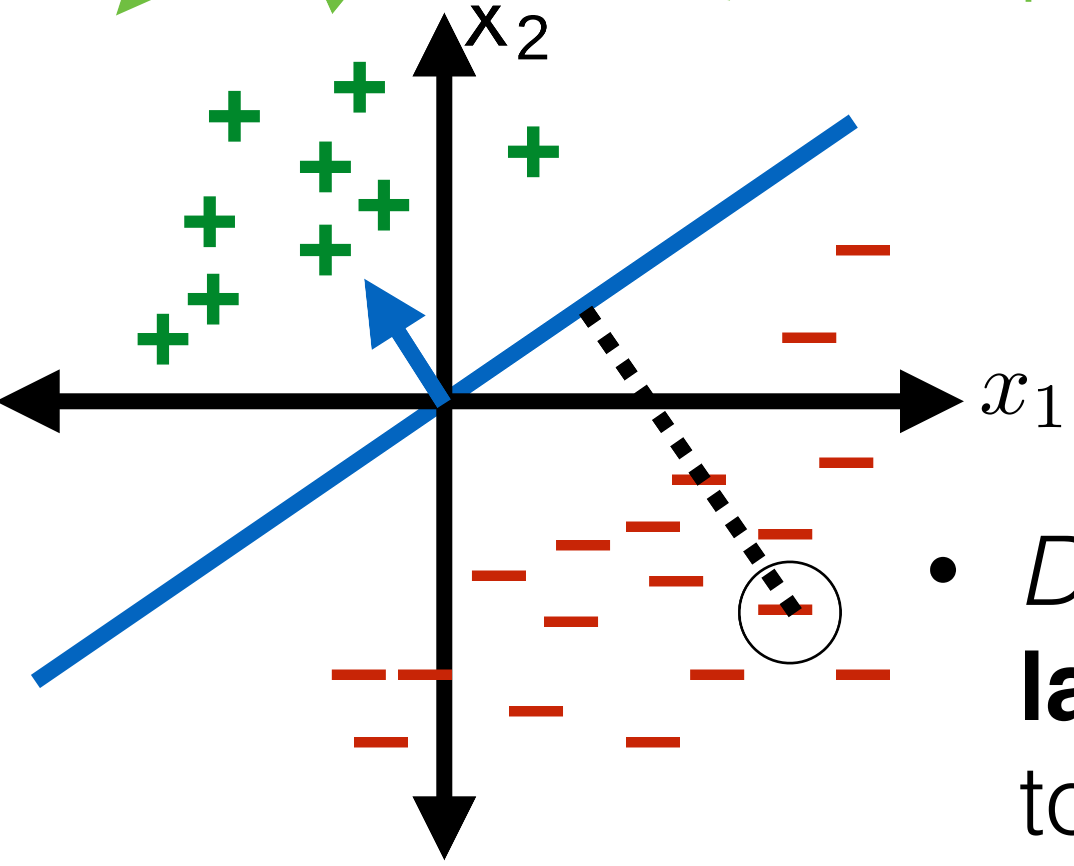

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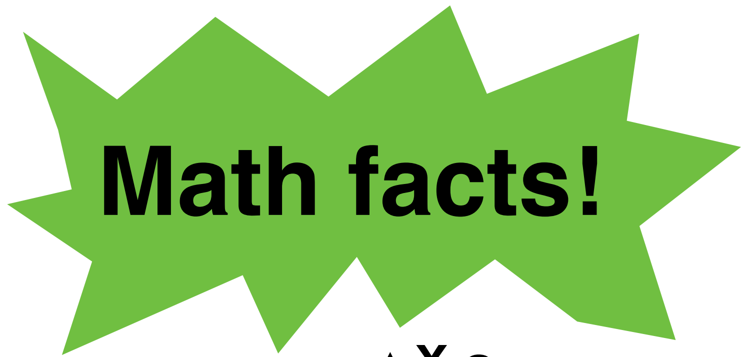

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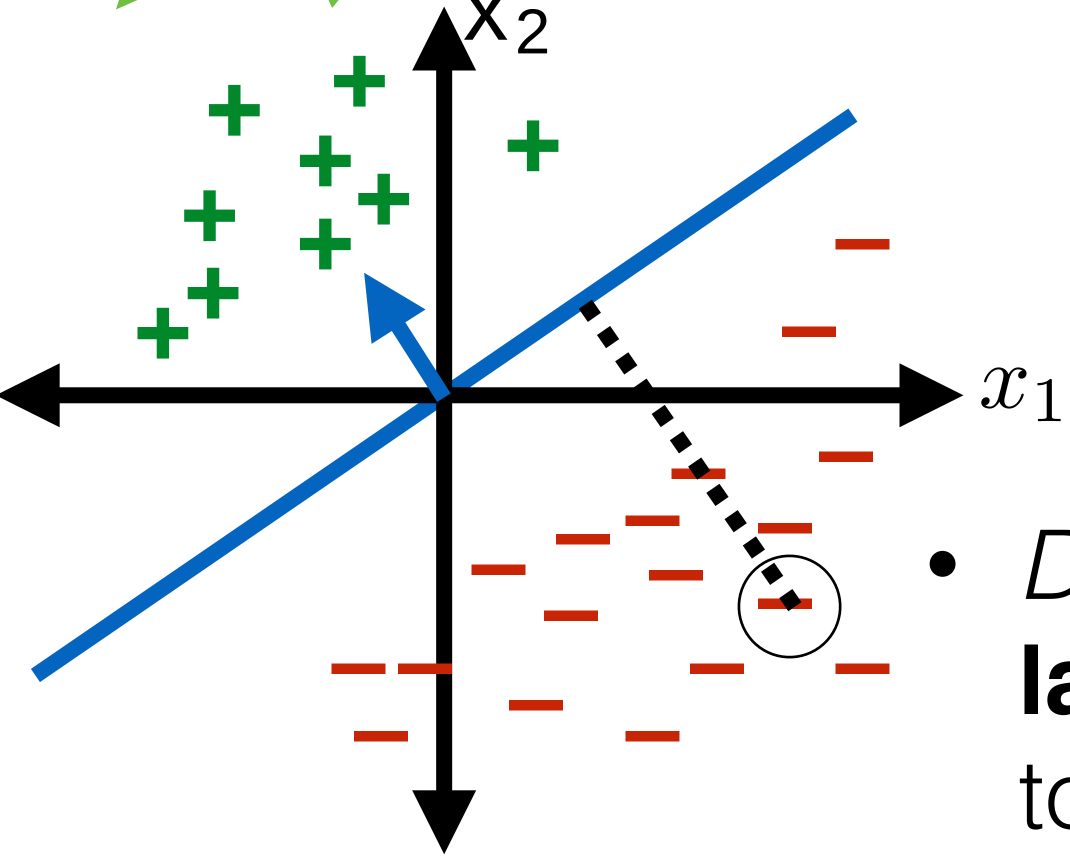

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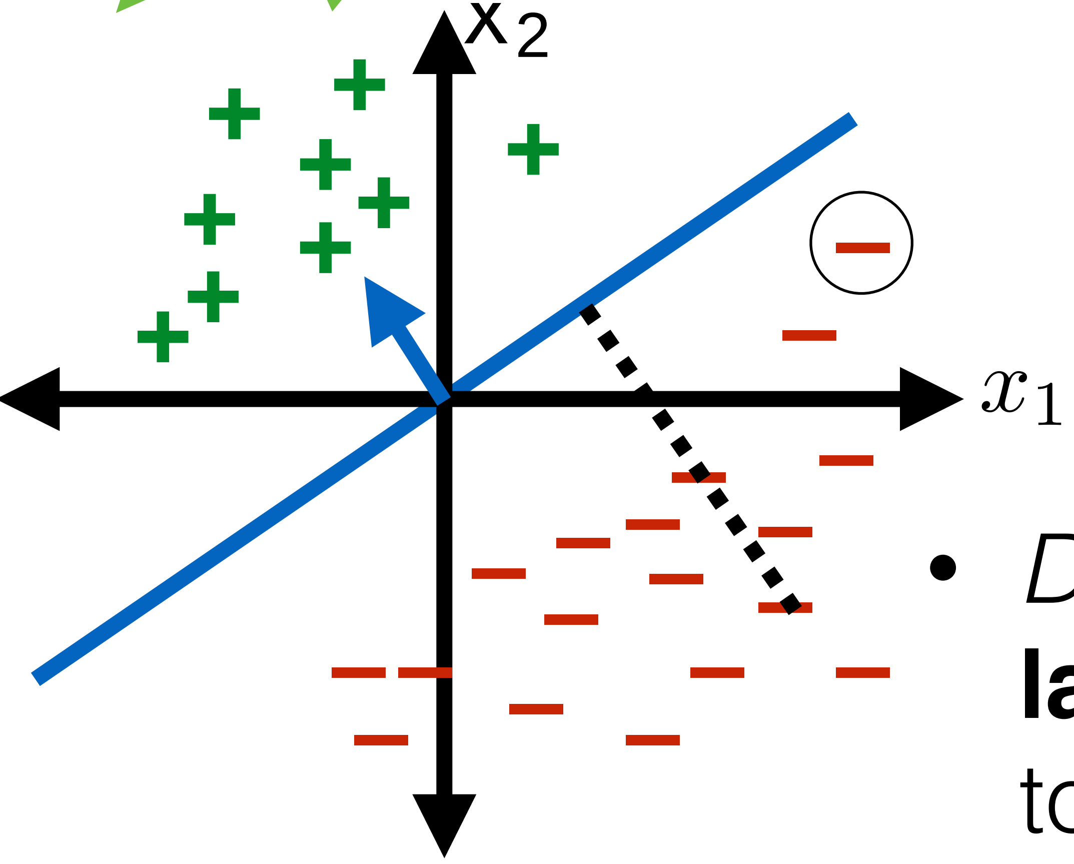

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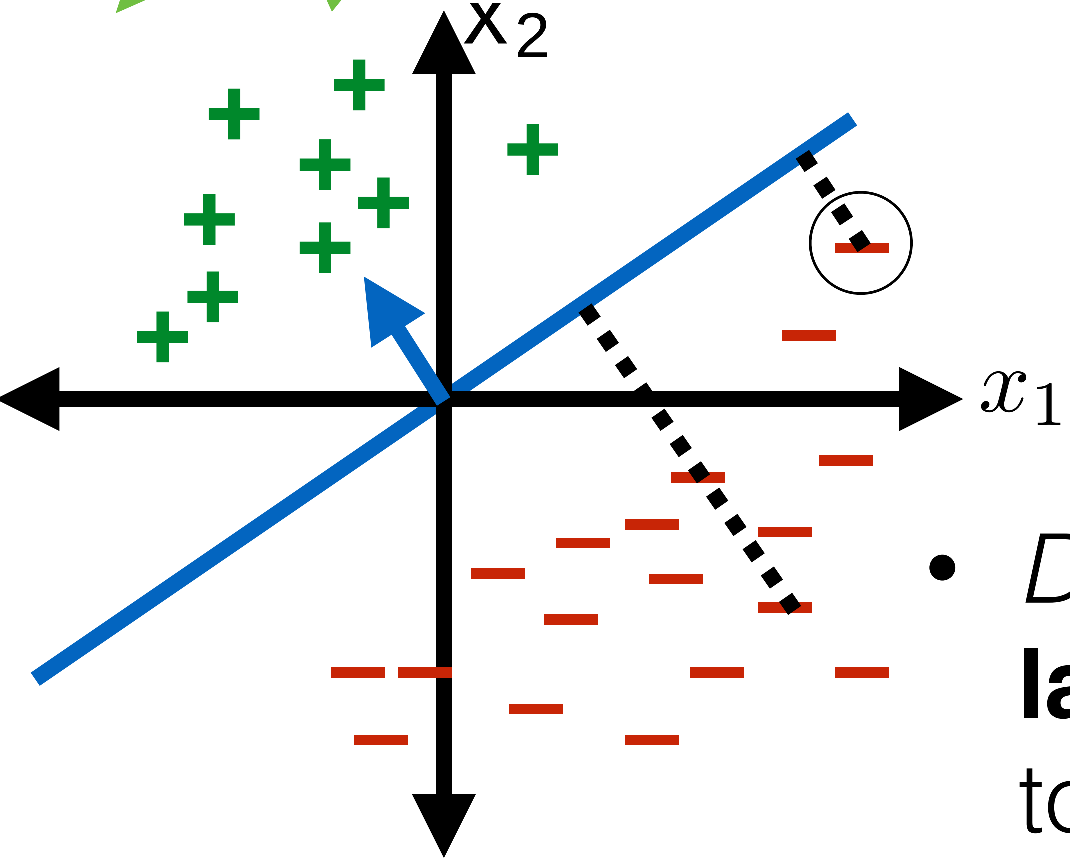

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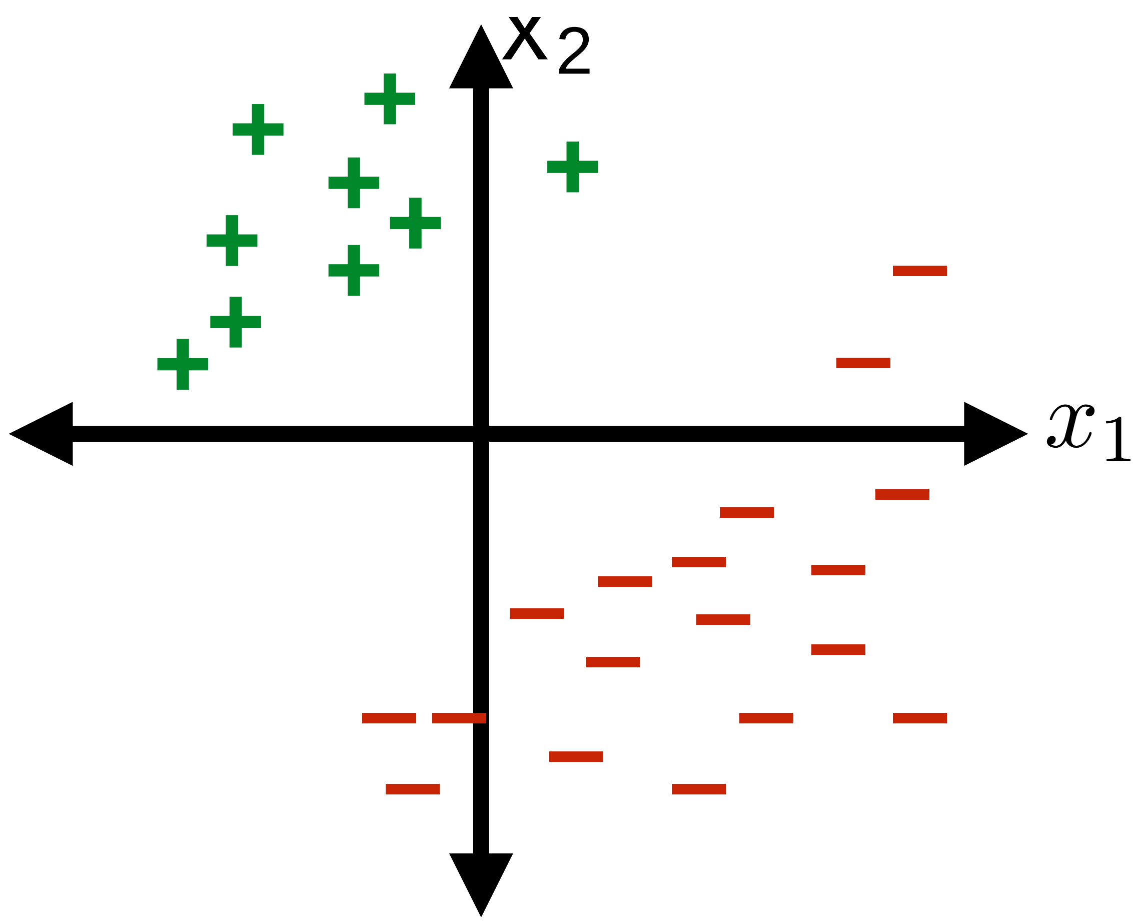

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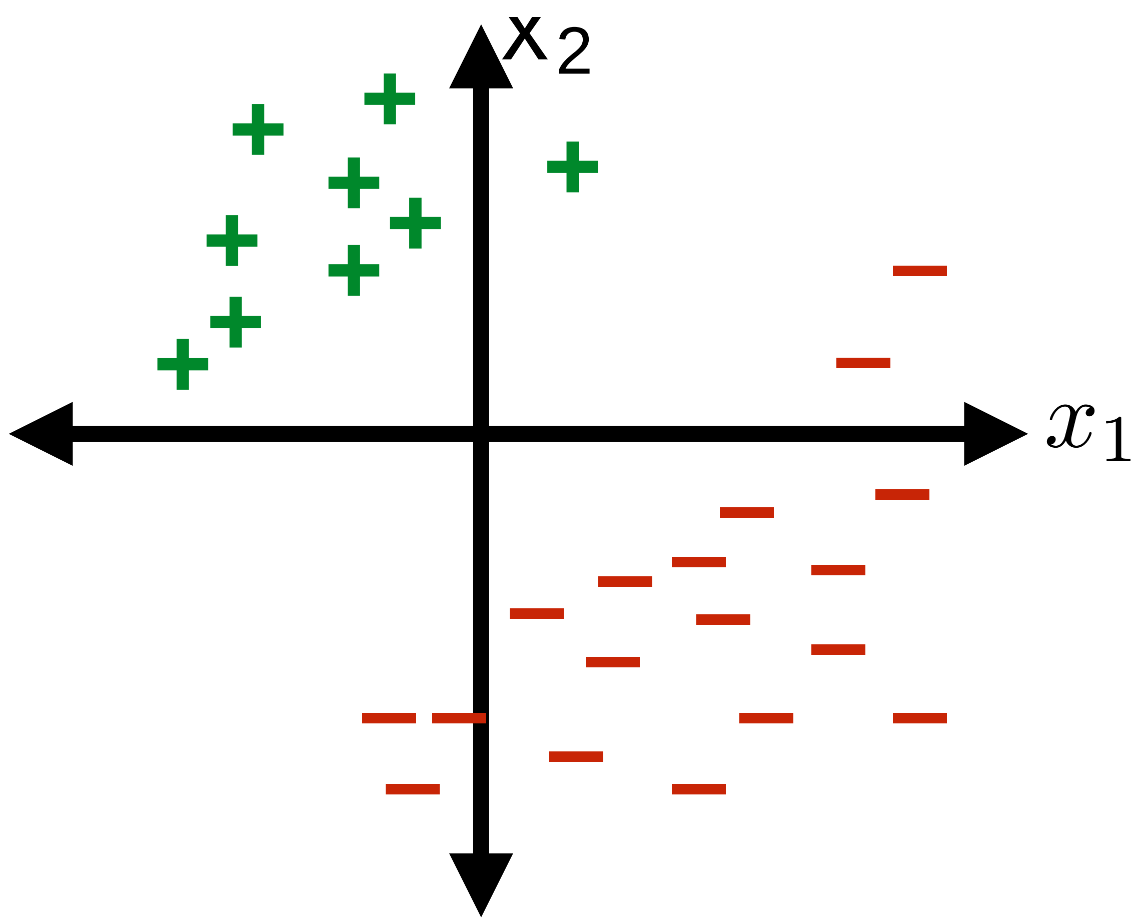

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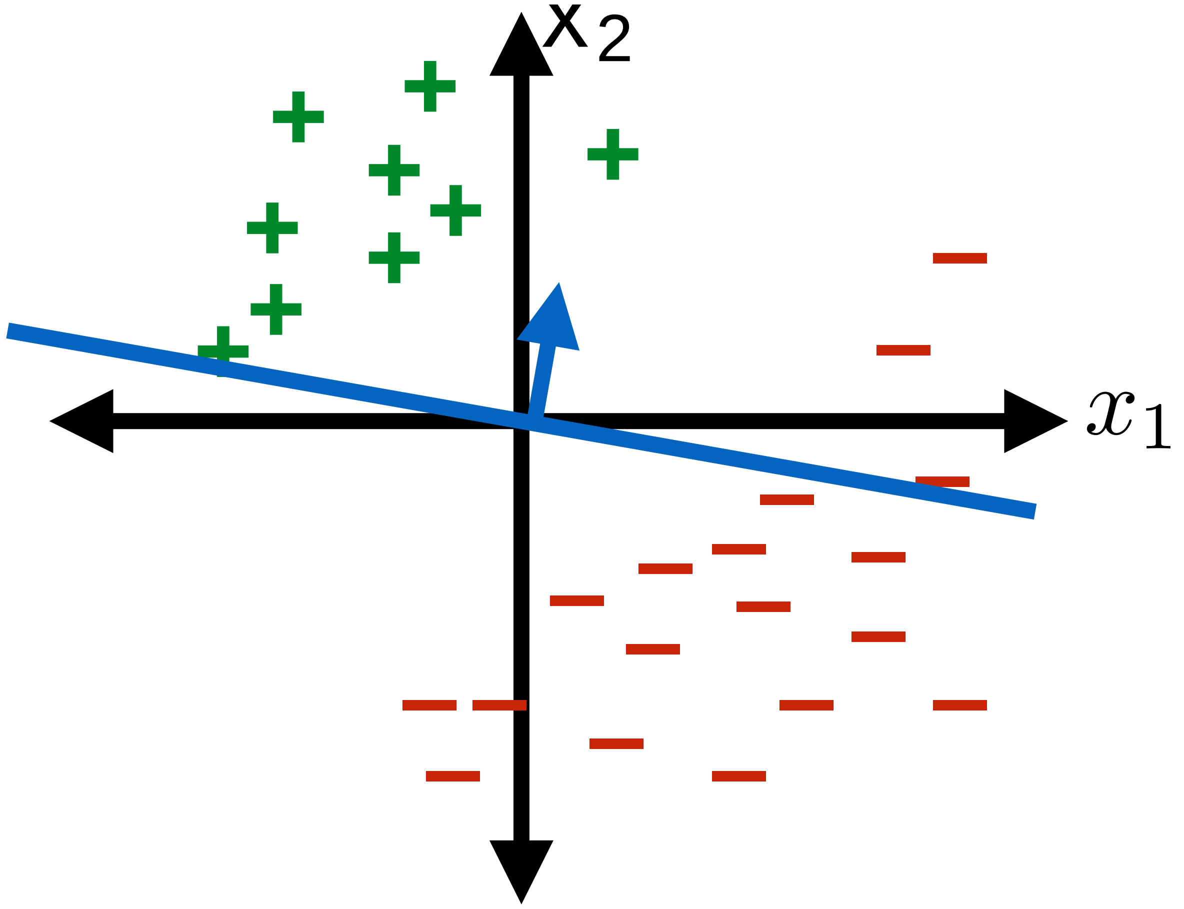

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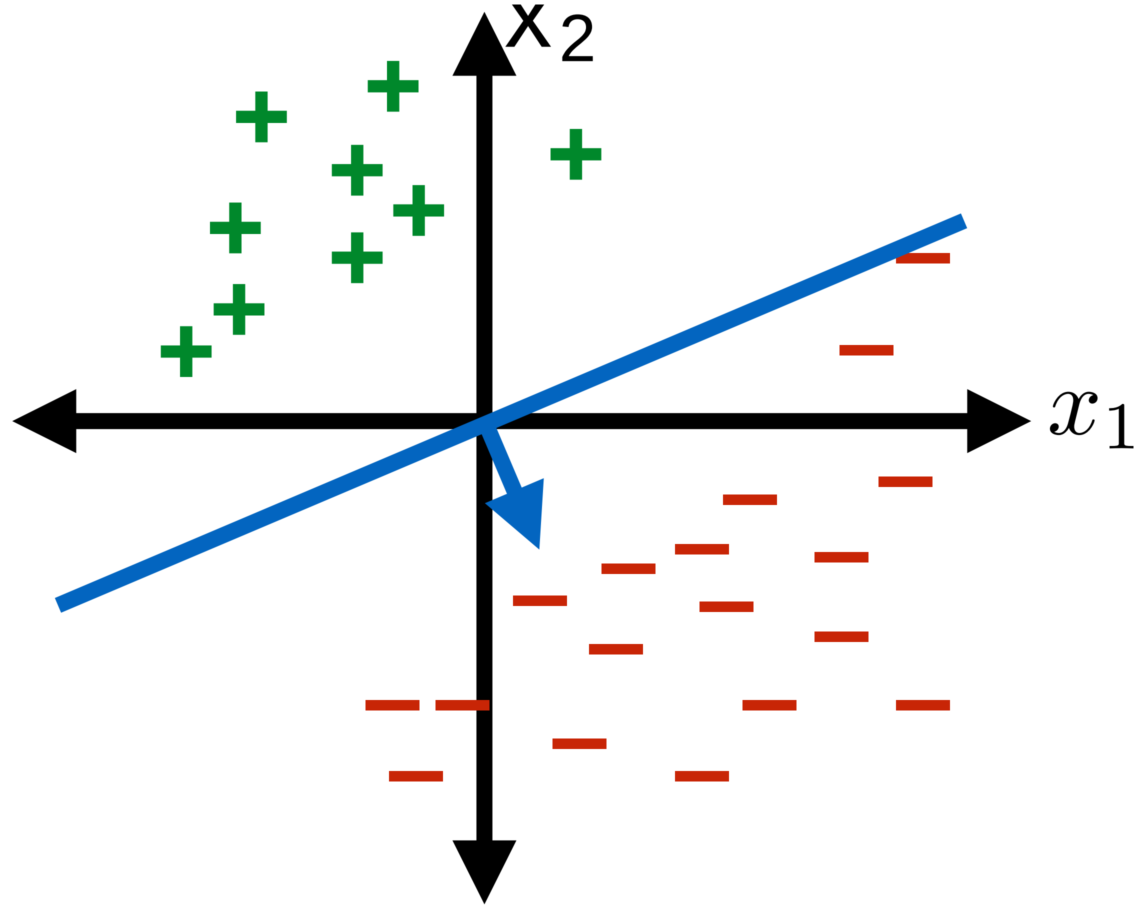

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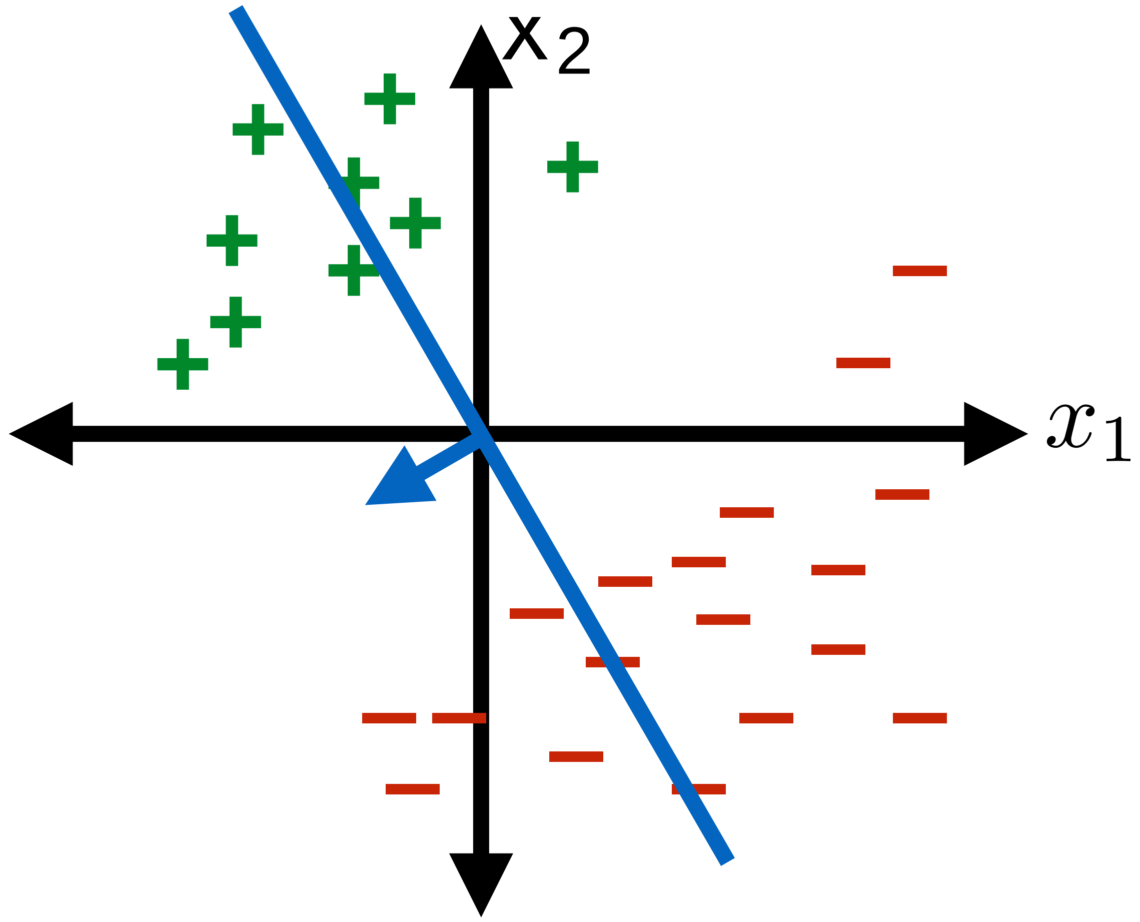

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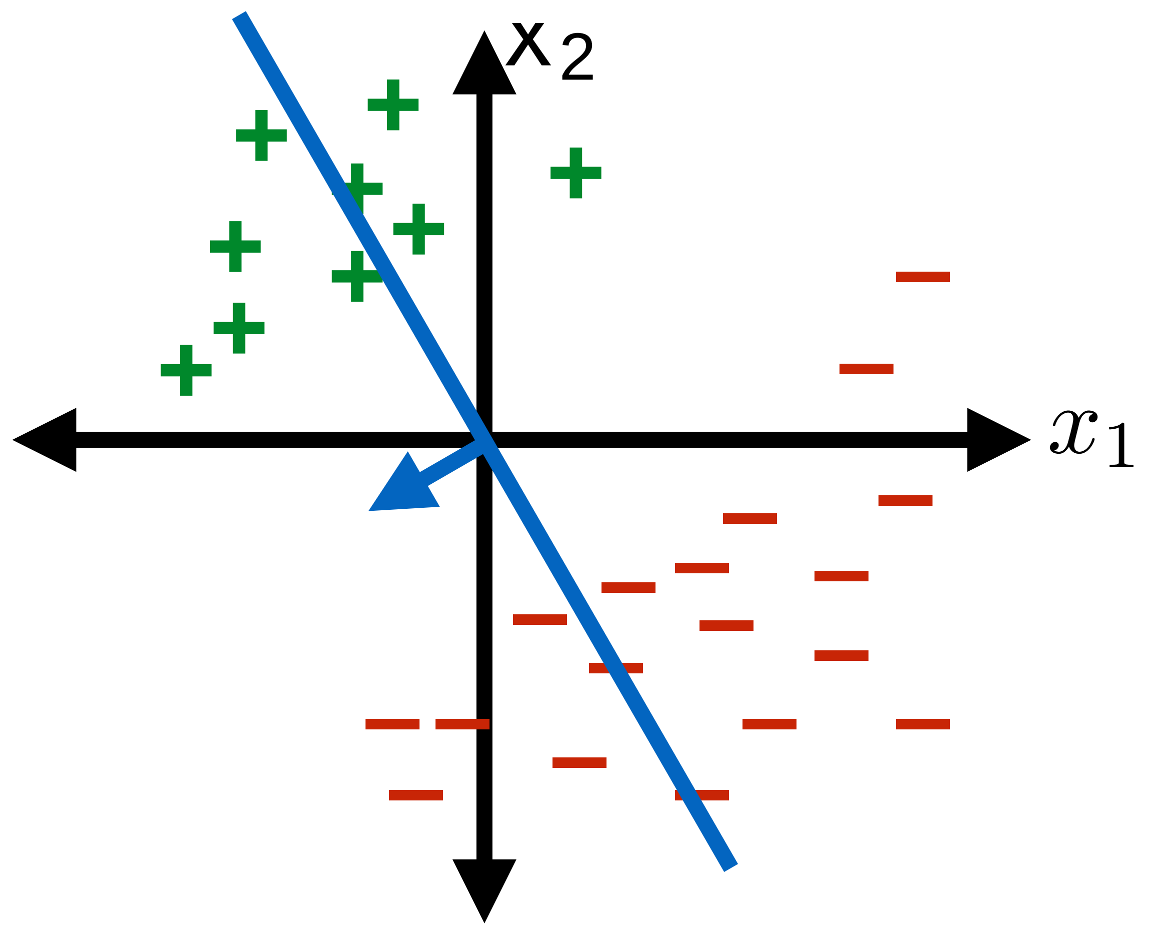

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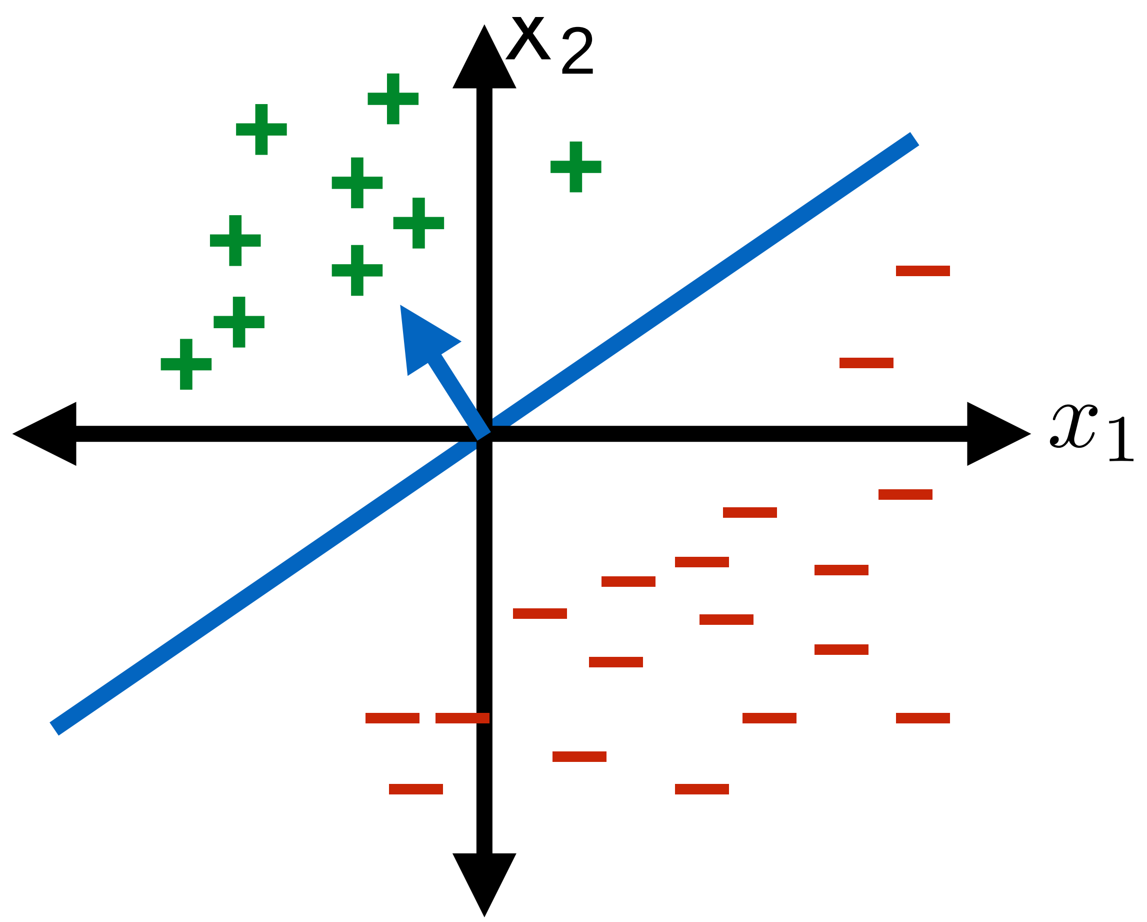

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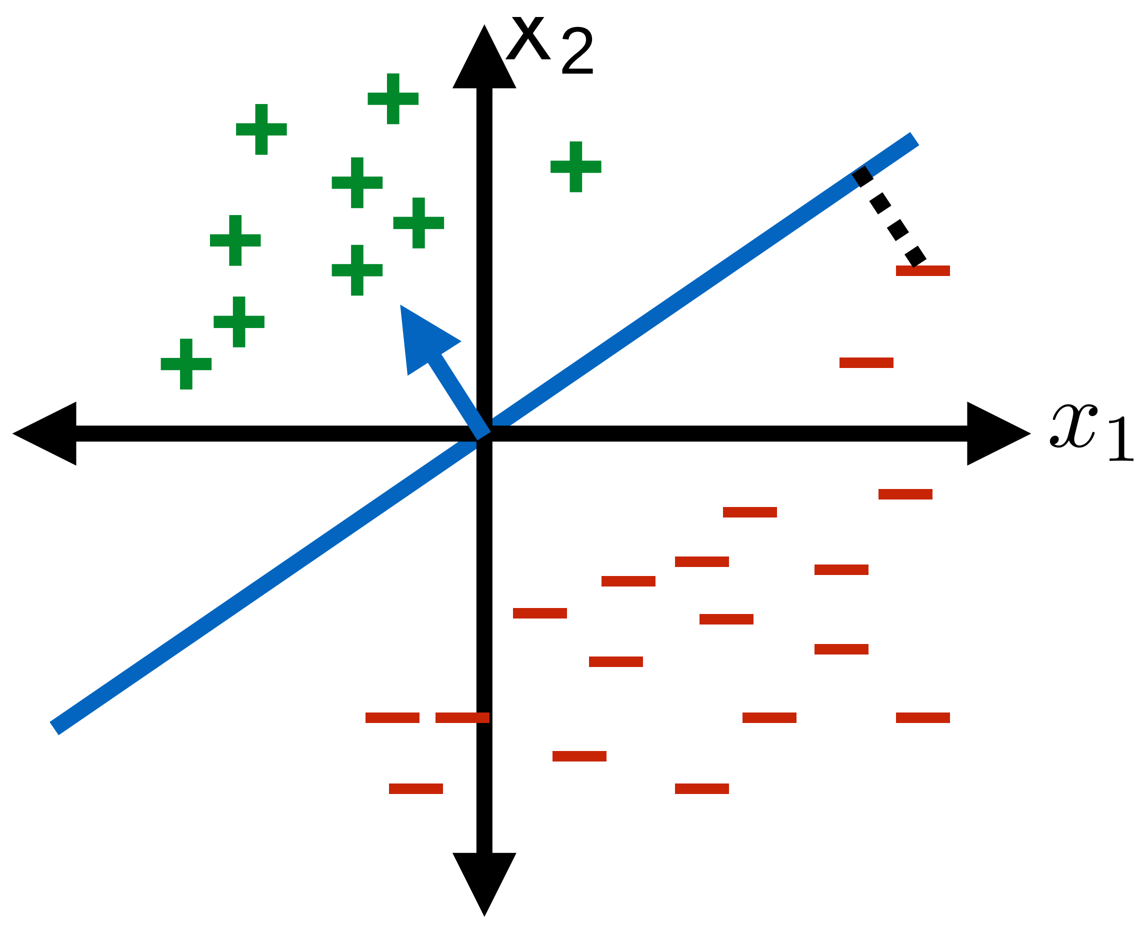

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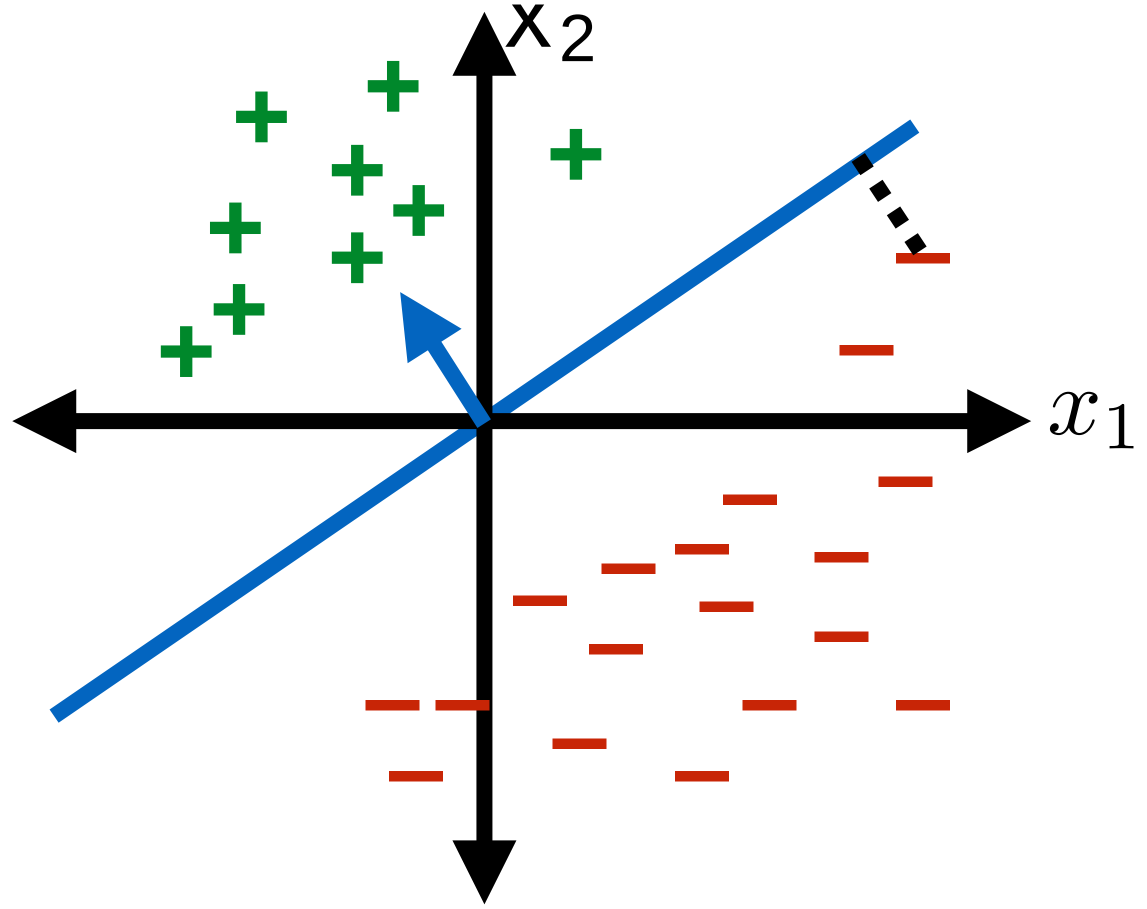

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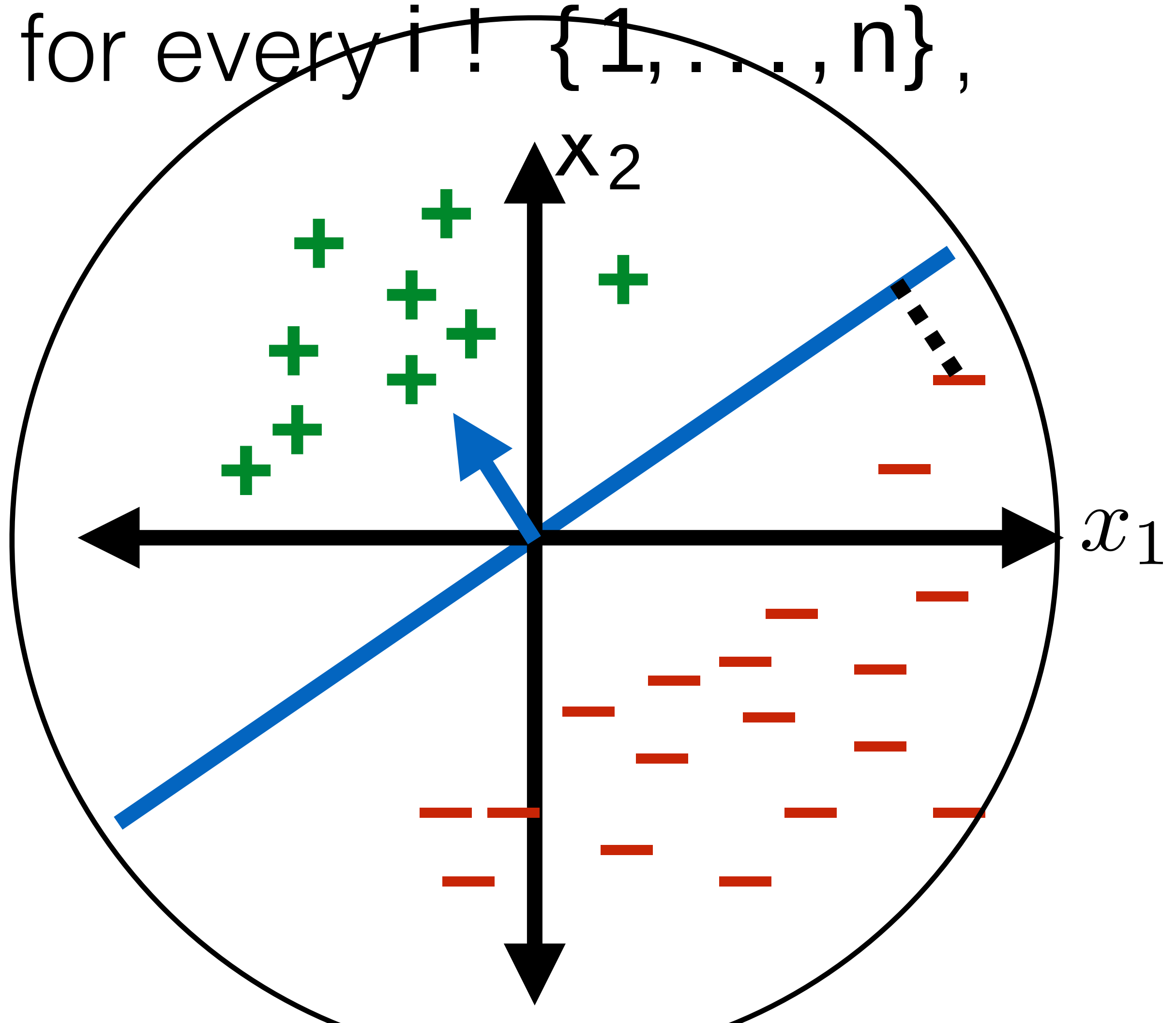

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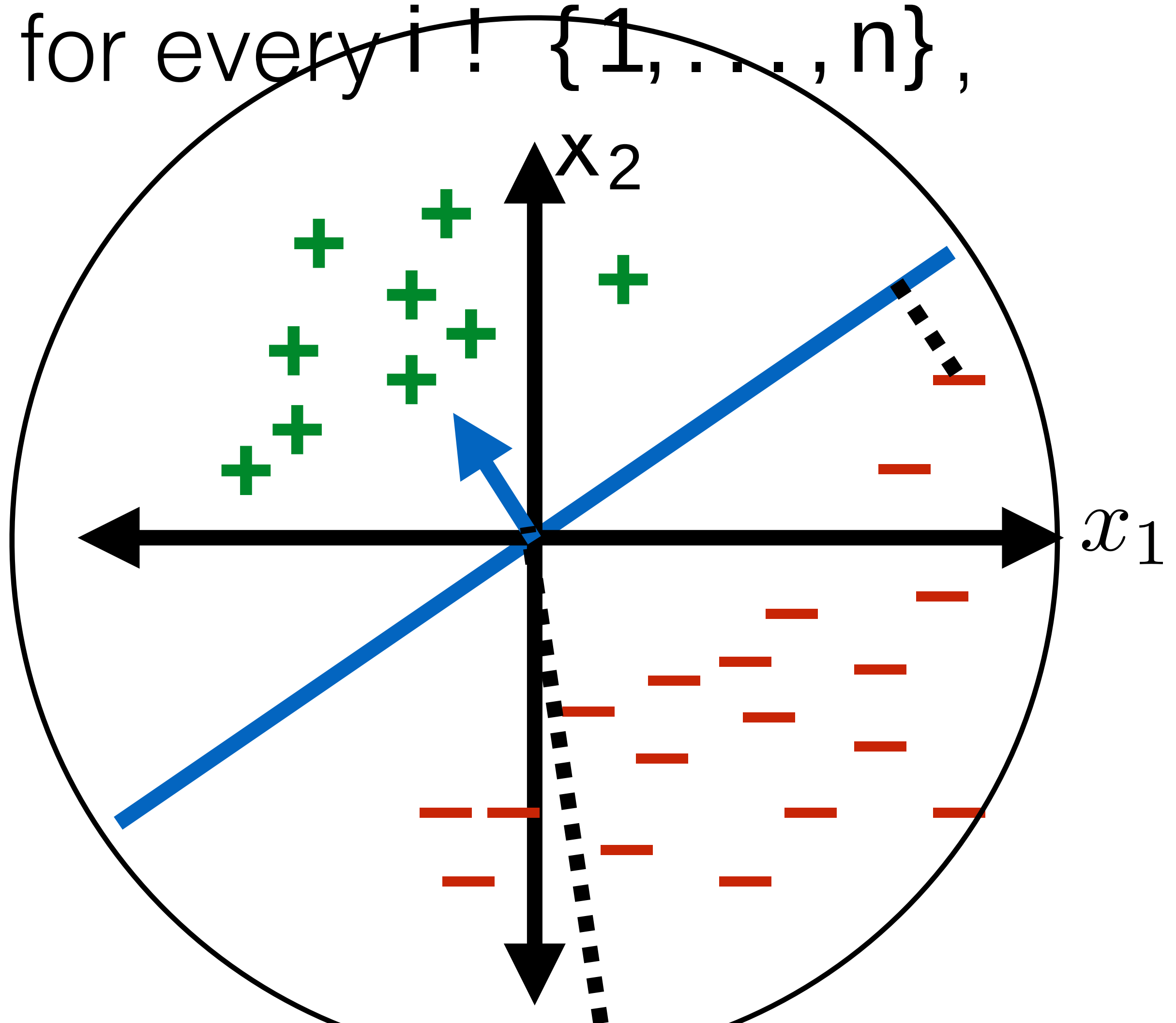

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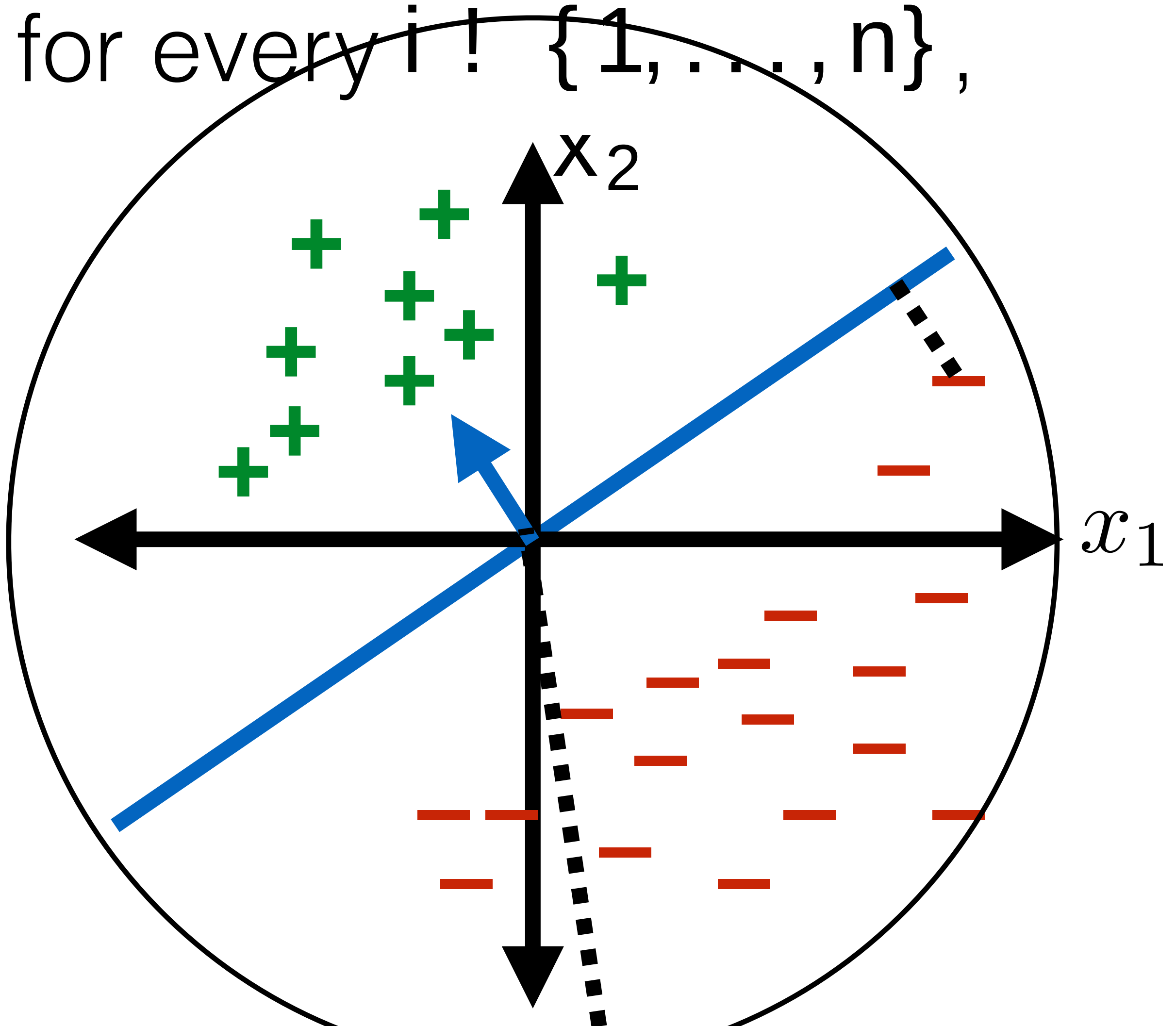
- **Conclusion**: Then the perceptron algorithm will make at most (R/ !)^2 updates to ! . Once it goes through a pass of *i* without changes, the training error of its hypothesis will be 0.



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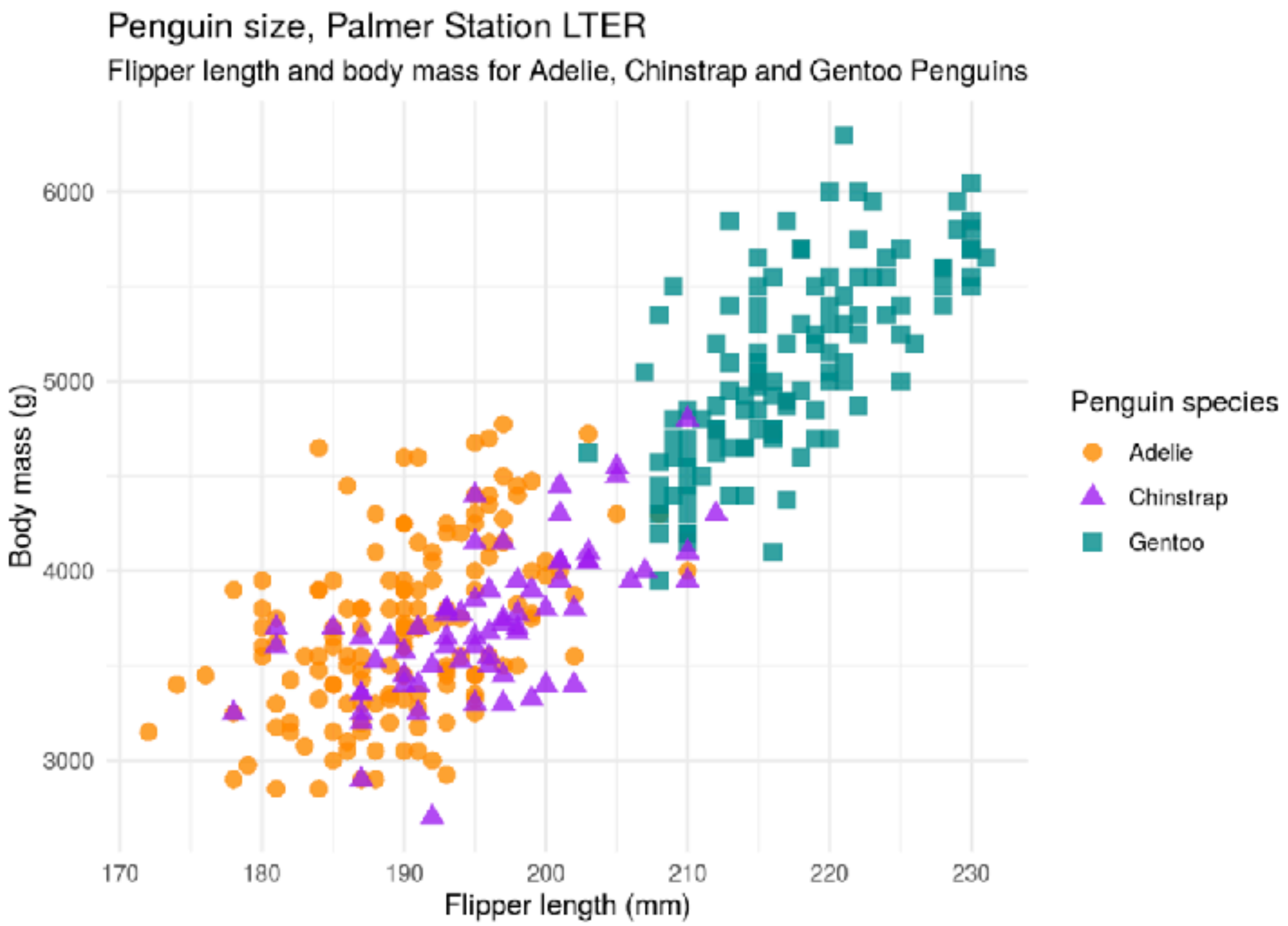
- Can first convert to "expanded" feature space, then apply theorem

Problem: data not linearly separable

- Typical real data sets aren't linearly separable



[https://towardsdatascience.com/penguins-dataset-overview-iris-alternative-9453bb8c8d95, https://github.com/allisonhorst/palmerpenguins]

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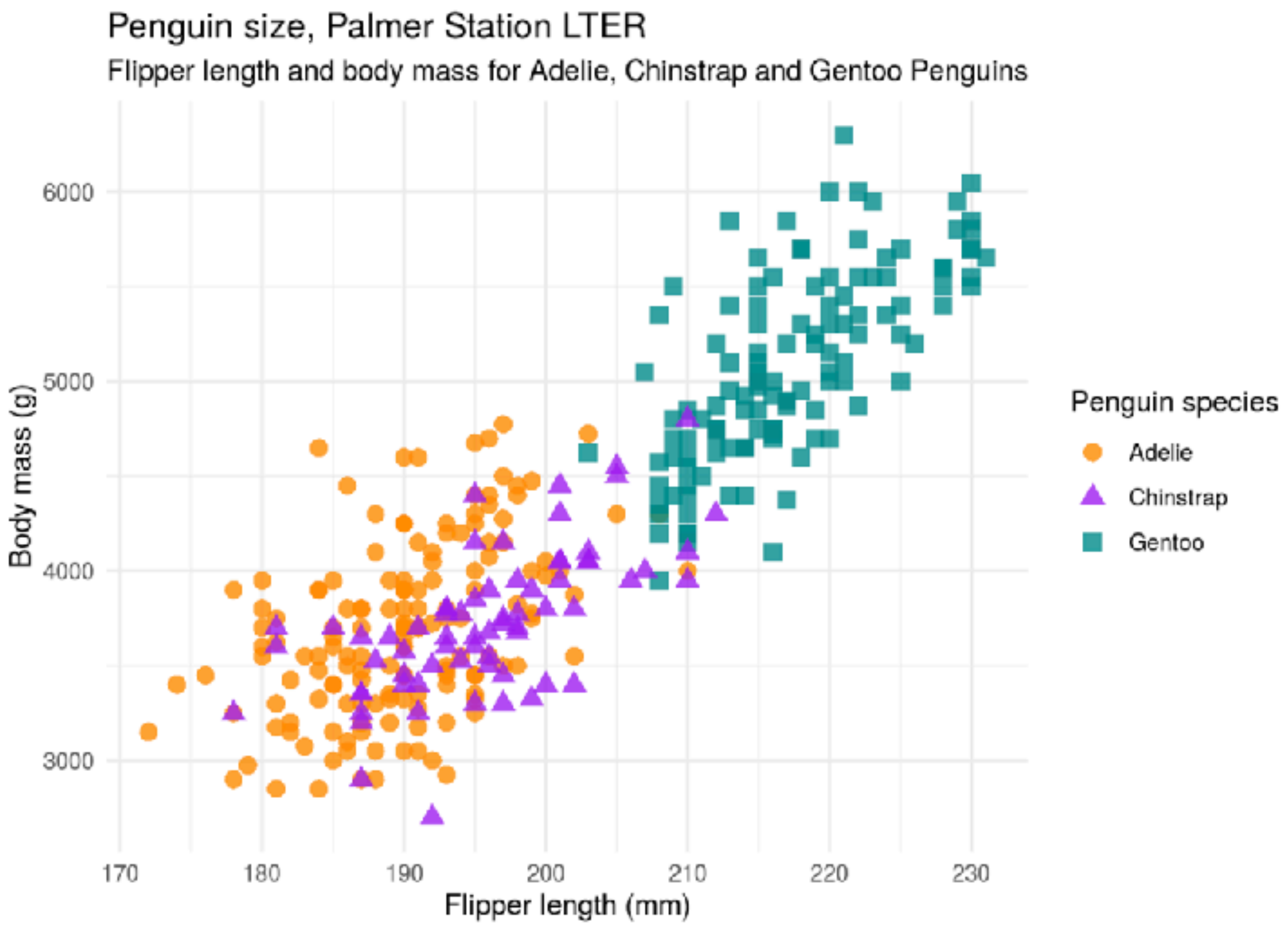

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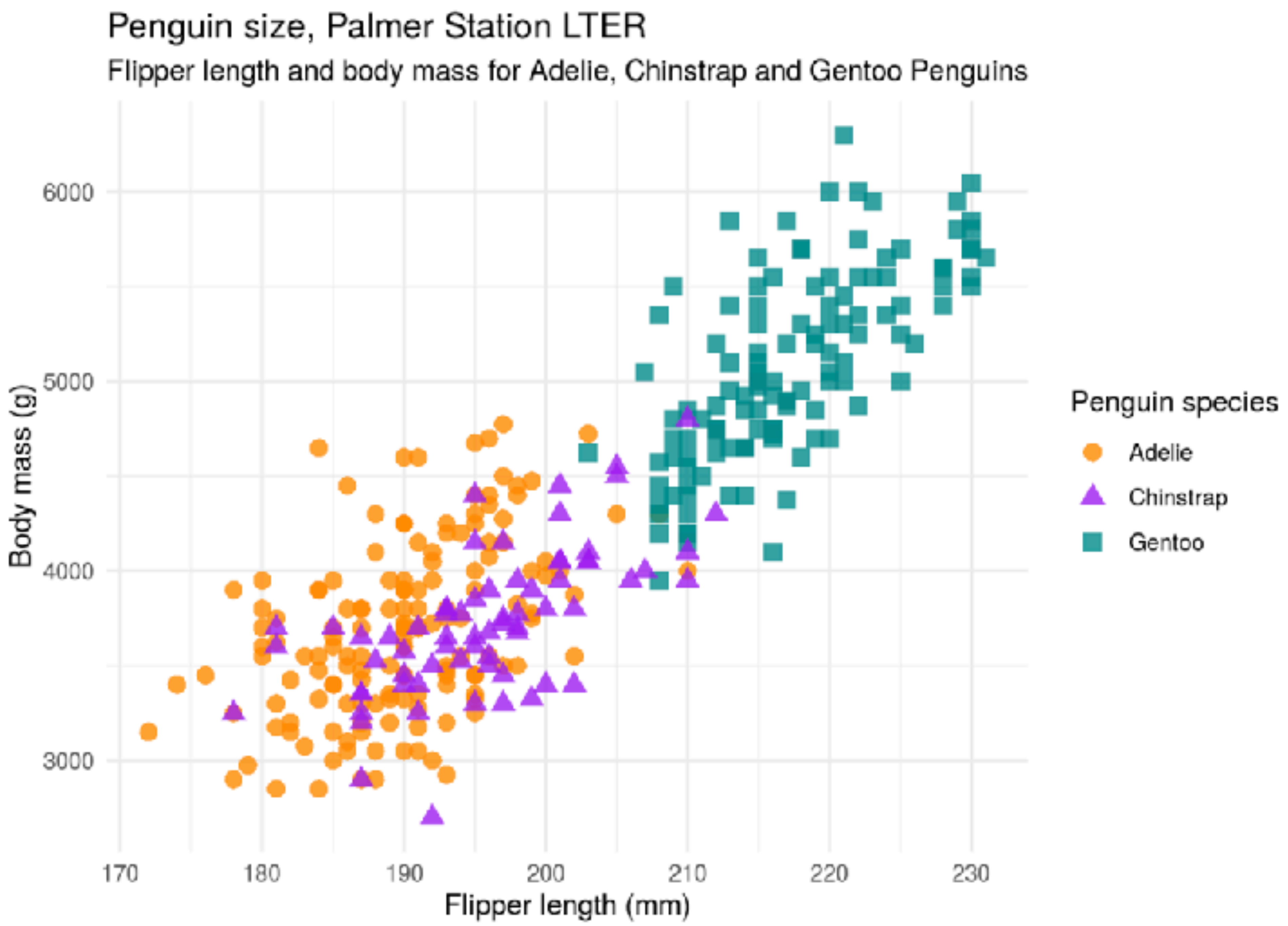

- What can we do?

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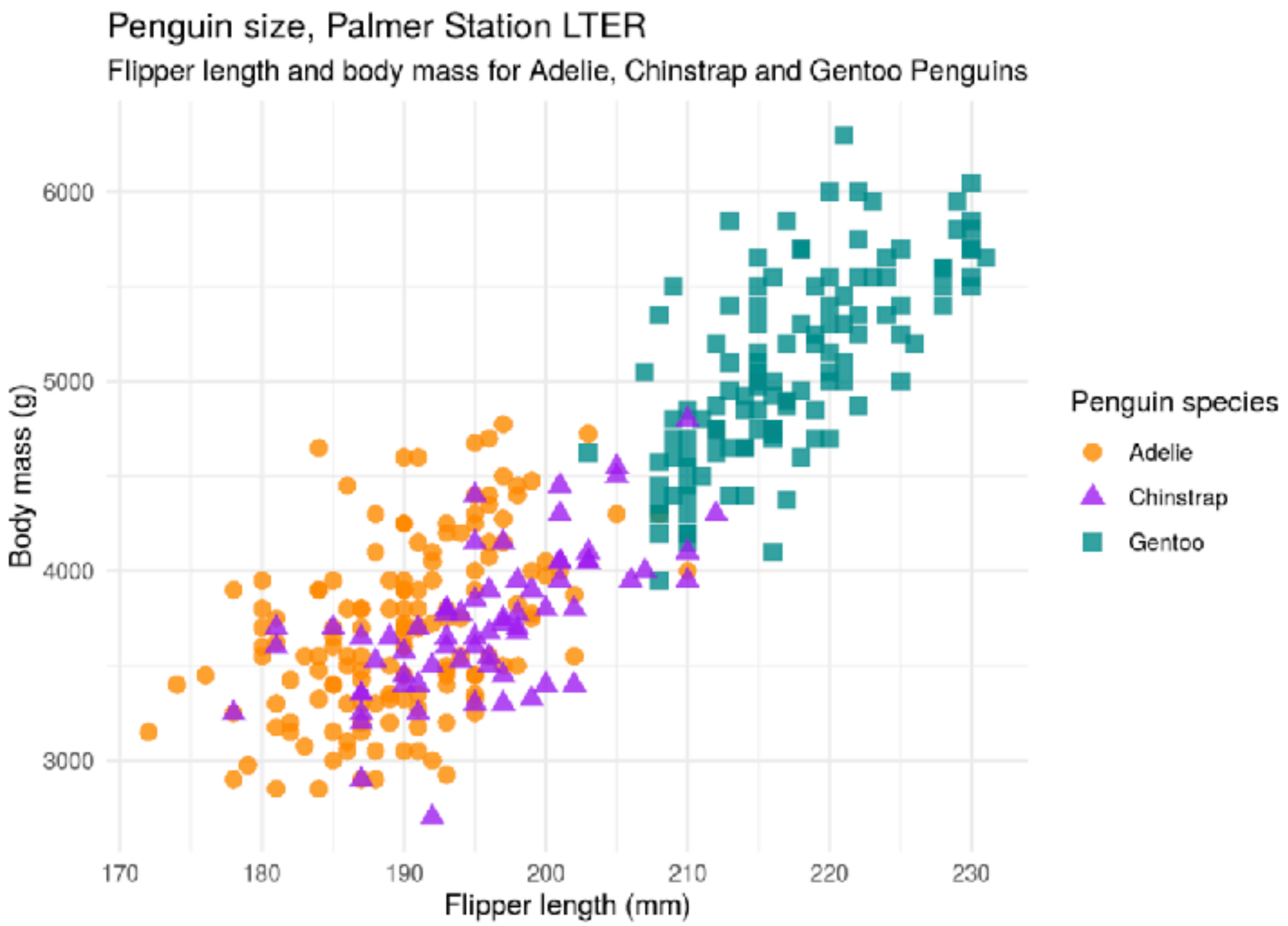

- What can we do? See upcoming lectures!

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Machine Learning Tasks

Machine Learning Tasks

- **Binary/two-class classification**

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- **Binary/two-class classification:** Learn a mapping: $\mathbb{R}^d \to \{-1, +1\}$

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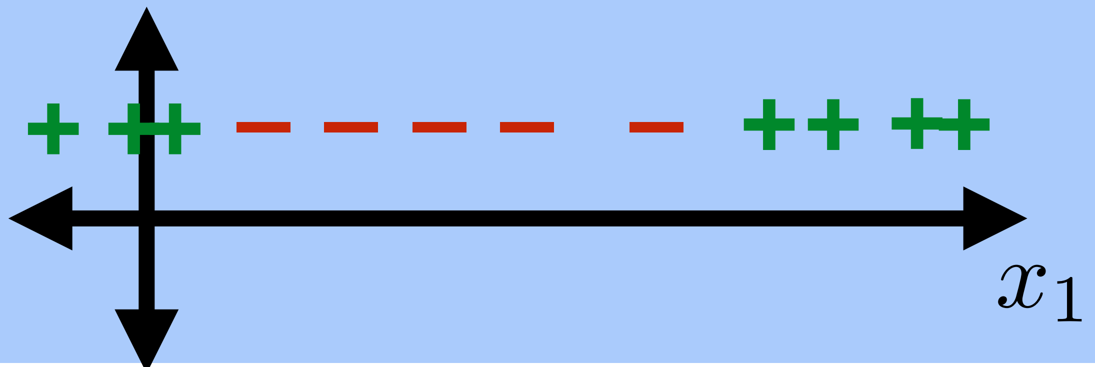

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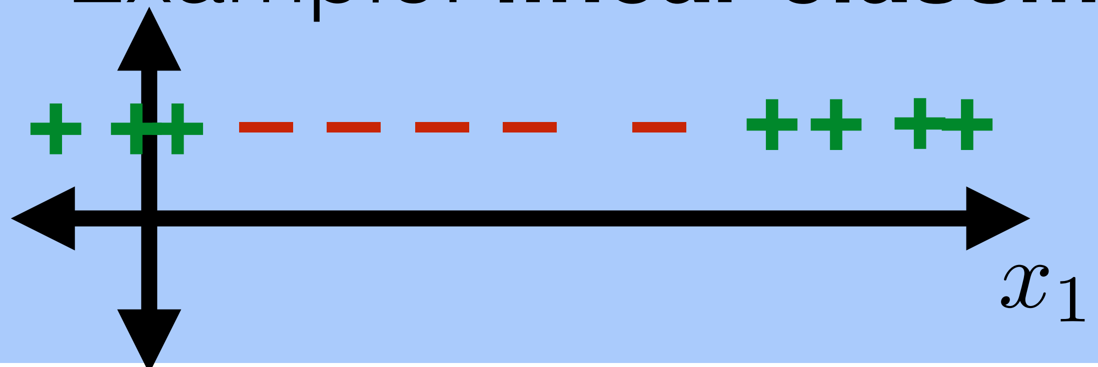
- **Binary/two-class classification:** Learn a mapping: $\mathbb{R}^d \rightarrow \{-1, +1\}$
    - Example: **linear classification**



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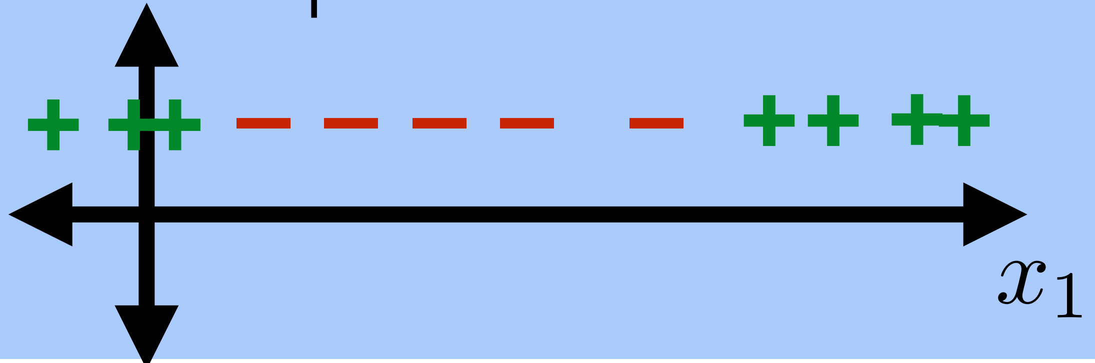

- **Multi-class classification:**

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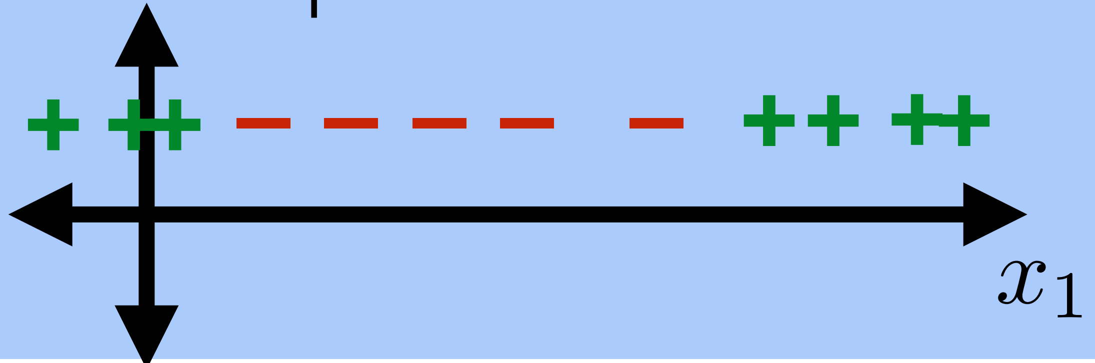

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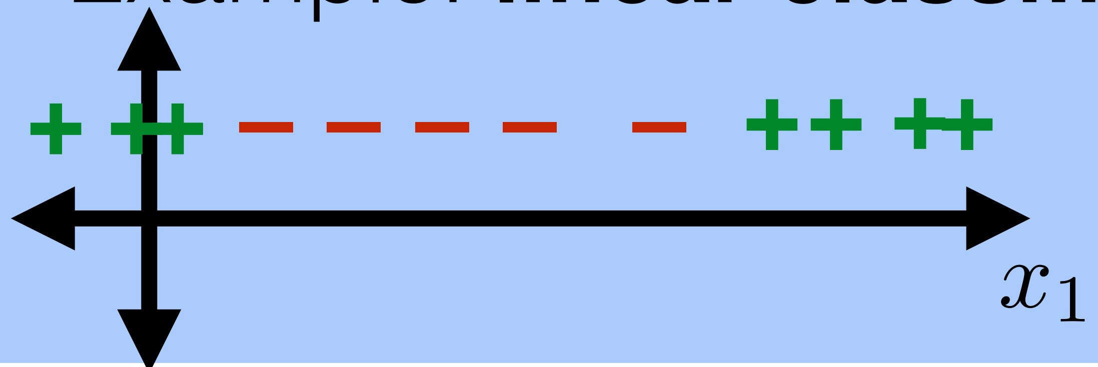

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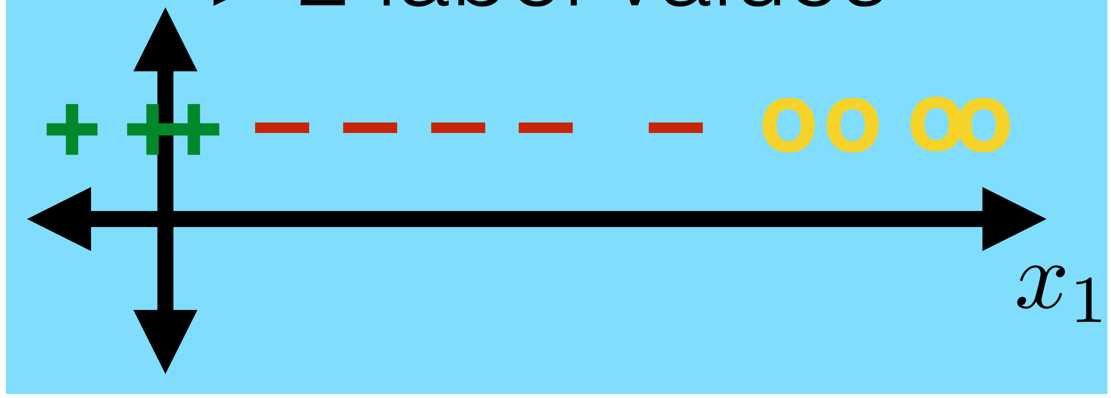

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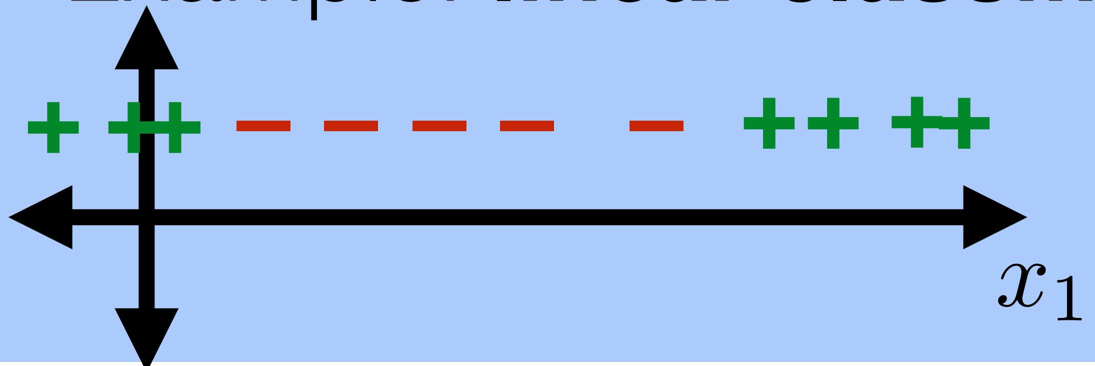

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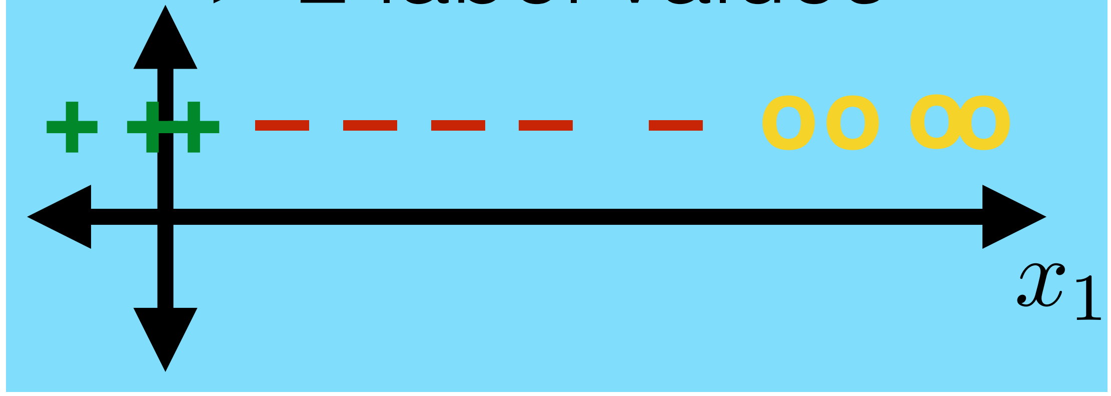

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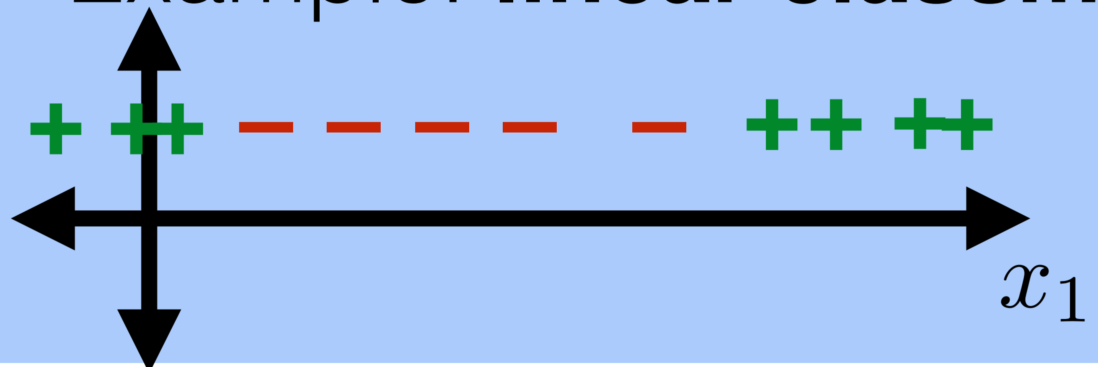

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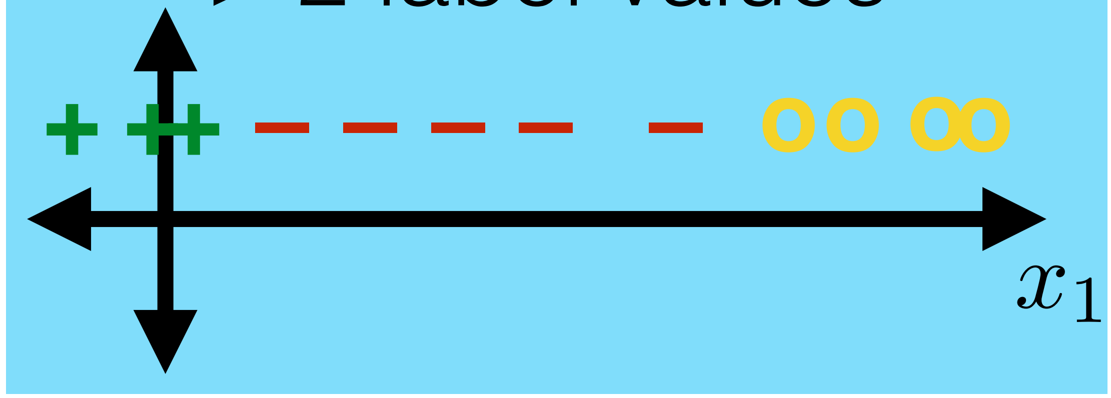

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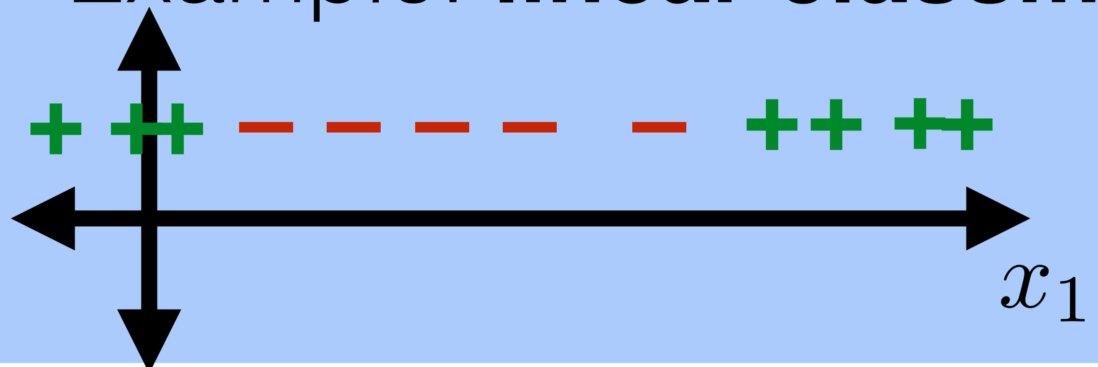

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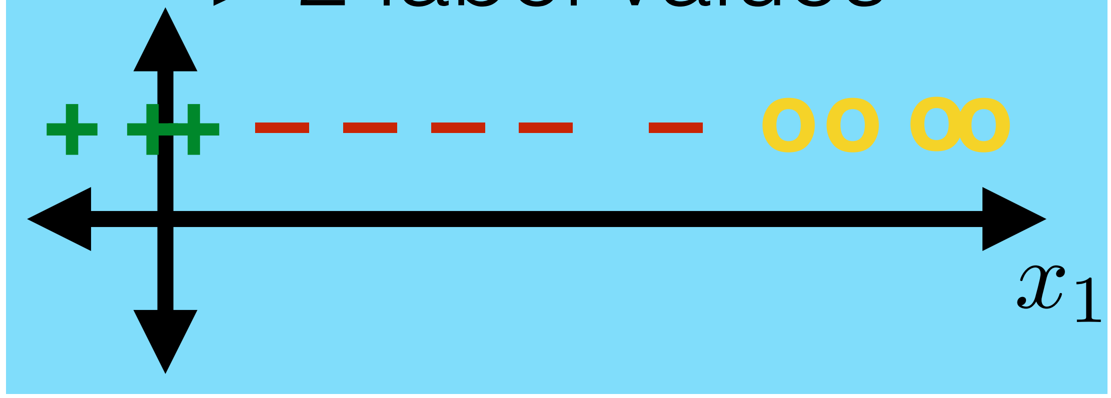

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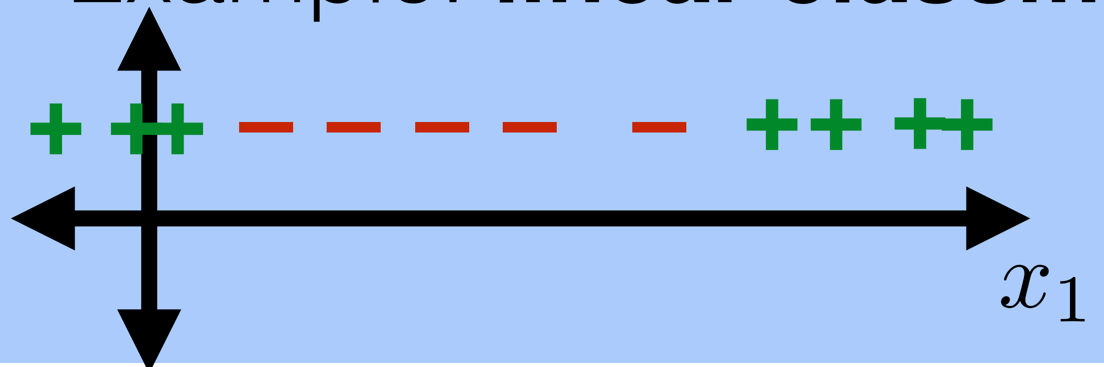

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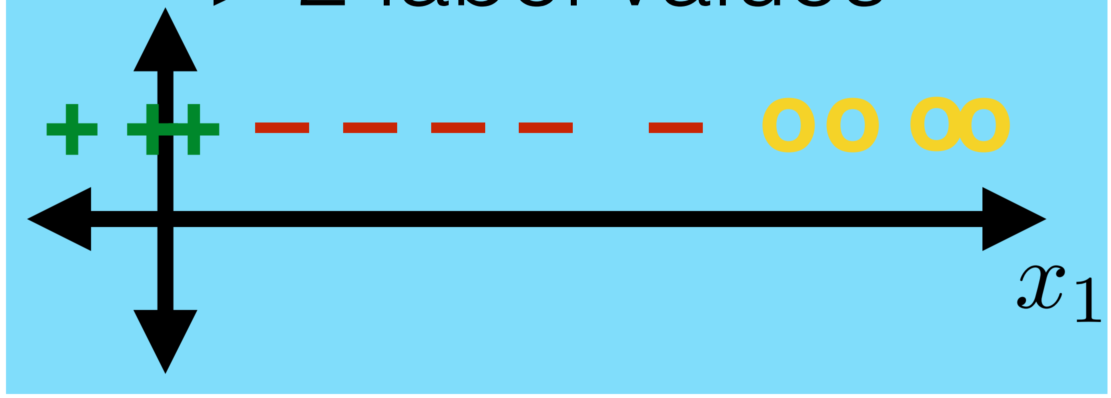

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- **Regression:** Learn a mapping to continuous values: R^d ! R^k

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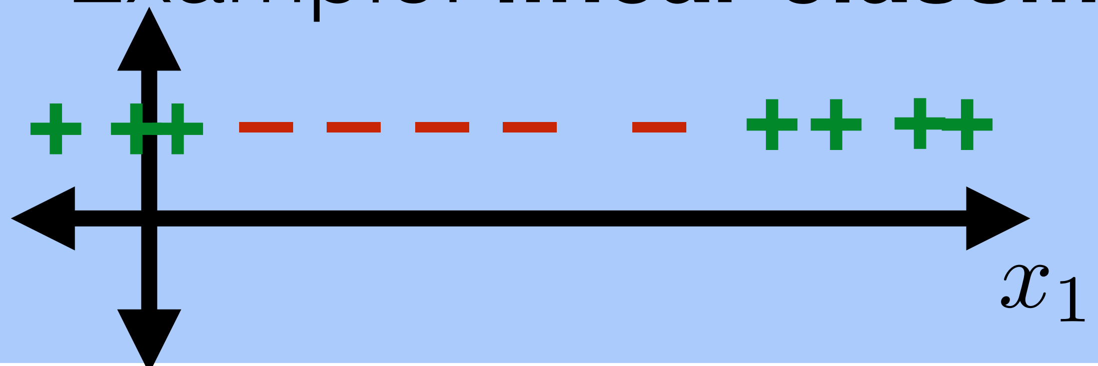

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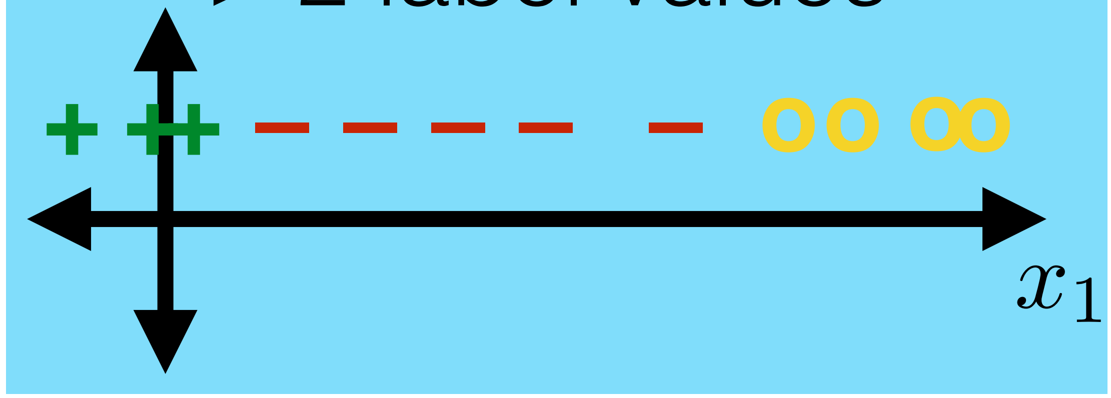

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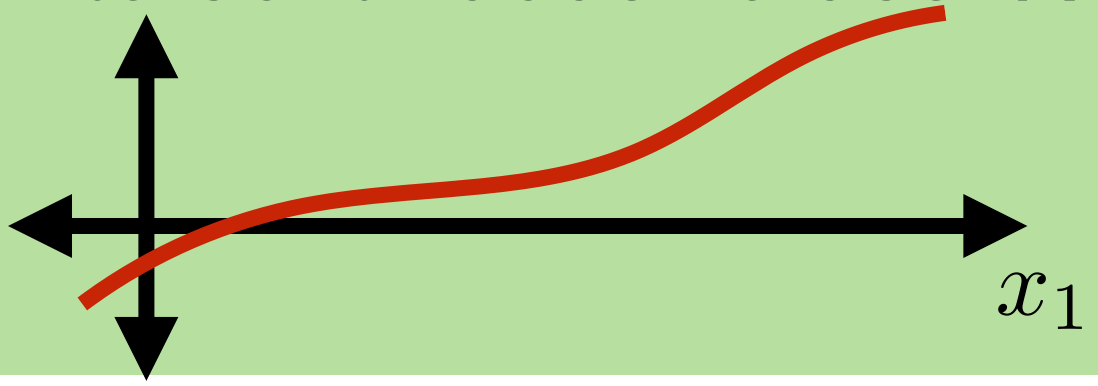

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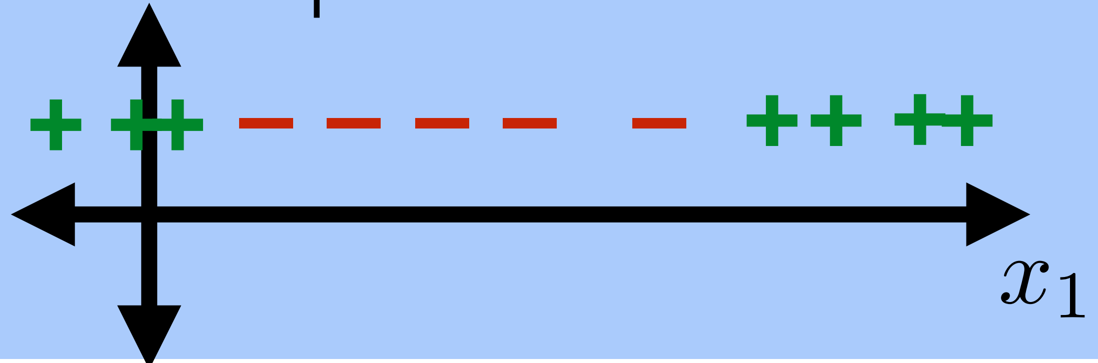

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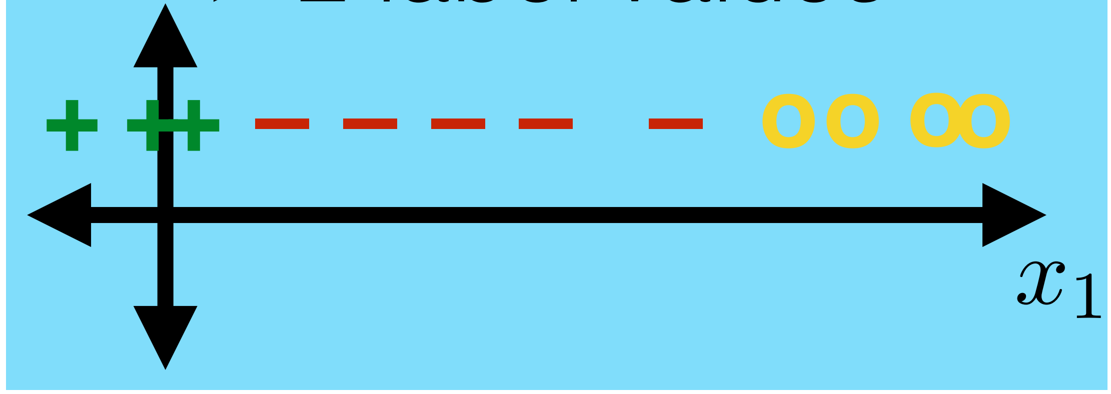

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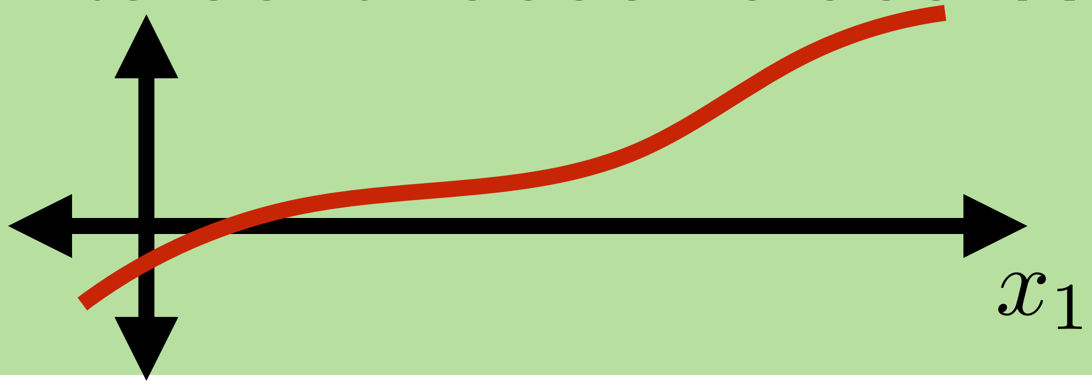

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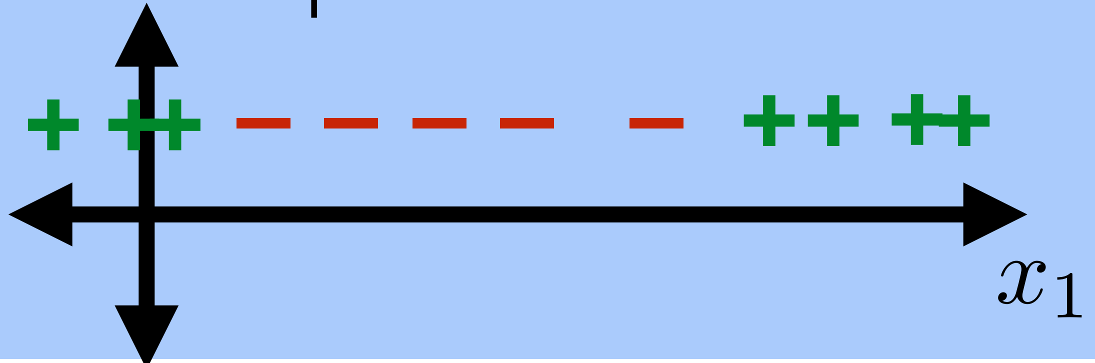

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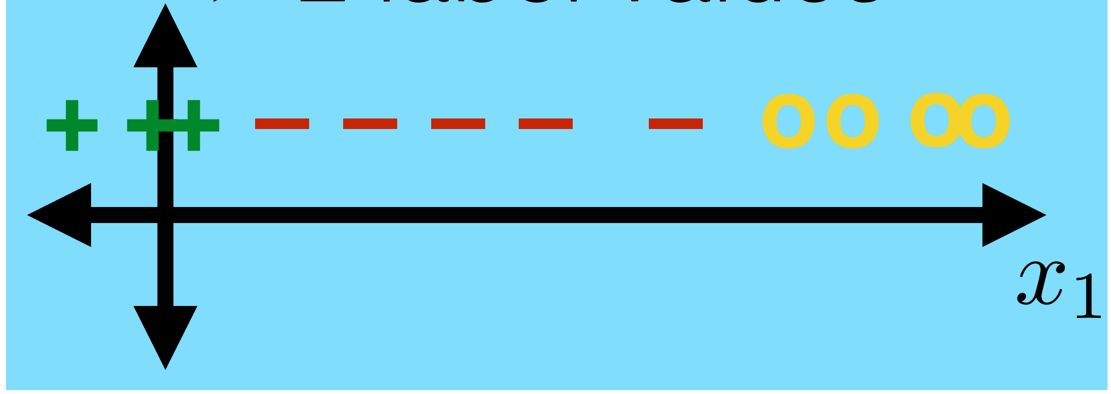

Machine Learning Tasks

- **Supervised learning**

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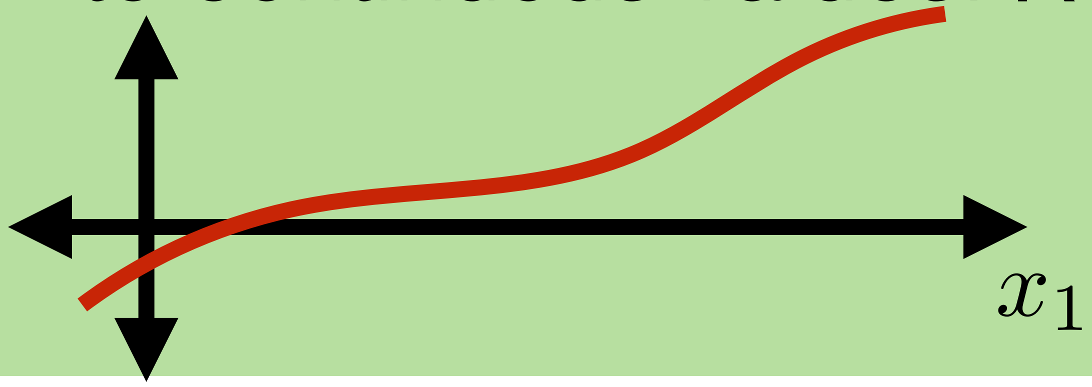

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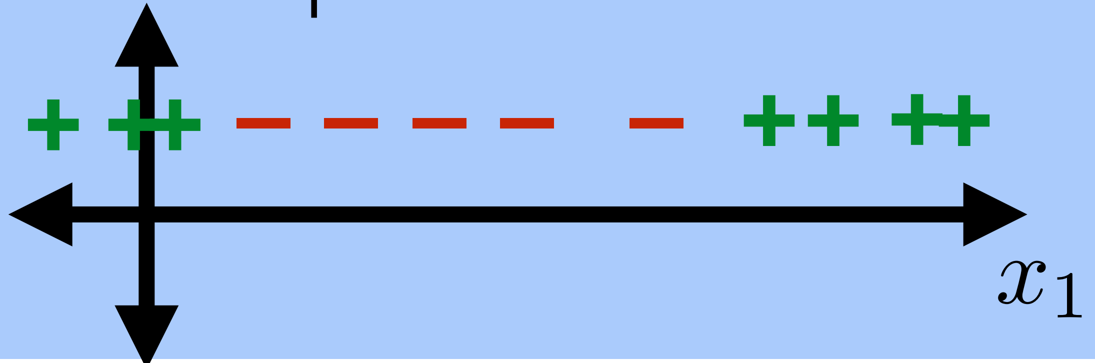

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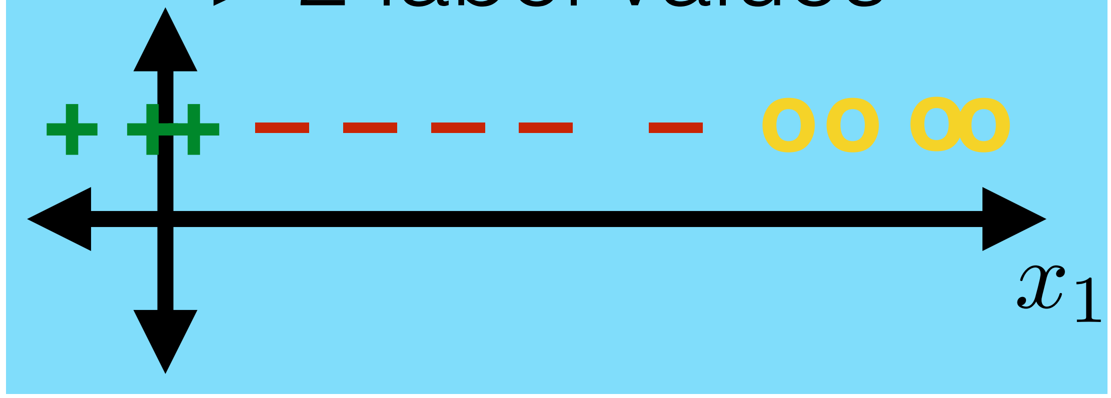
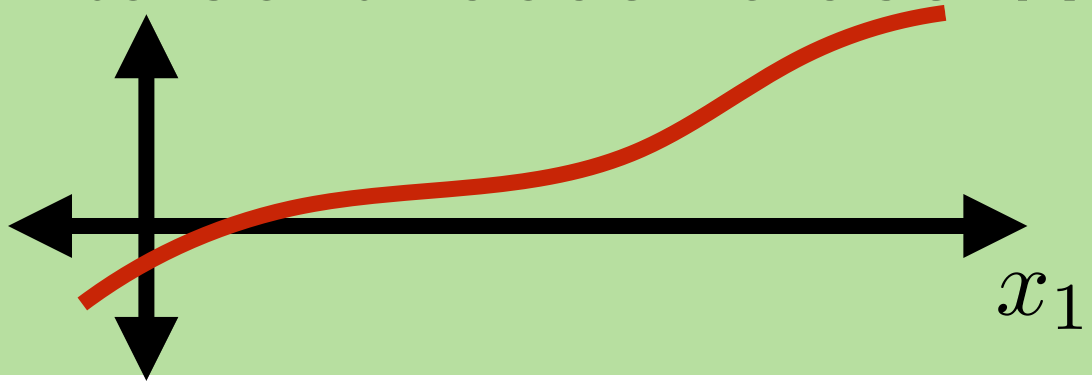


Machine Learning Tasks

- **Supervised learning:** Learn a mapping from features to labels

- **Regression:** Learn a mapping to continuous values: R^d ! R^k



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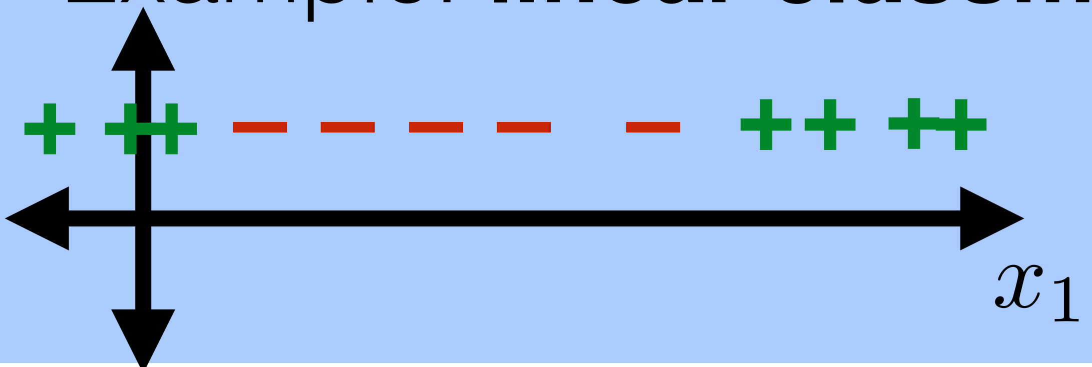

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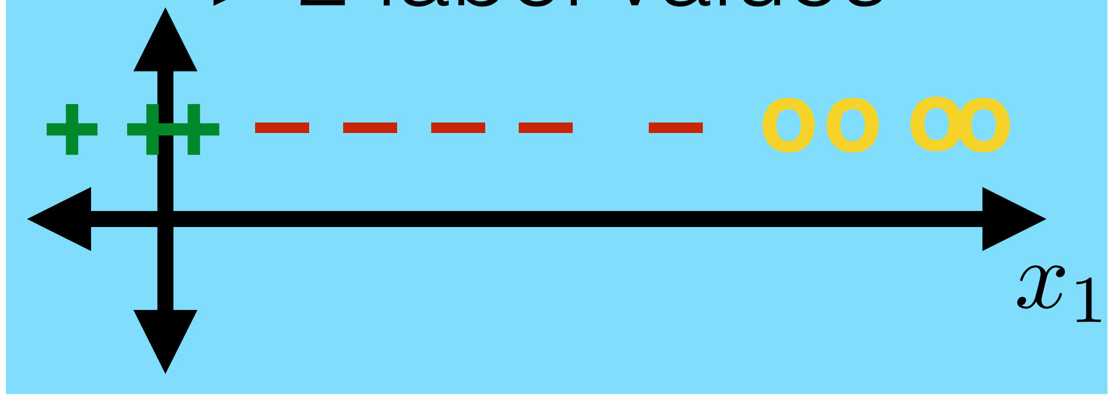

Machine Learning Tasks

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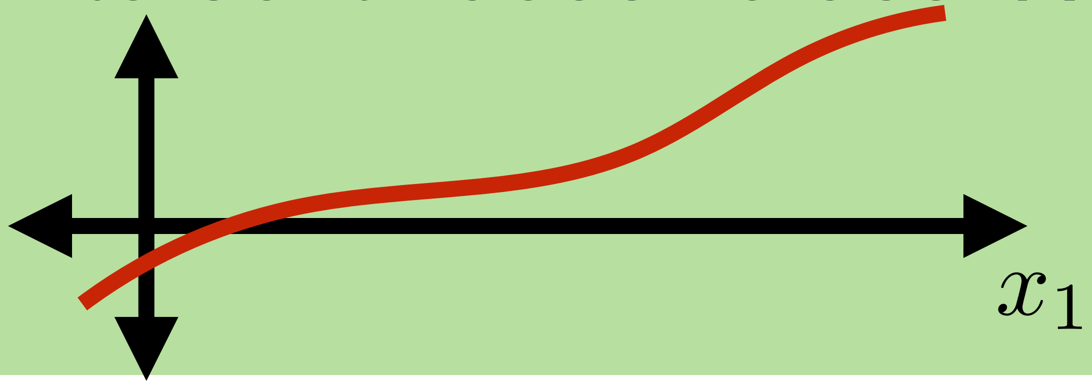

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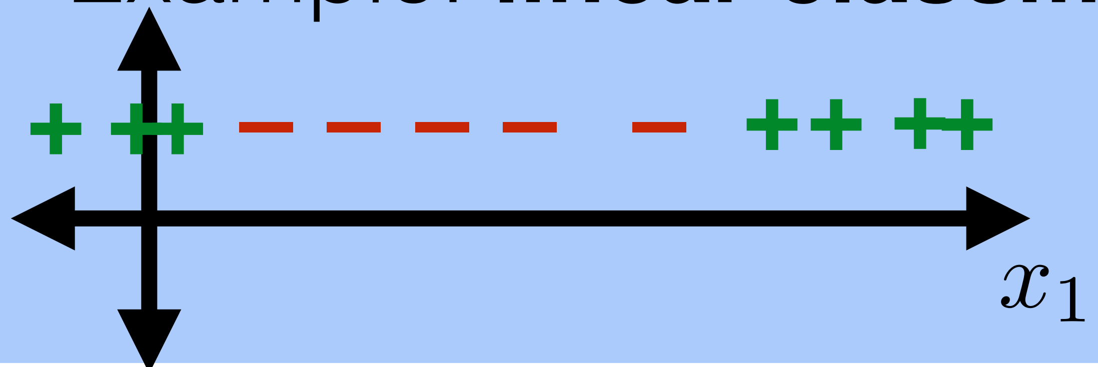

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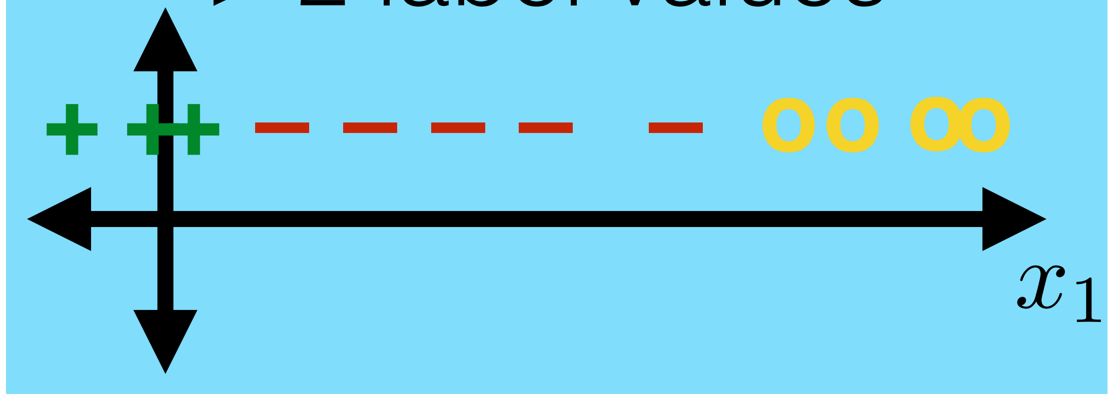
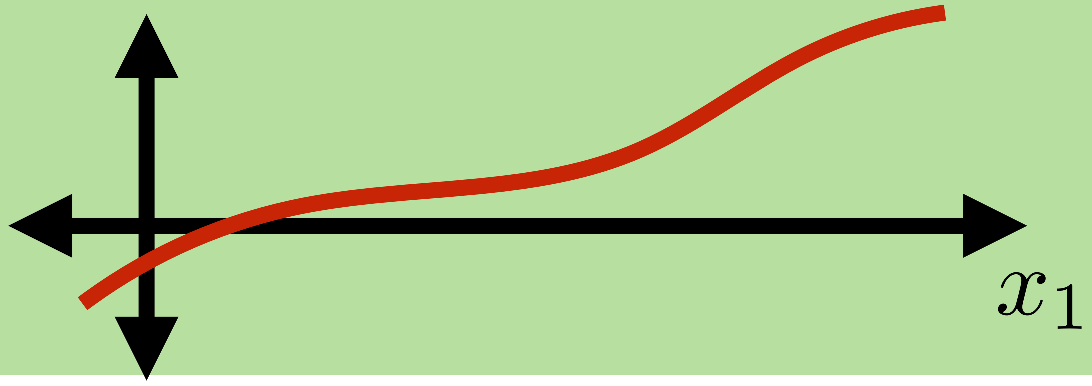


Machine Learning Tasks

- **Supervised learning:** Learn a mapping from features to labels

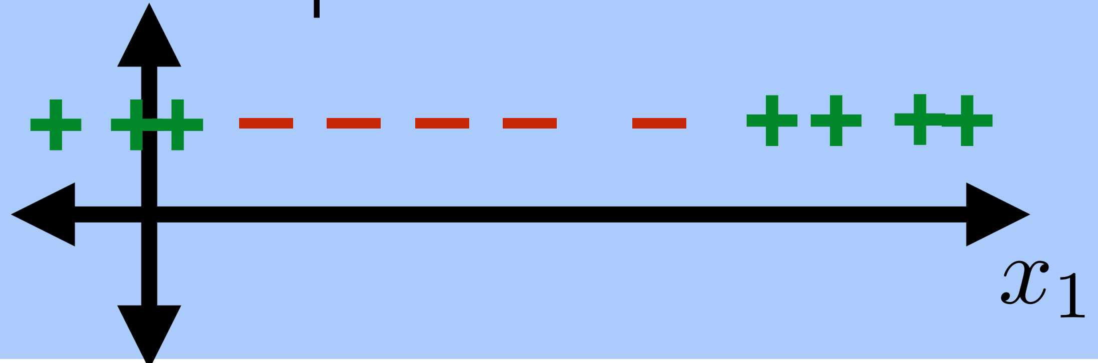
- **Unsupervised learning:** No labels; find patterns

- **Regression:** Learn a mapping to continuous values: R^d ! R^k

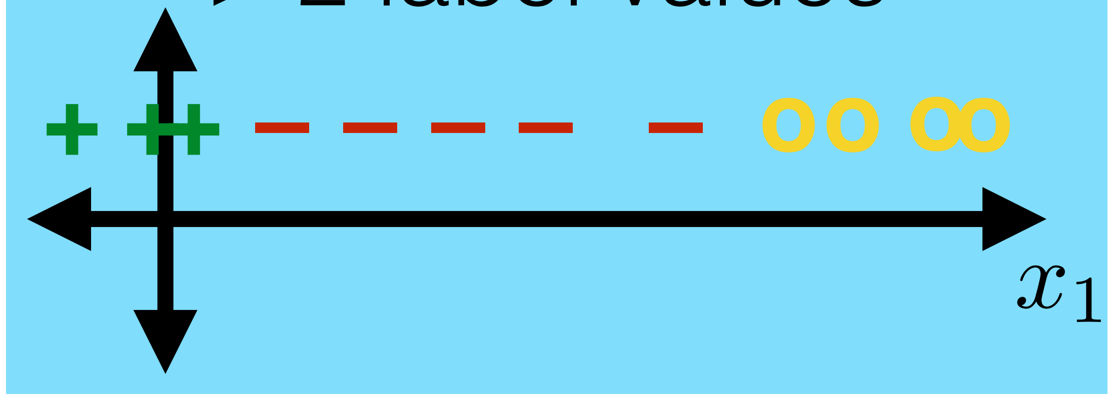


- **Classification:** Learn a mapping to a discrete set

- **Binary/two-class classification:** Learn a mapping: $\mathbb{R}^d \rightarrow \{-1,+1\}$
  - Example: **linear classification**



- **Multi-class classification:** > 2 label values



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