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? Ask on Discourse: discourse.odl.mit.edu

Materials: Will all be available at course website

Today's Plan

I. (More) logistics

II. Machine learning setup

III. Linear classifiers

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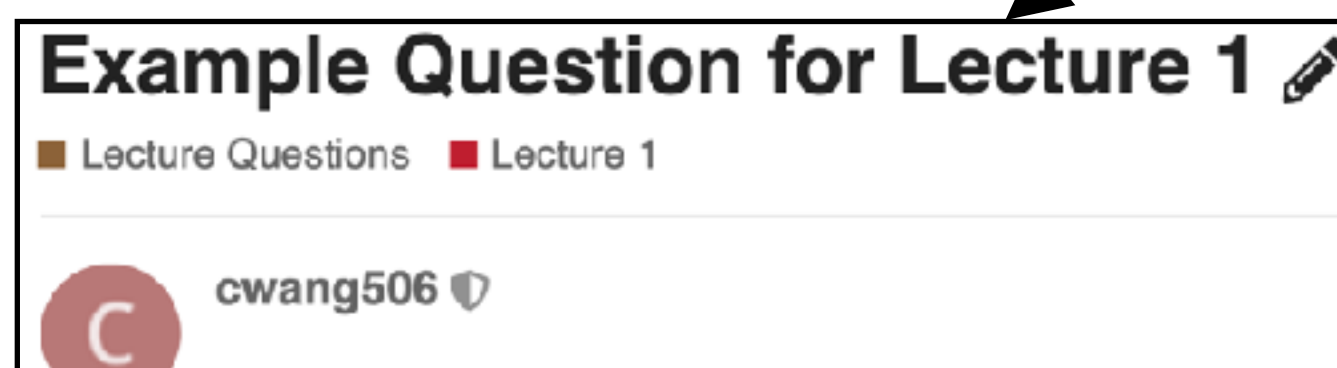

(set "Lecture 1" category)

Is Introduction to Machine Learning (6.036/6.862) right for you?

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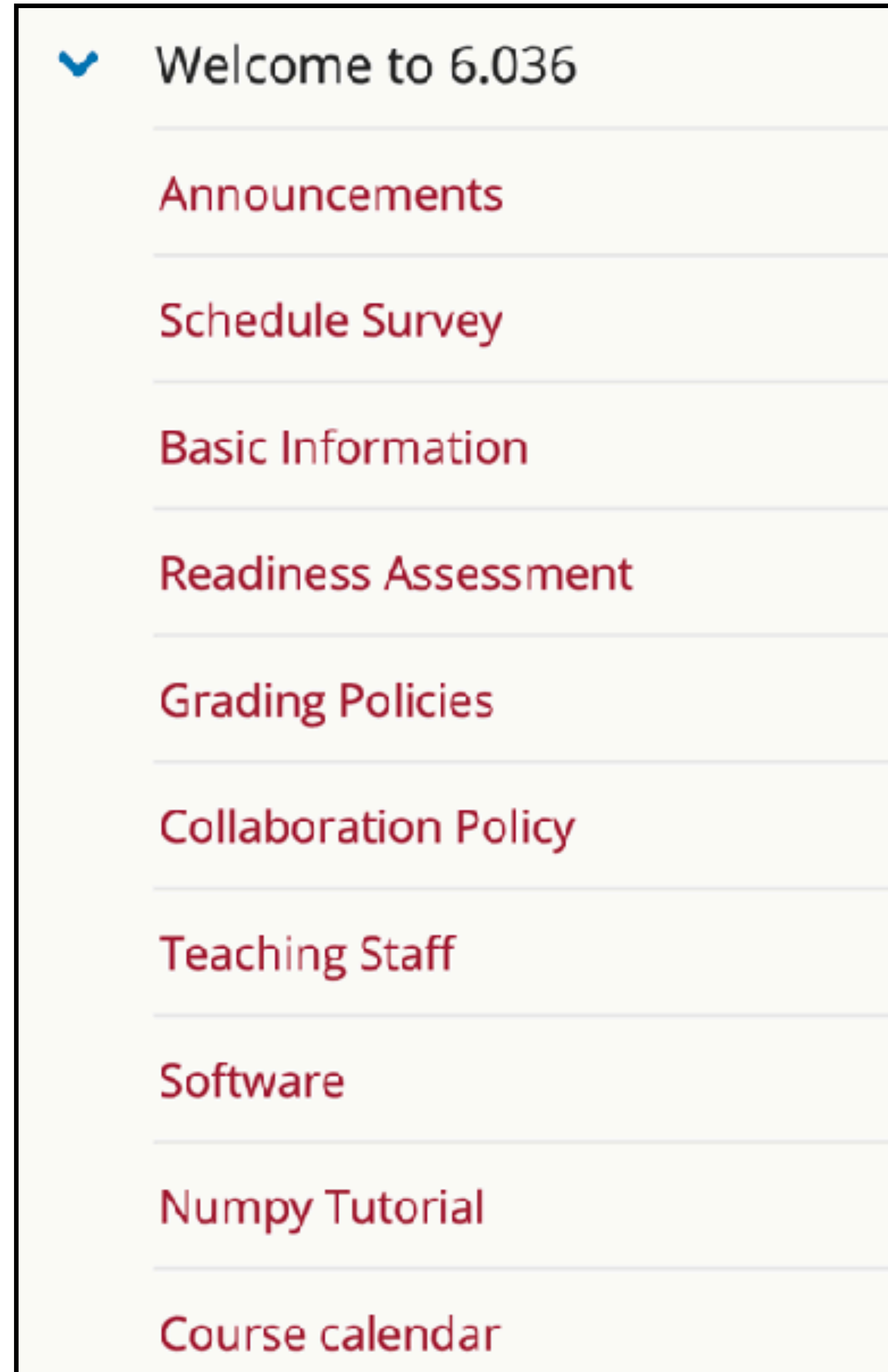

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- Grading Policies
- Collaboration Policy
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- Software
- Numpy Tutorial
- Course calendar

6.036/6.862: Introduction to Machine Learning

6.036/6.862: Introduction to Machine Learning, Staff

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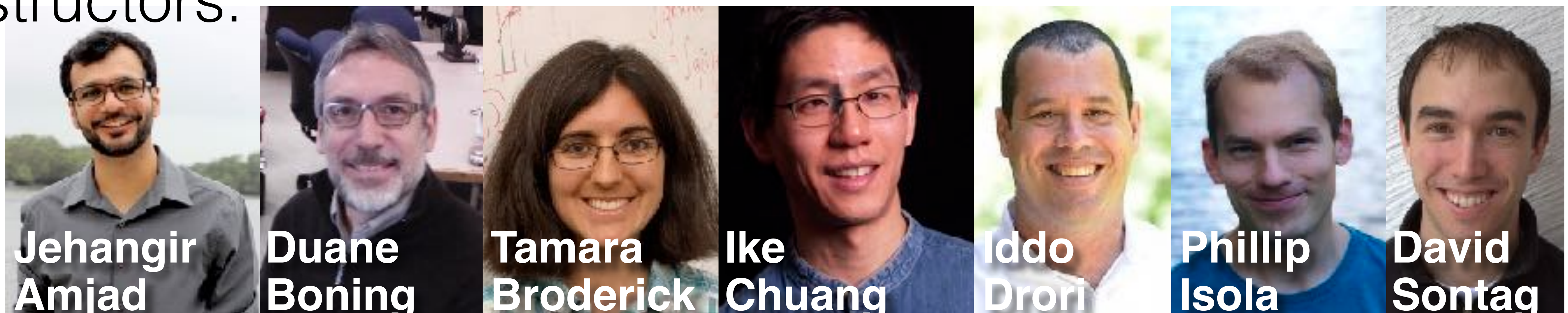

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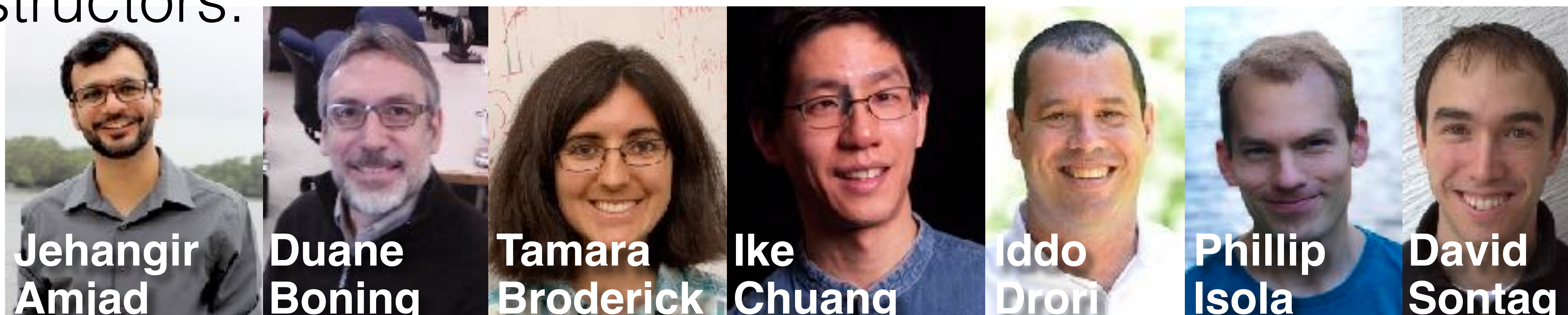
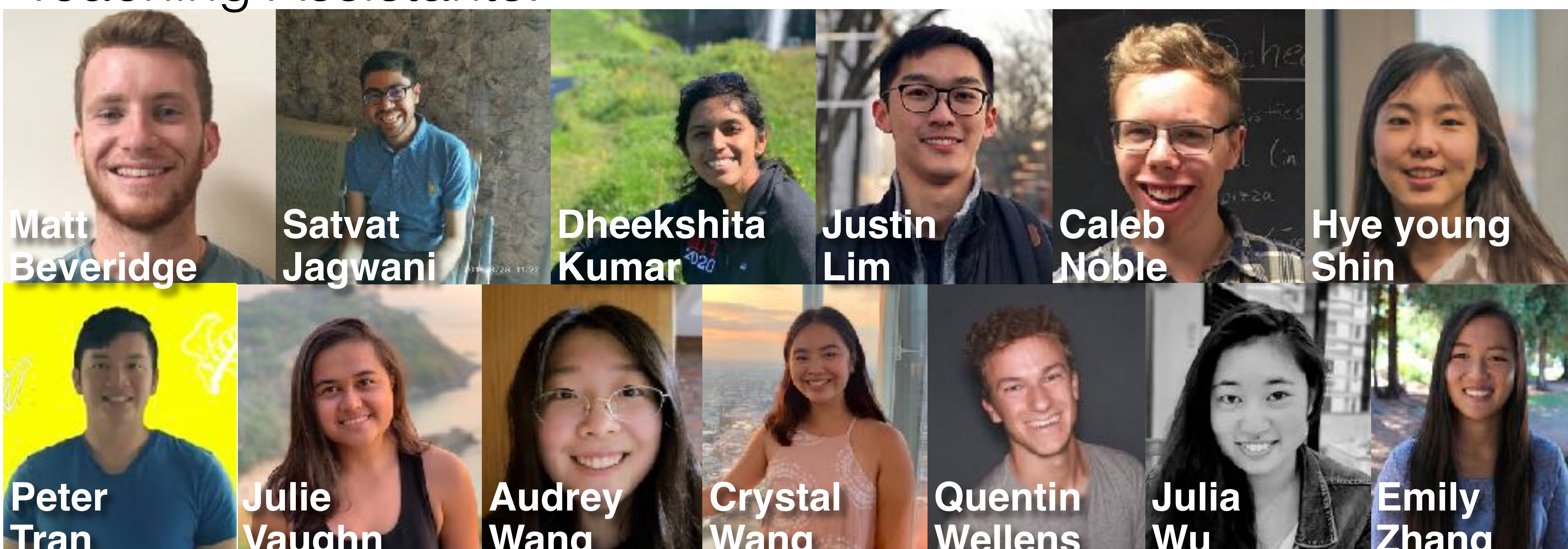


Teaching Assistants:



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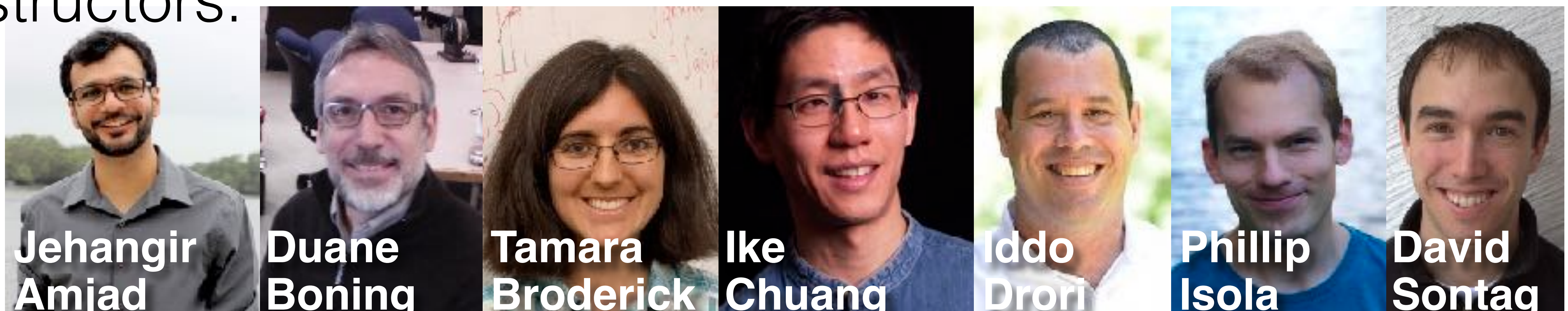

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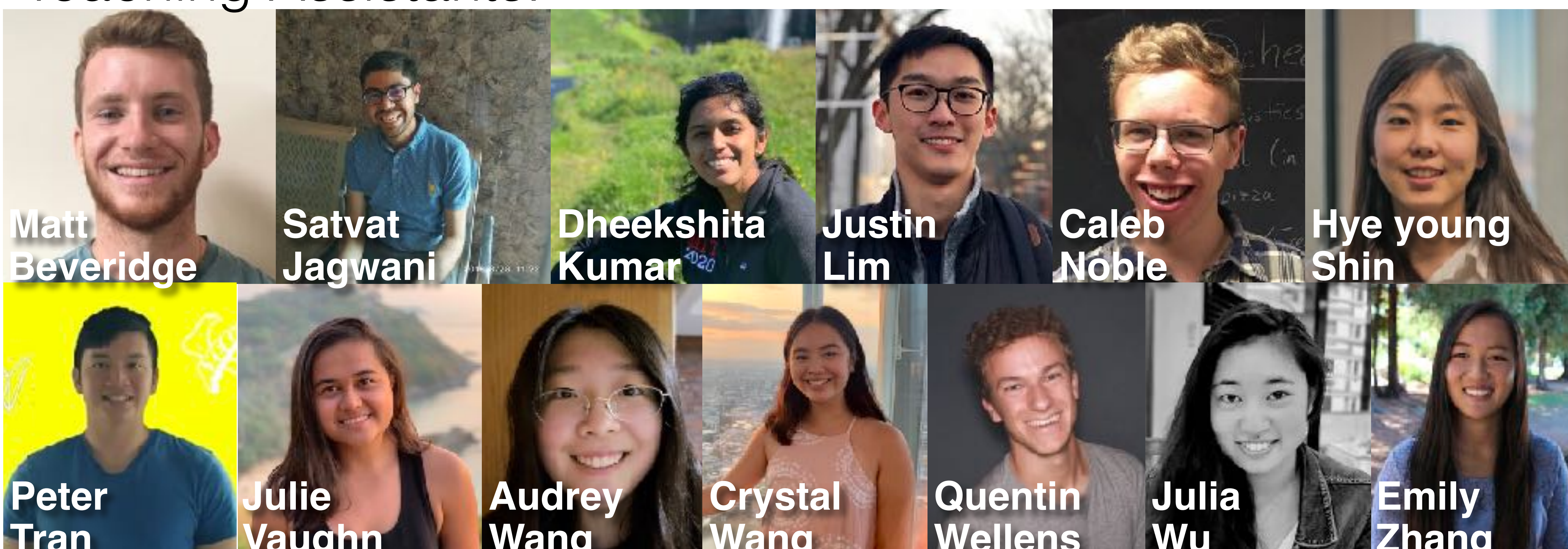

And Lab Assistants!

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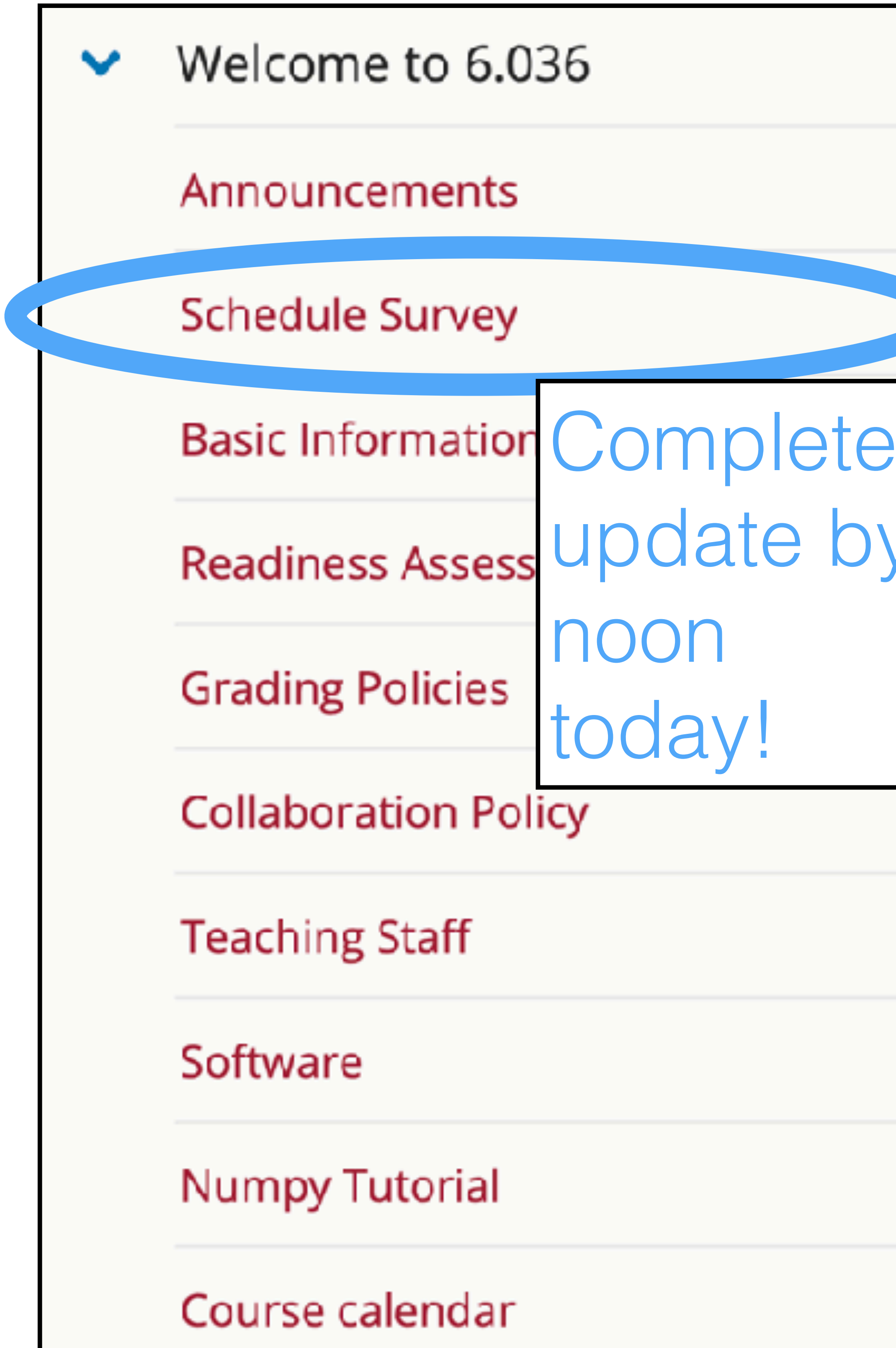

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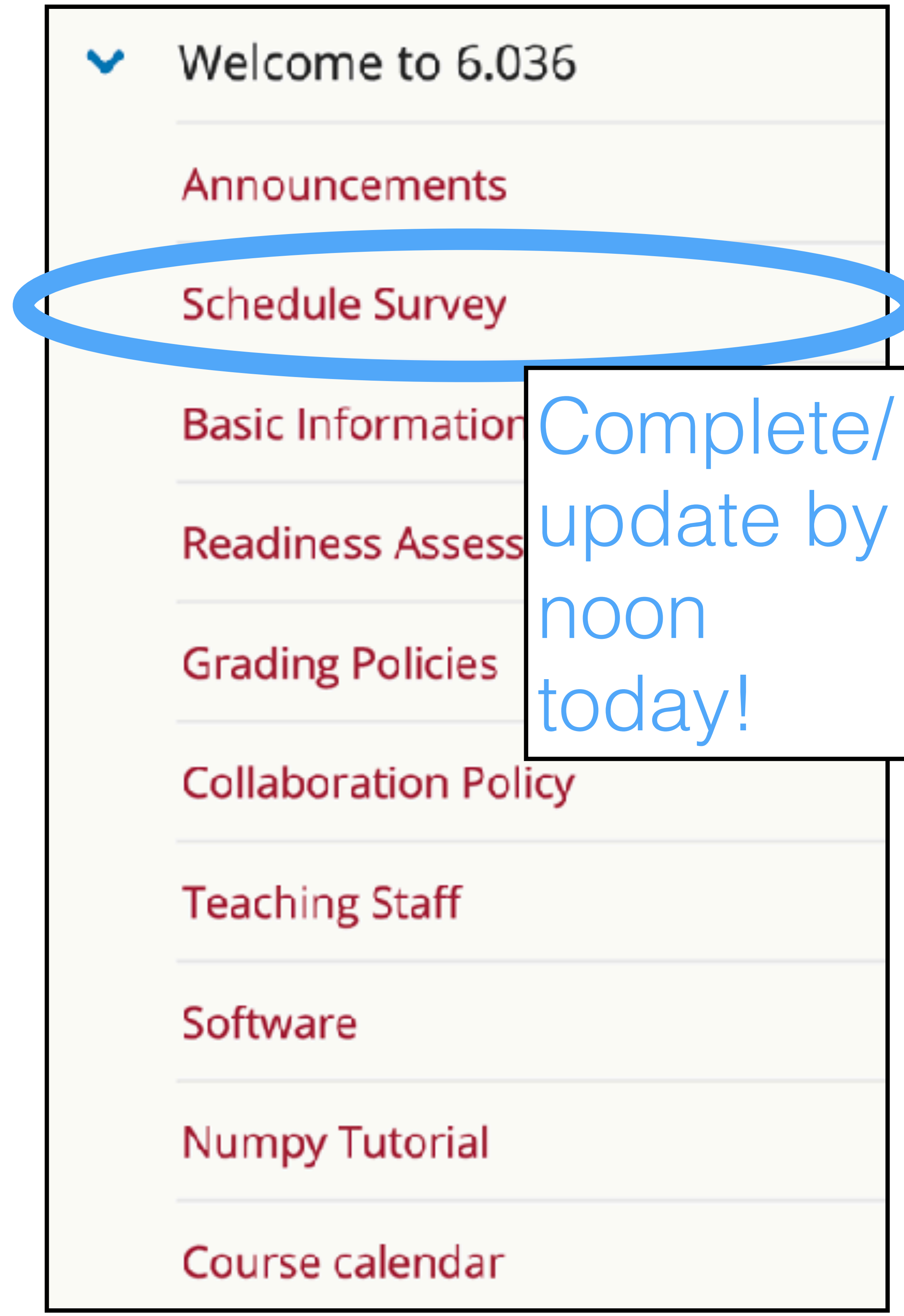

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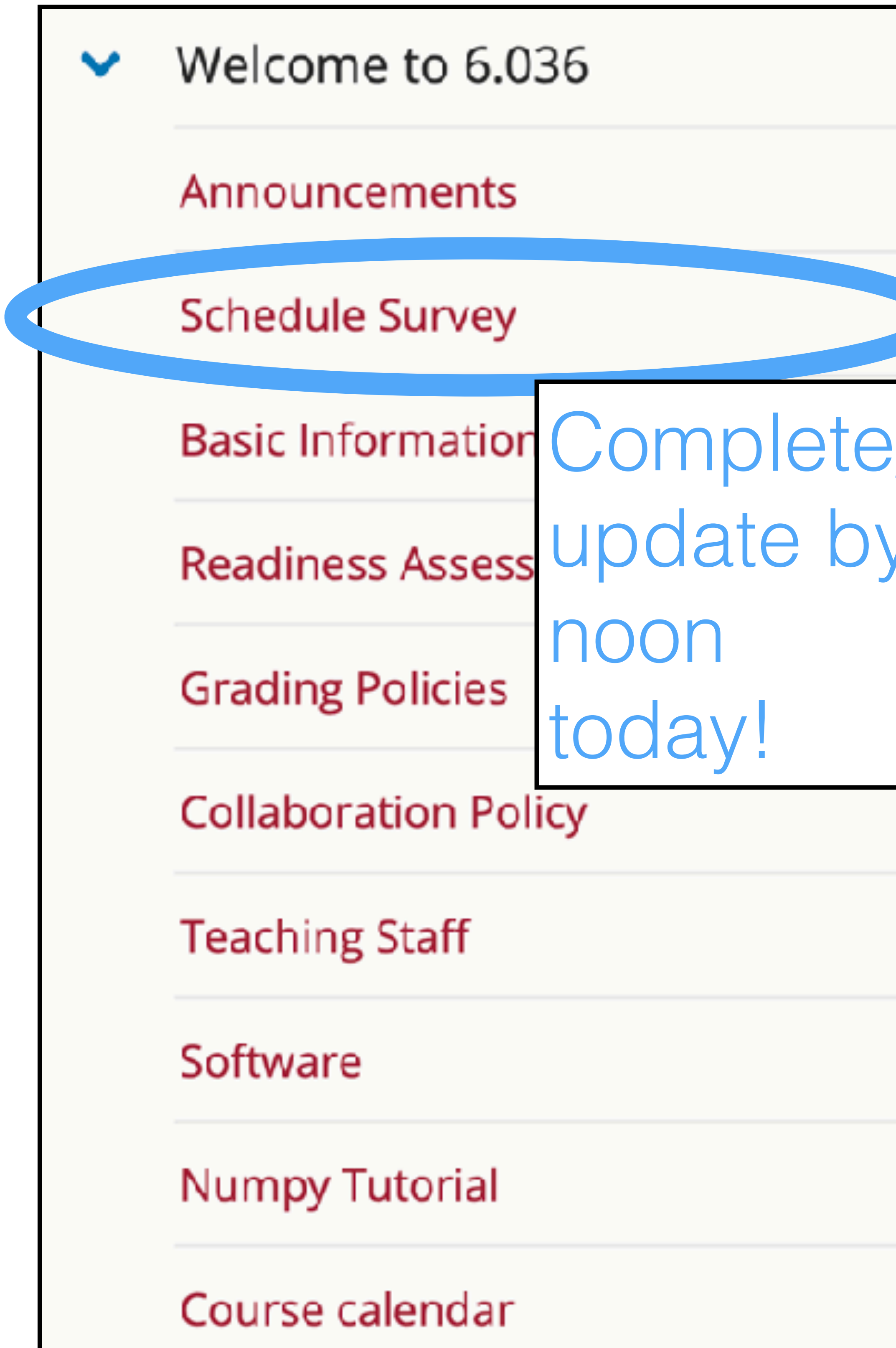

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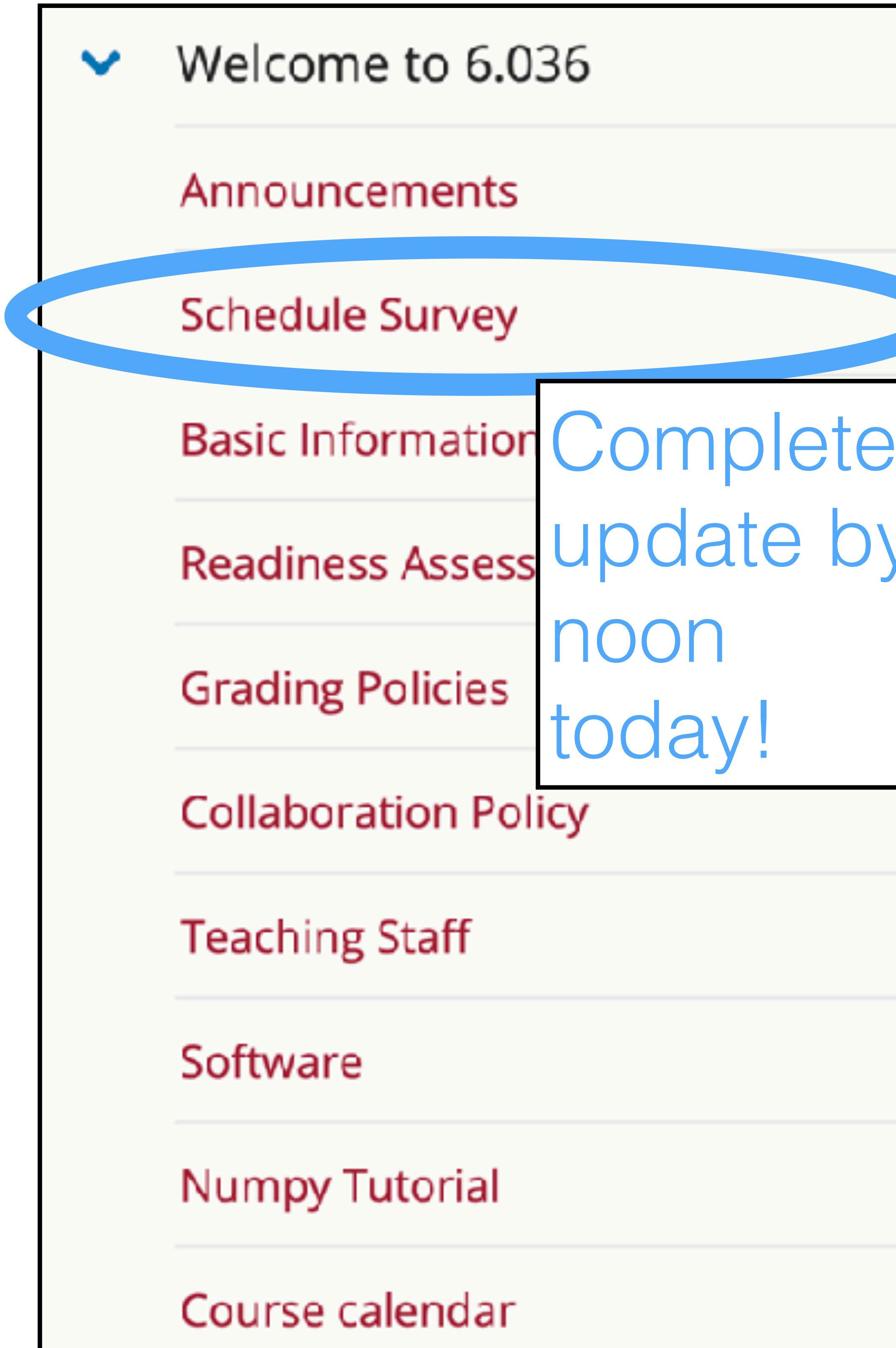

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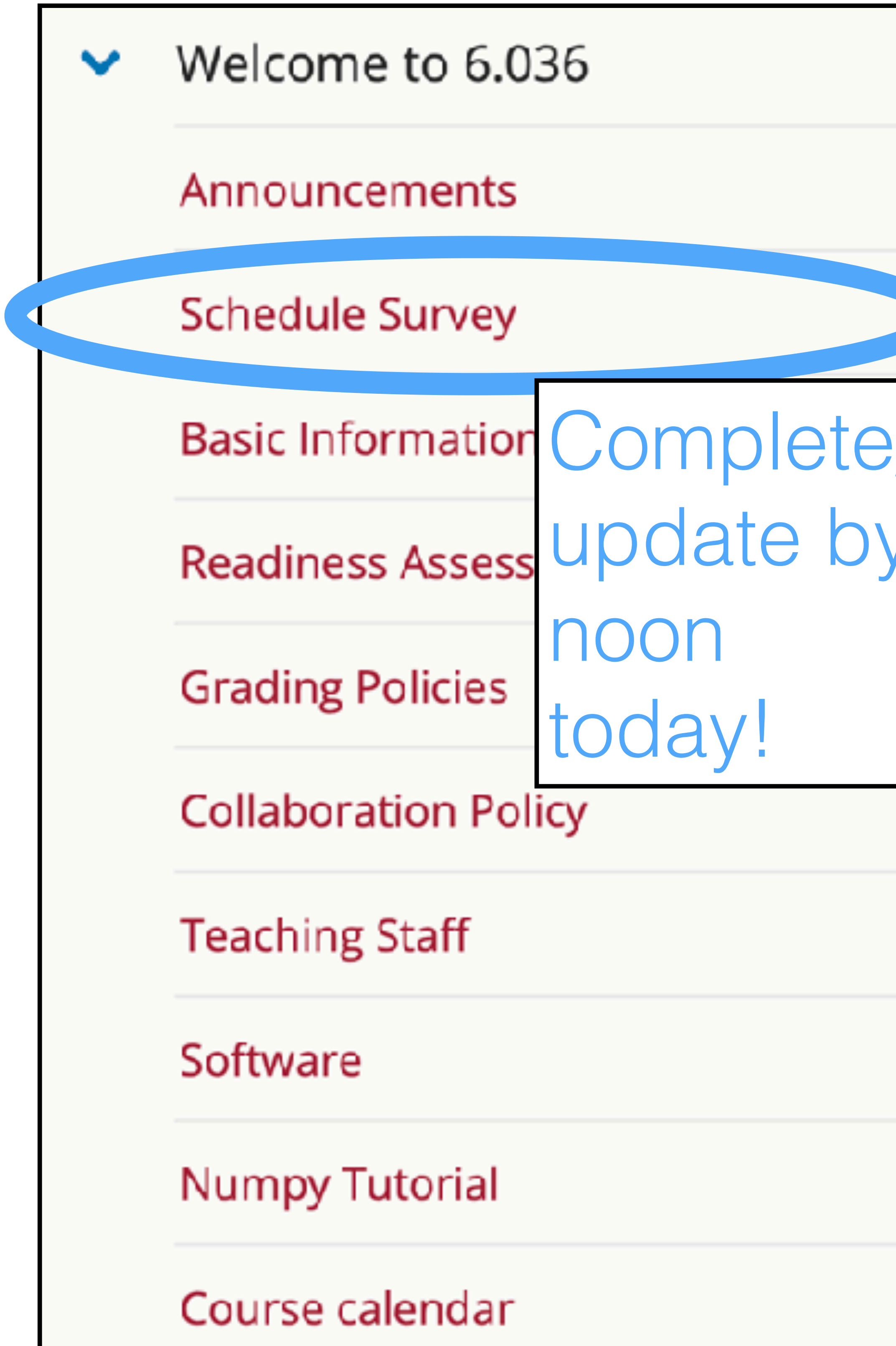

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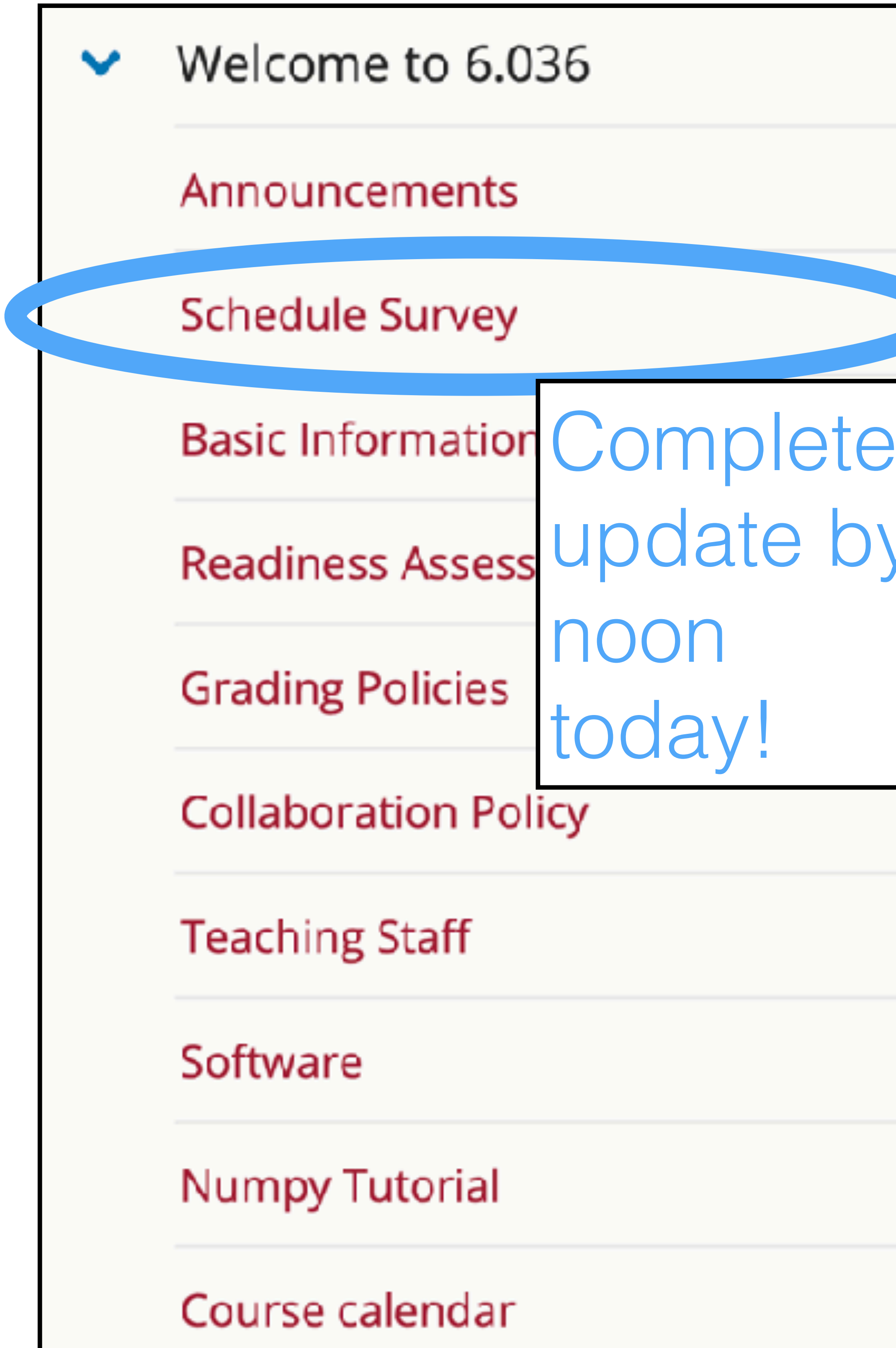

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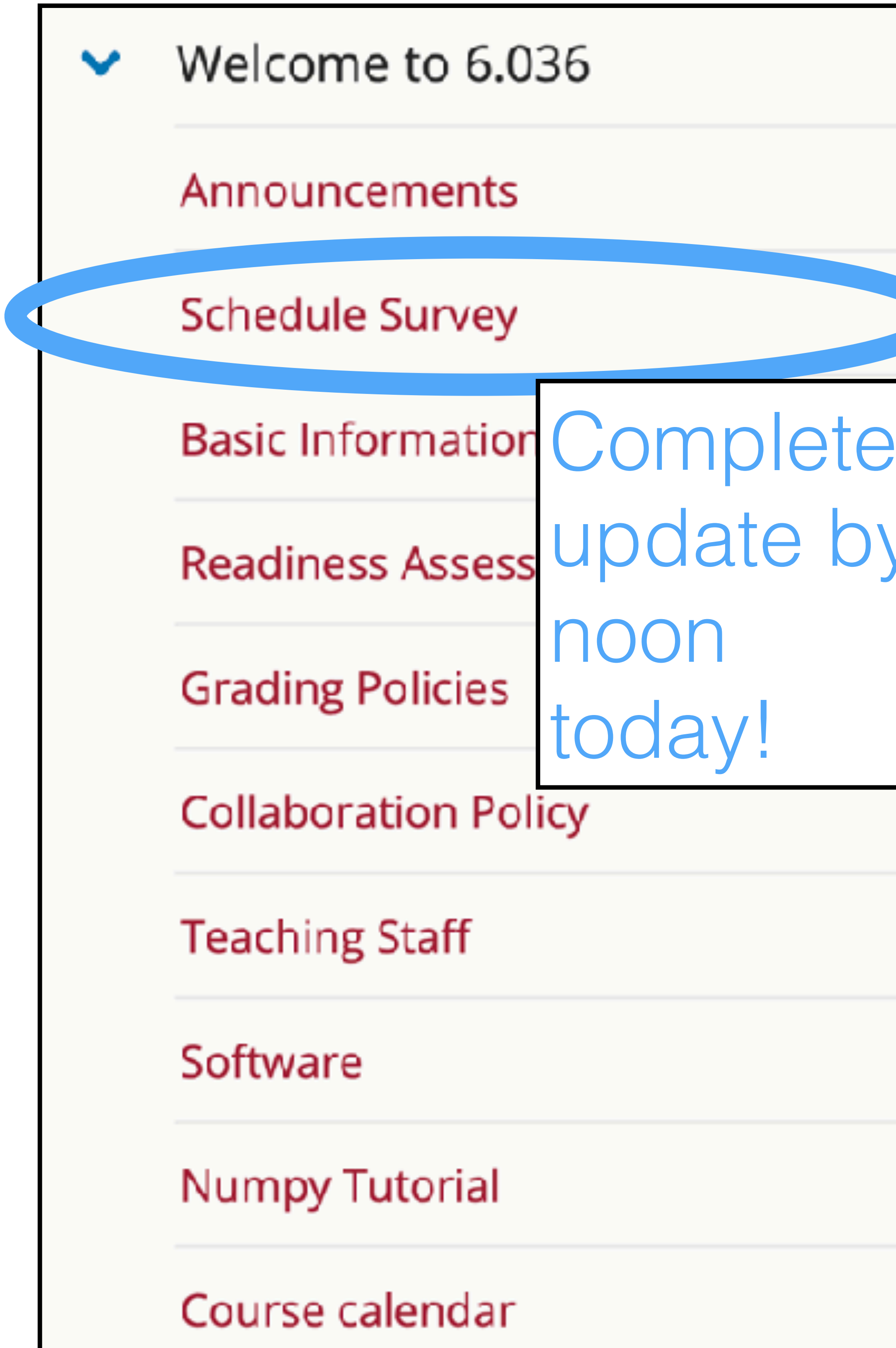

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  NQ due Sep 4, 2020 16:00 EDT
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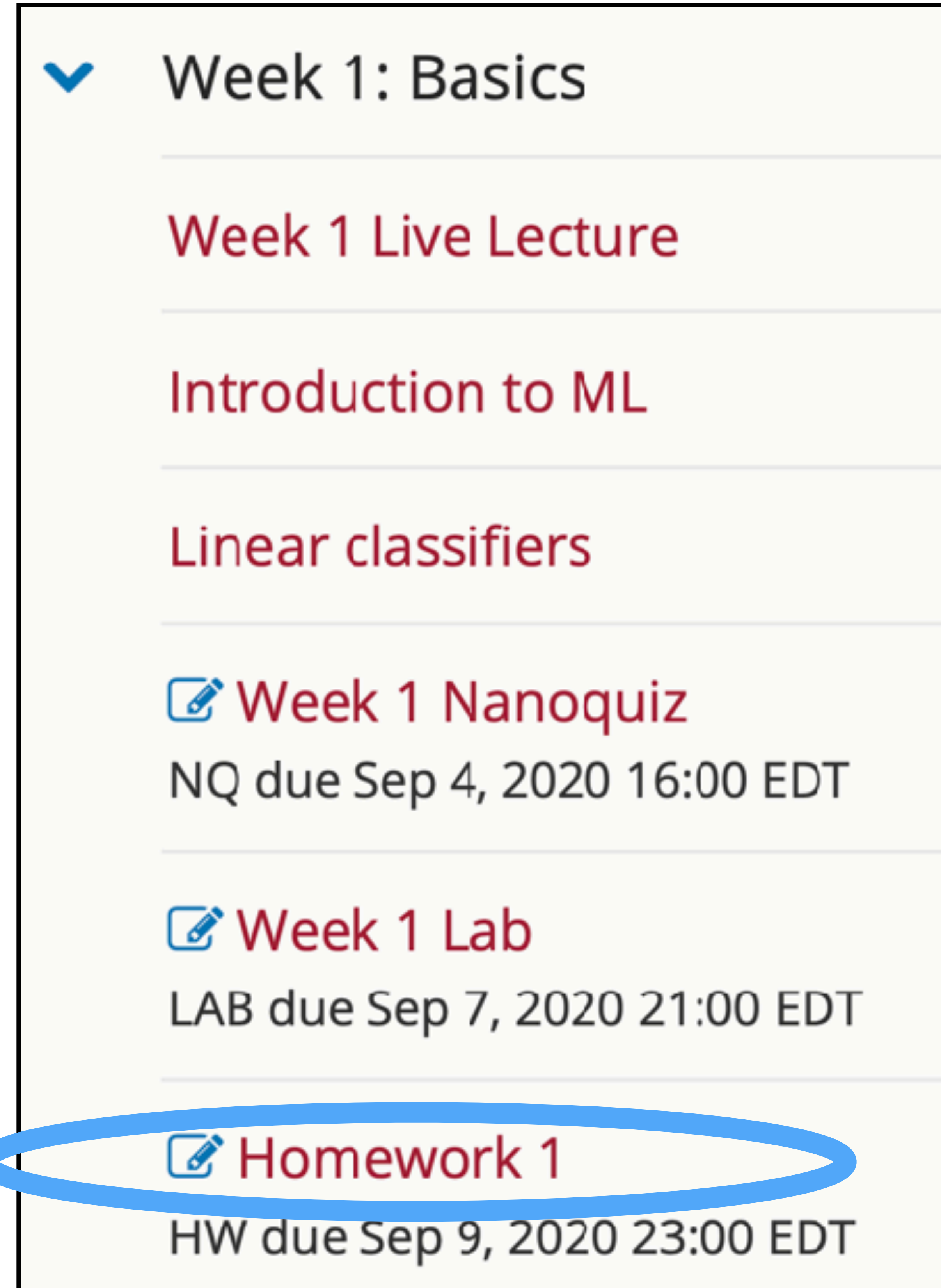

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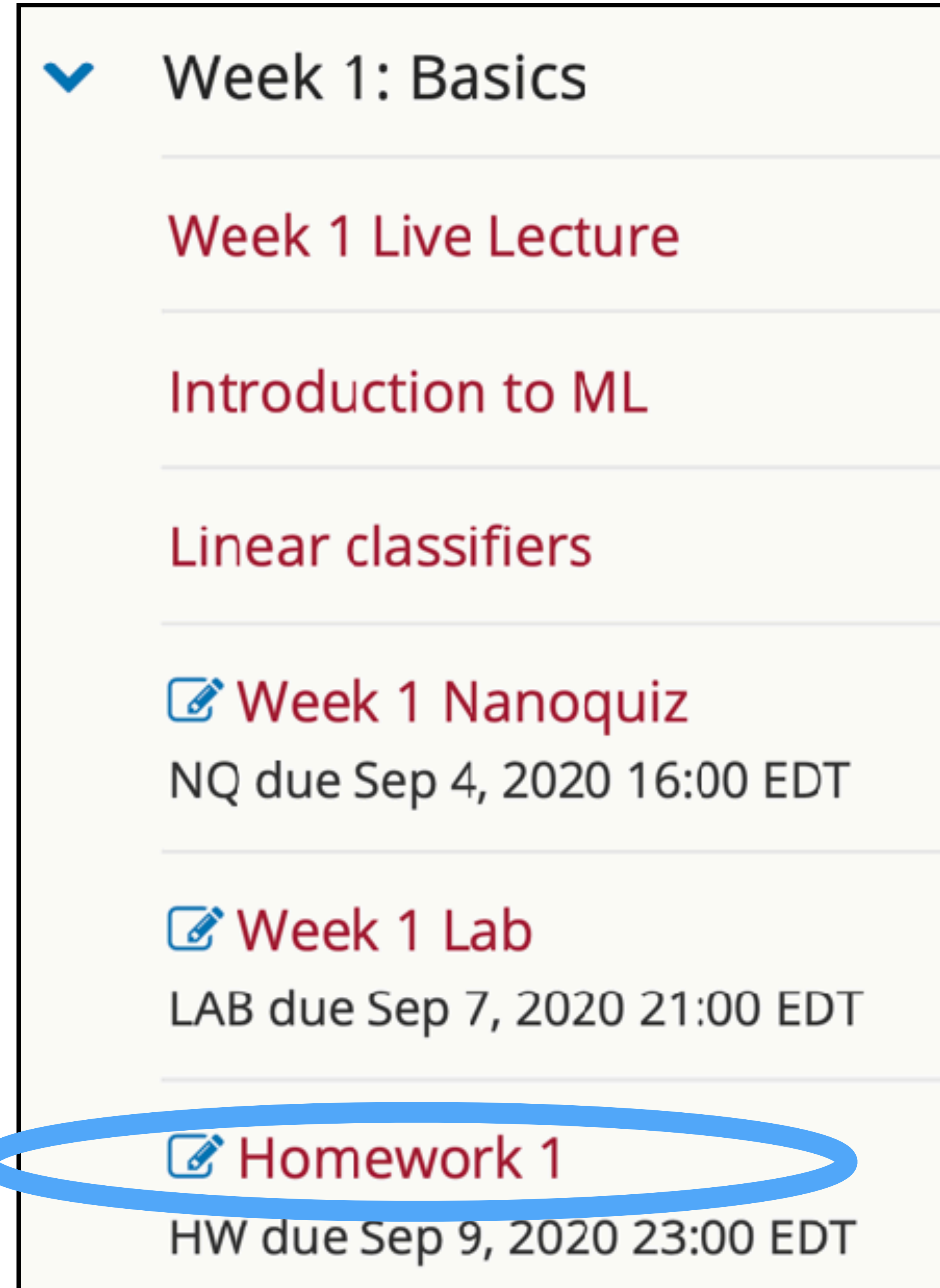

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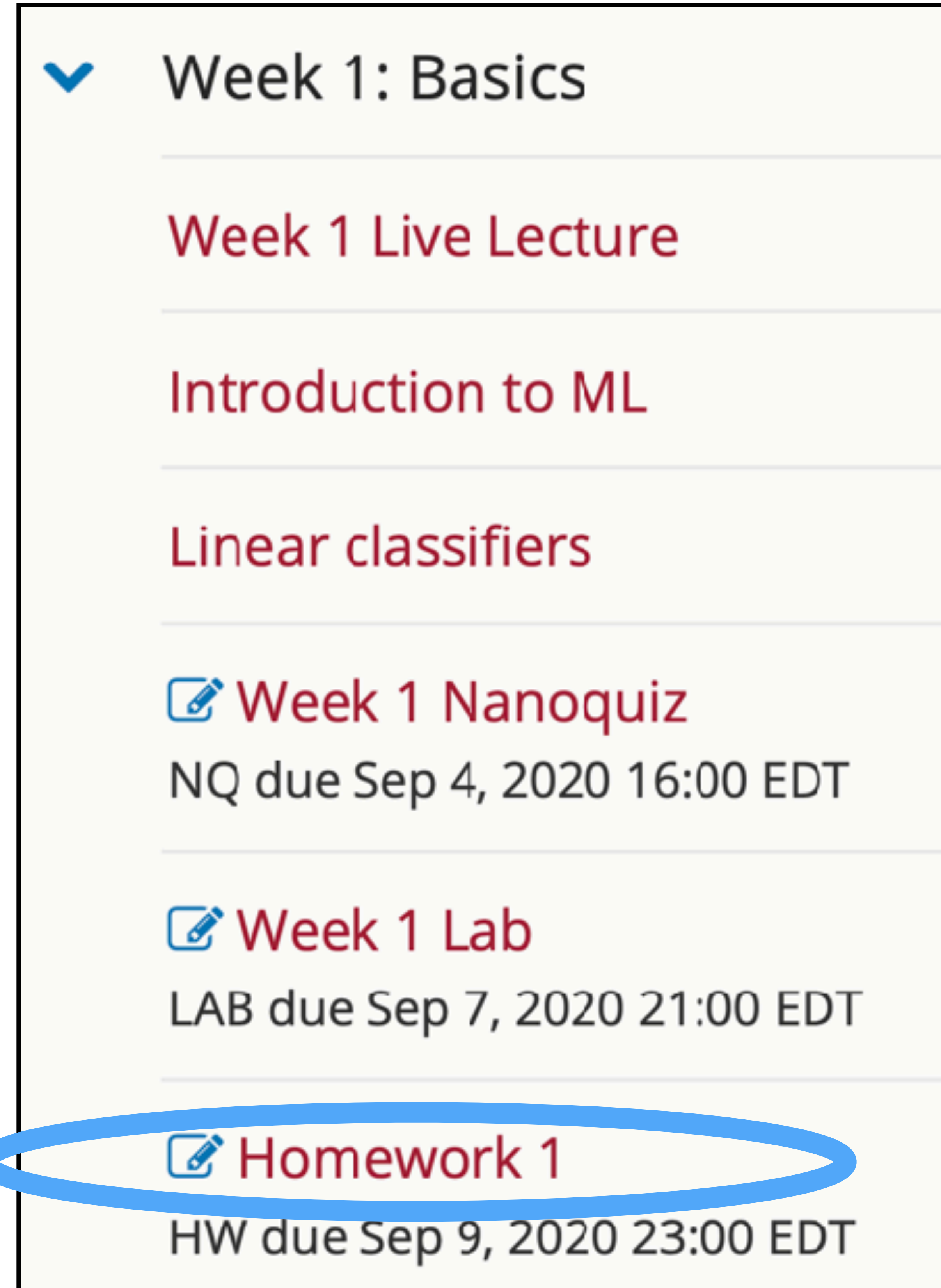

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- **6.862:** project (canvas.mit.edu)

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Machine learning (ML): why & what

Machine learning (ML): why & what

Machine learning algorithm confirms 50 new exoplanets in historic first

by R. Dallon Adams in Innovation
on August 26, 2020, 9:07 AM PST

A new machine learning technique can be used to sift through massive datasets to discern exoplanets from false positives.

TechRepublic.

[https://www.techrepublic.com/article/machine-learning-algorithm-confirms-50-new-exoplanets-in-historic-first/]

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[https://www.thelancet.com/journals/lanchi/article/PIIS2352-4642(20)30239-X/fulltext]

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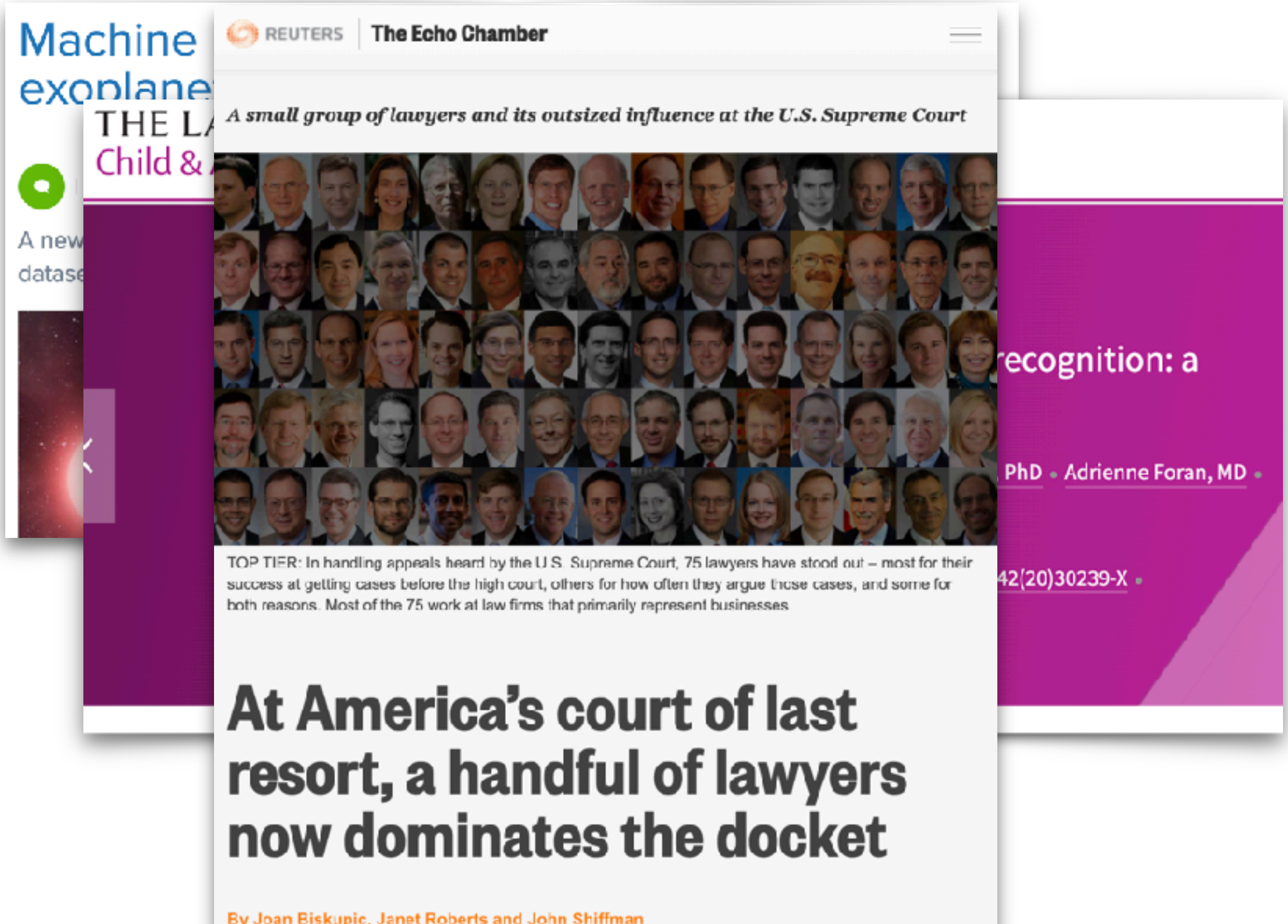

[https://www.reuters.com/investigates/special-report/scotus/]

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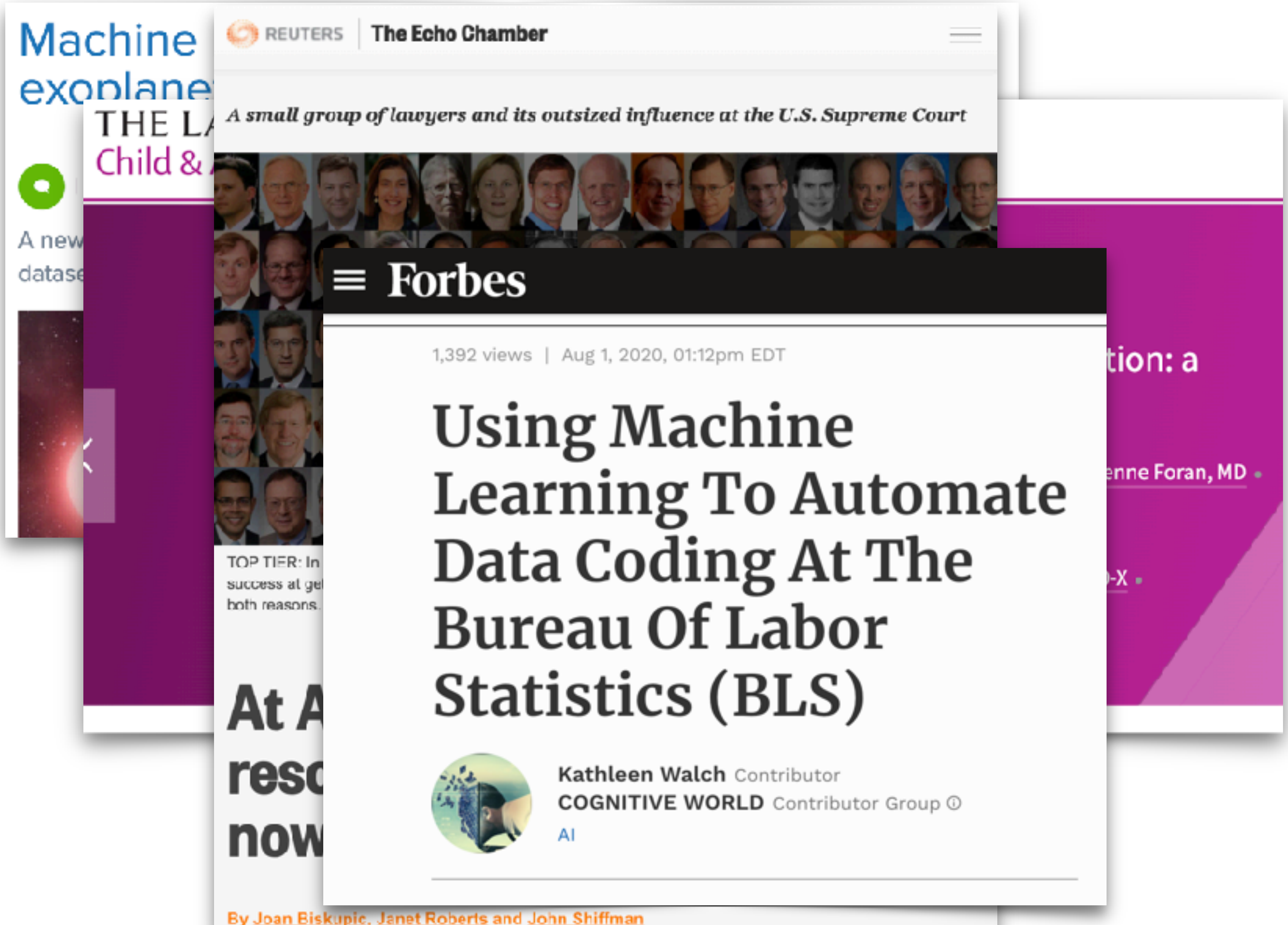

[https://www.forbes.com/sites/cognitiveworld/2020/08/01/using-machine-learning-to-automate-data-coding-at-the-bureau-of-labor-statistics-bls]

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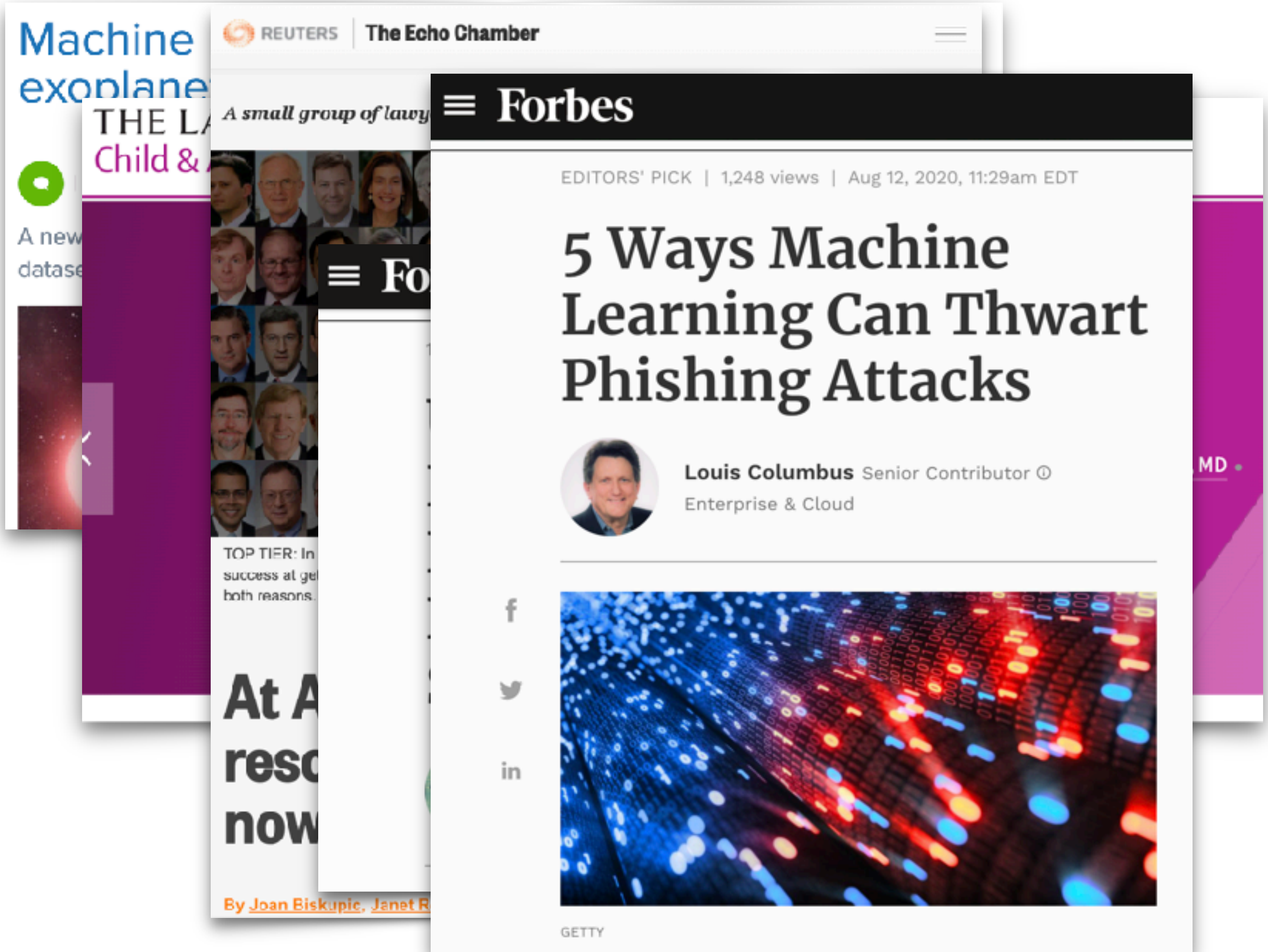

[https://www.forbes.com/sites/louiscolumbus/2020/08/12/5-ways-machine-learning-can-thwart-phishing-attacks]

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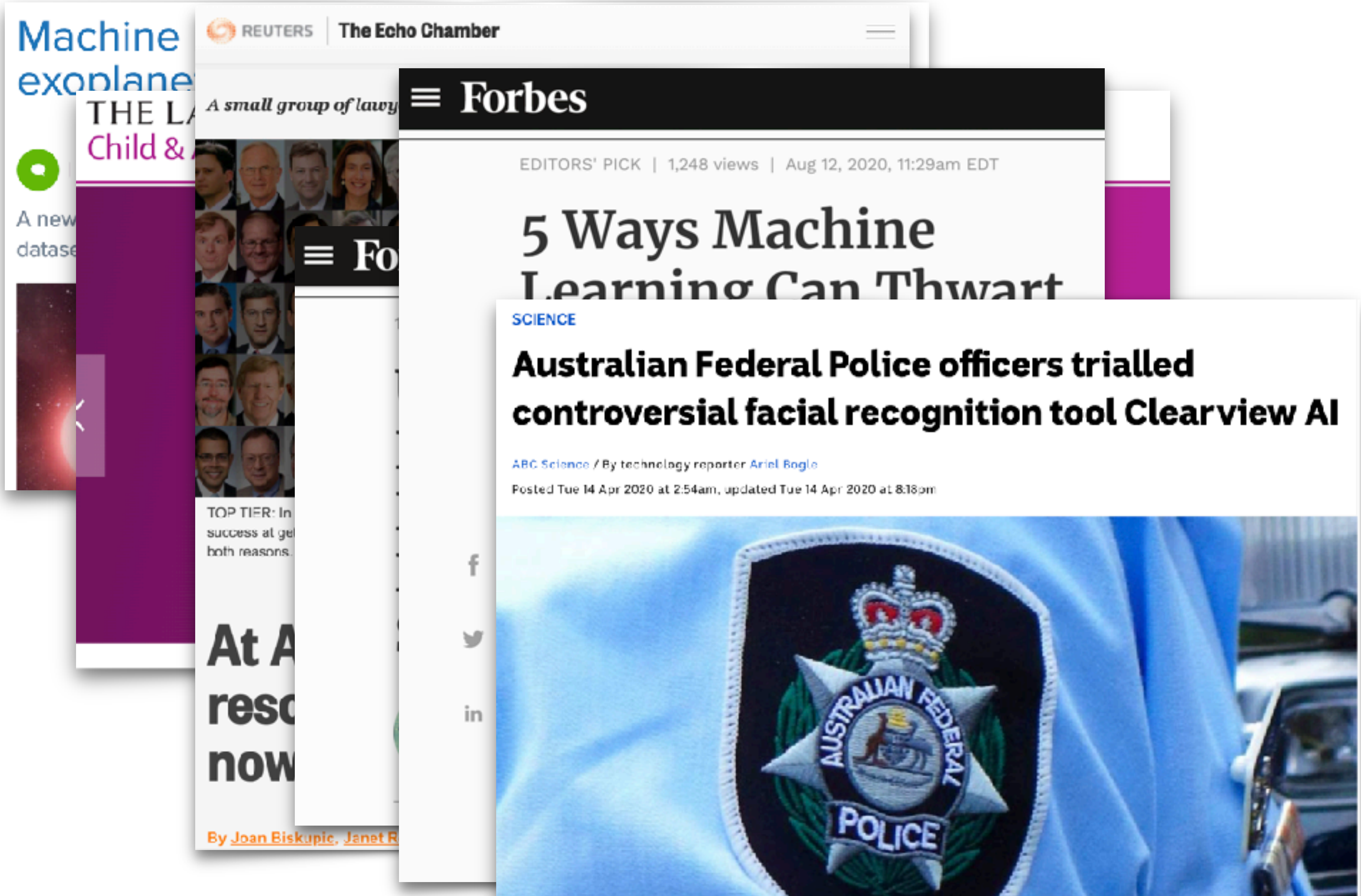

[https://www.abc.net.au/news/science/2020-04-14/clearview-ai-facial-recognition-tech-australian-federal-police/12146894]

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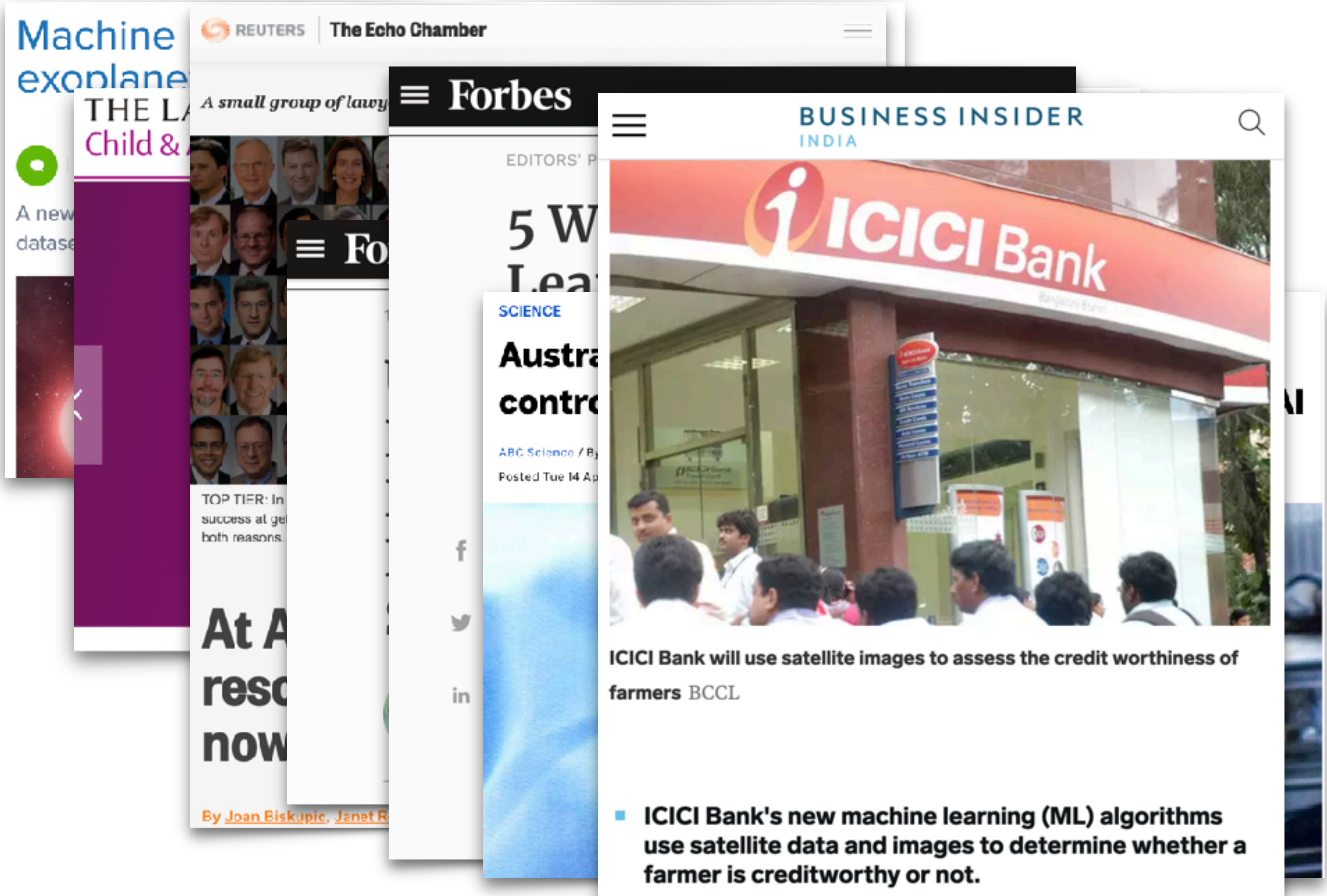

[https://www.businessinsider.in/finance/banks/news/icici-bank-is-looking-to-pump-out-more-kisan-credit-cards-with-satellite-data-and-machine-learning-at-its-side/articleshow/77741696.cms]

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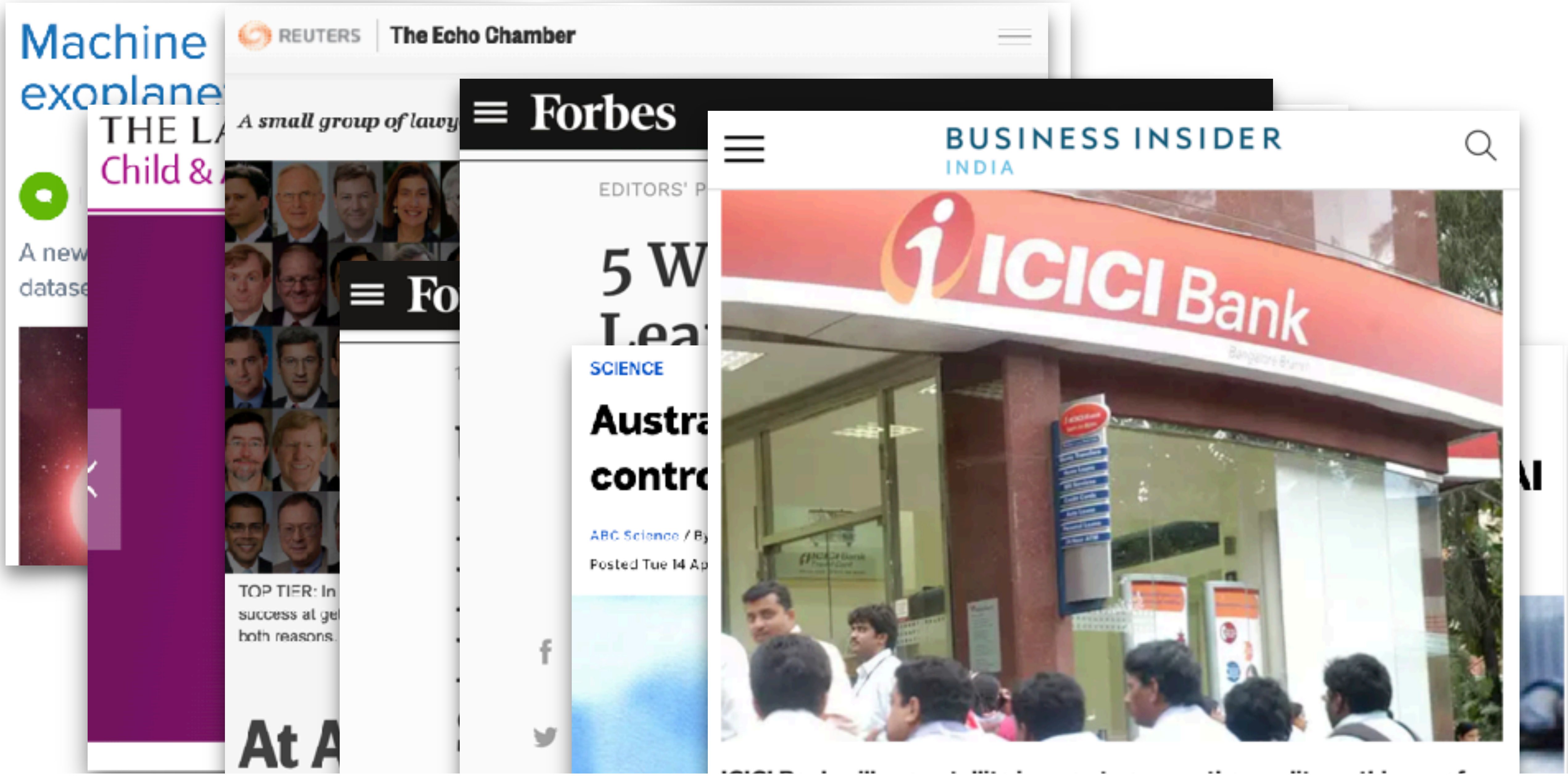

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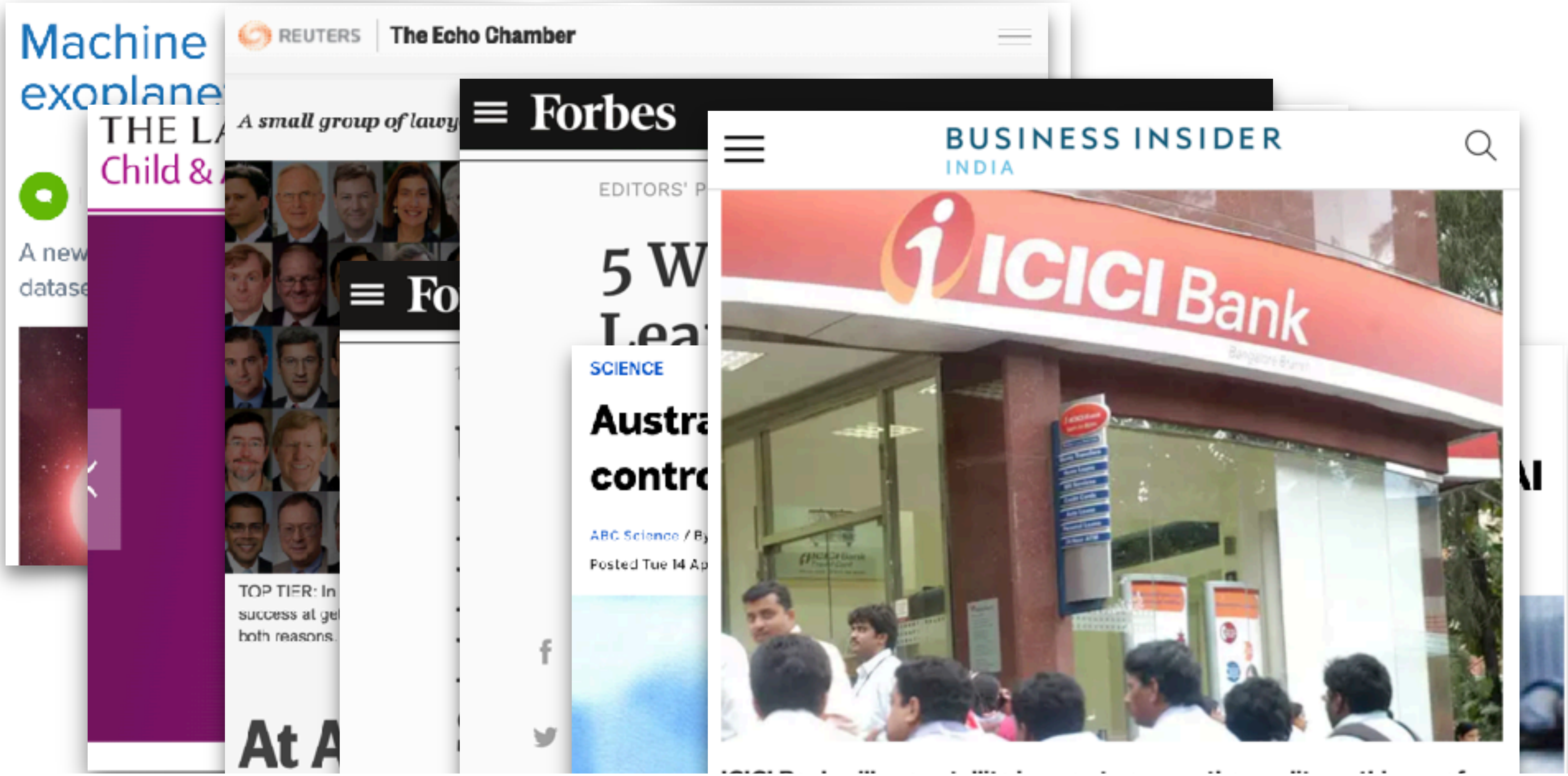

- **What is ML?**

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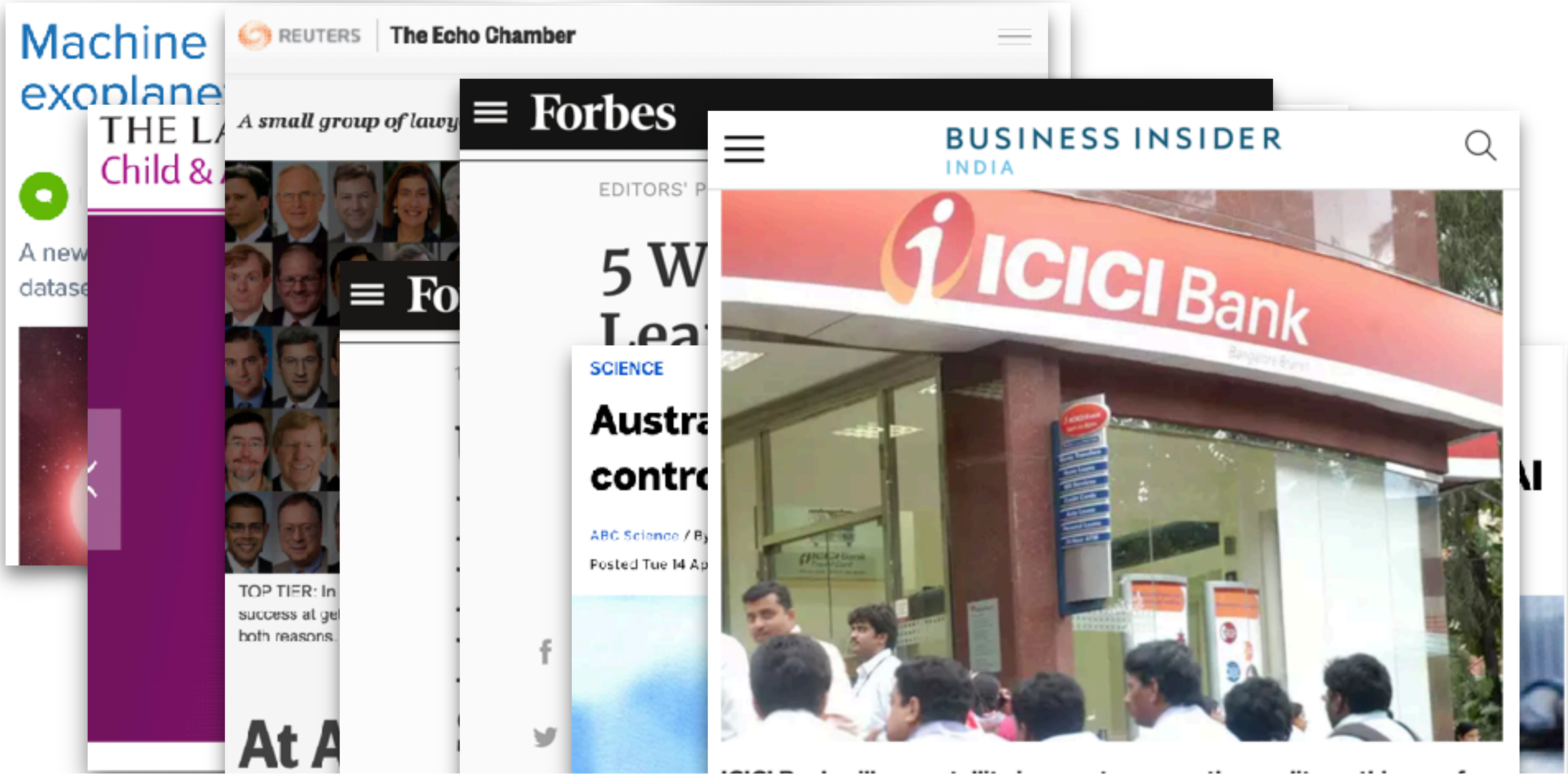

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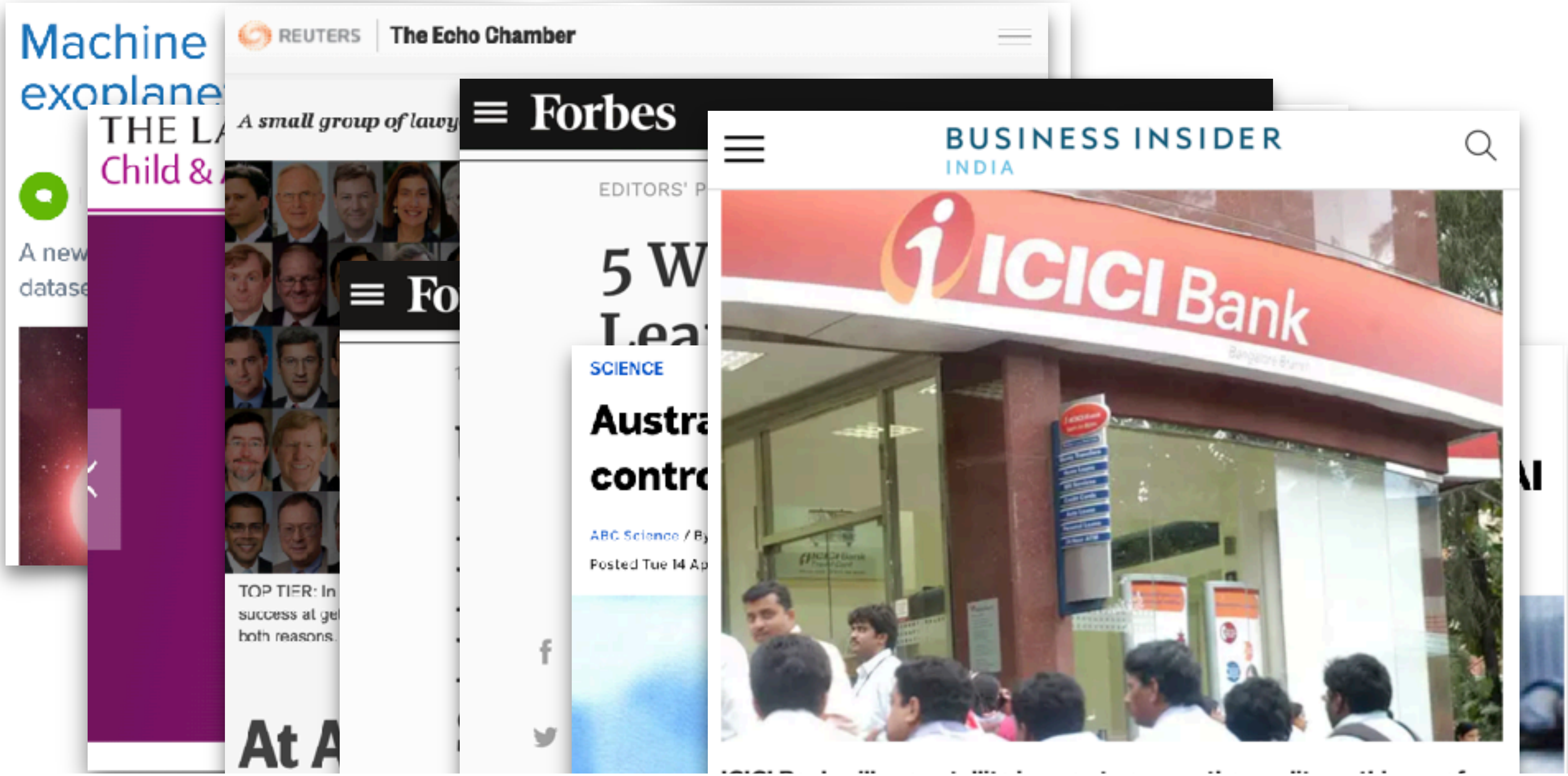

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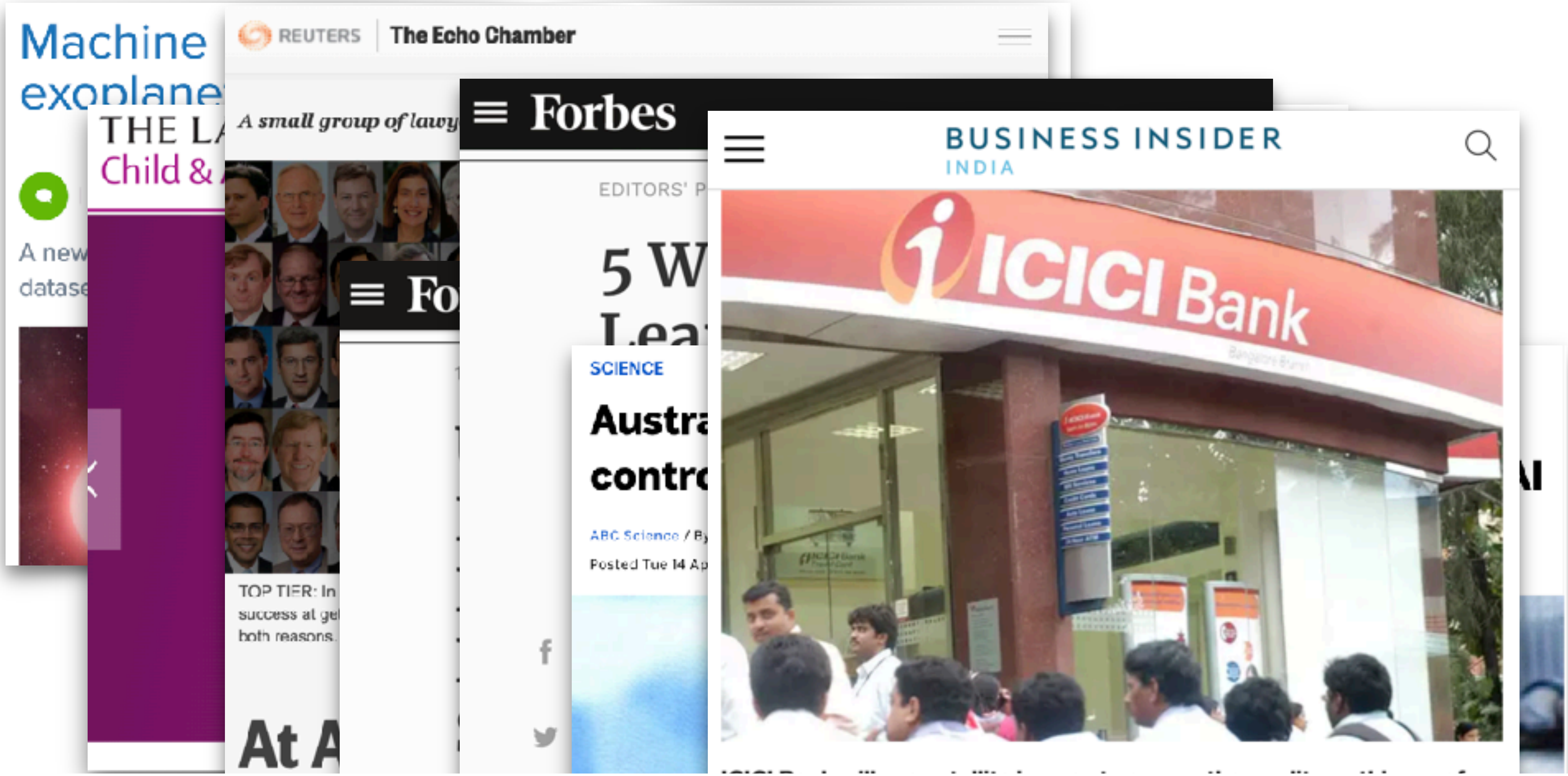

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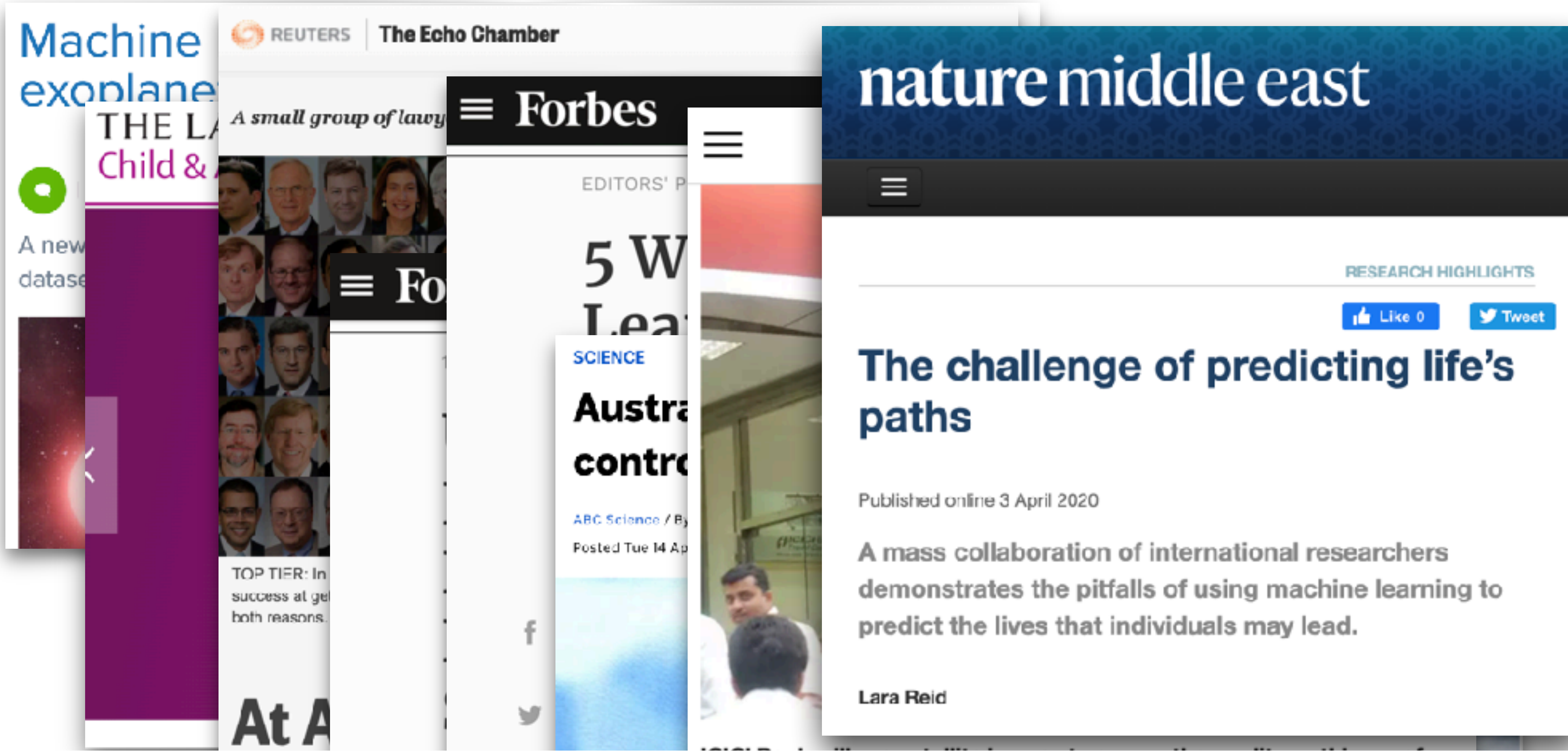

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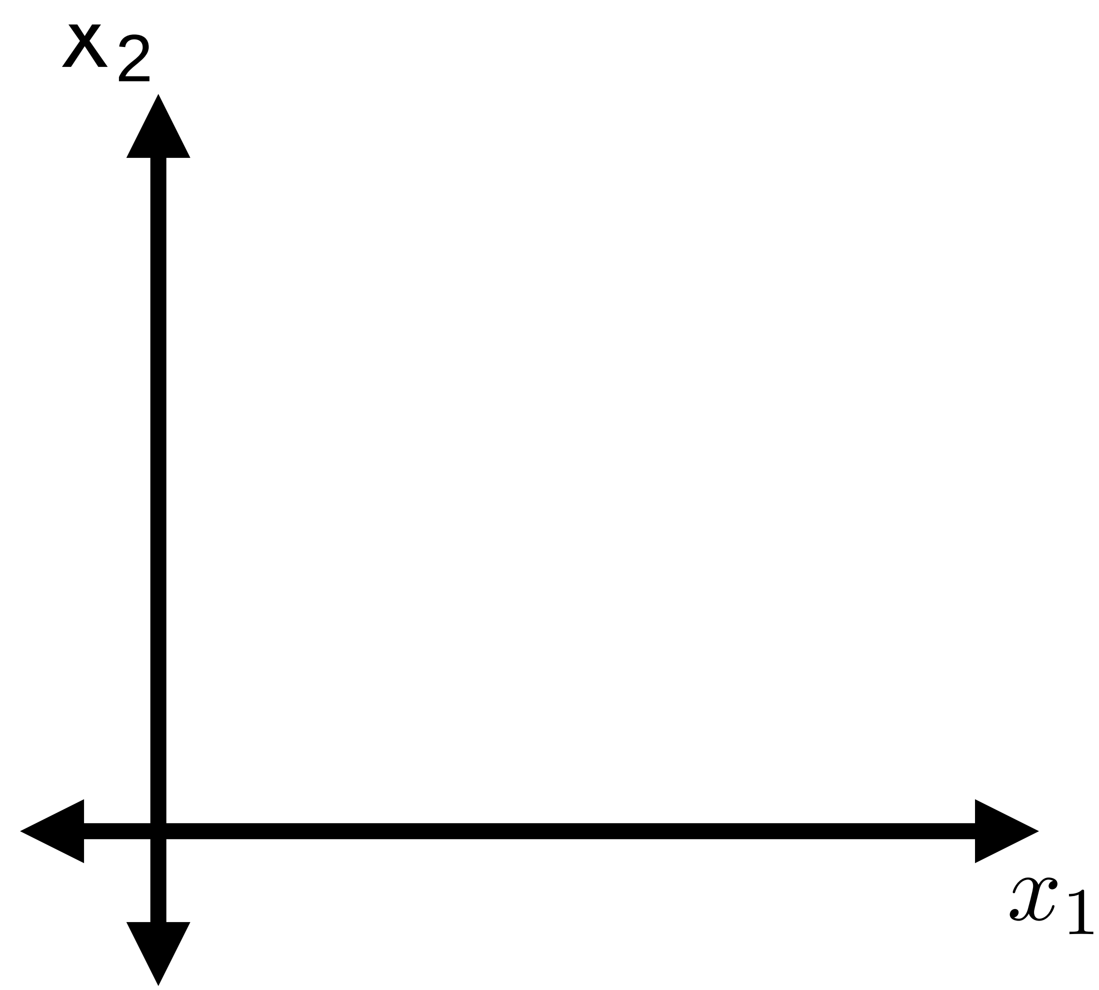

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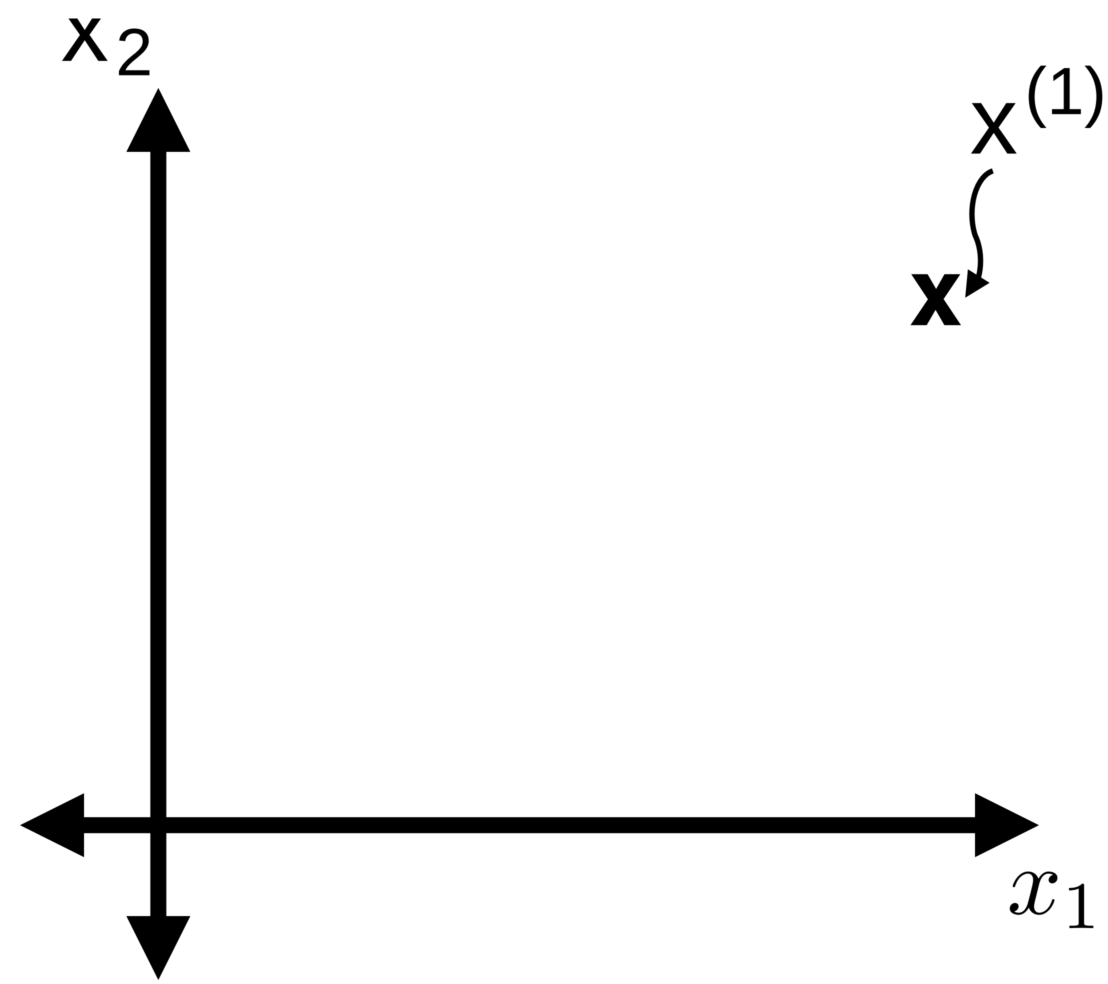

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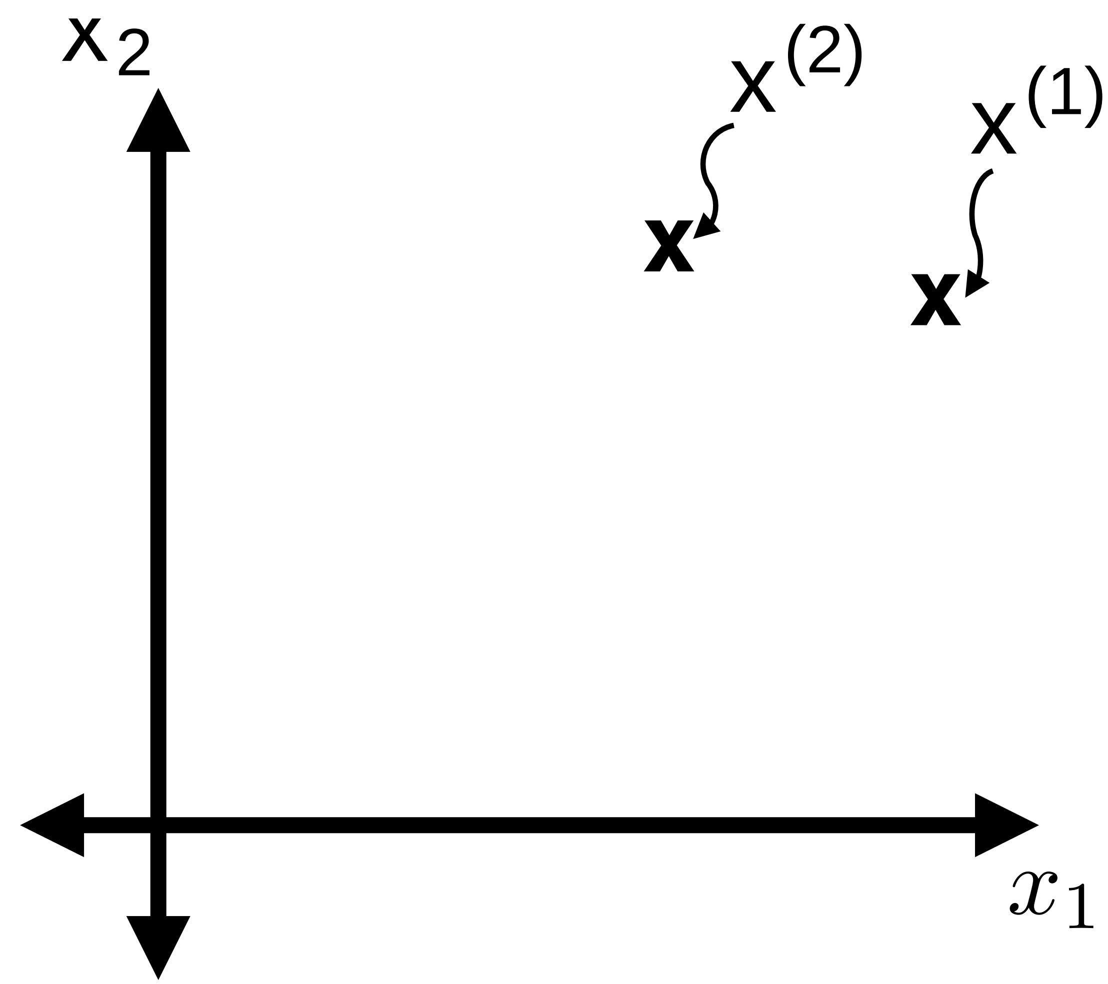

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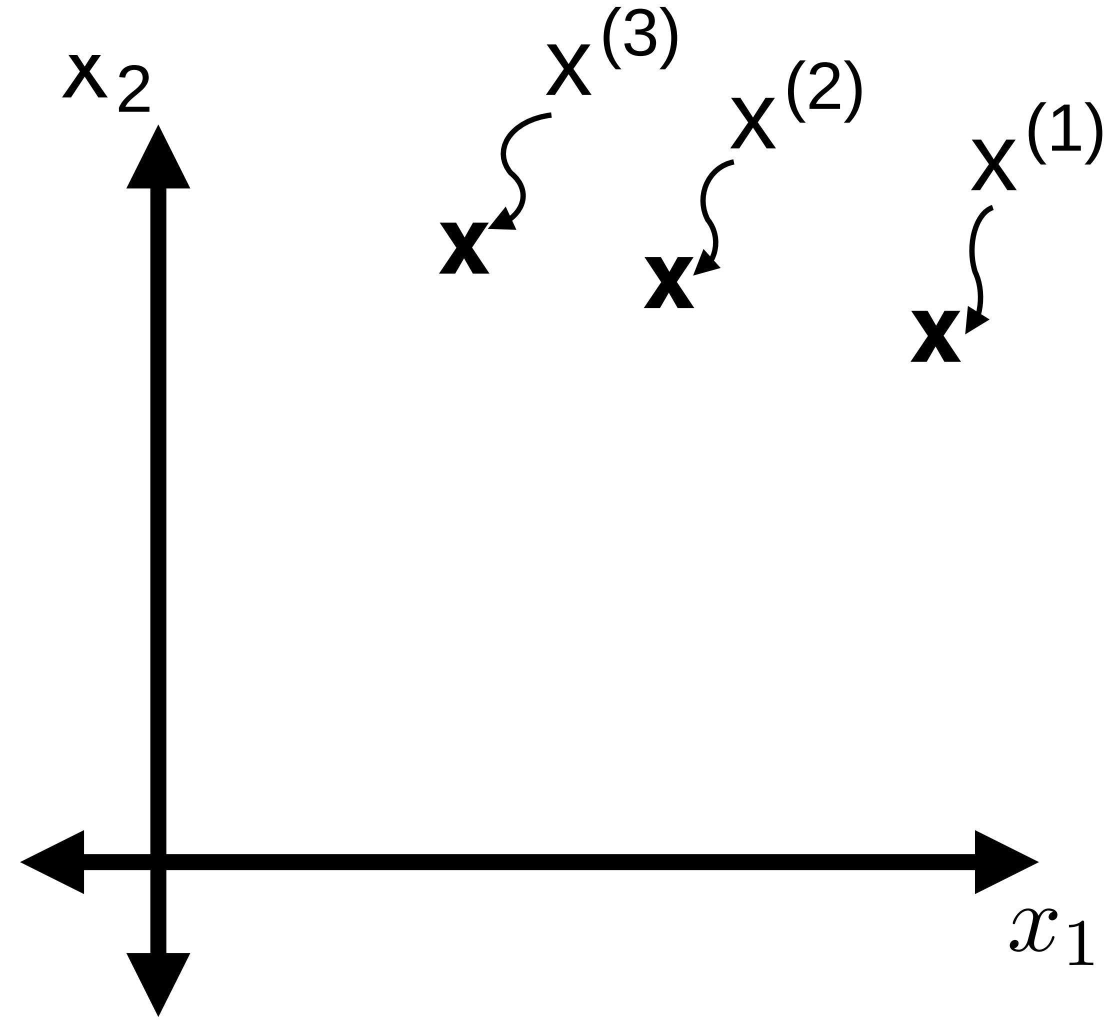

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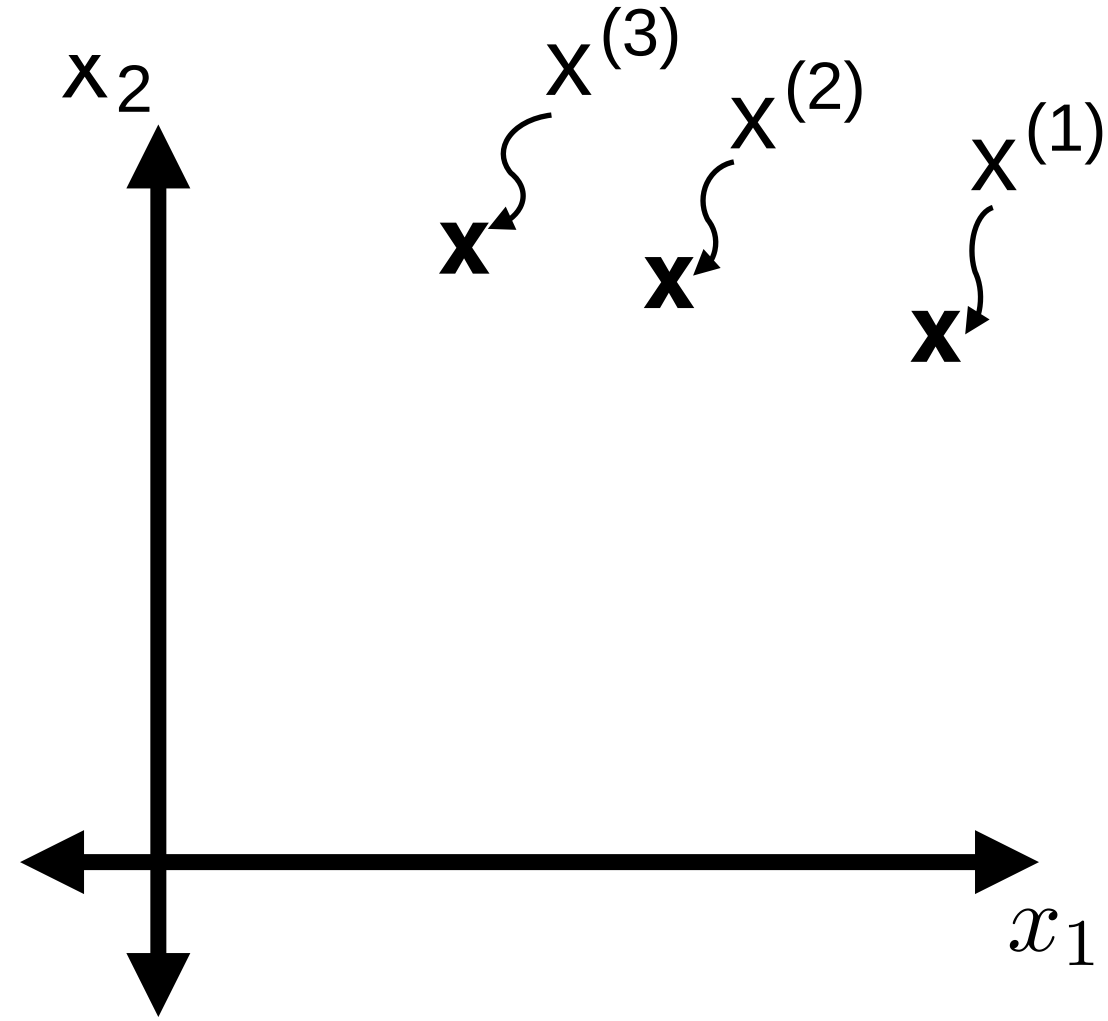

Getting started

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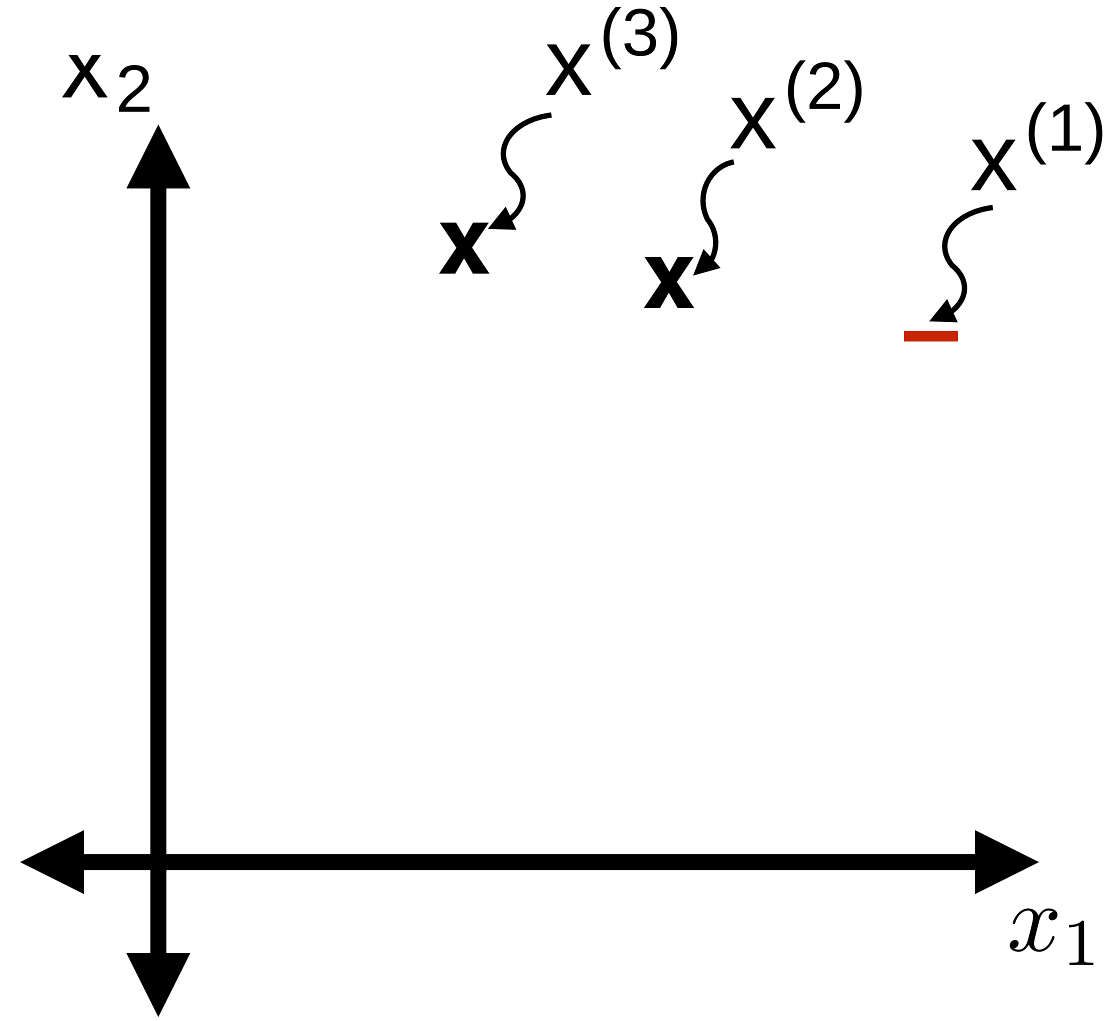

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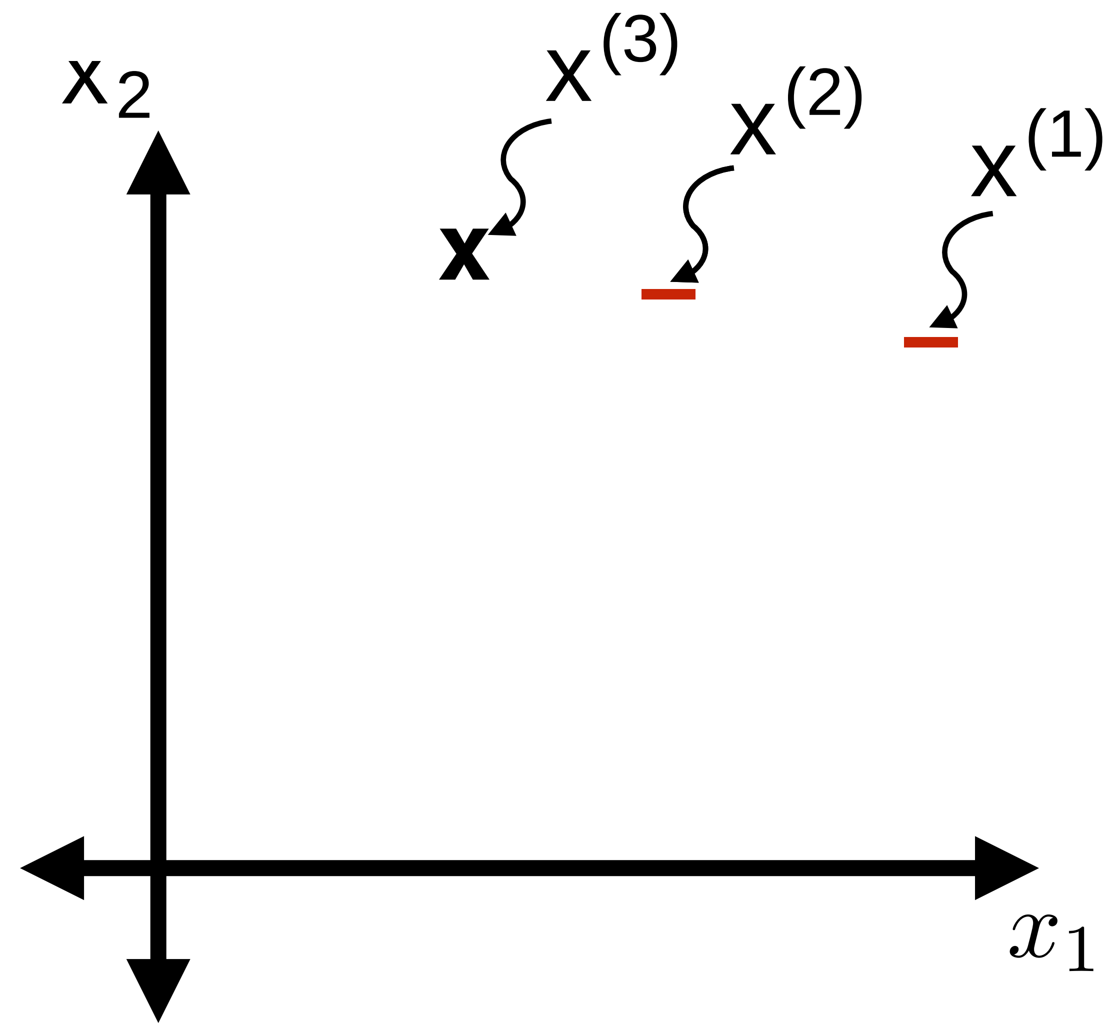

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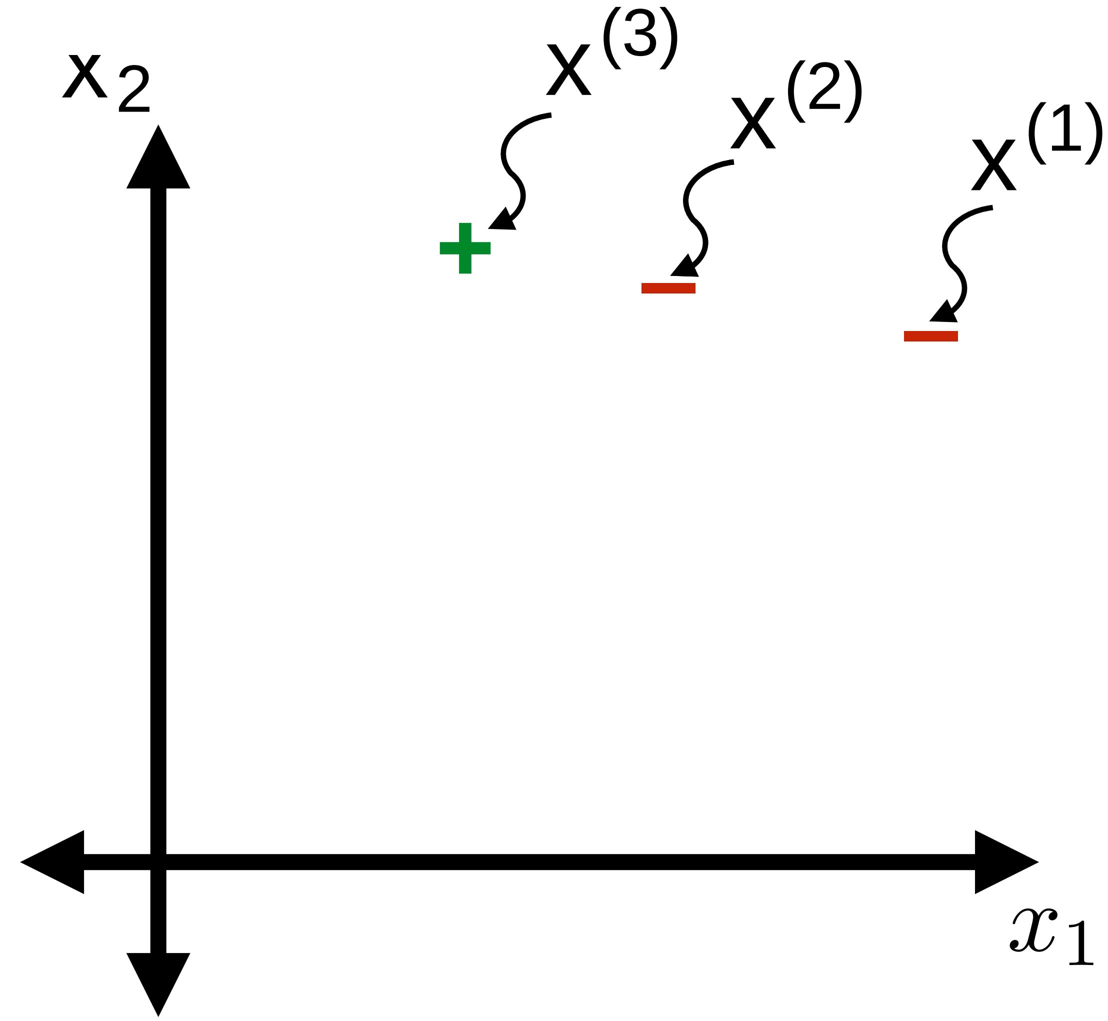

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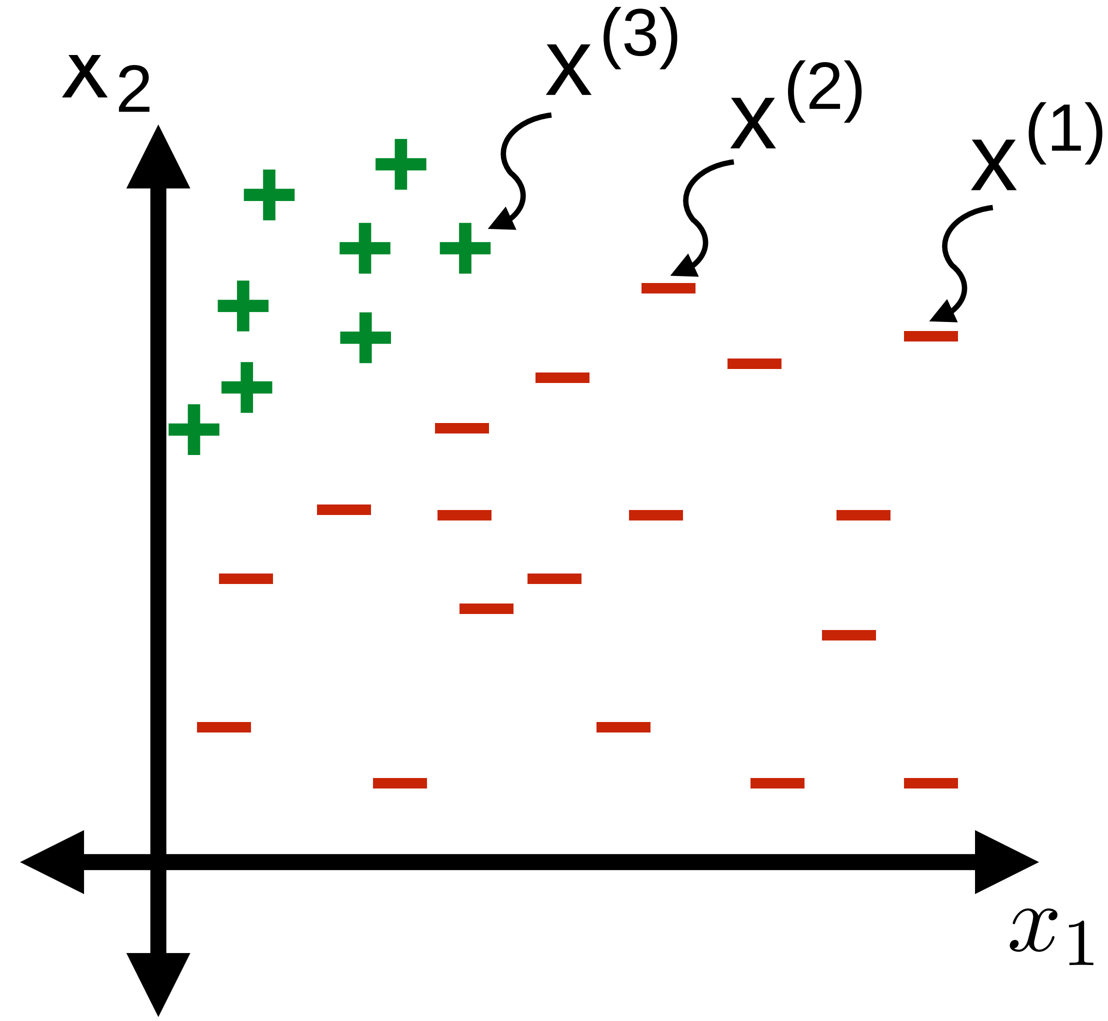

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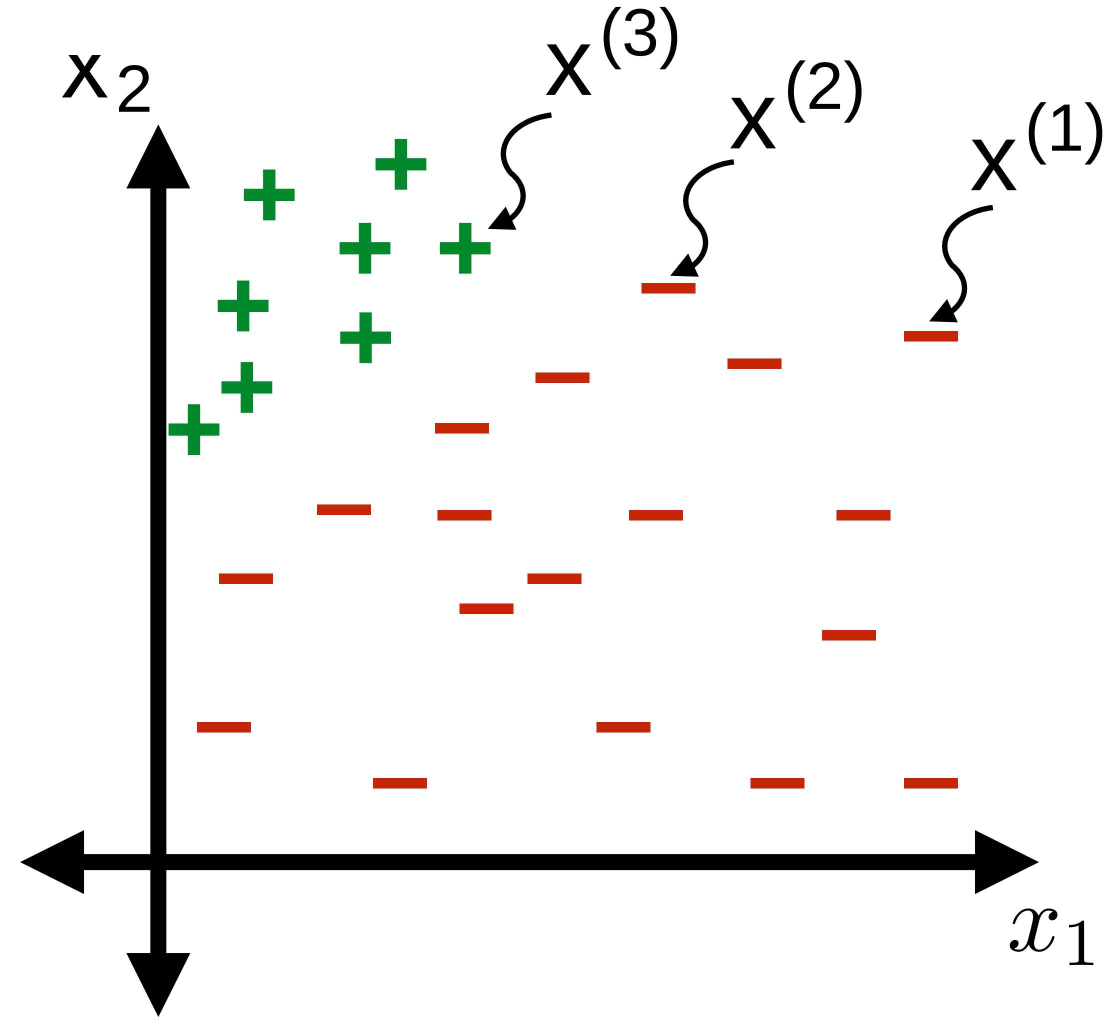

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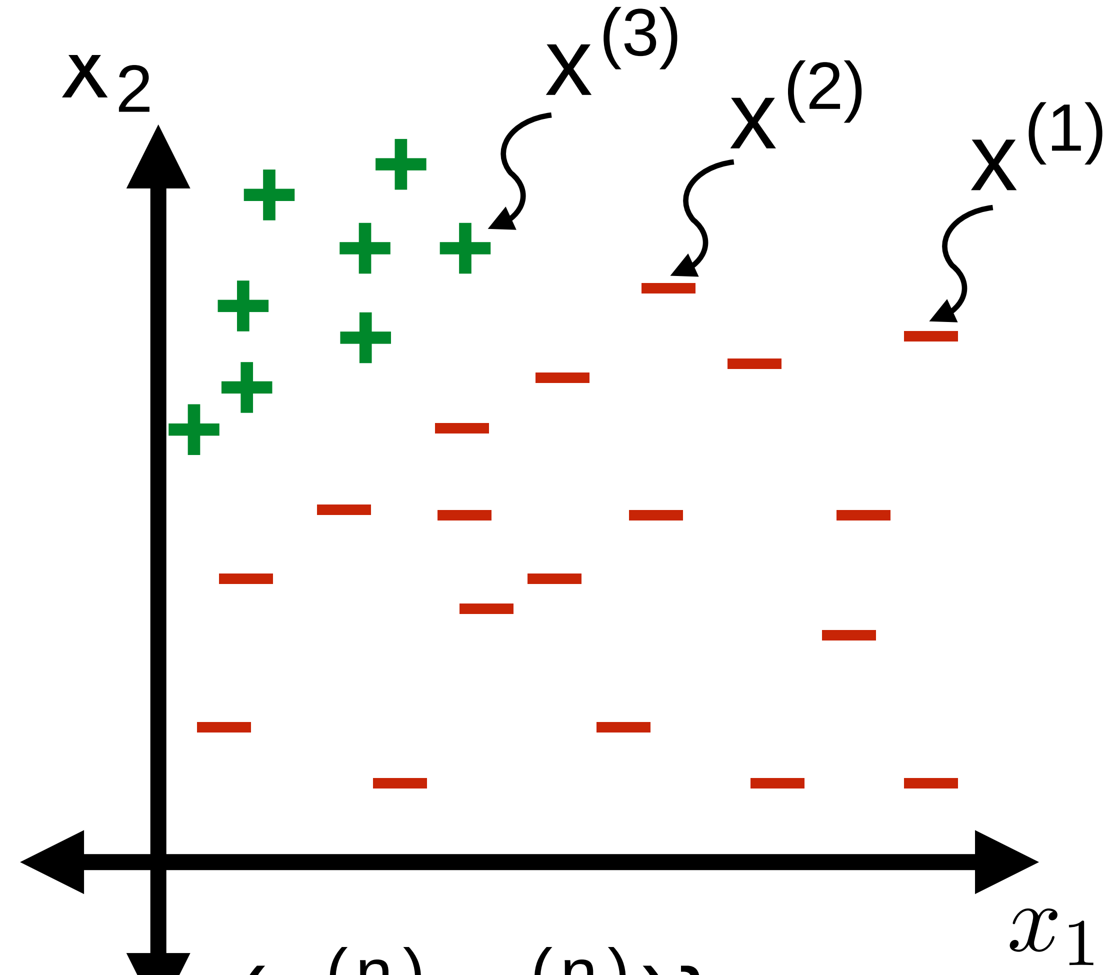

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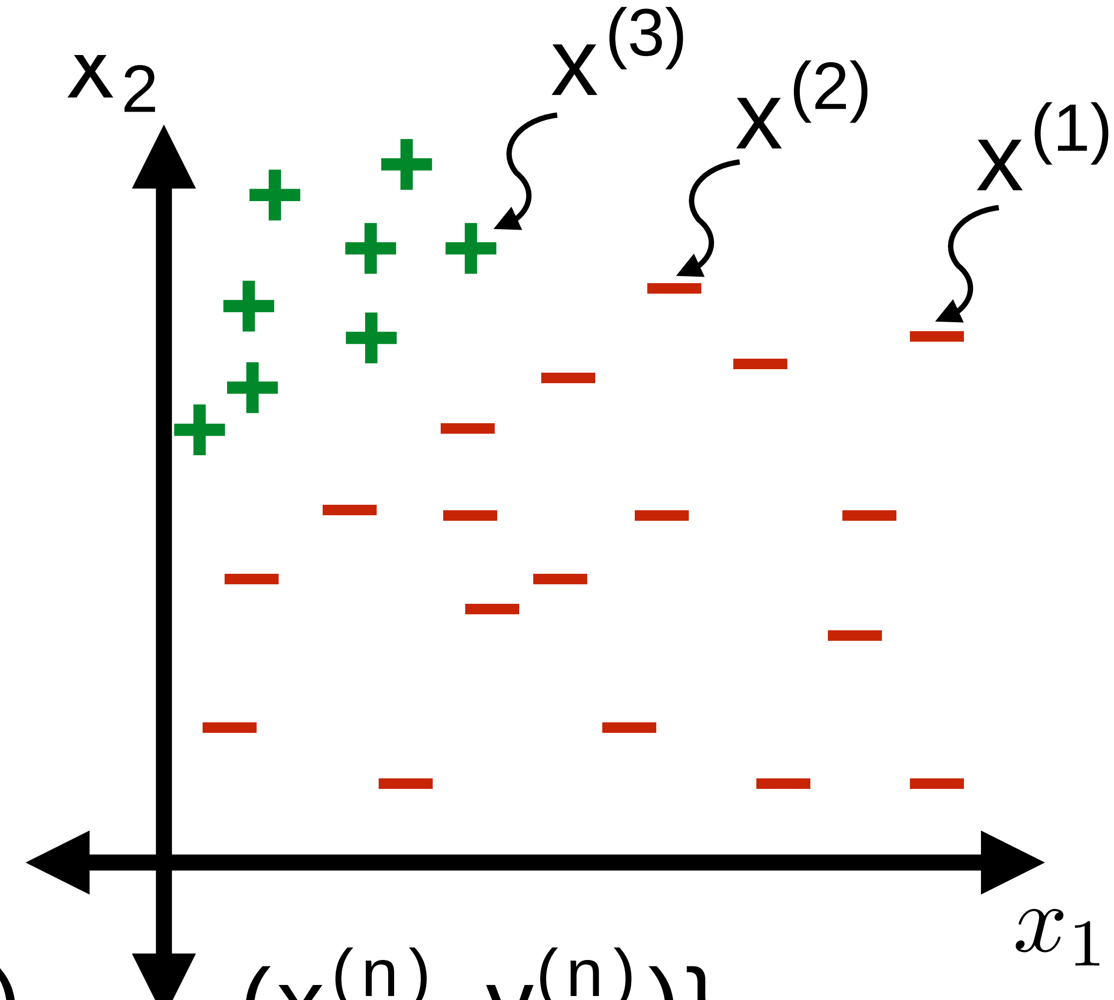

What do we want?

Getting started

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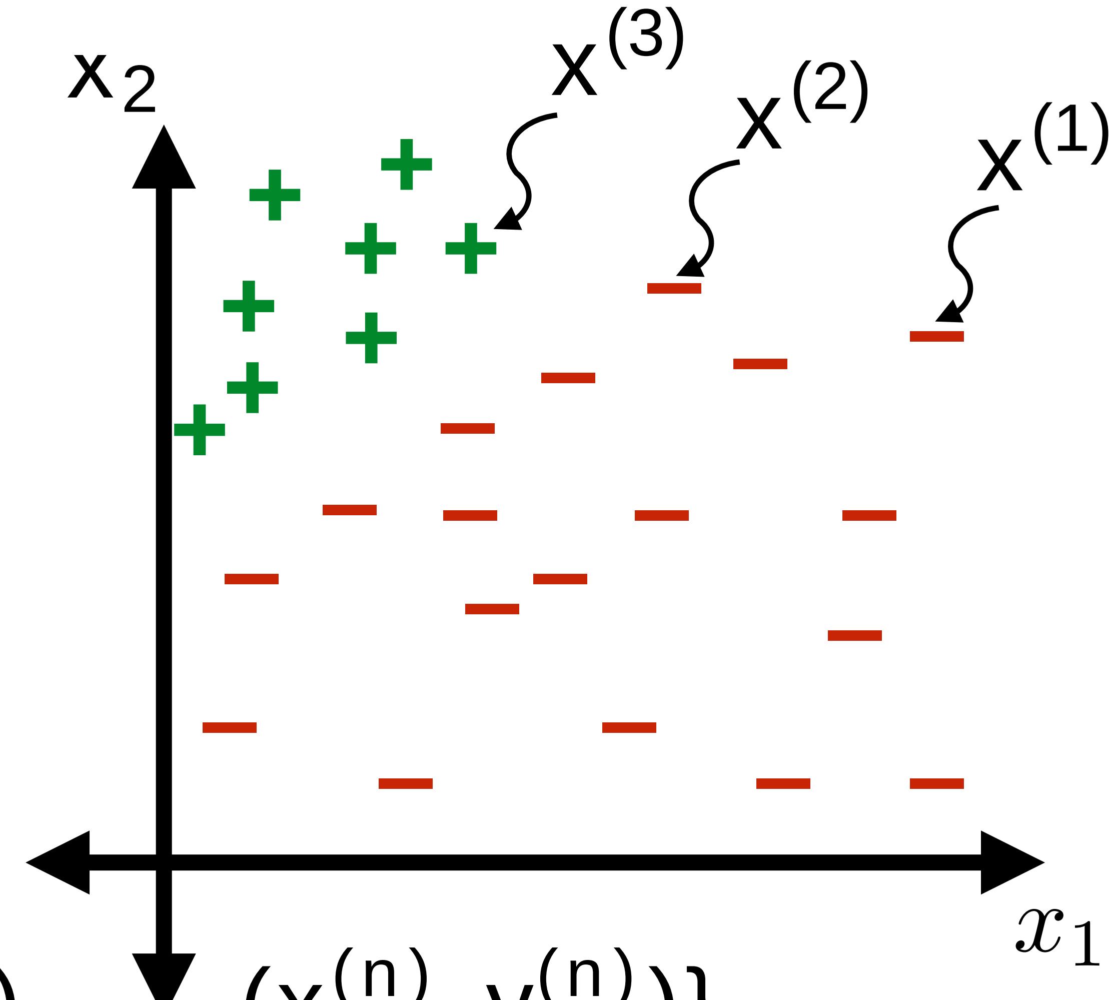

What do we want? A good way to label new points

Getting started

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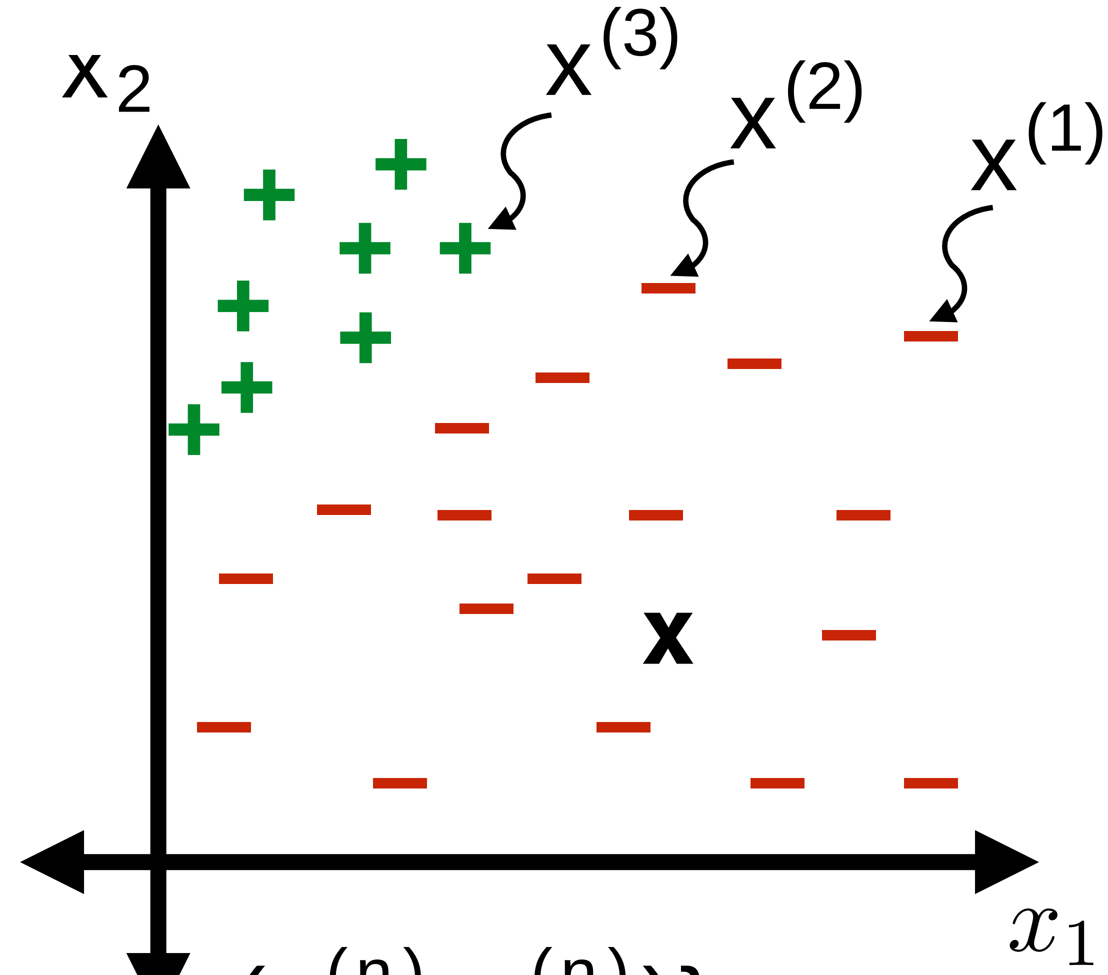

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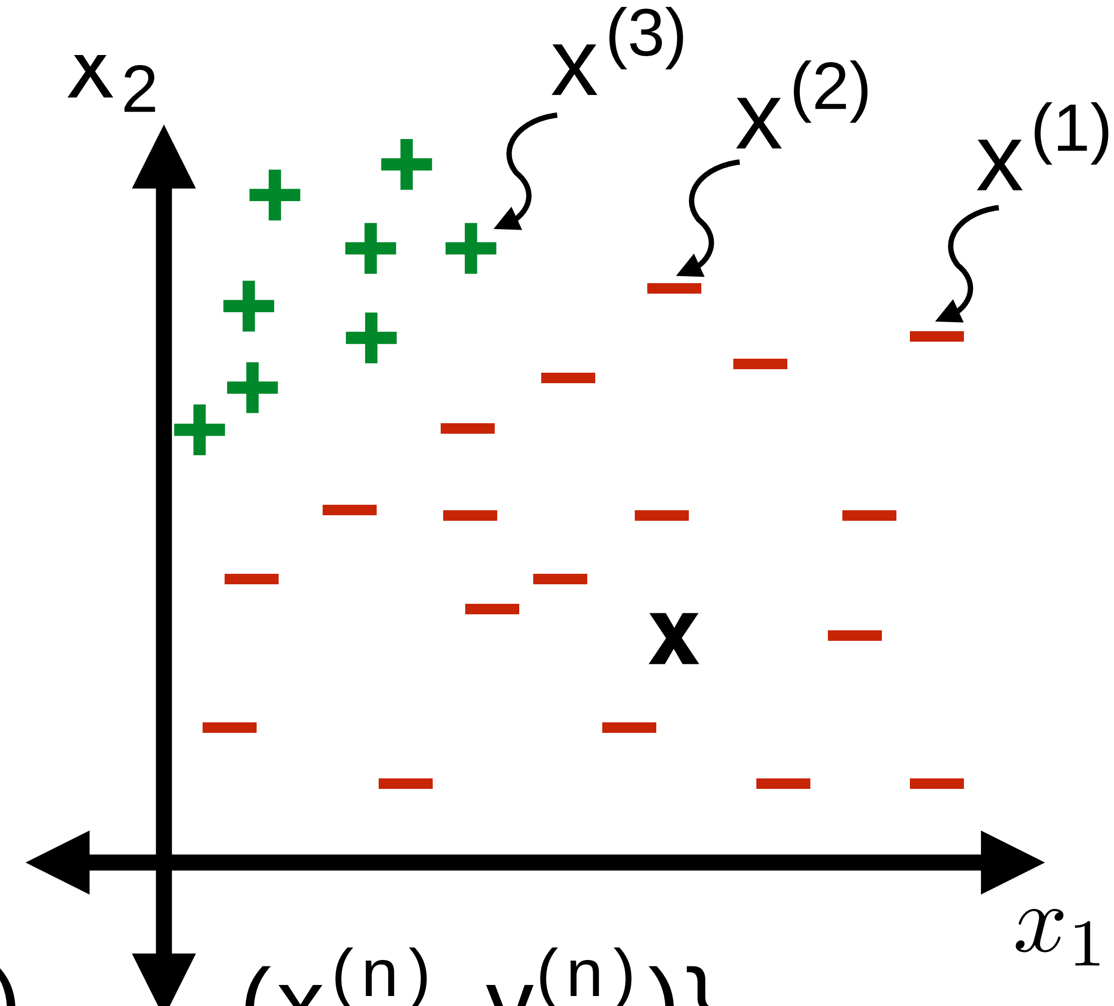

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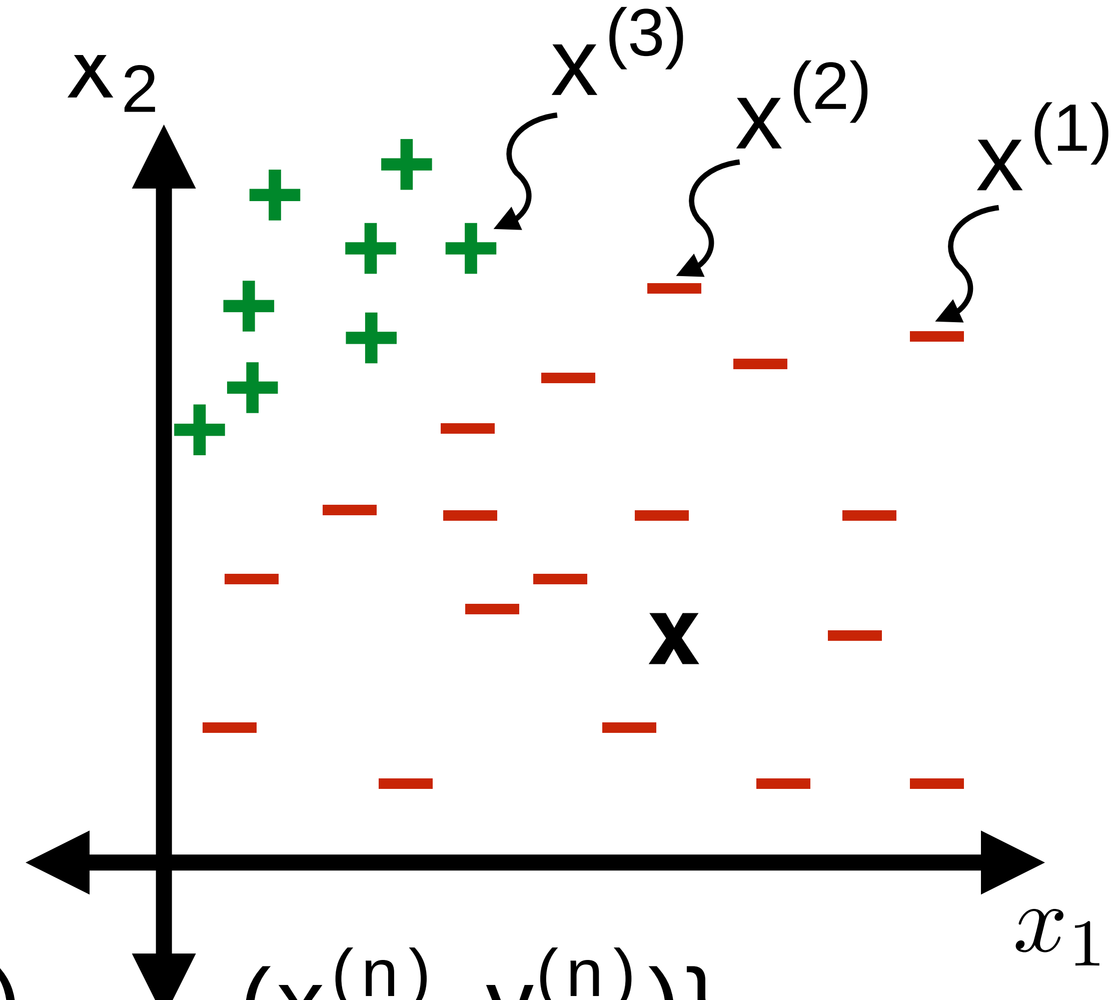

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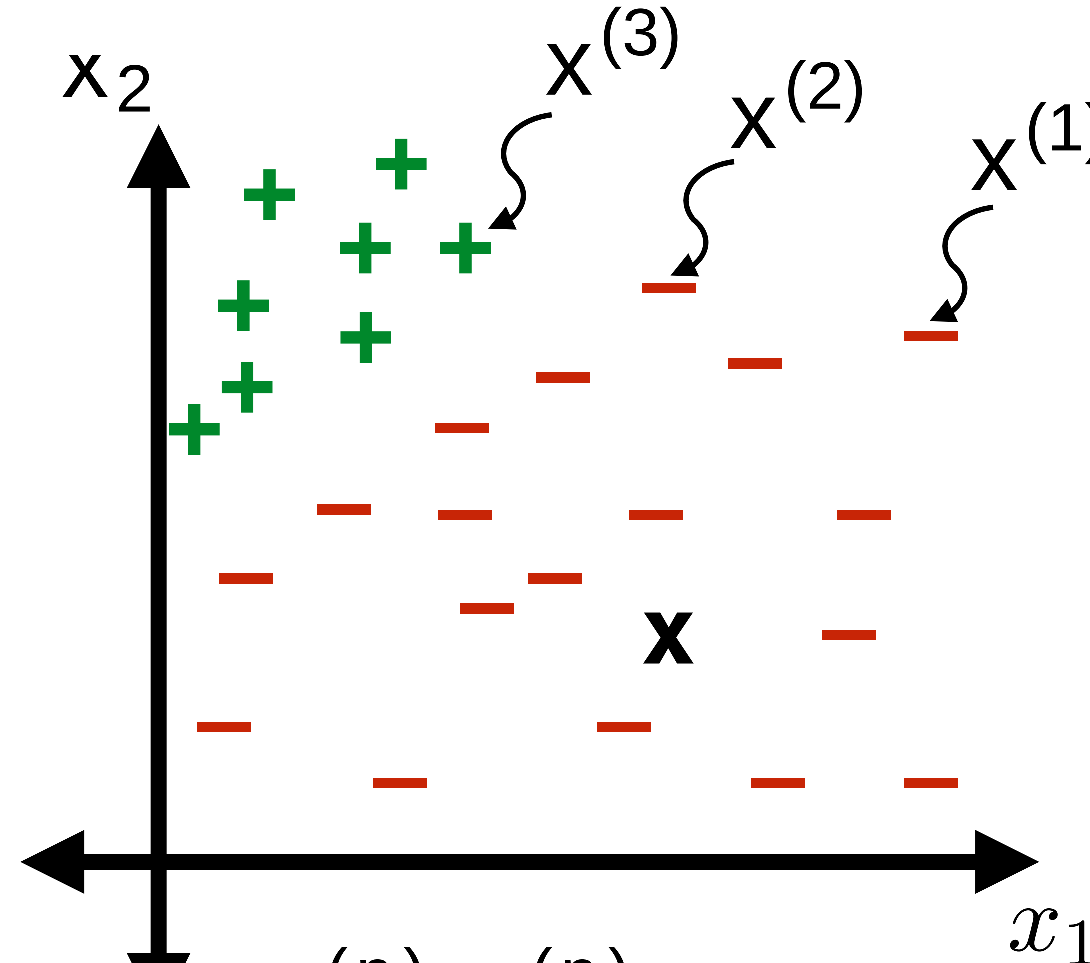

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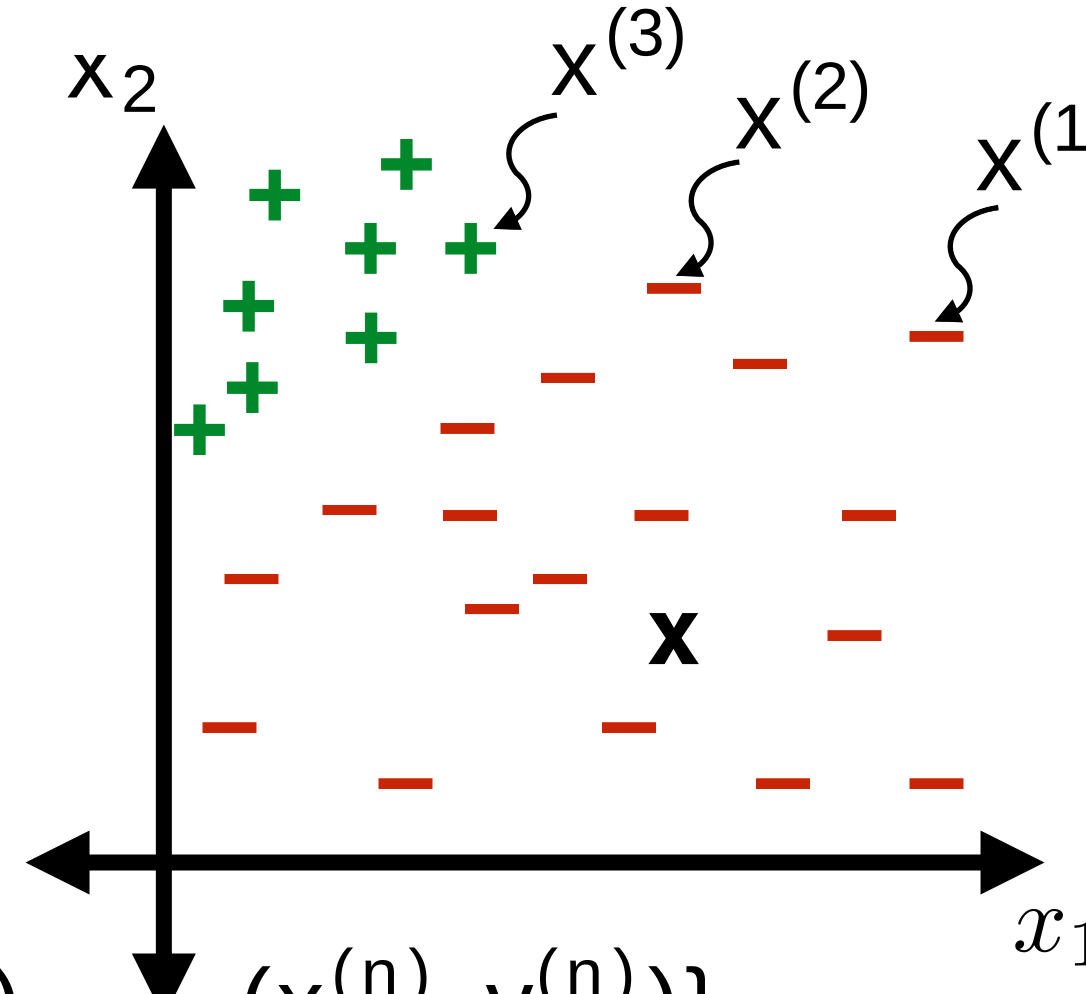
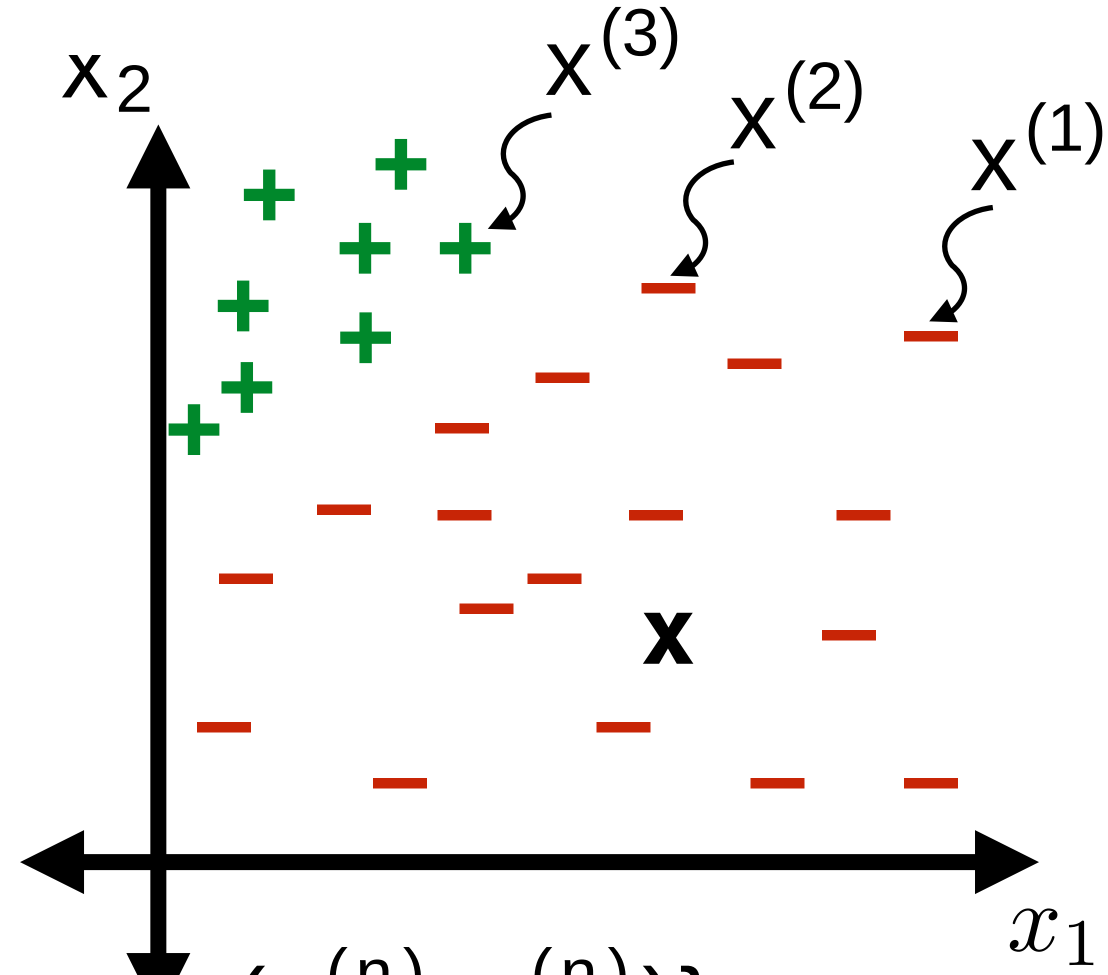


What do we want? A good way to label new points

- How to label?

Getting started

What do we have? (Training) data



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- How to label? Hypothesis $h : \mathbb{R}^d \to \{-1, +1\}$

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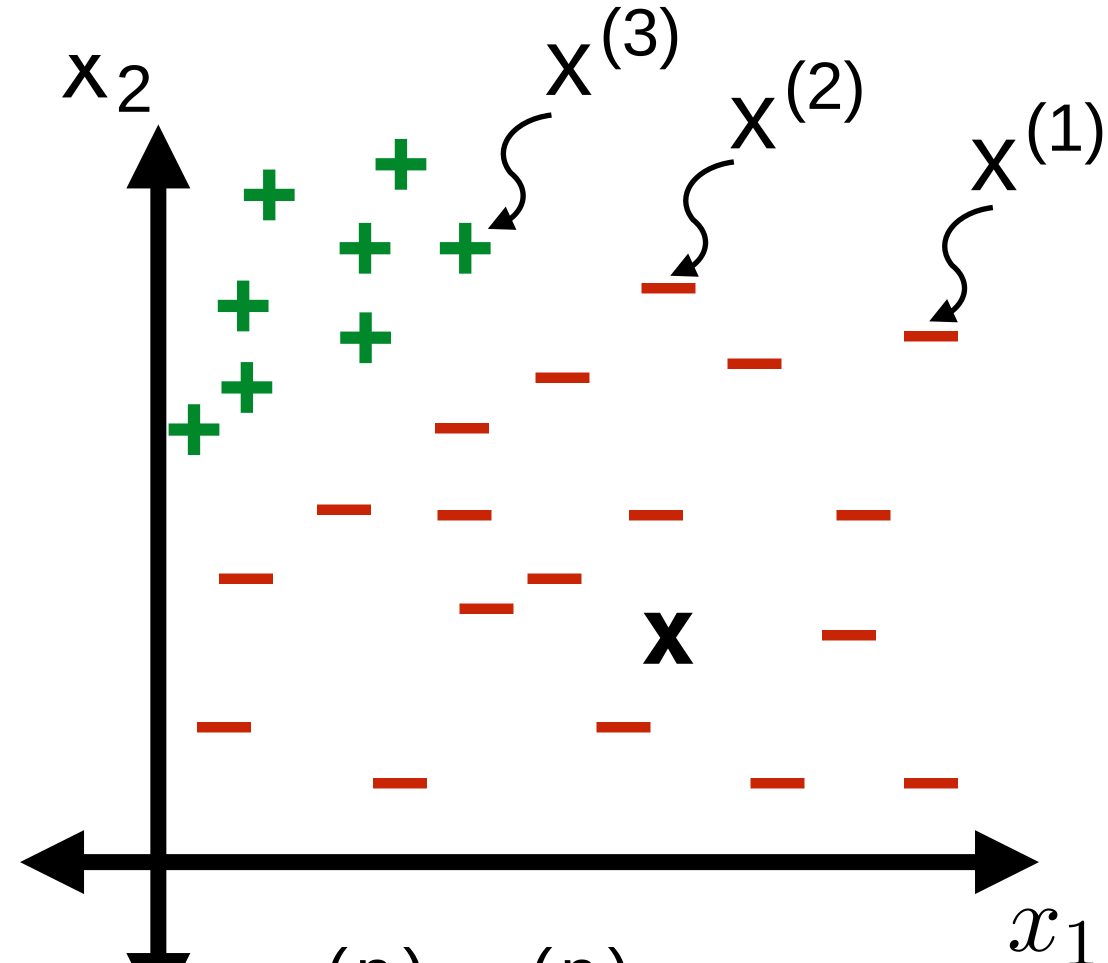

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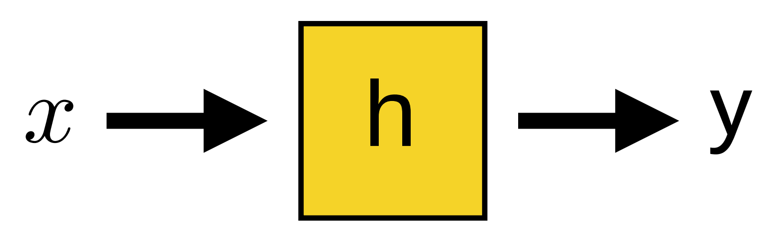

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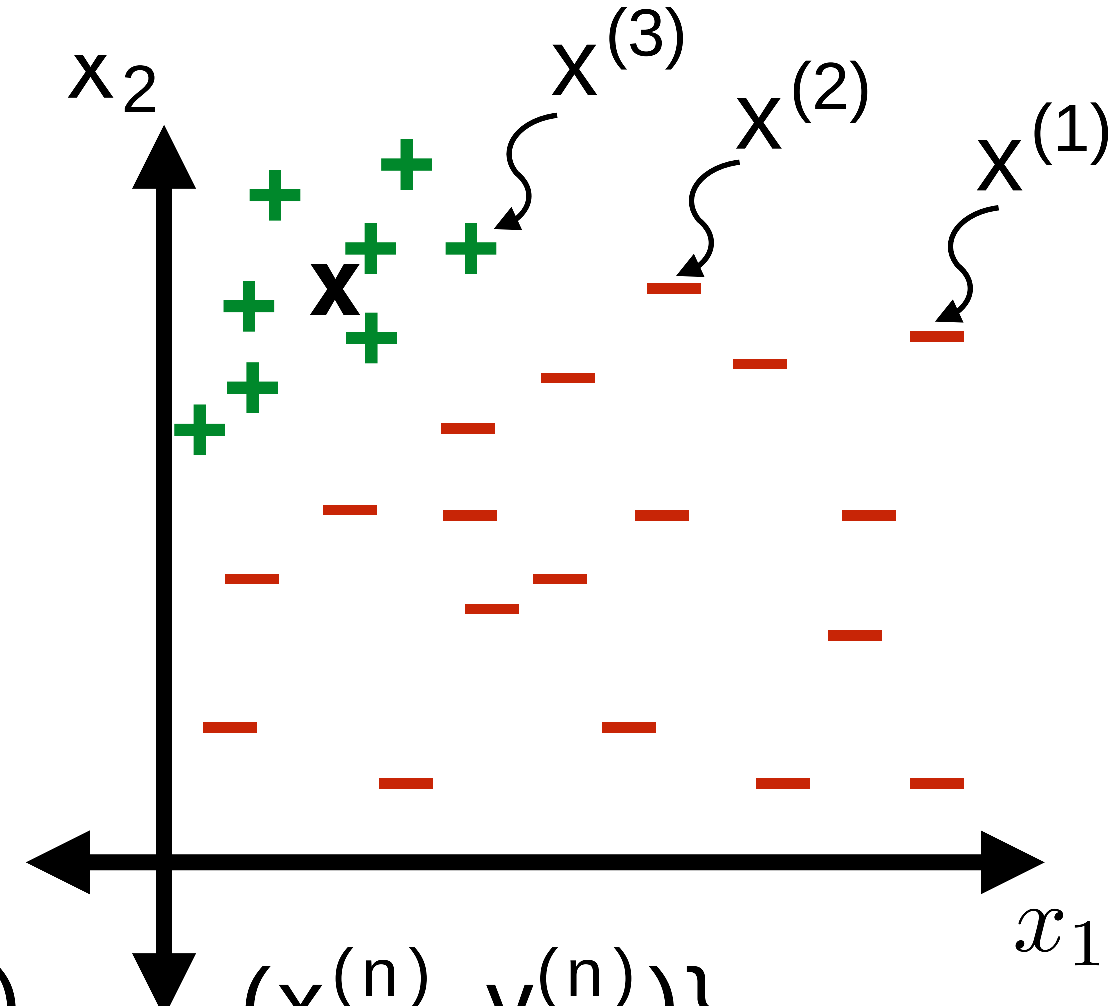

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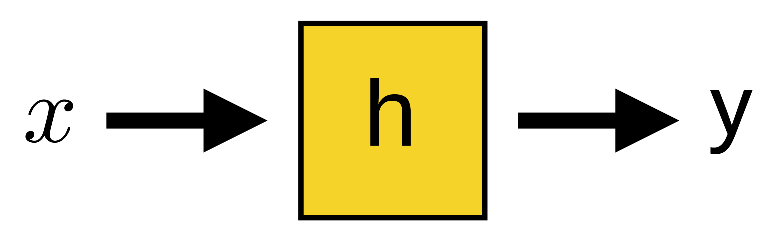
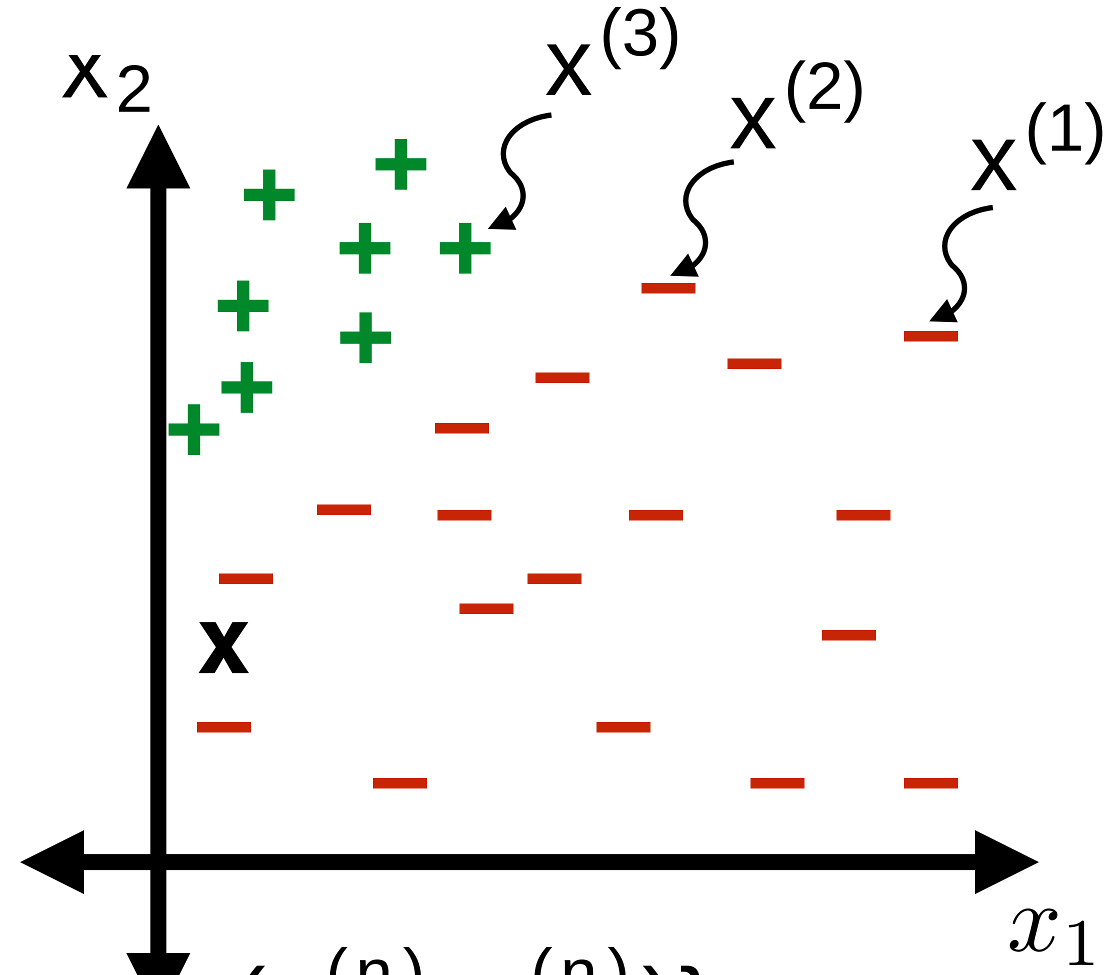


Getting started



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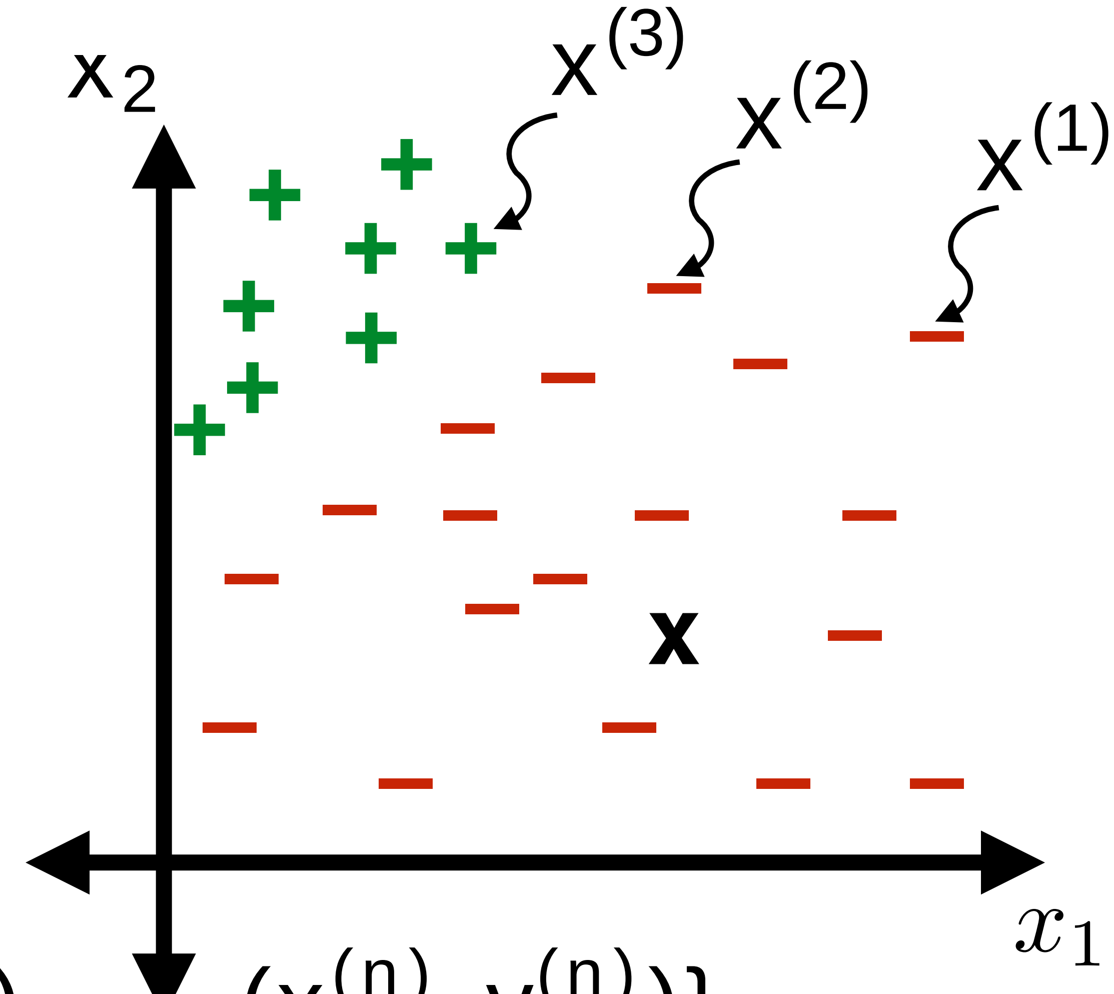
$$x \to \boxed{h} \to y$$

Getting started



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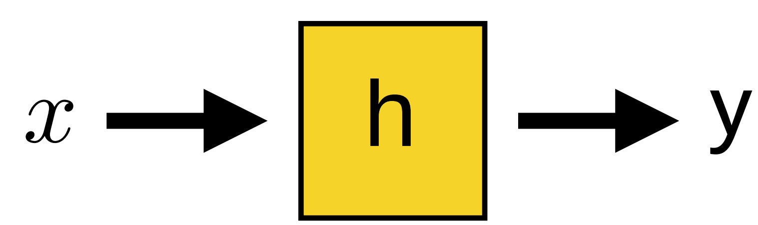
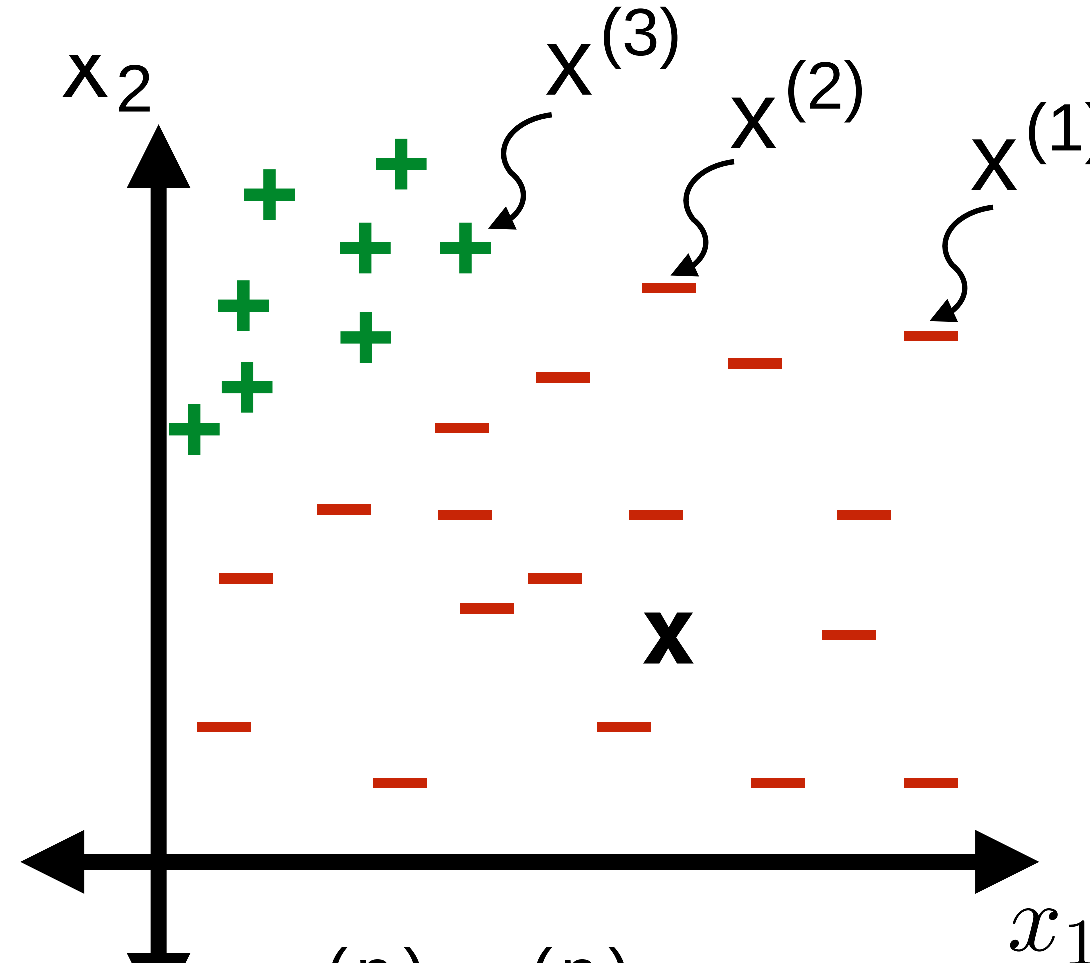


Getting started



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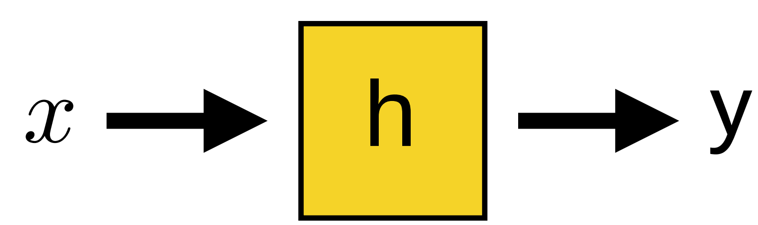

- Example *h*: For any *x*, *h*(*x*) = +1

Getting started

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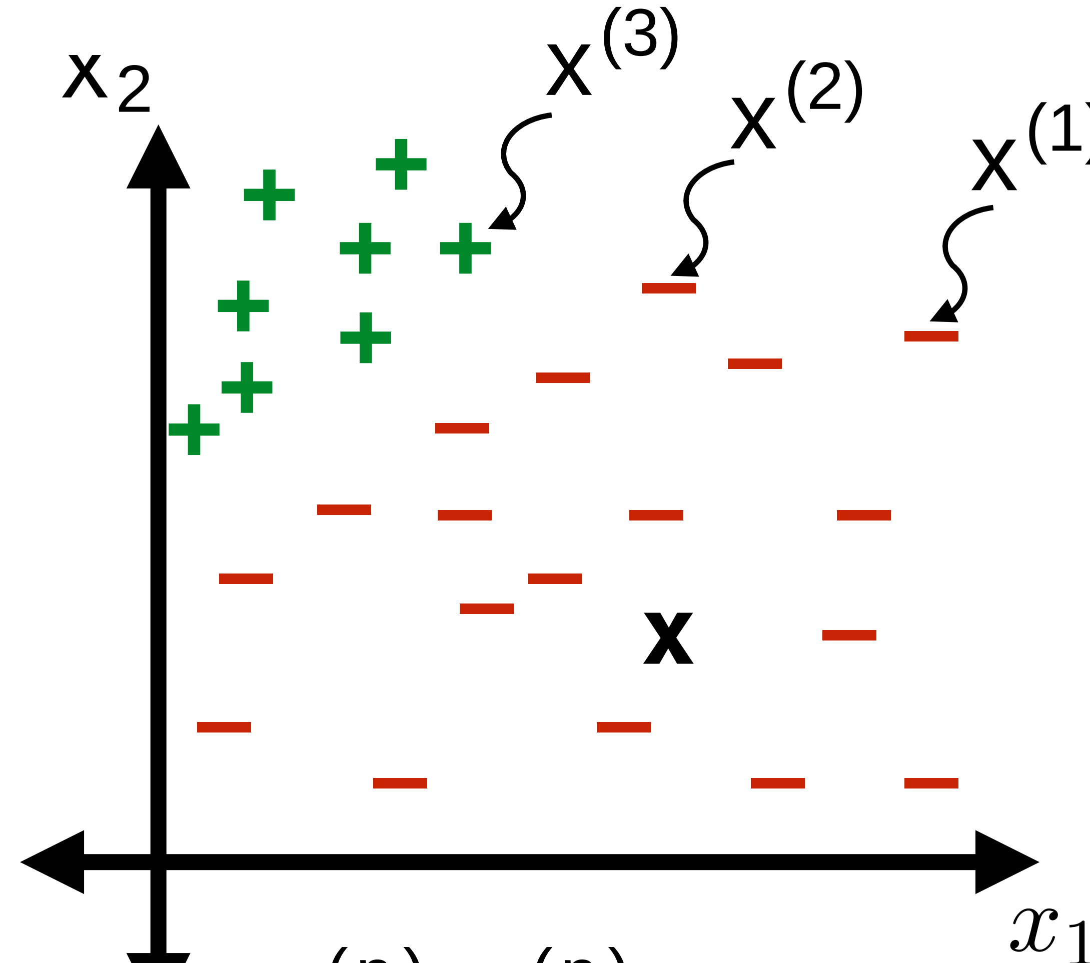

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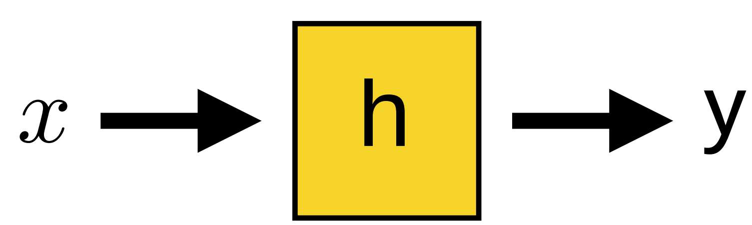
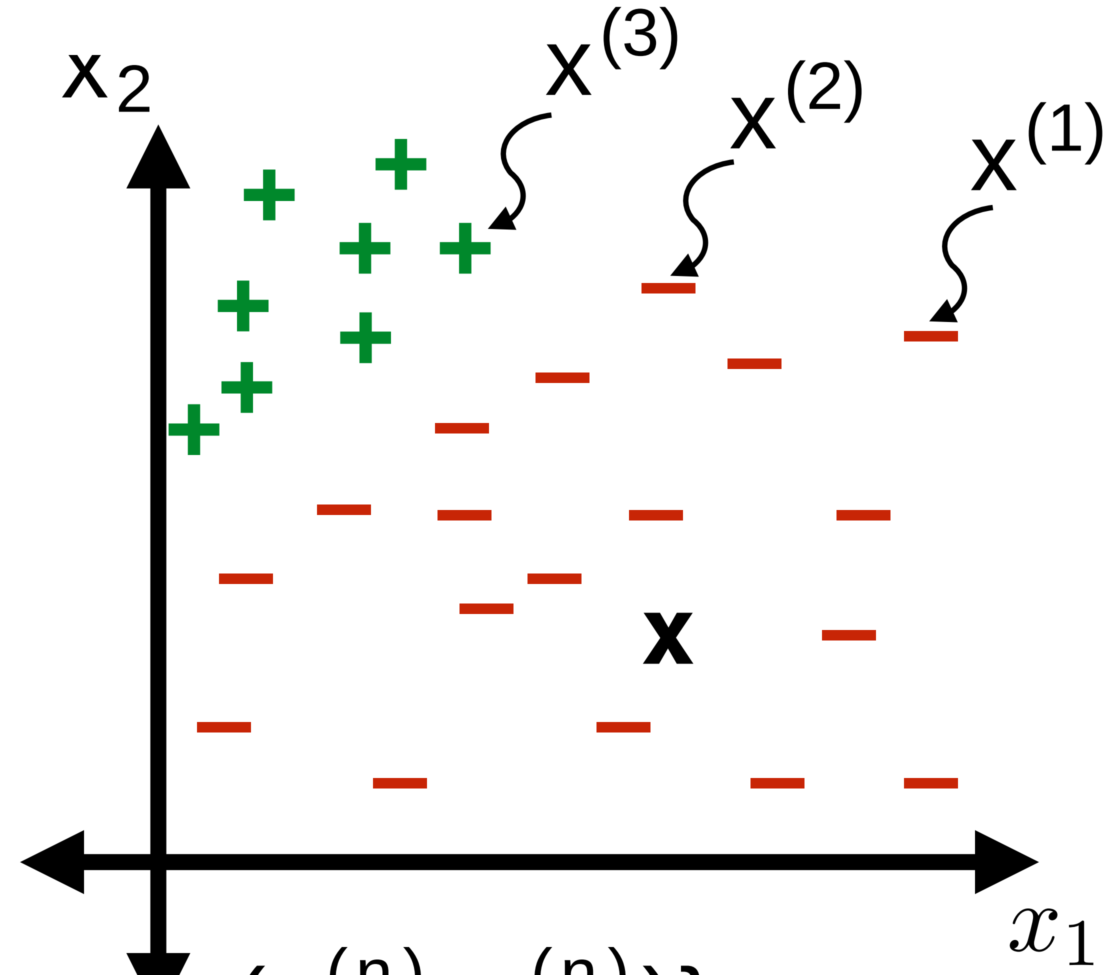


- Example *h*: For any *x*, *h*(*x*) = +1
    - Is this a hypothesis?

Getting started



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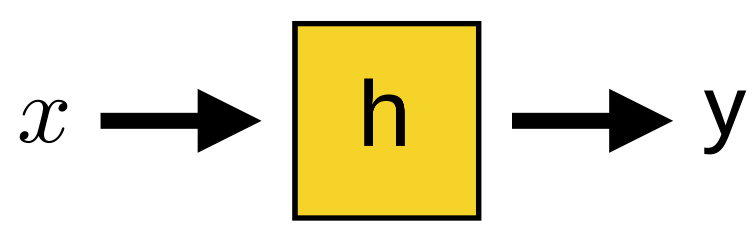

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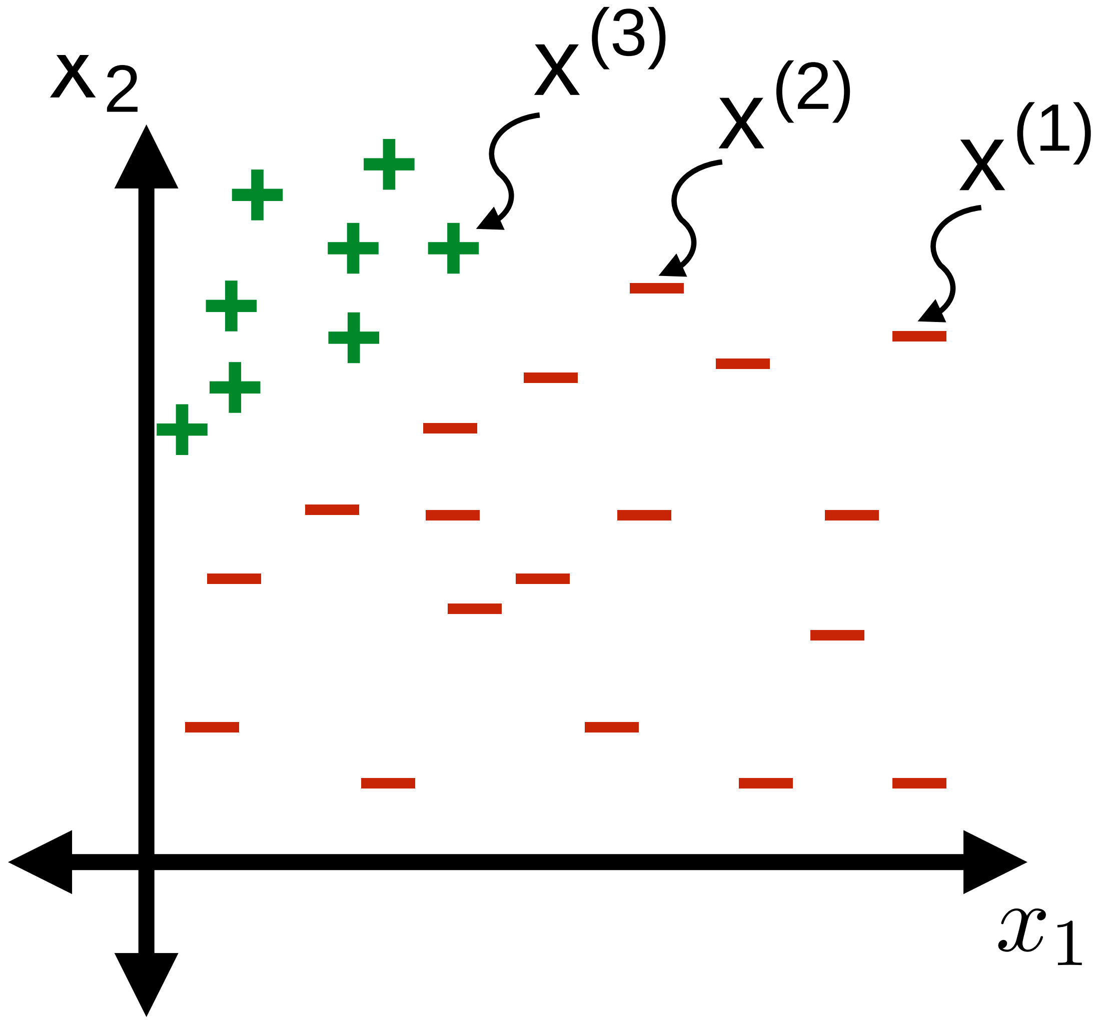
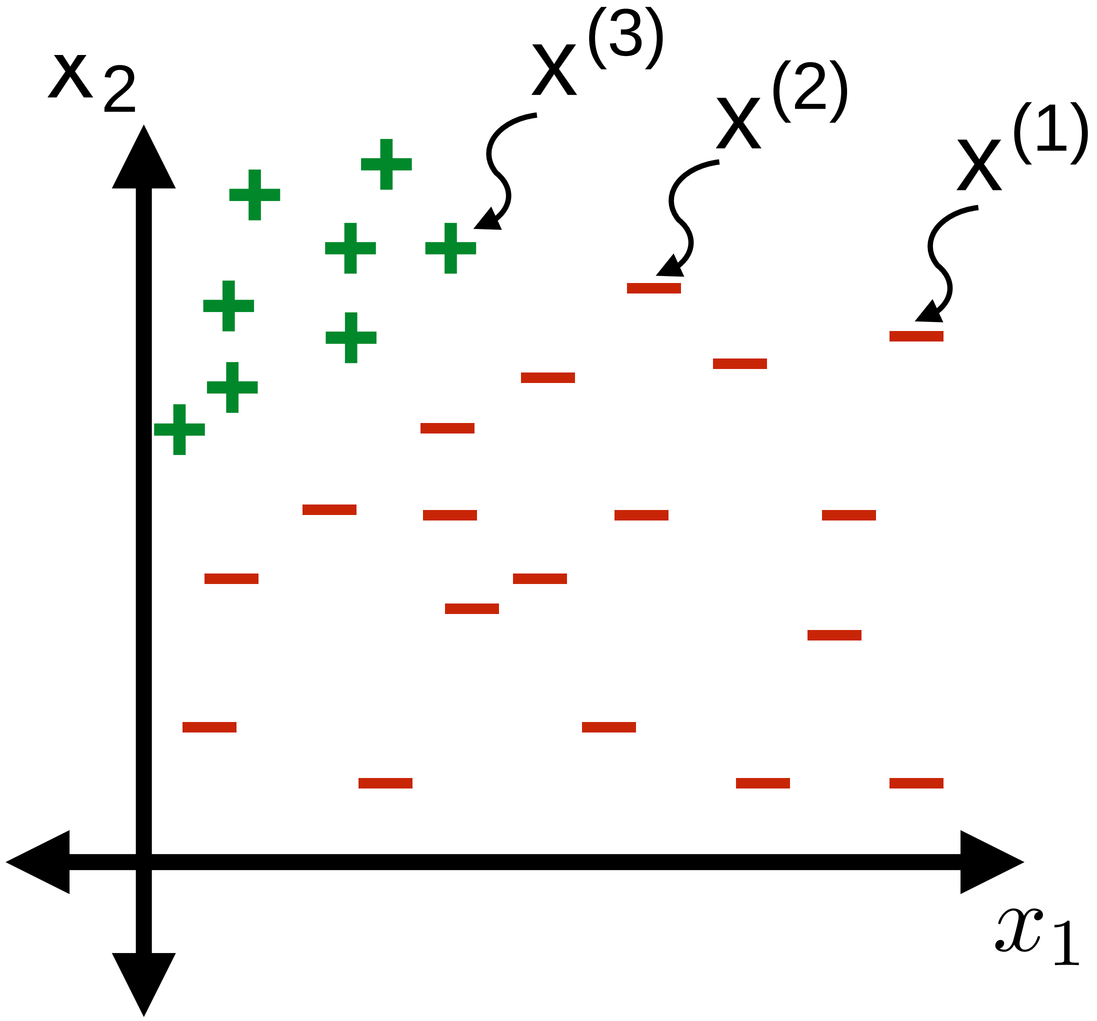
Linear classifiers



Linear classifiers

- Hypothesis class $\mathcal{H}$: set of **h** ! H



Linear classifiers

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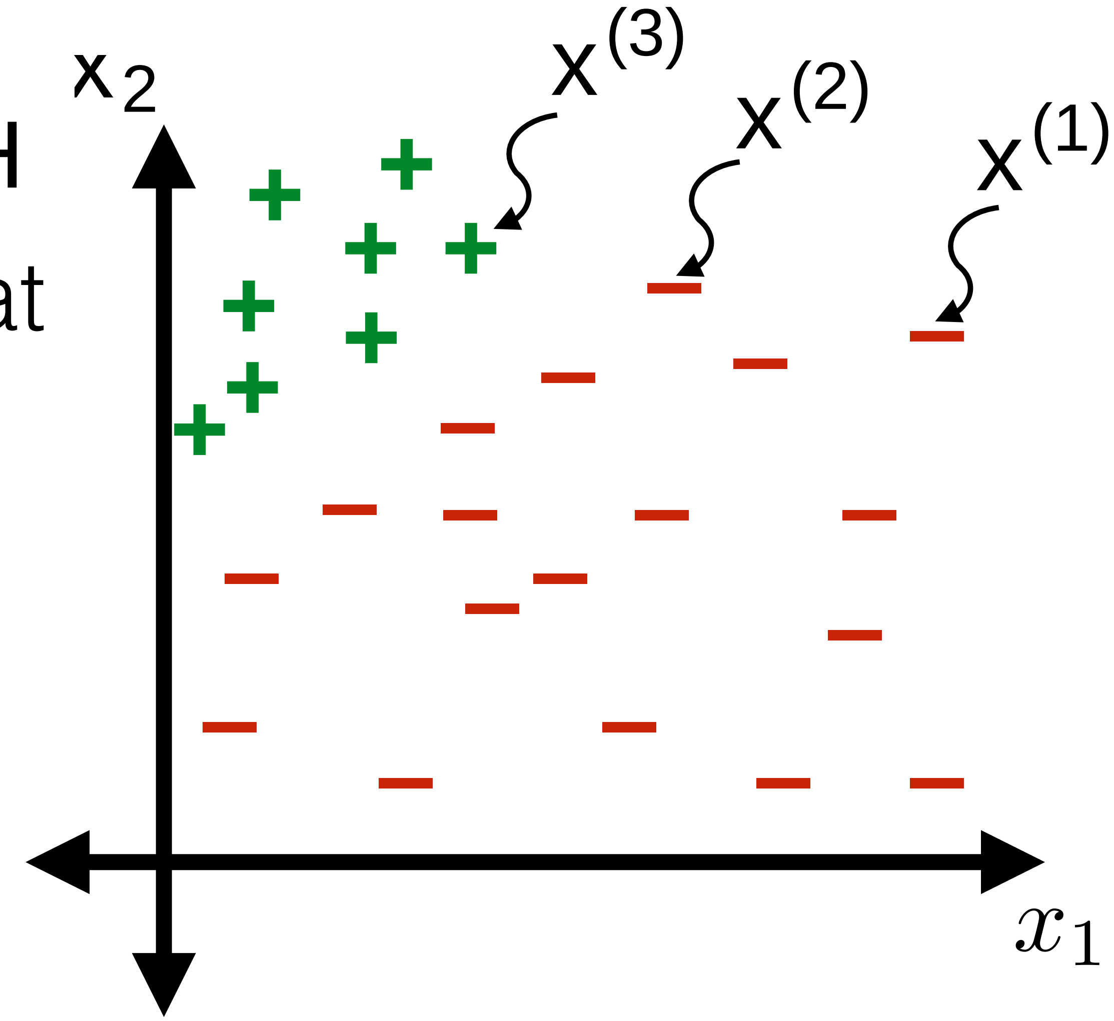

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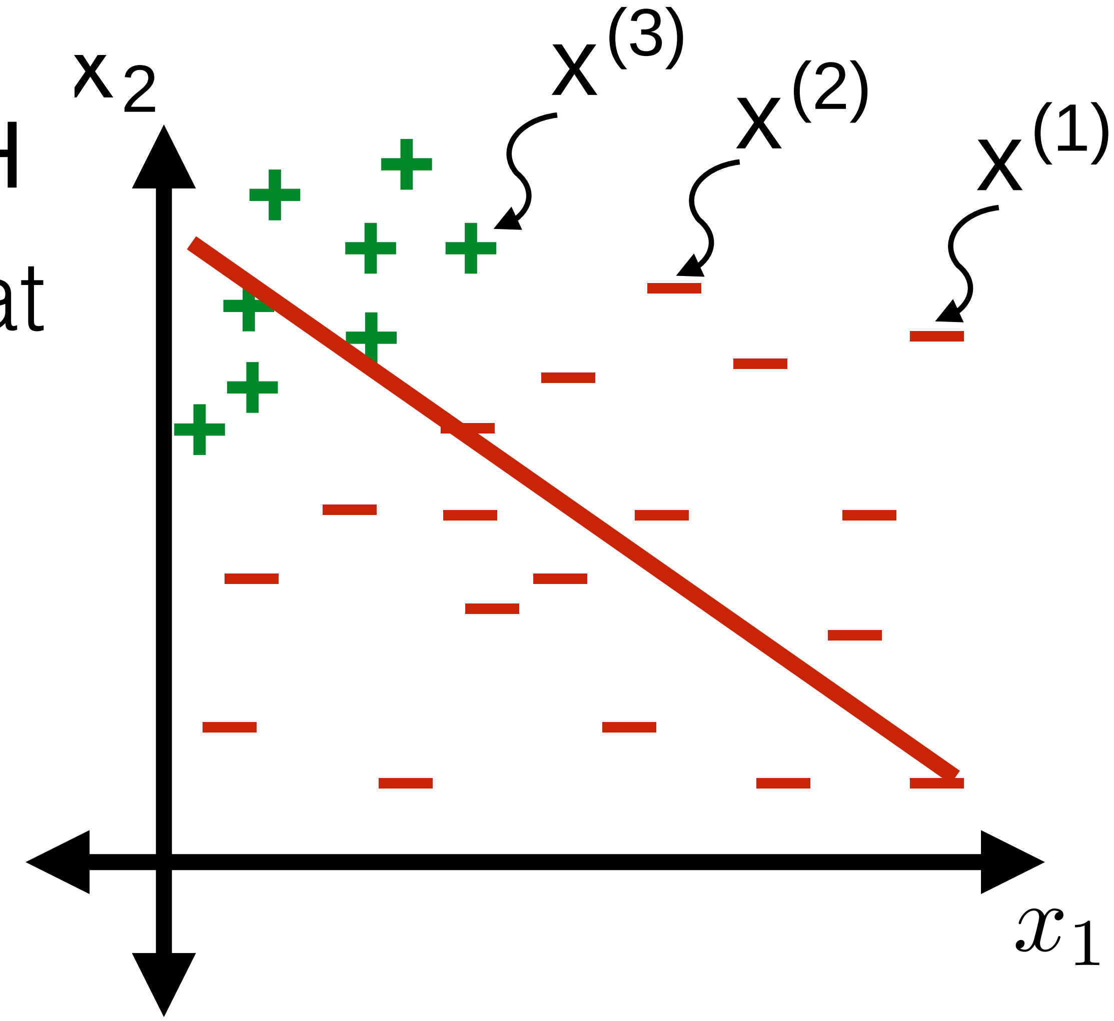

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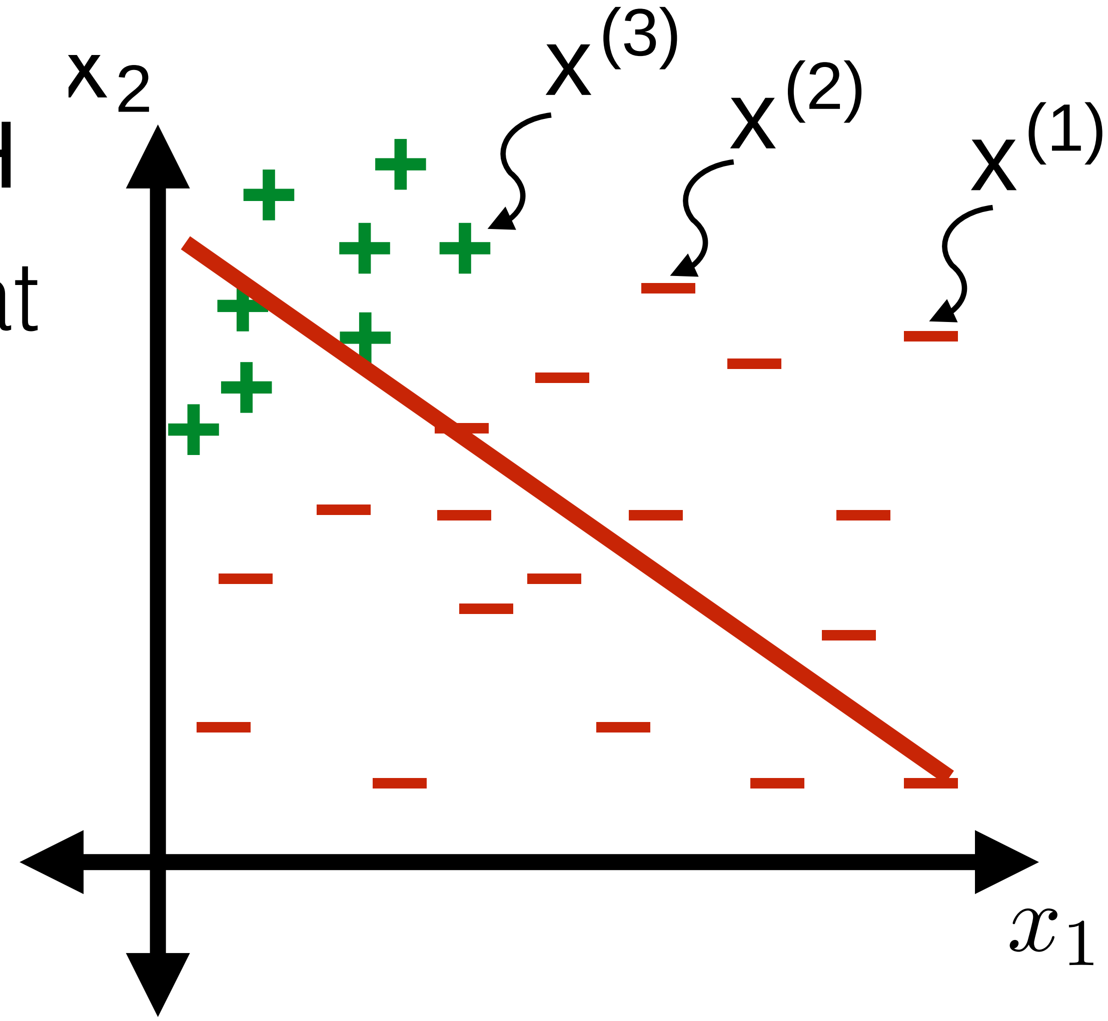

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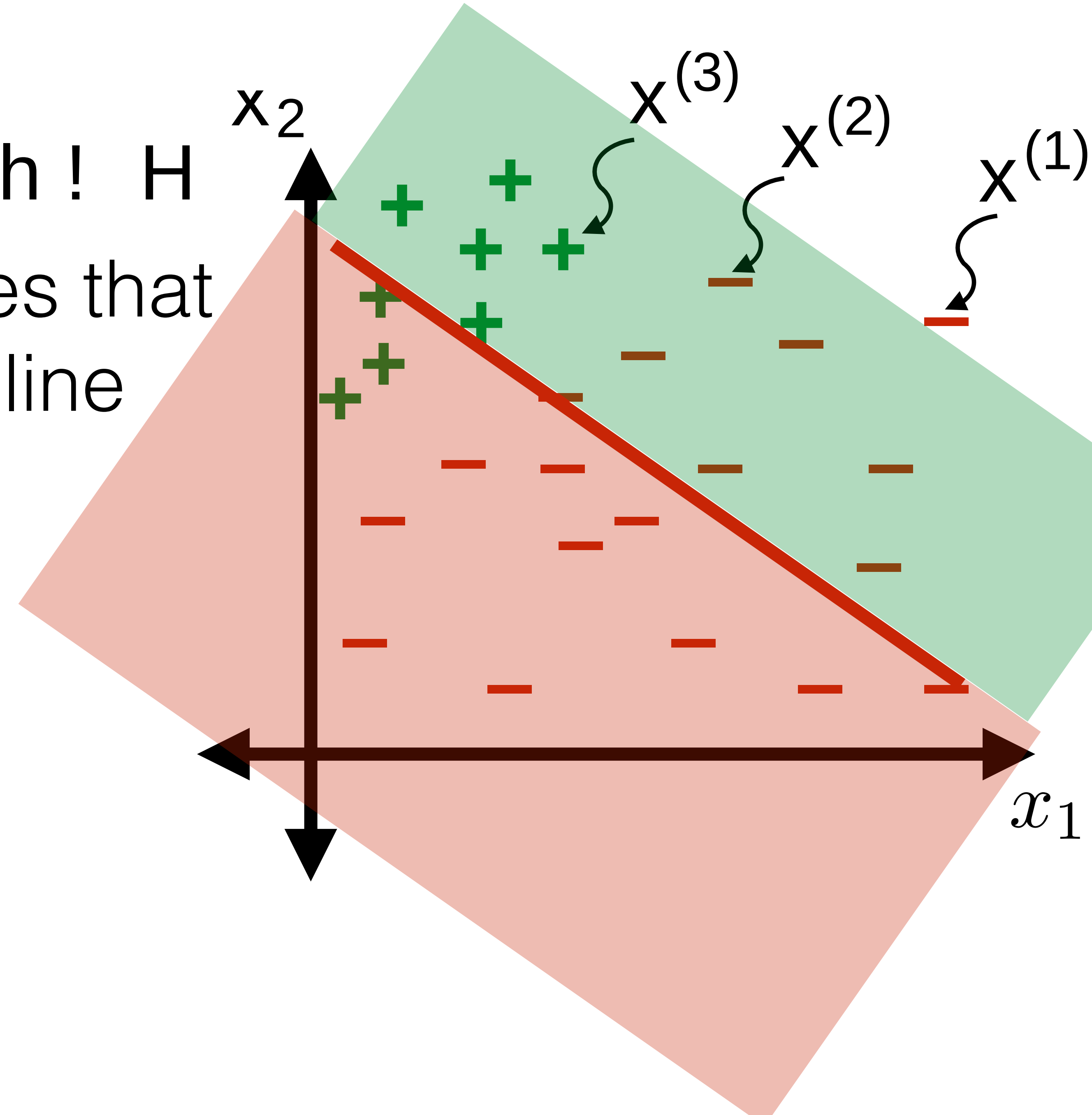

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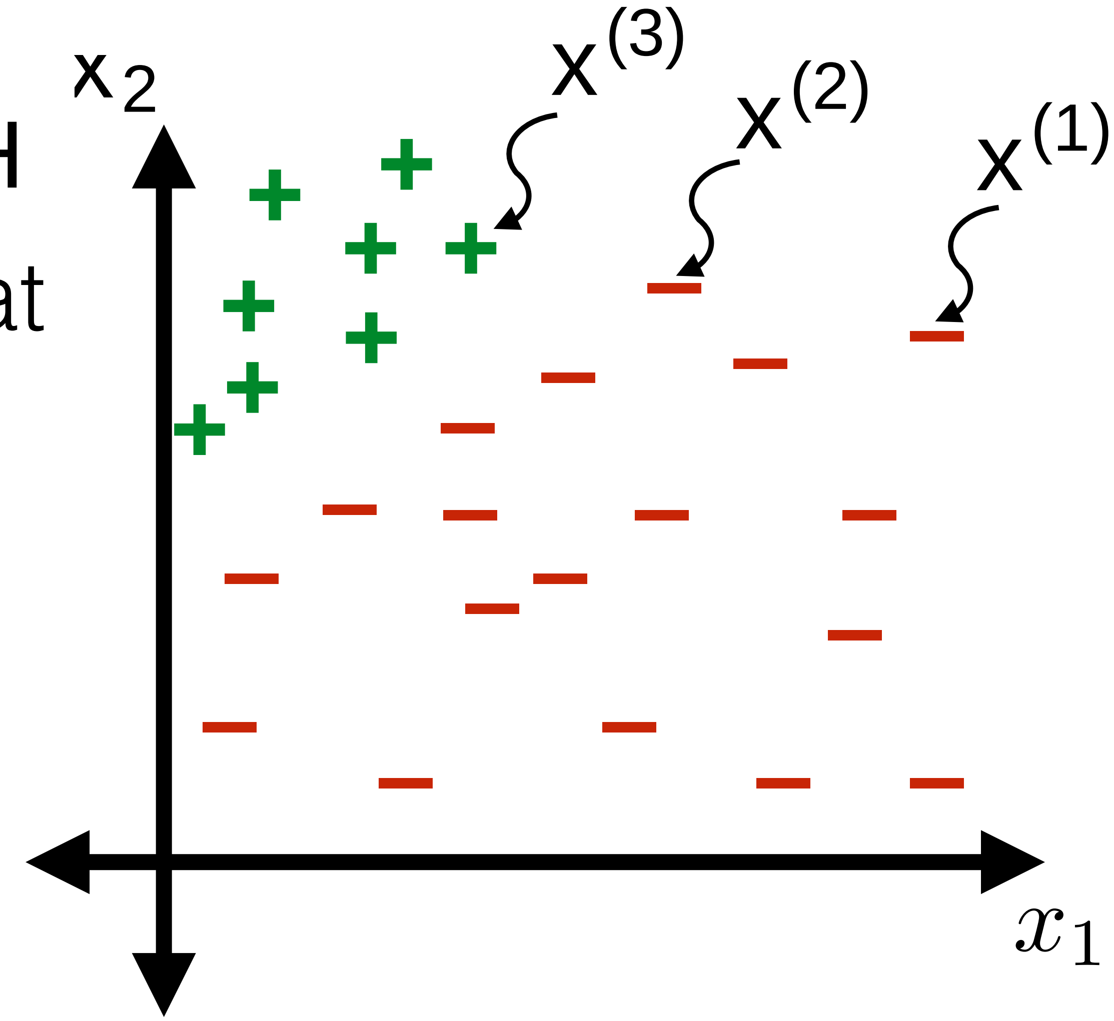

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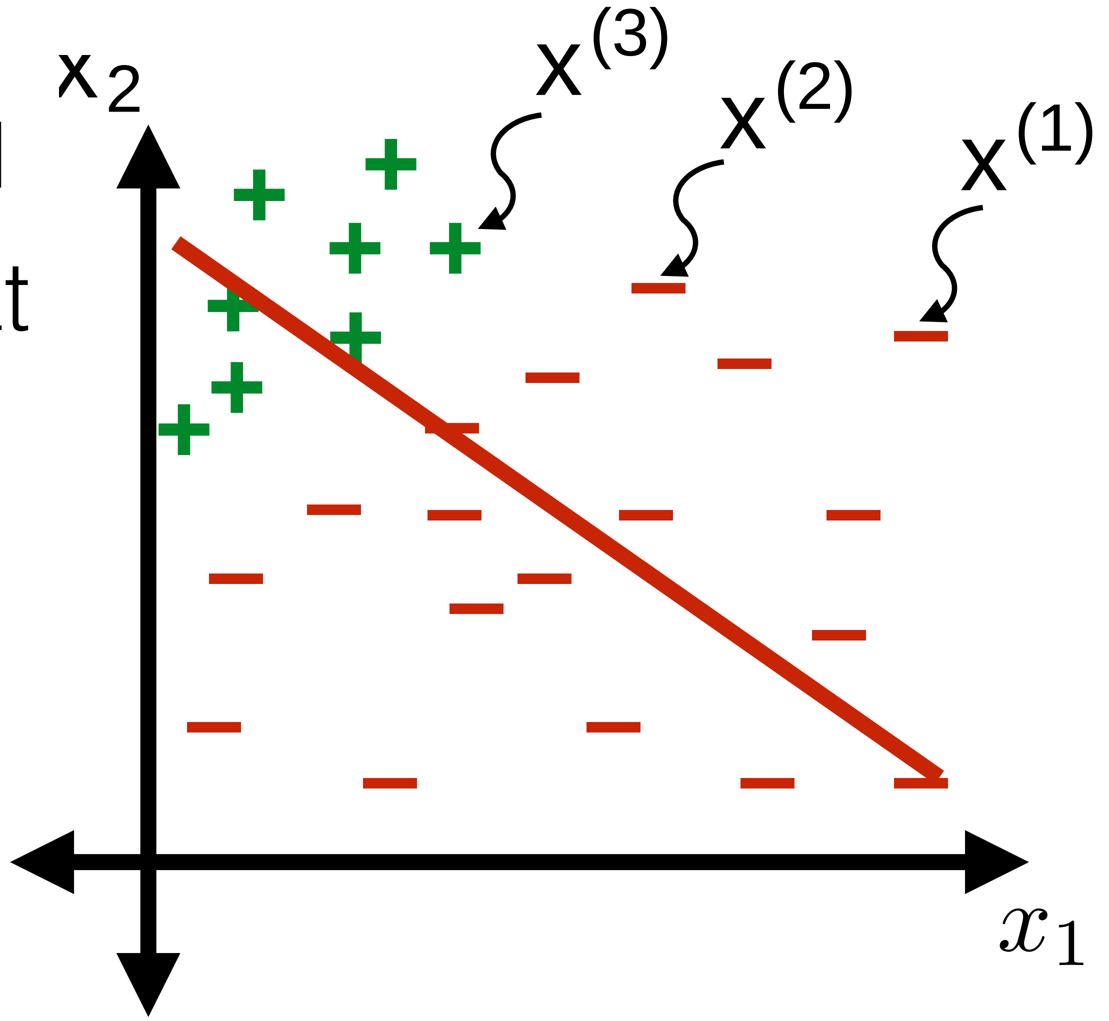

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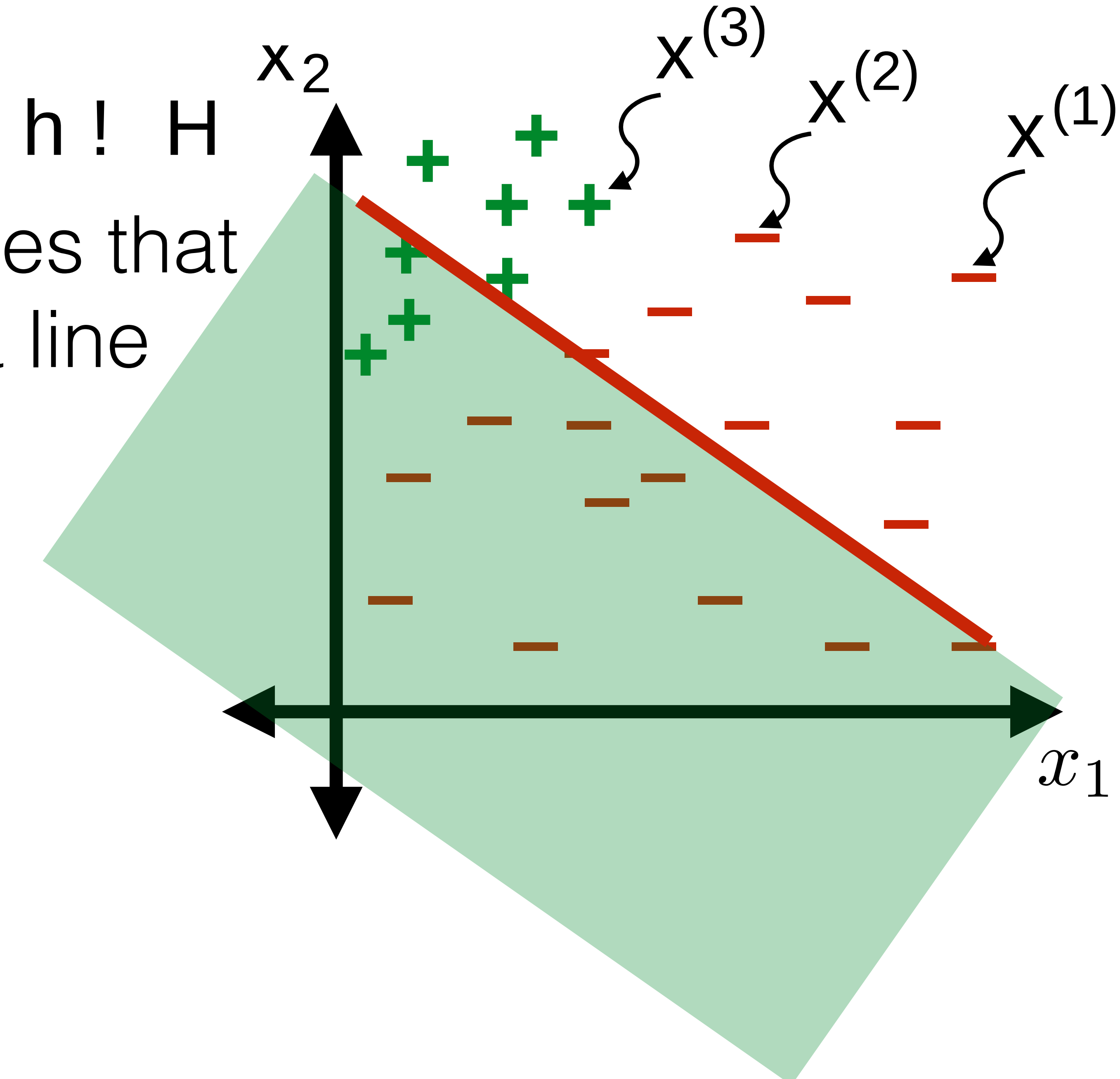

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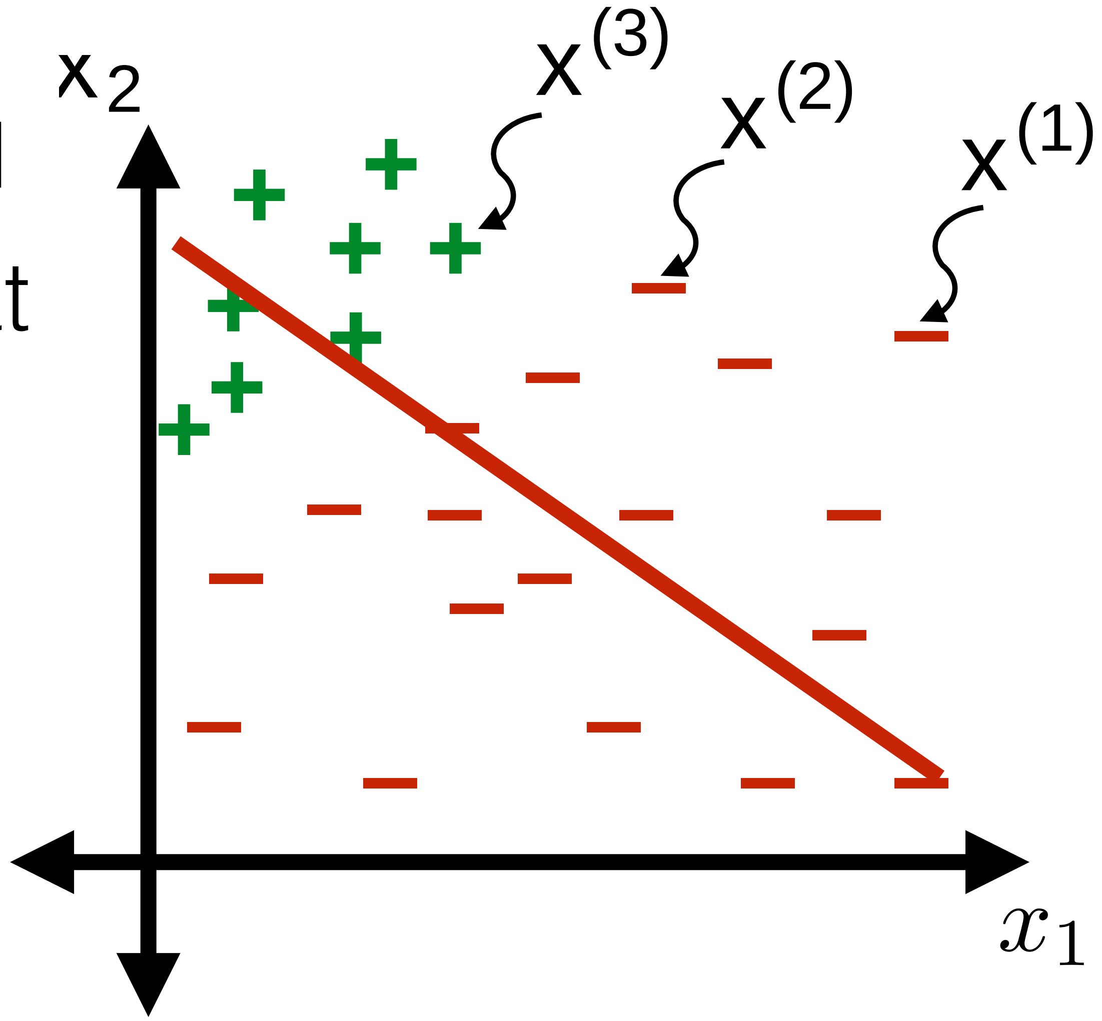

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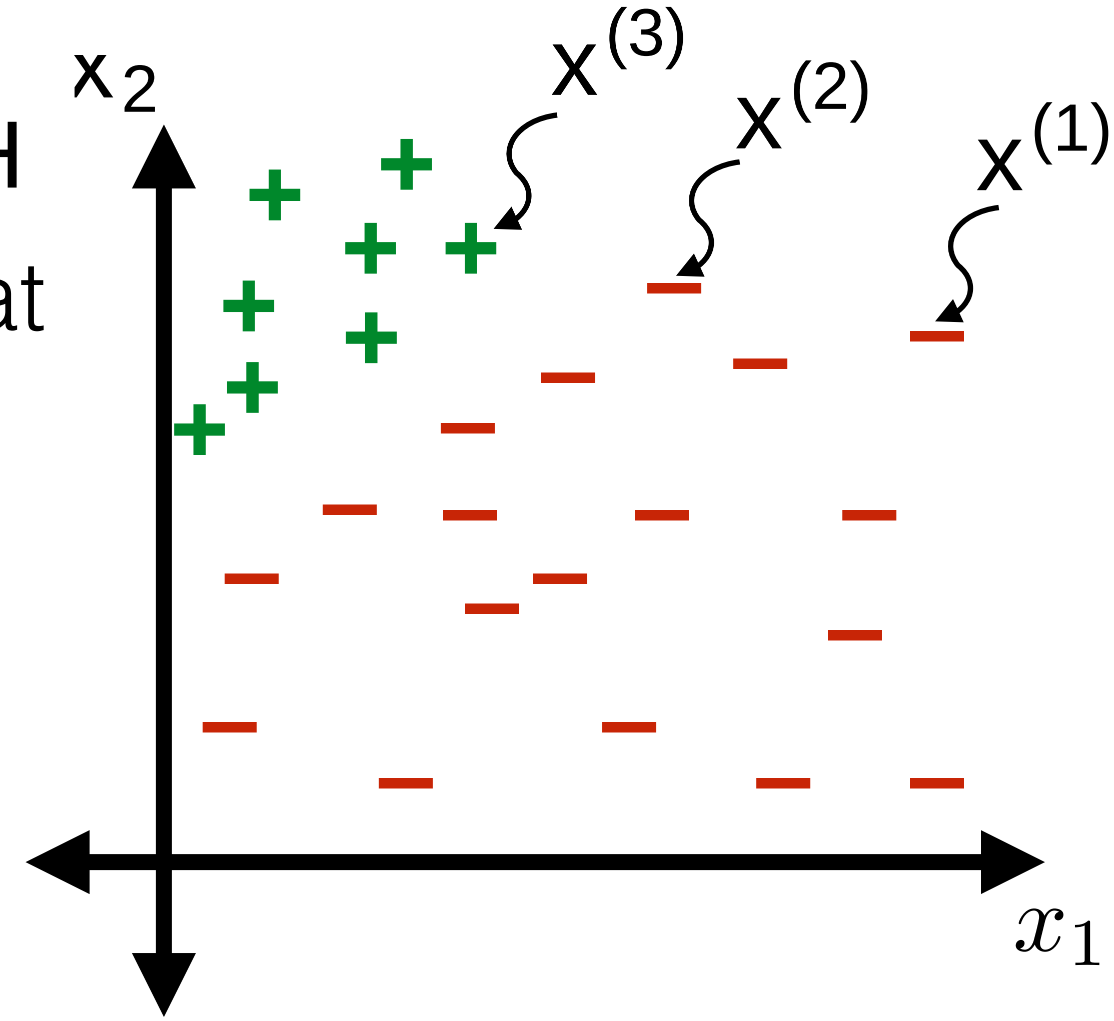

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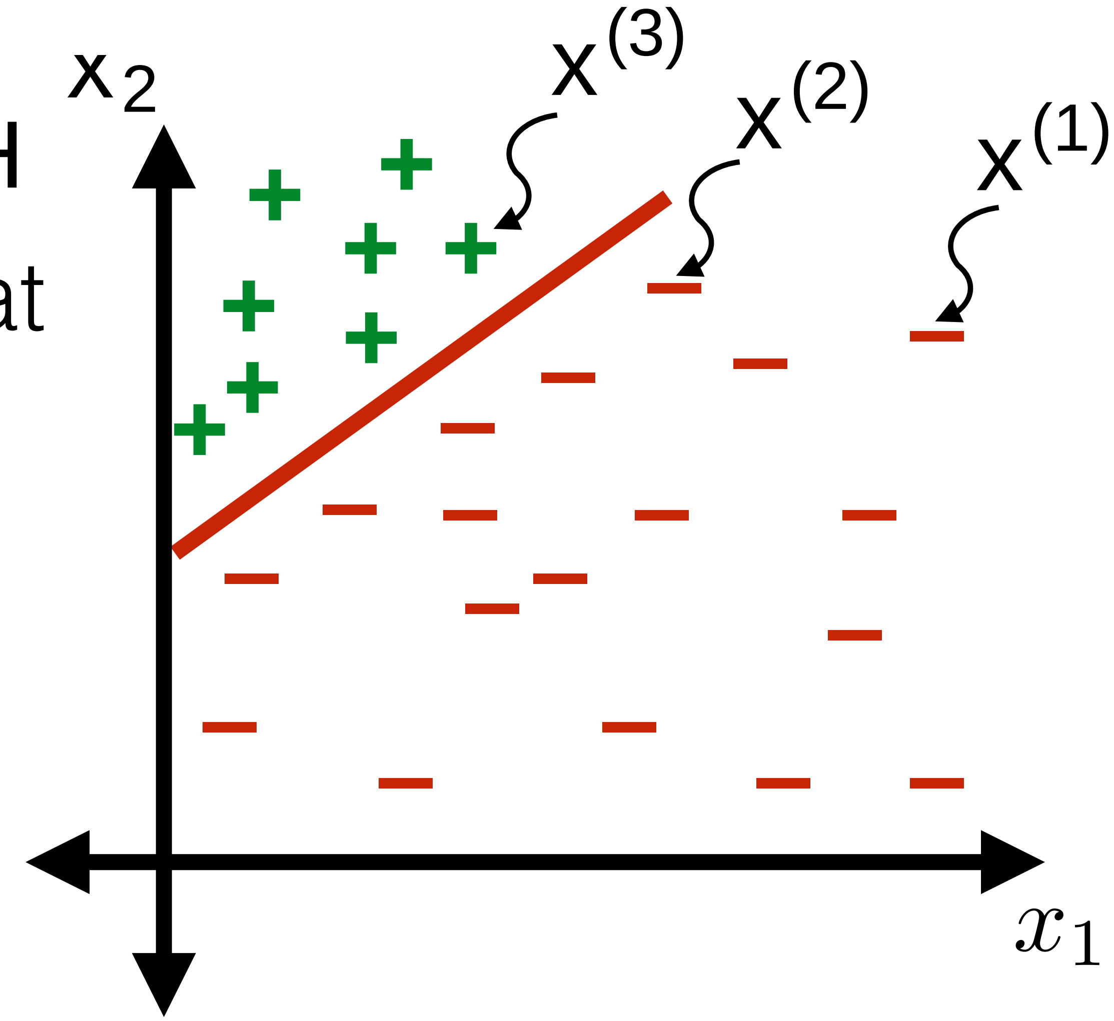

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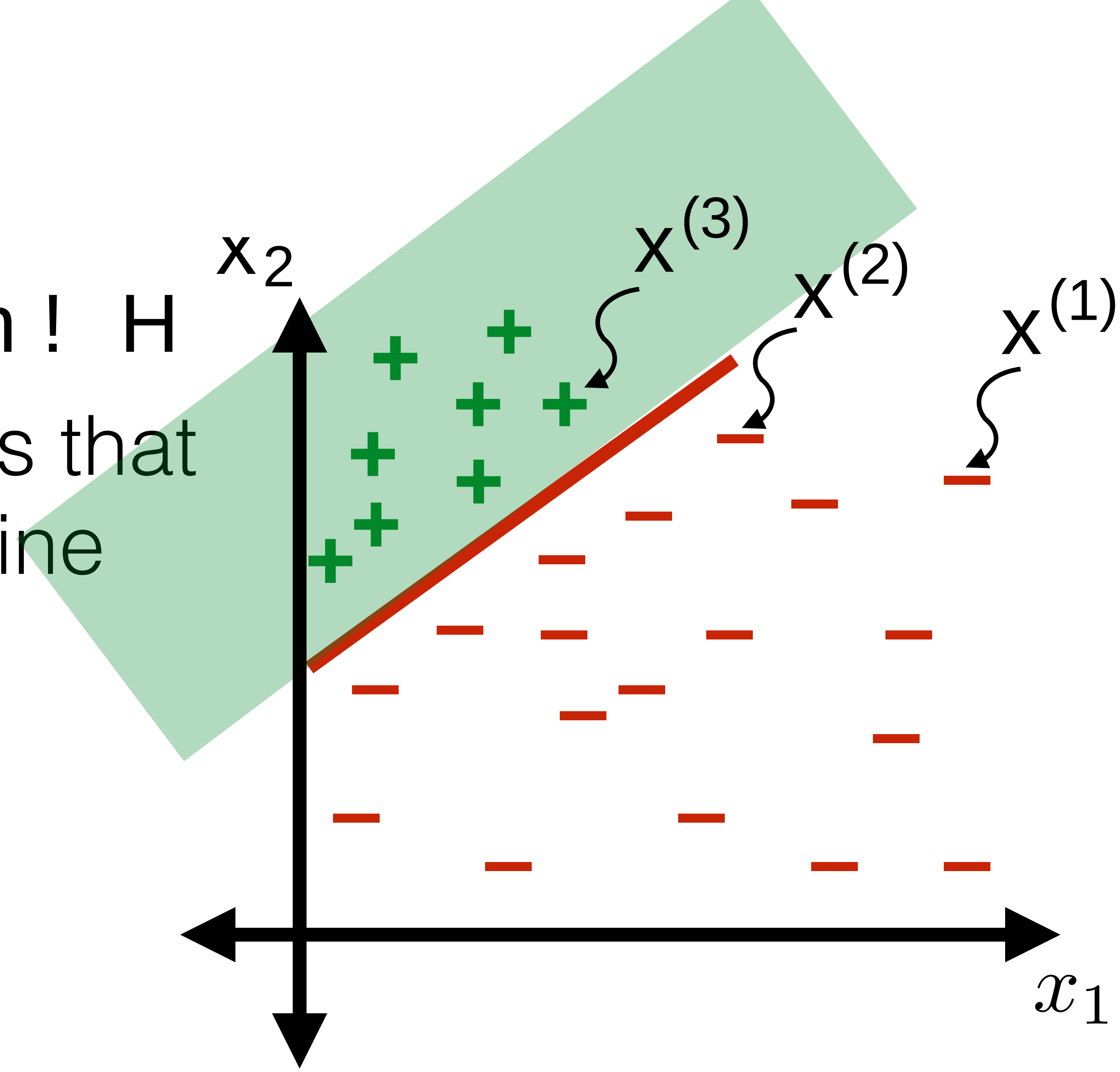

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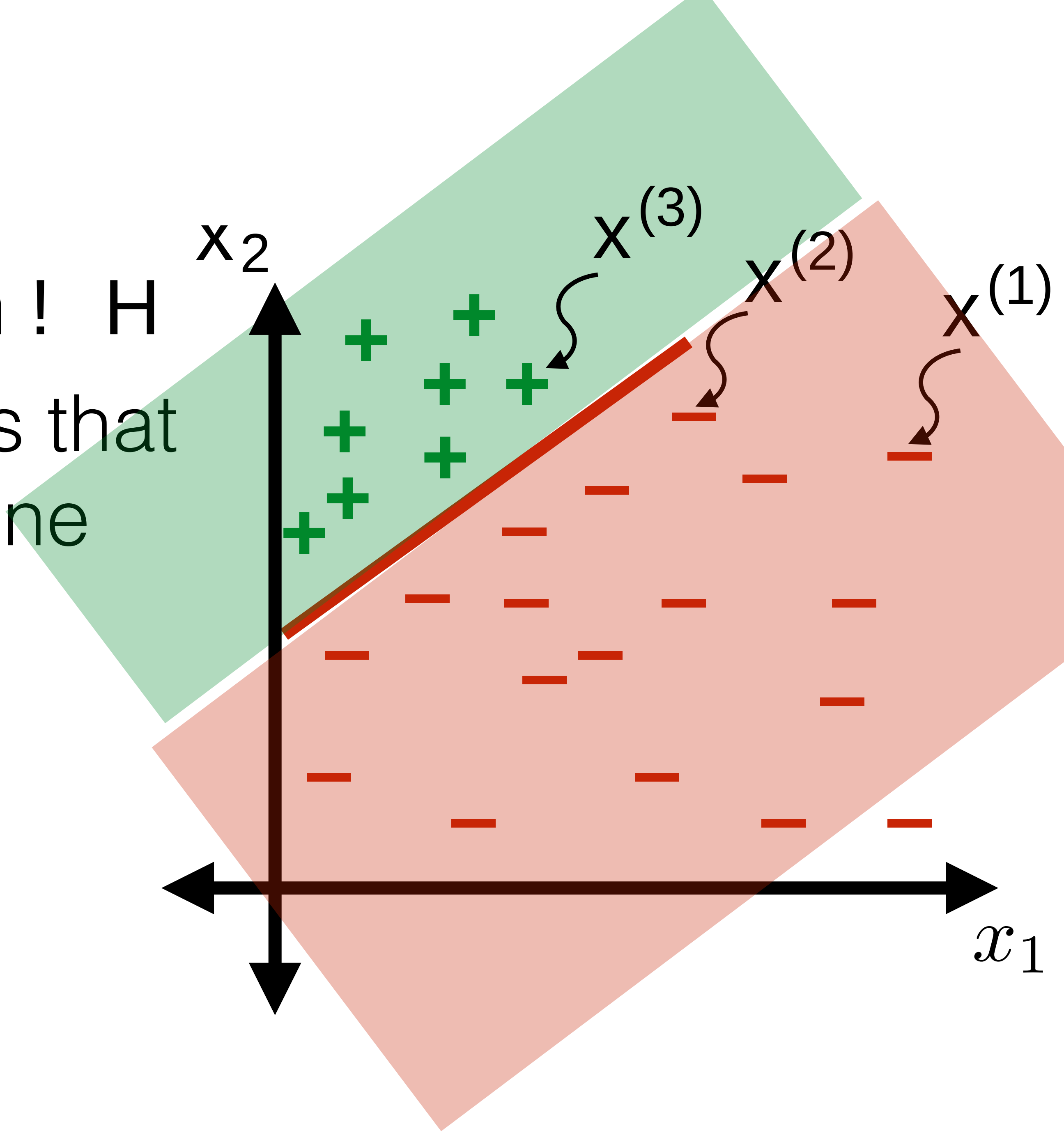

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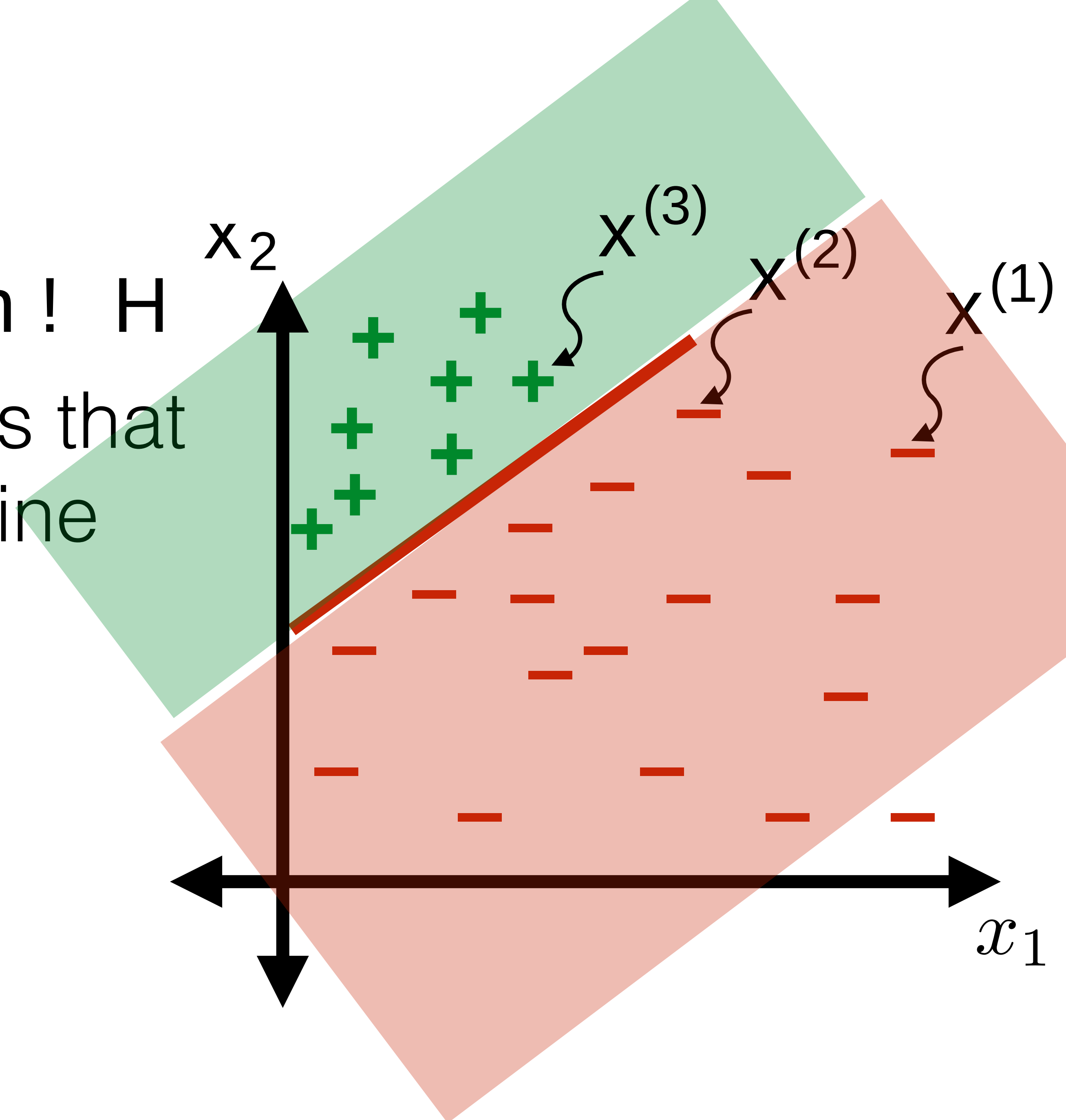
Math facts!



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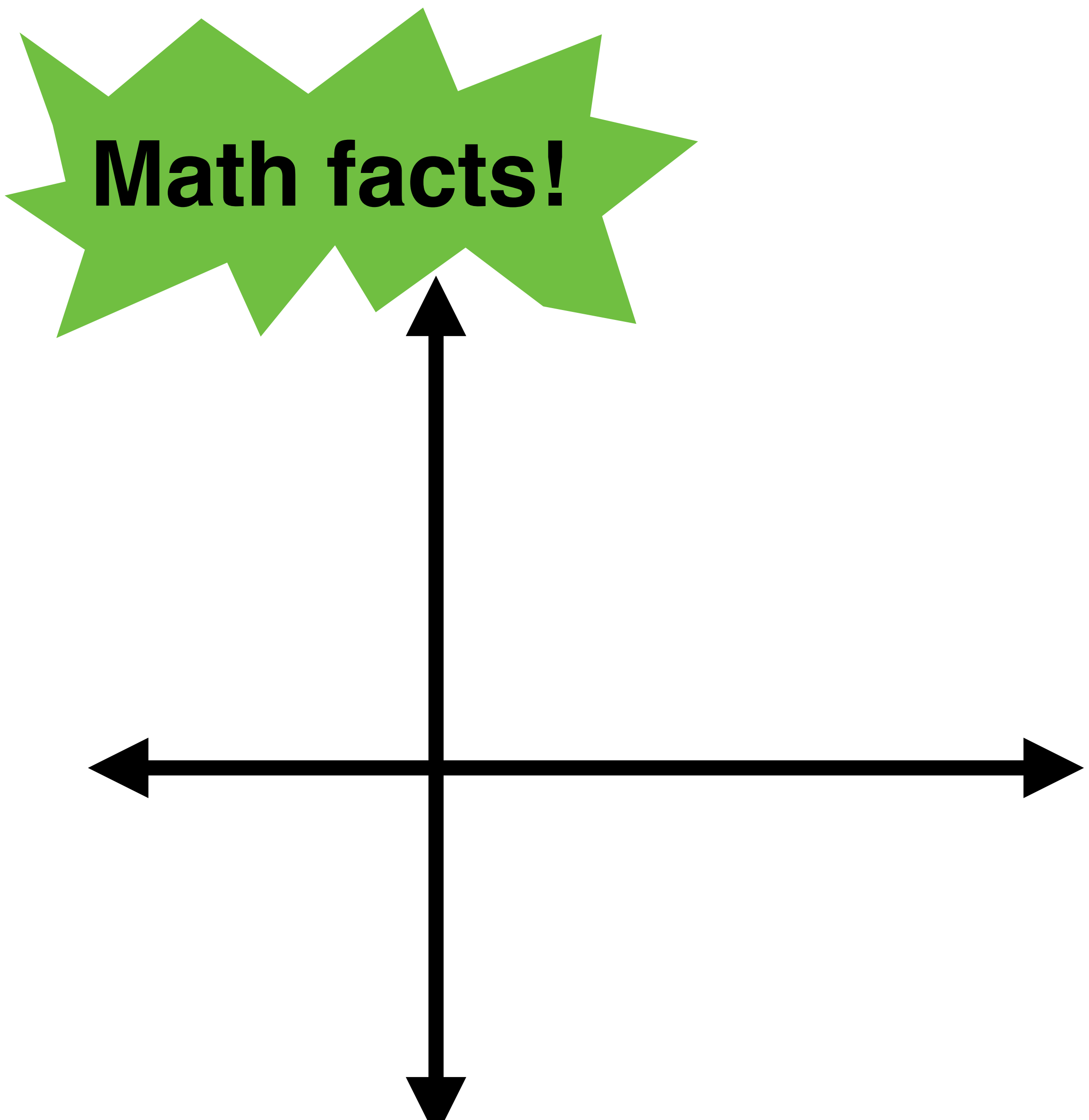

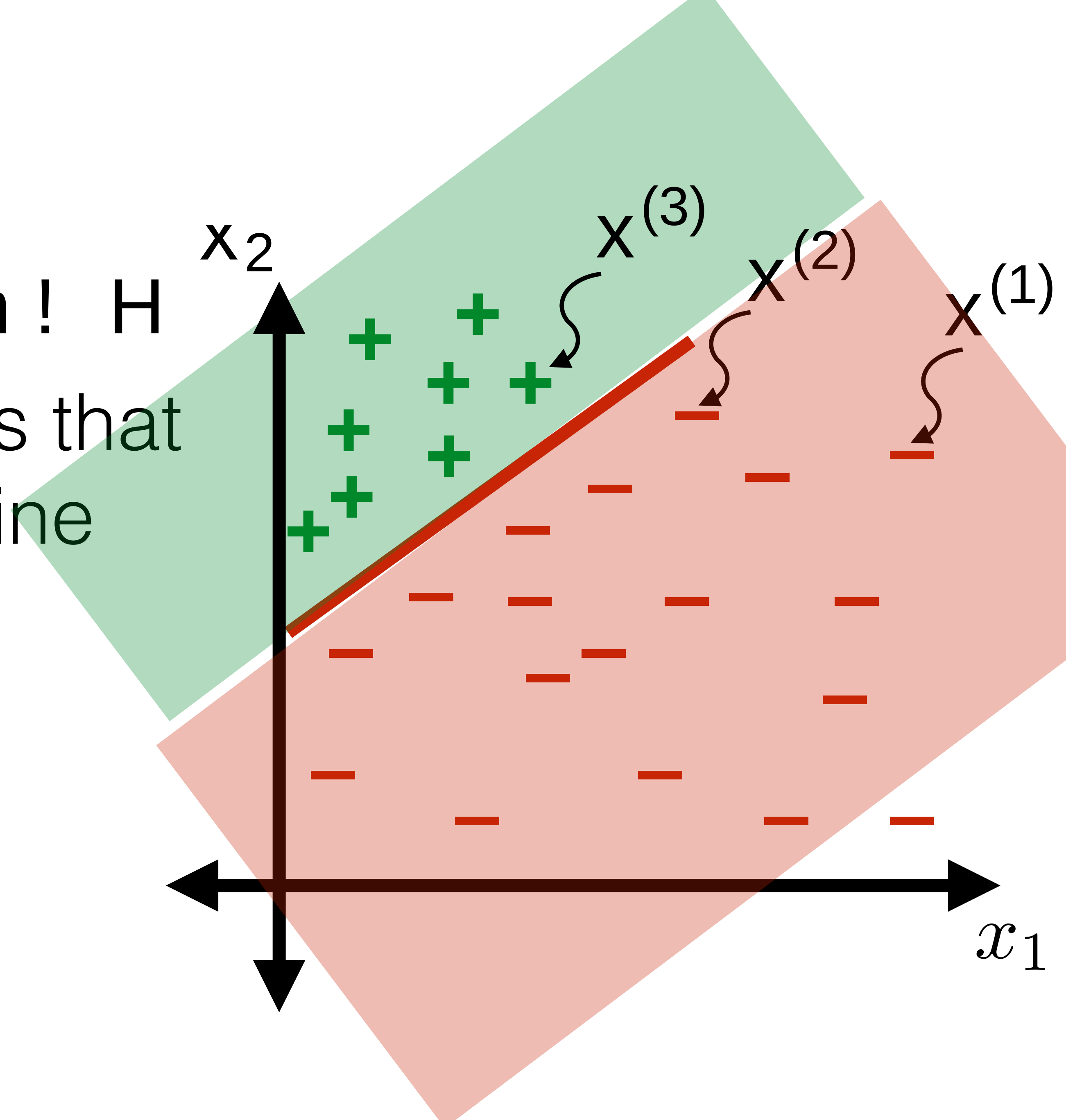

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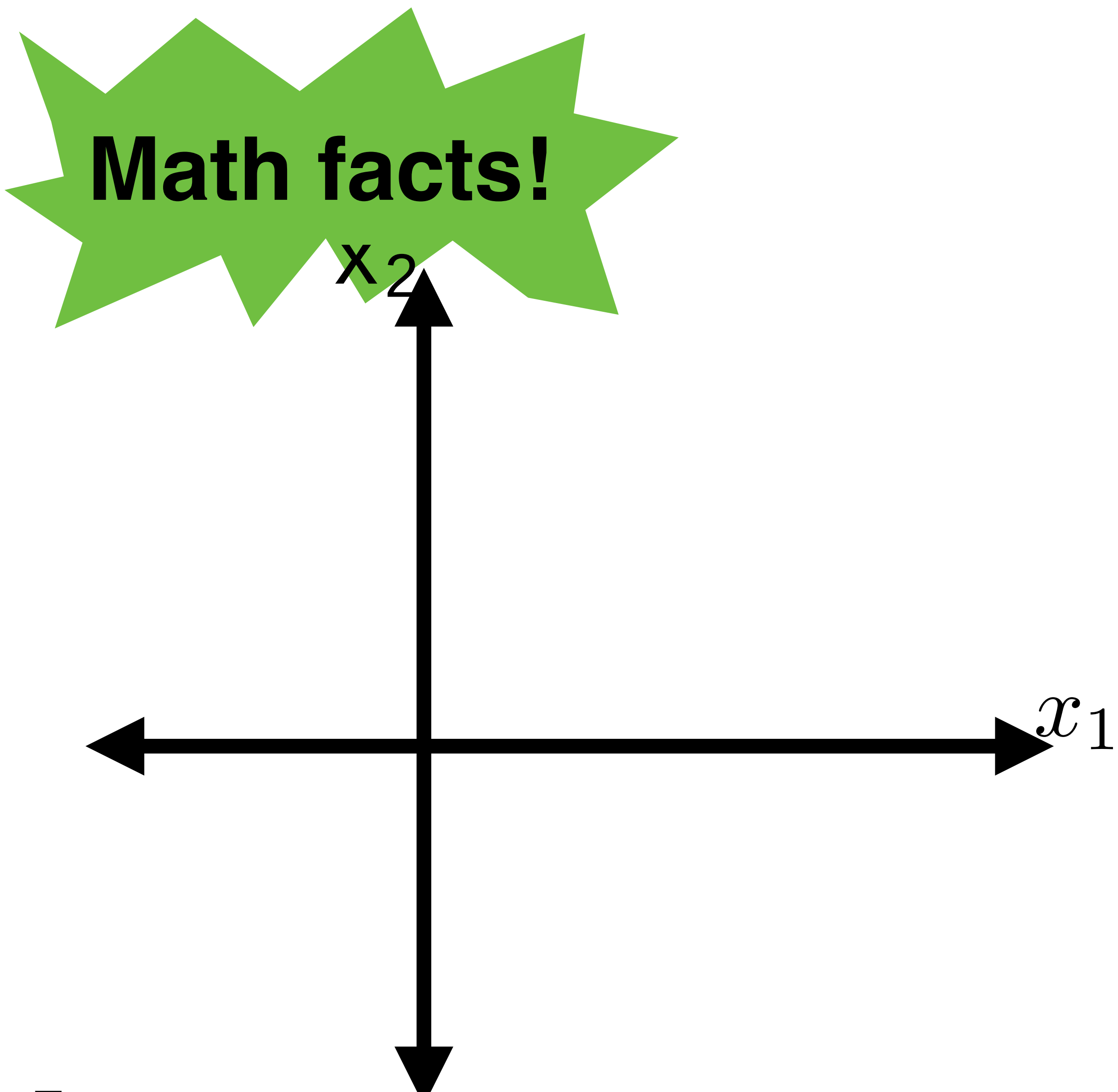

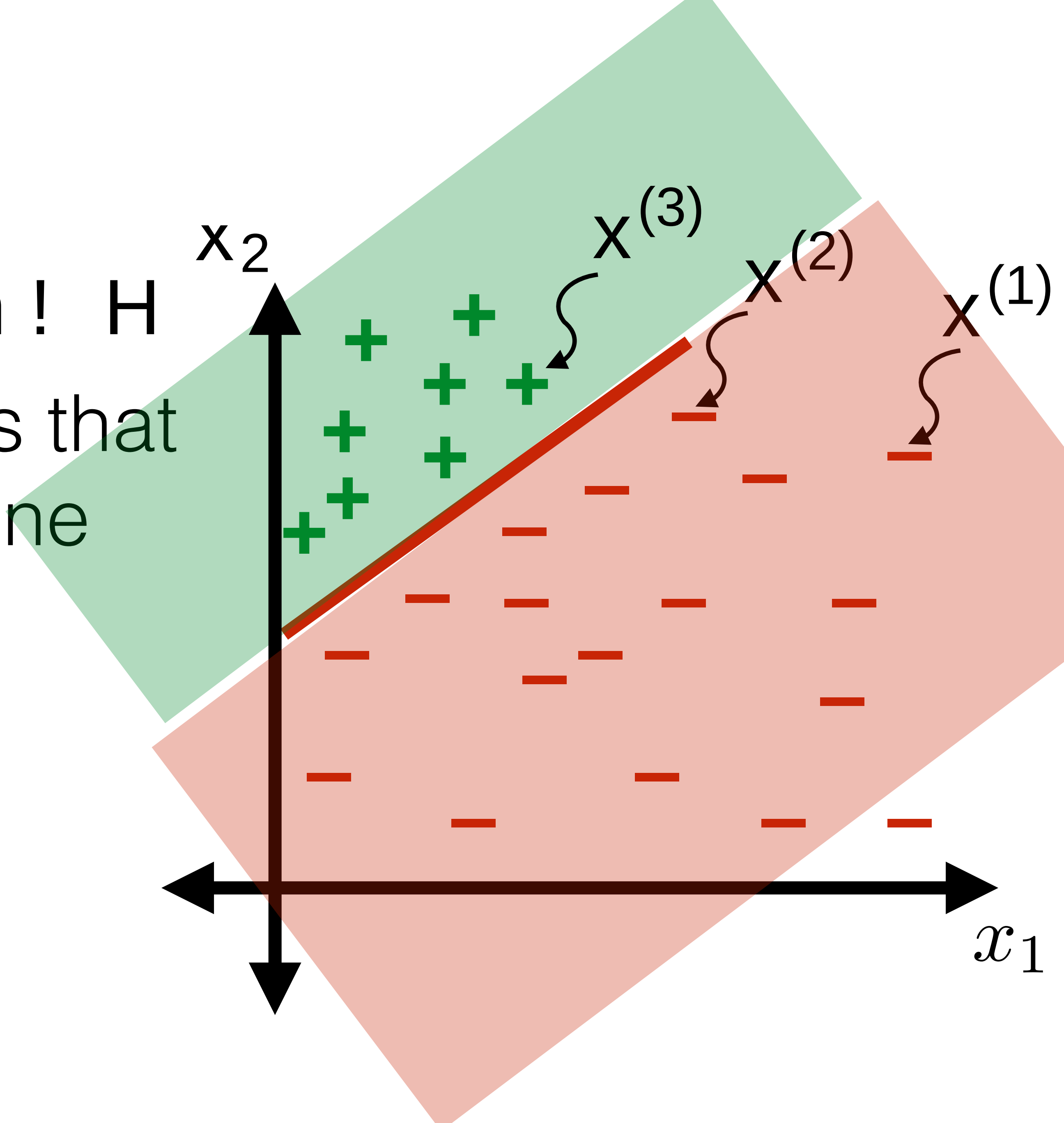

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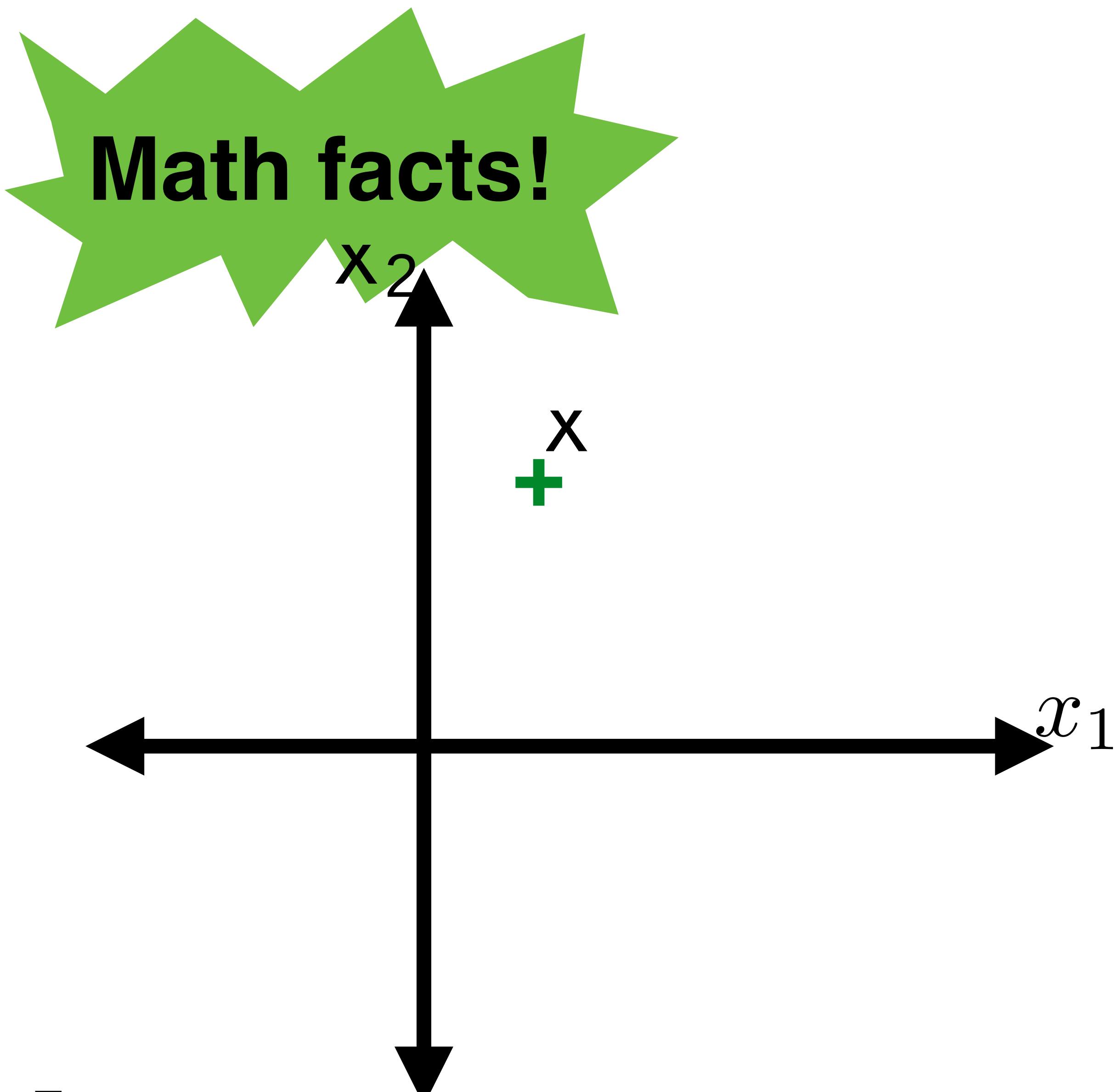

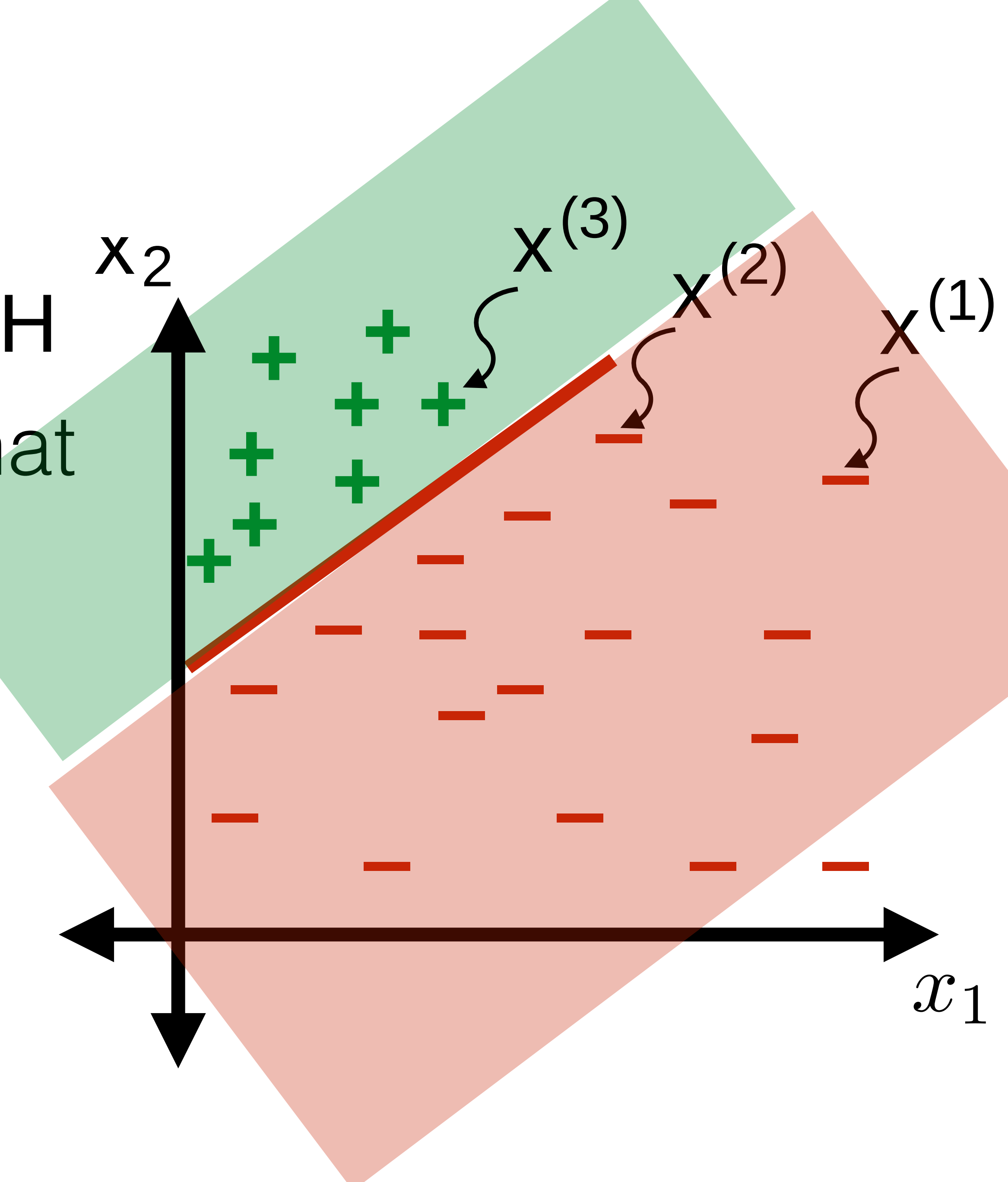

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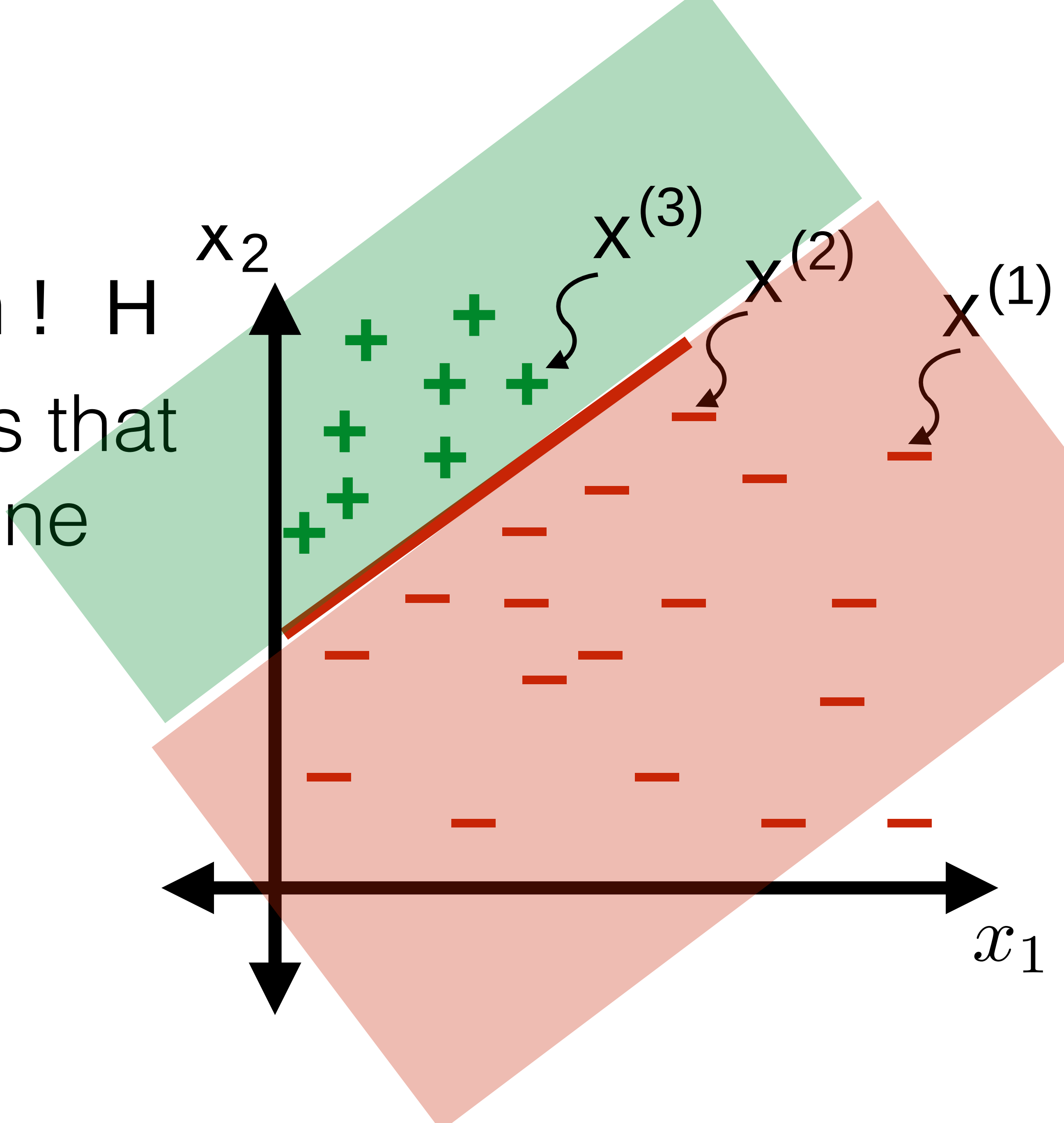

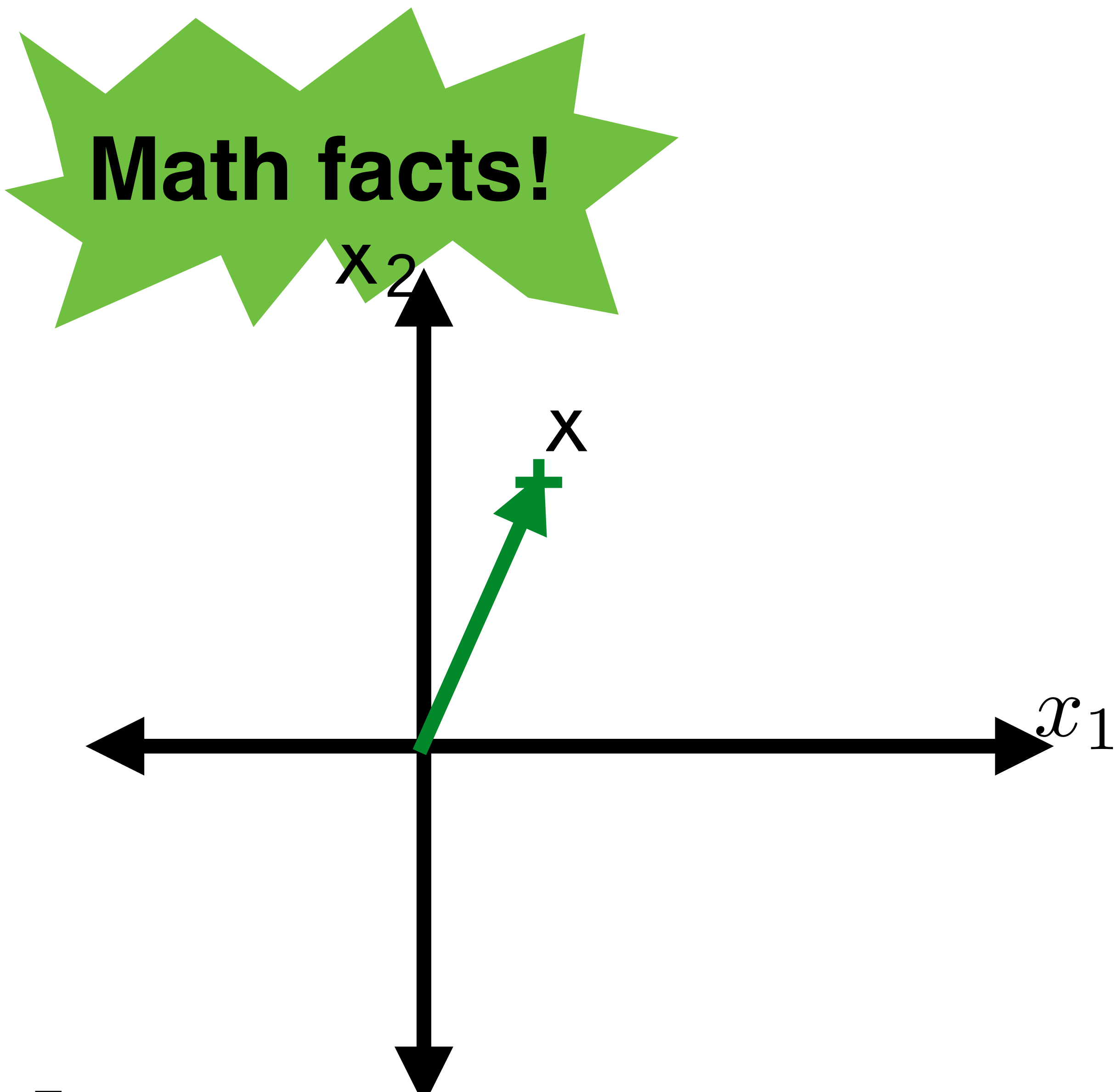

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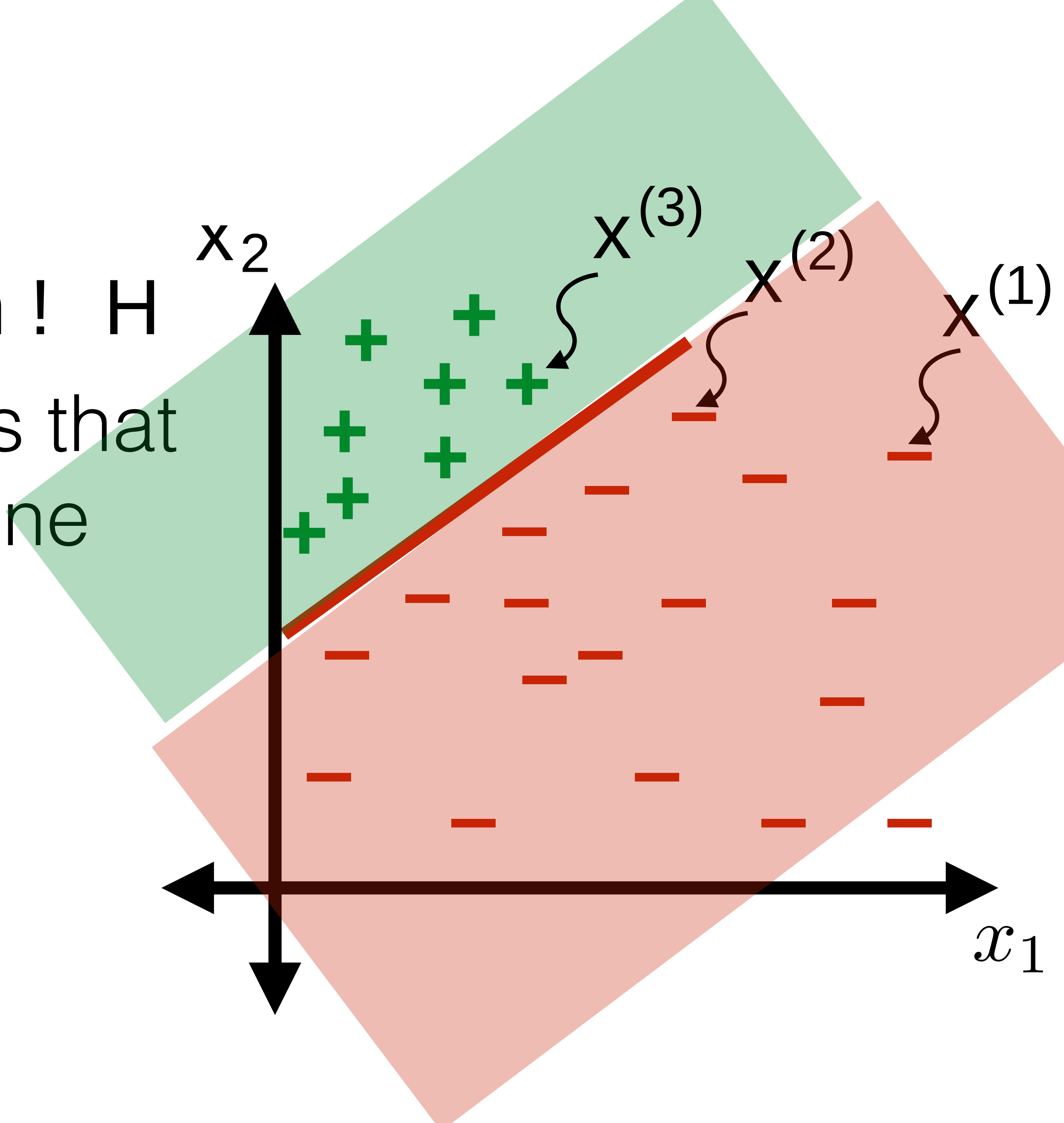

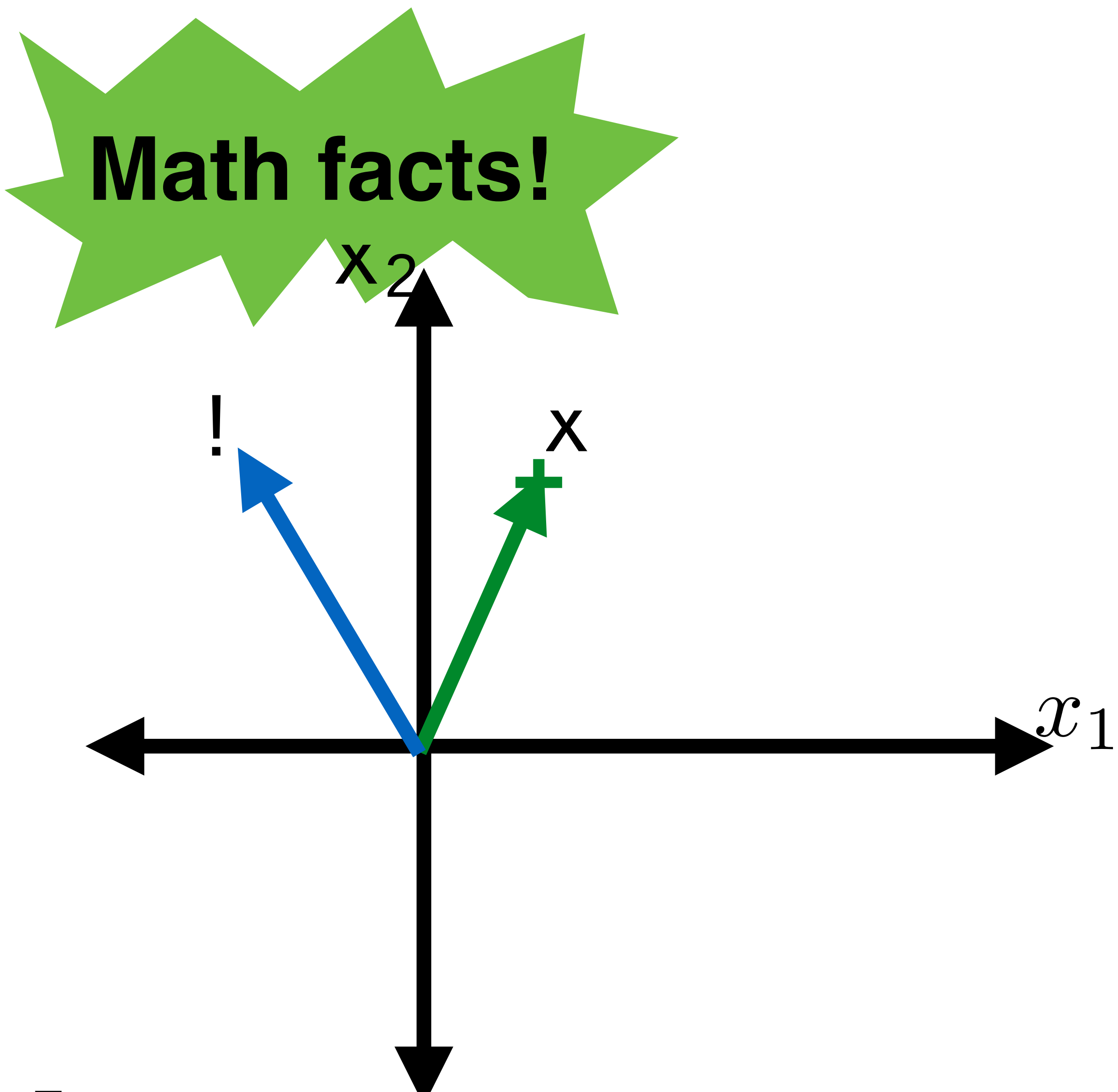

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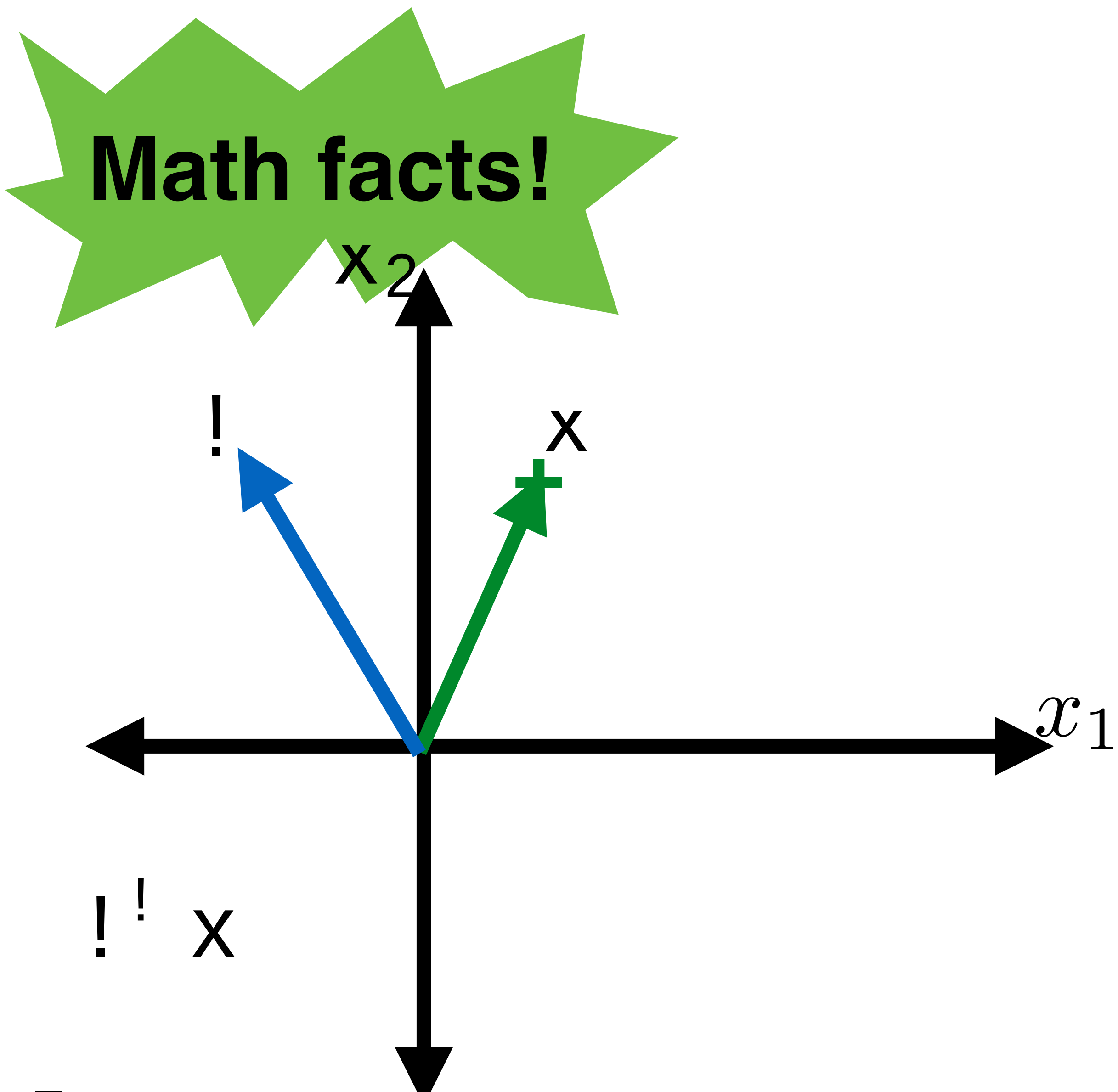

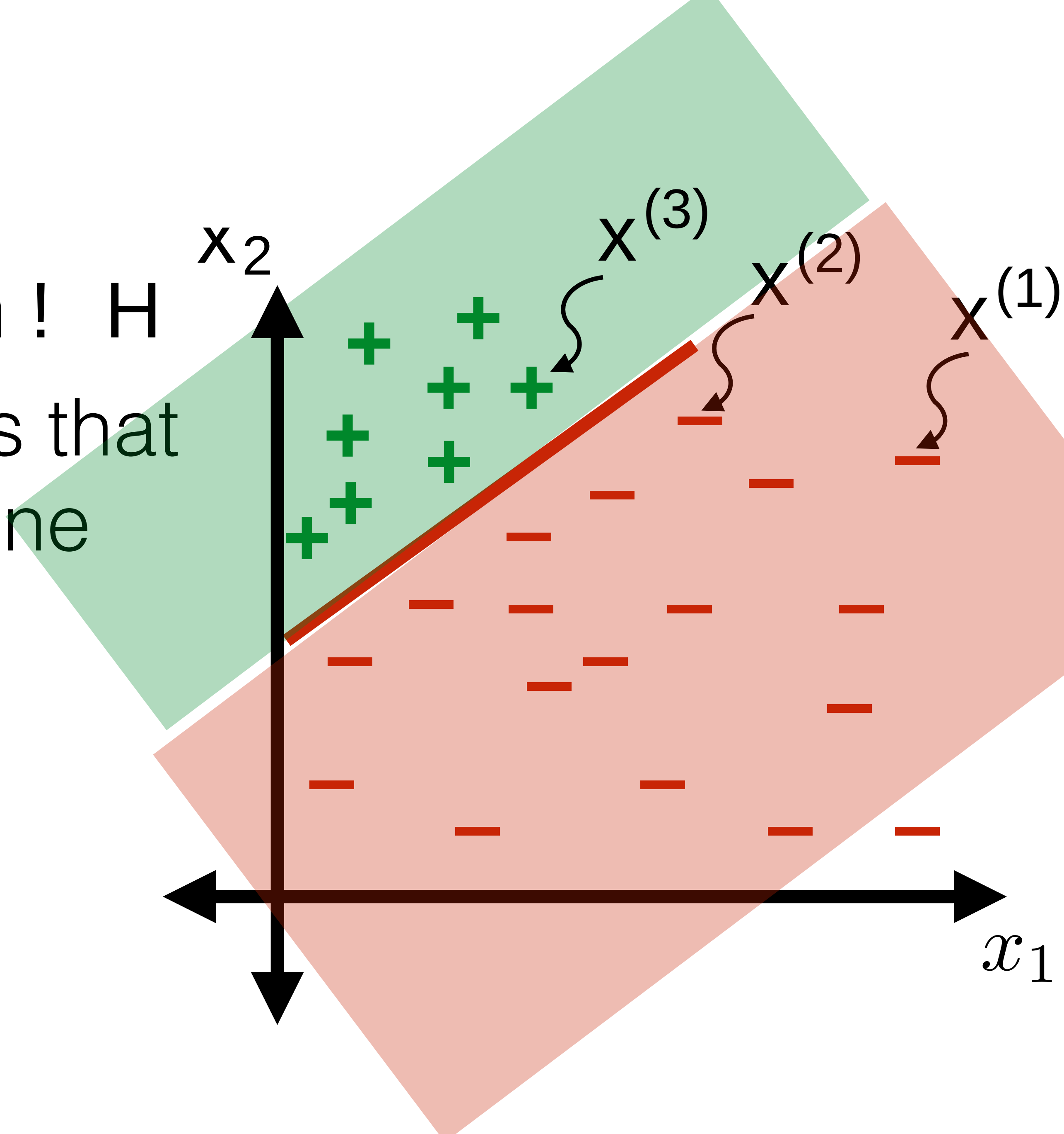

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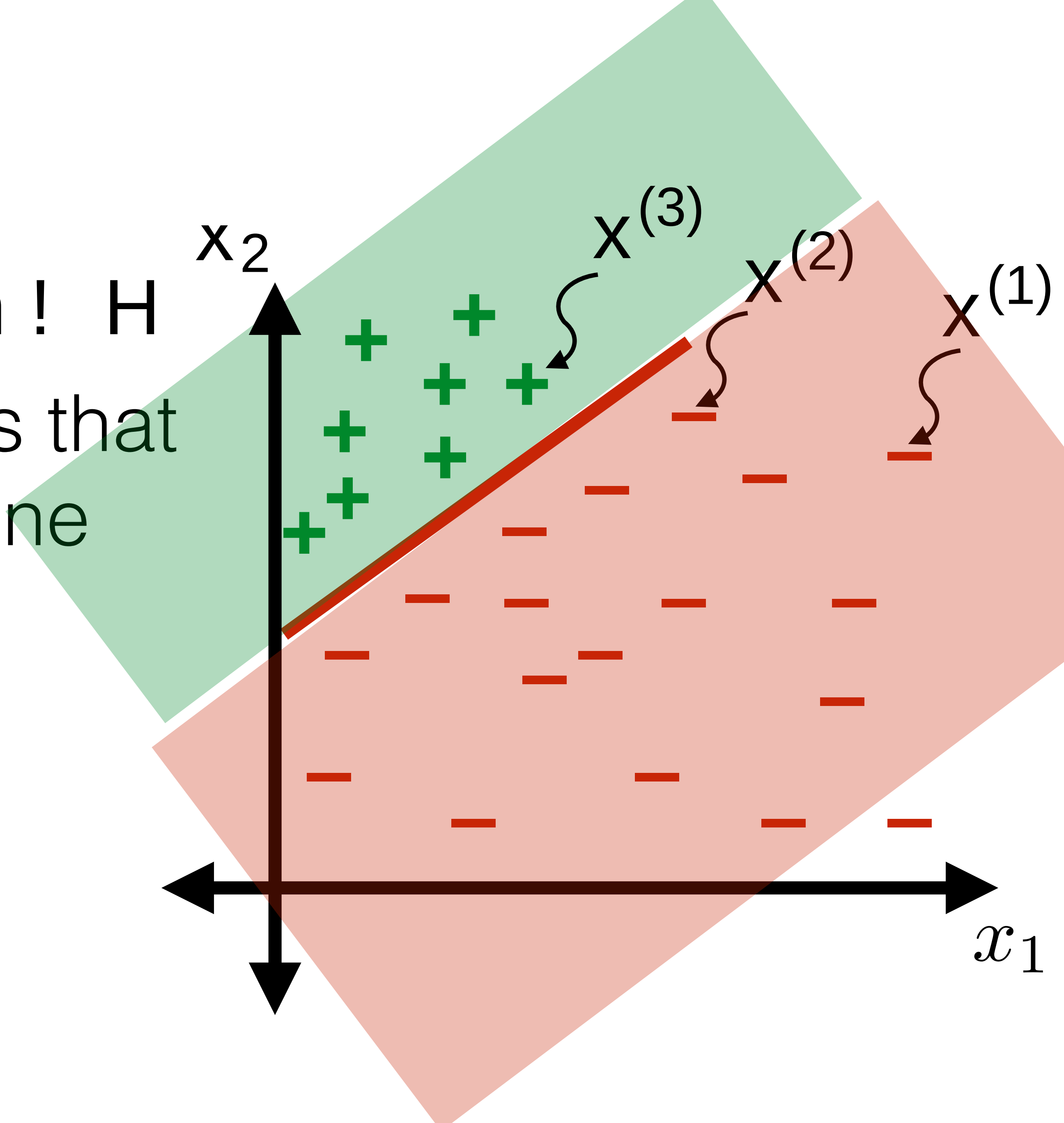

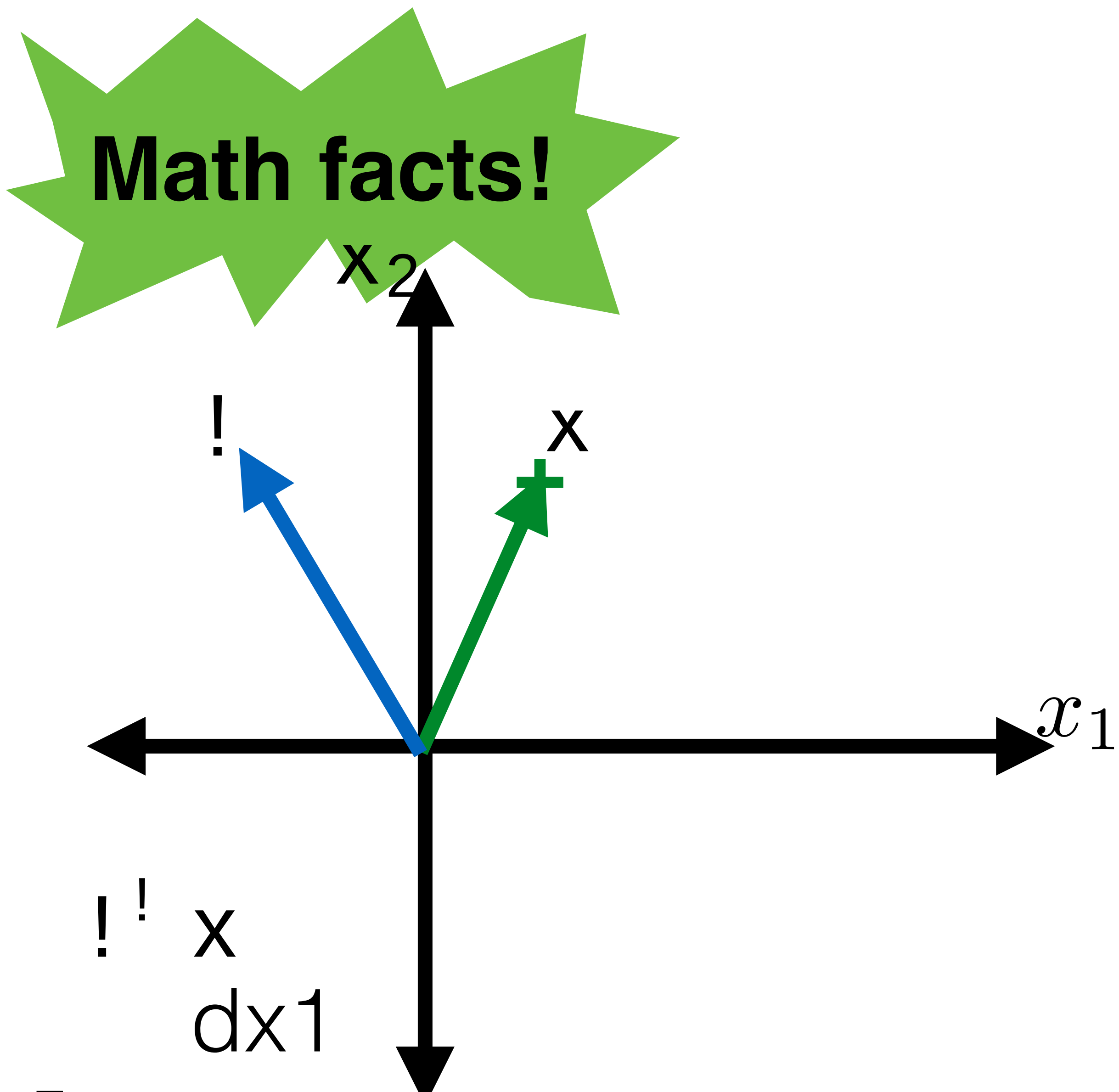

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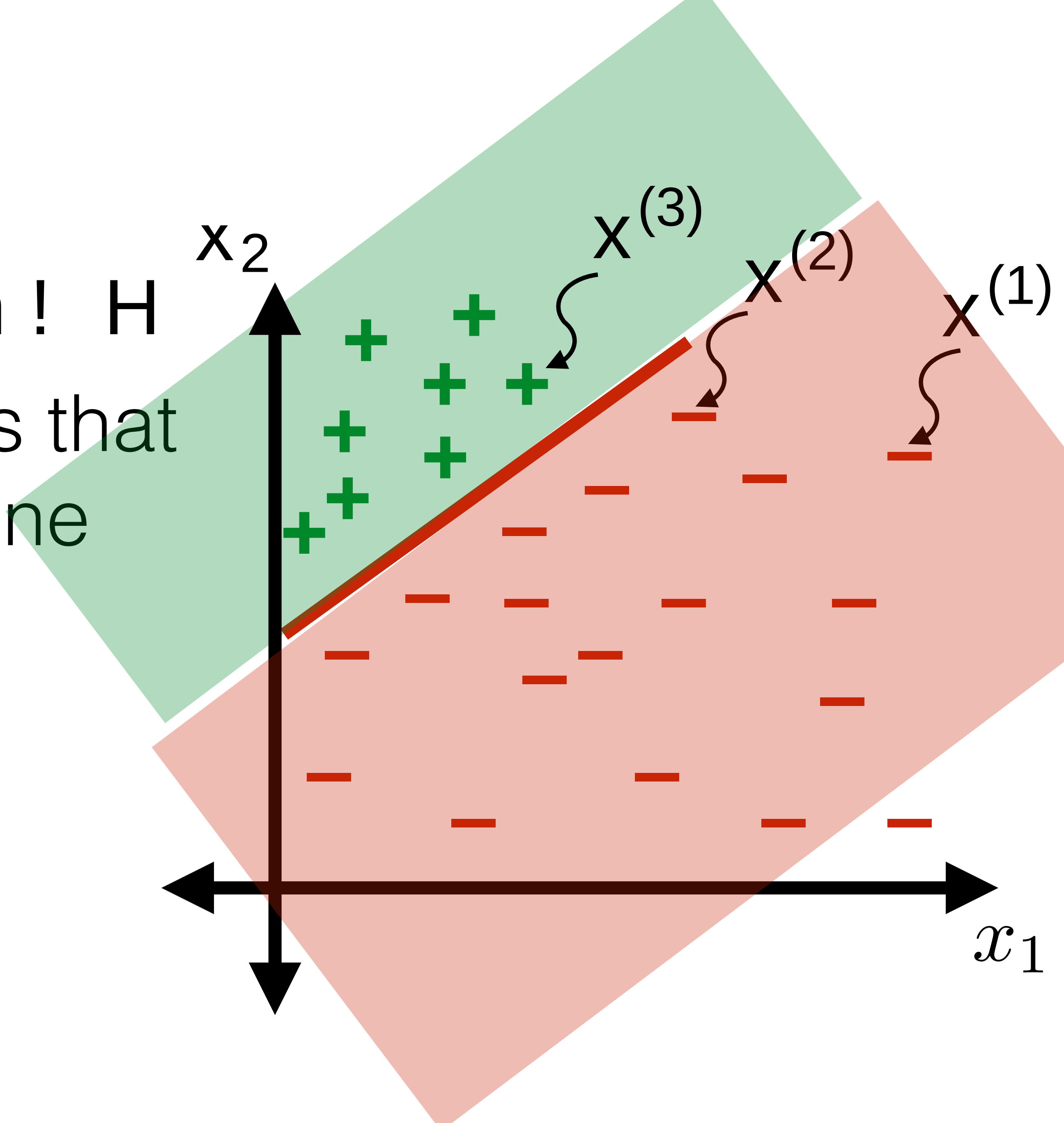

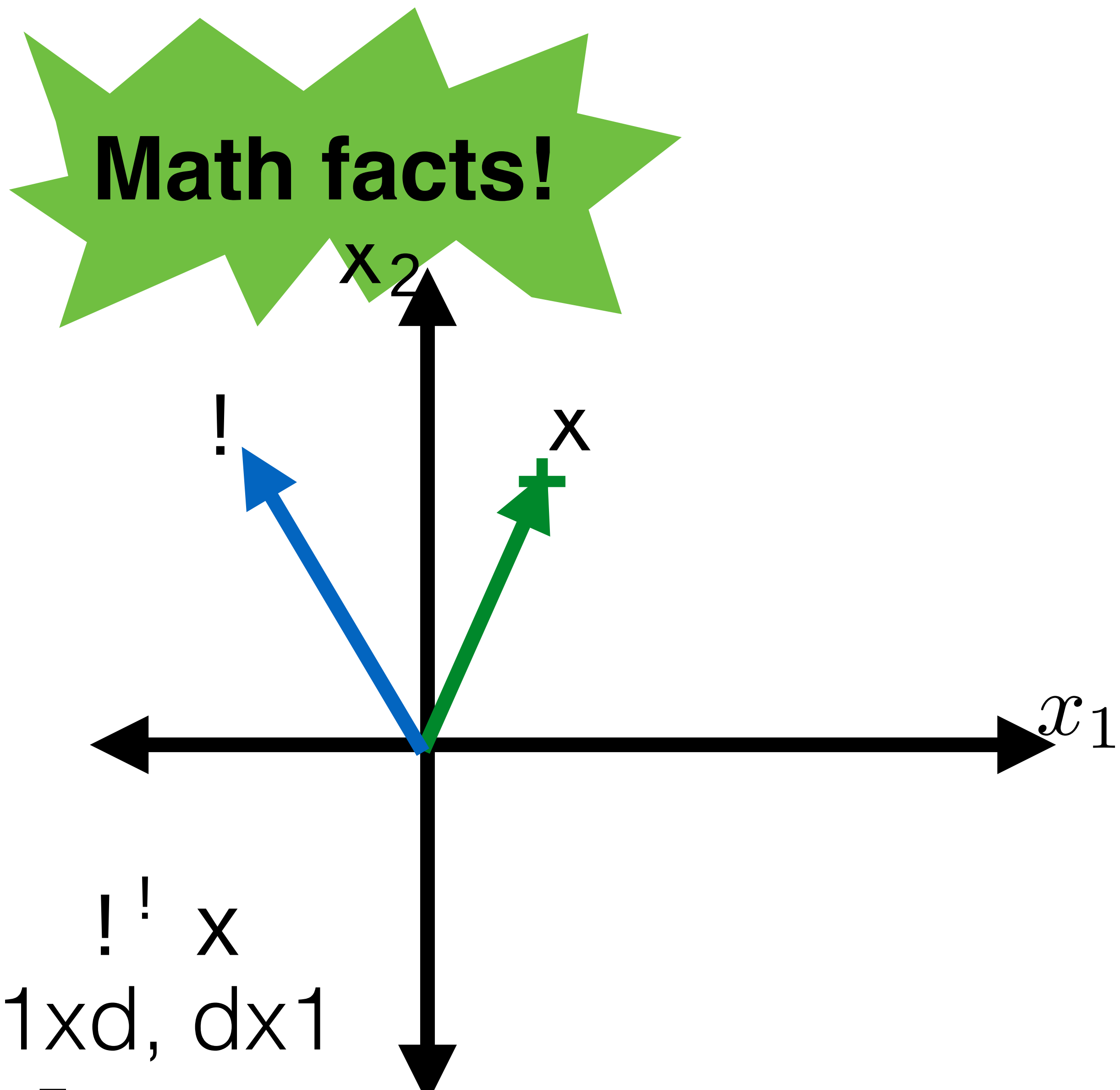

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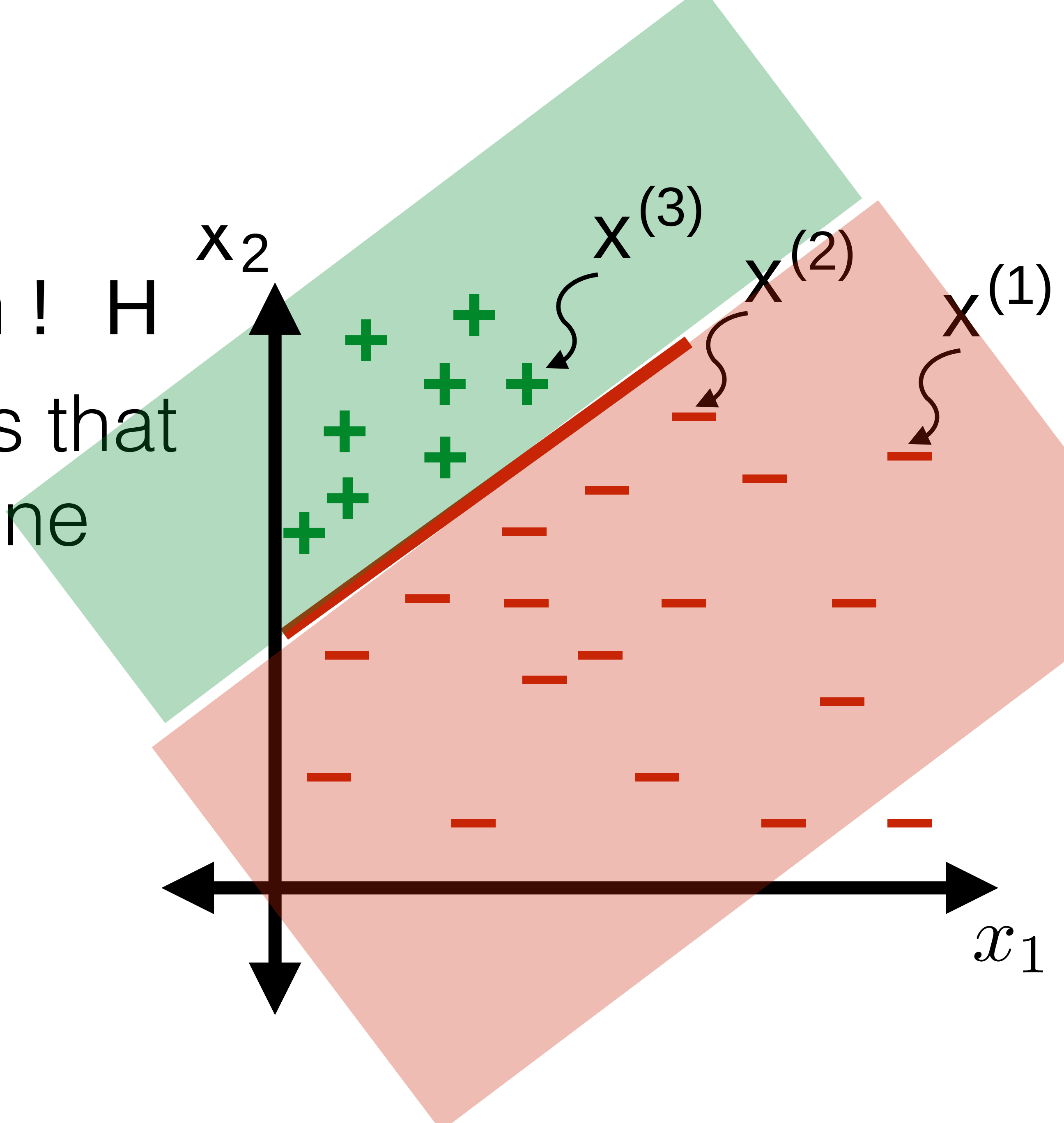

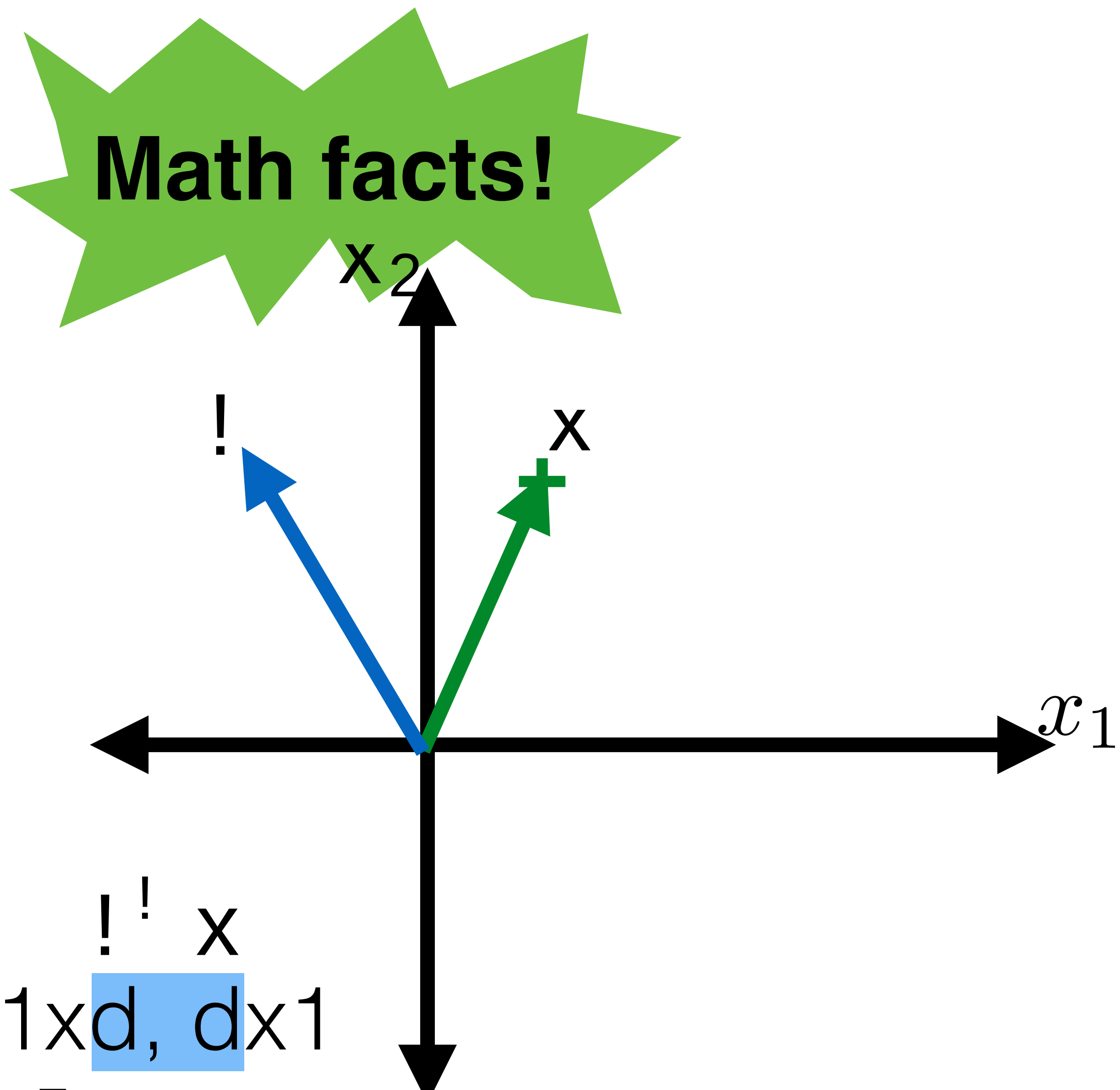

! ! x

1xd, dx1

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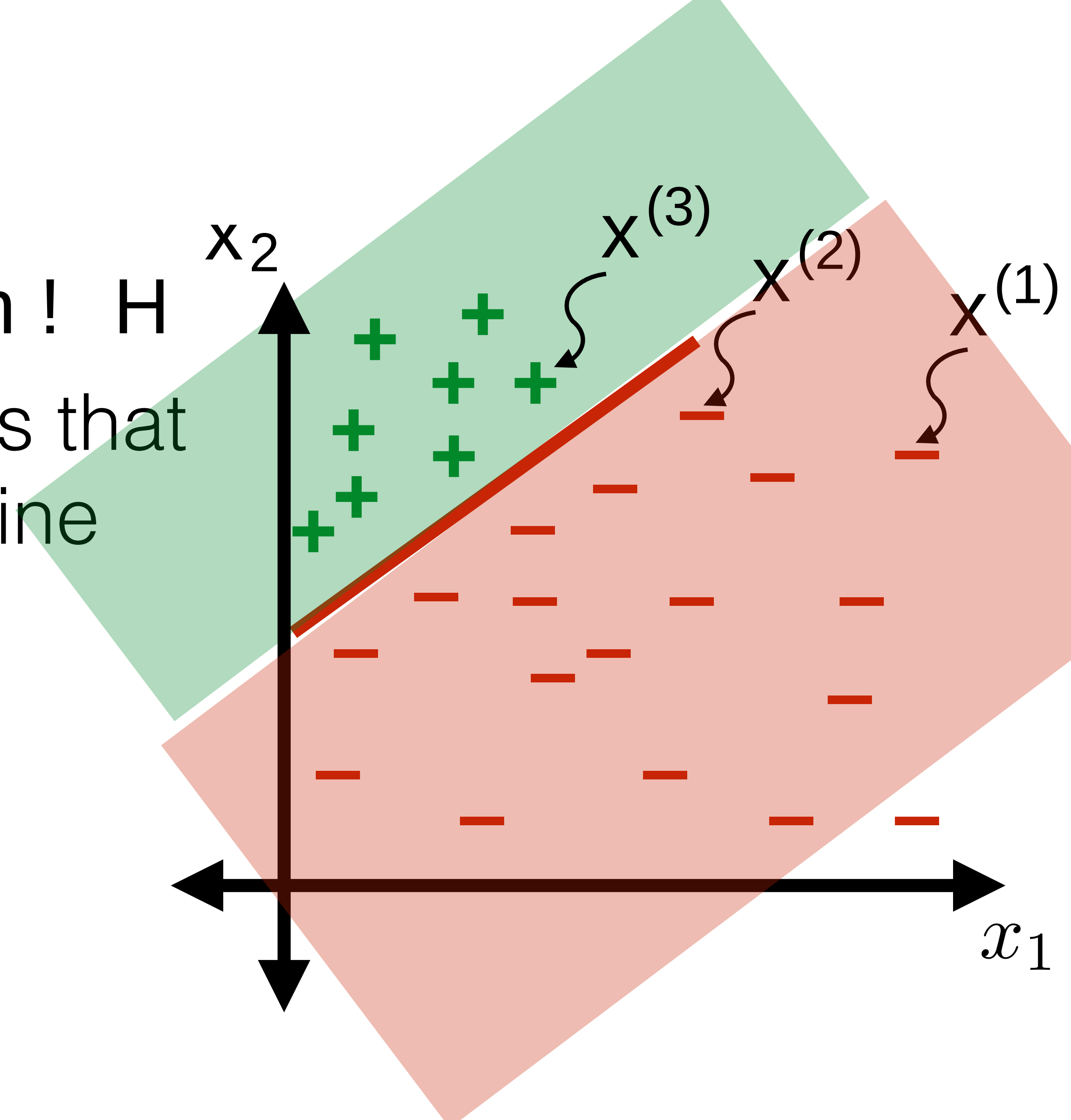

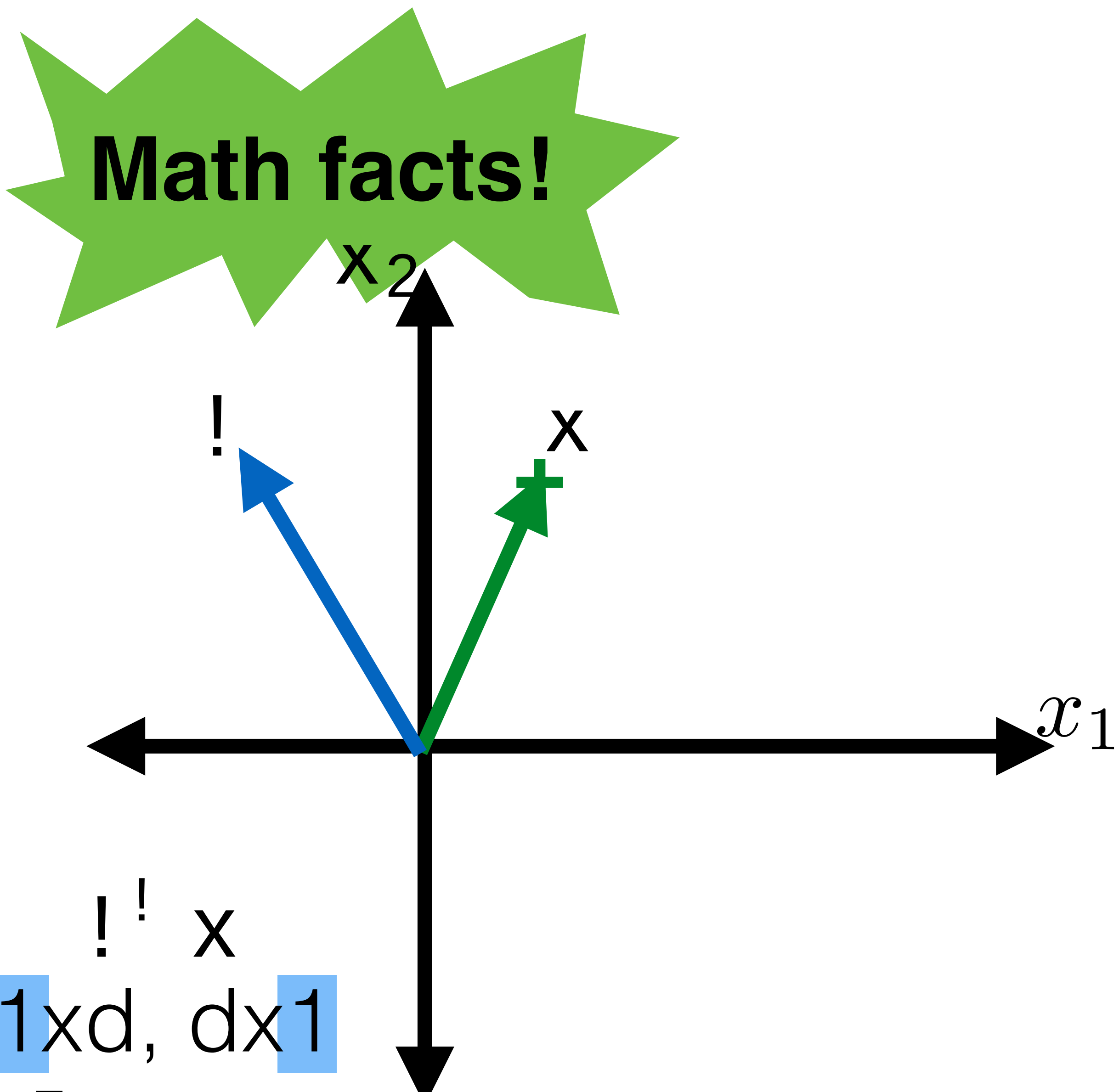

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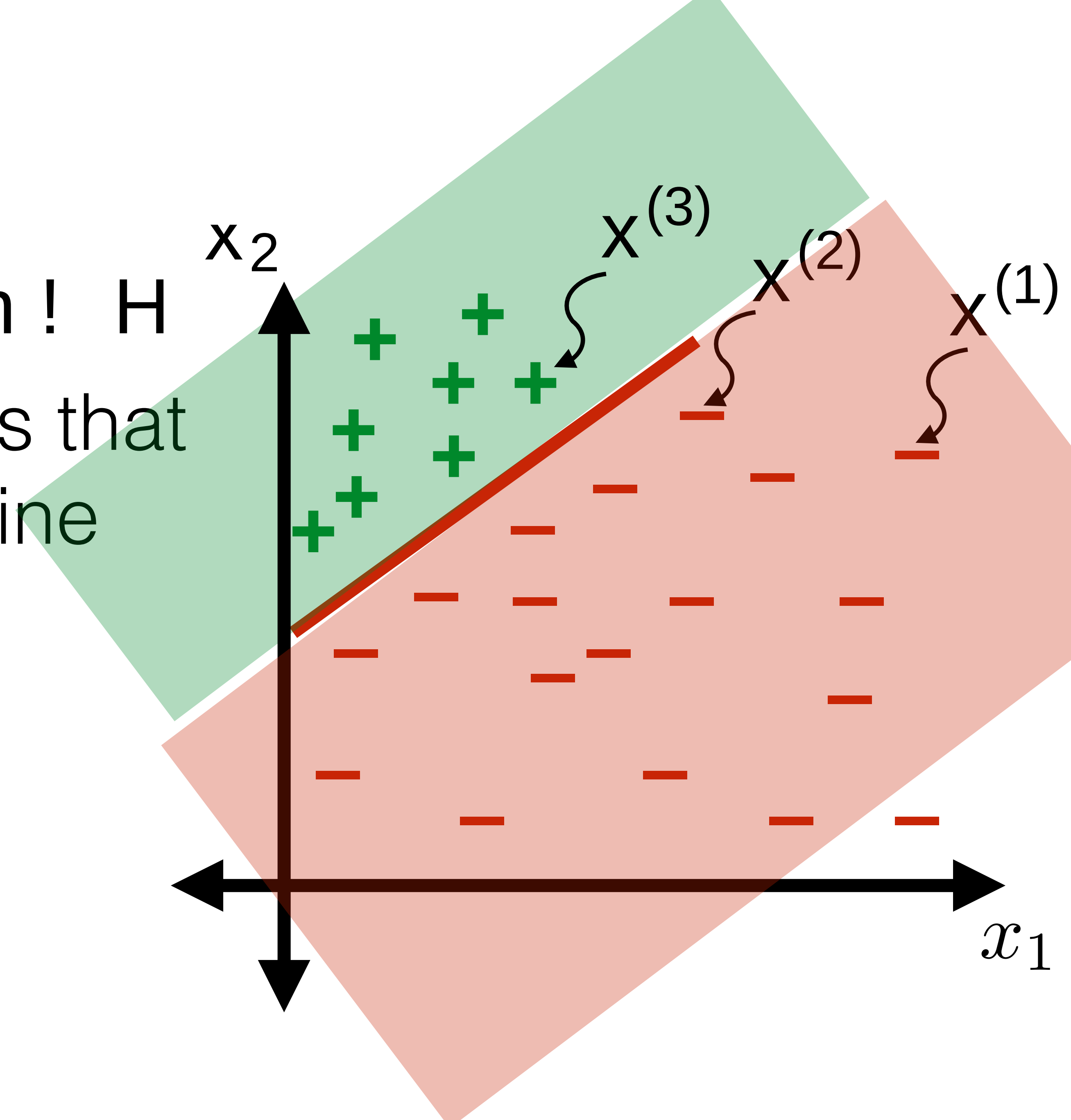

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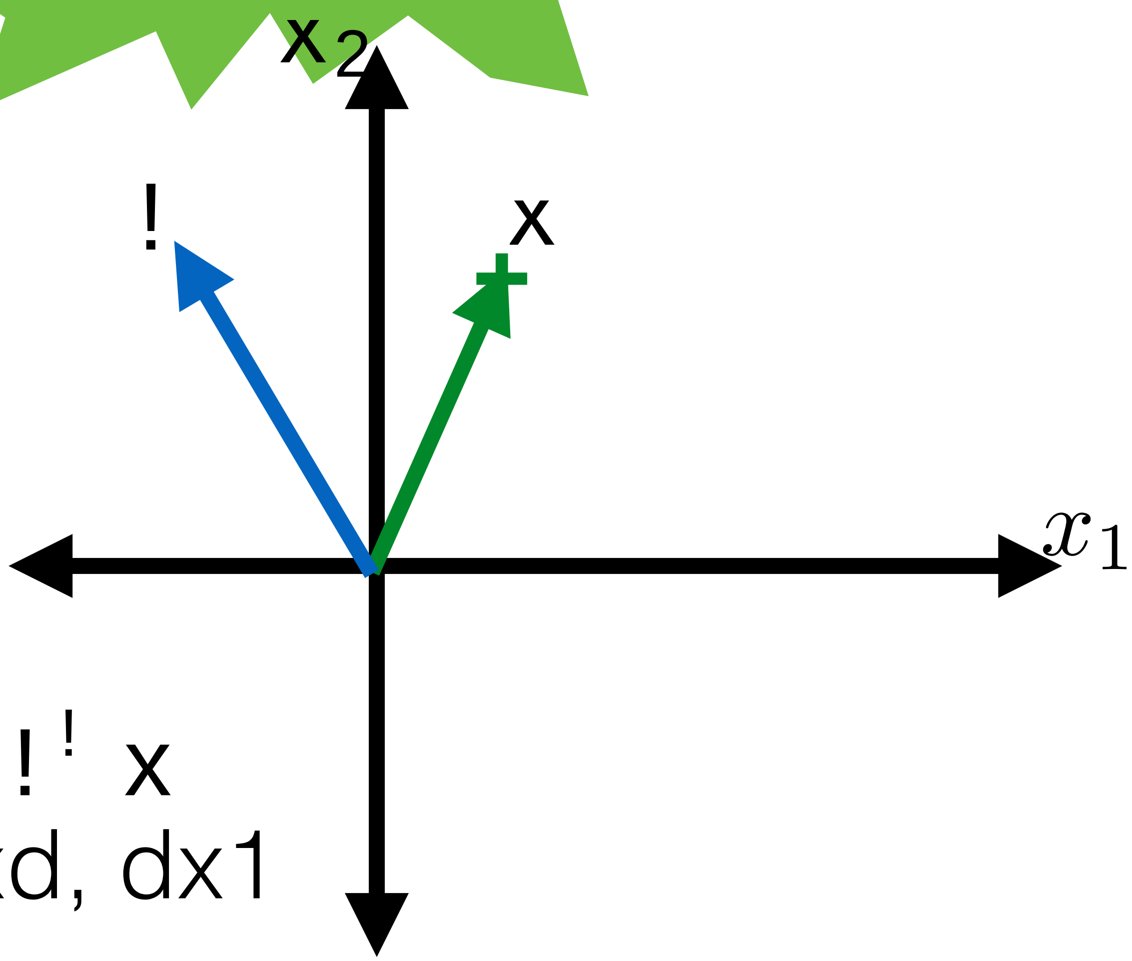

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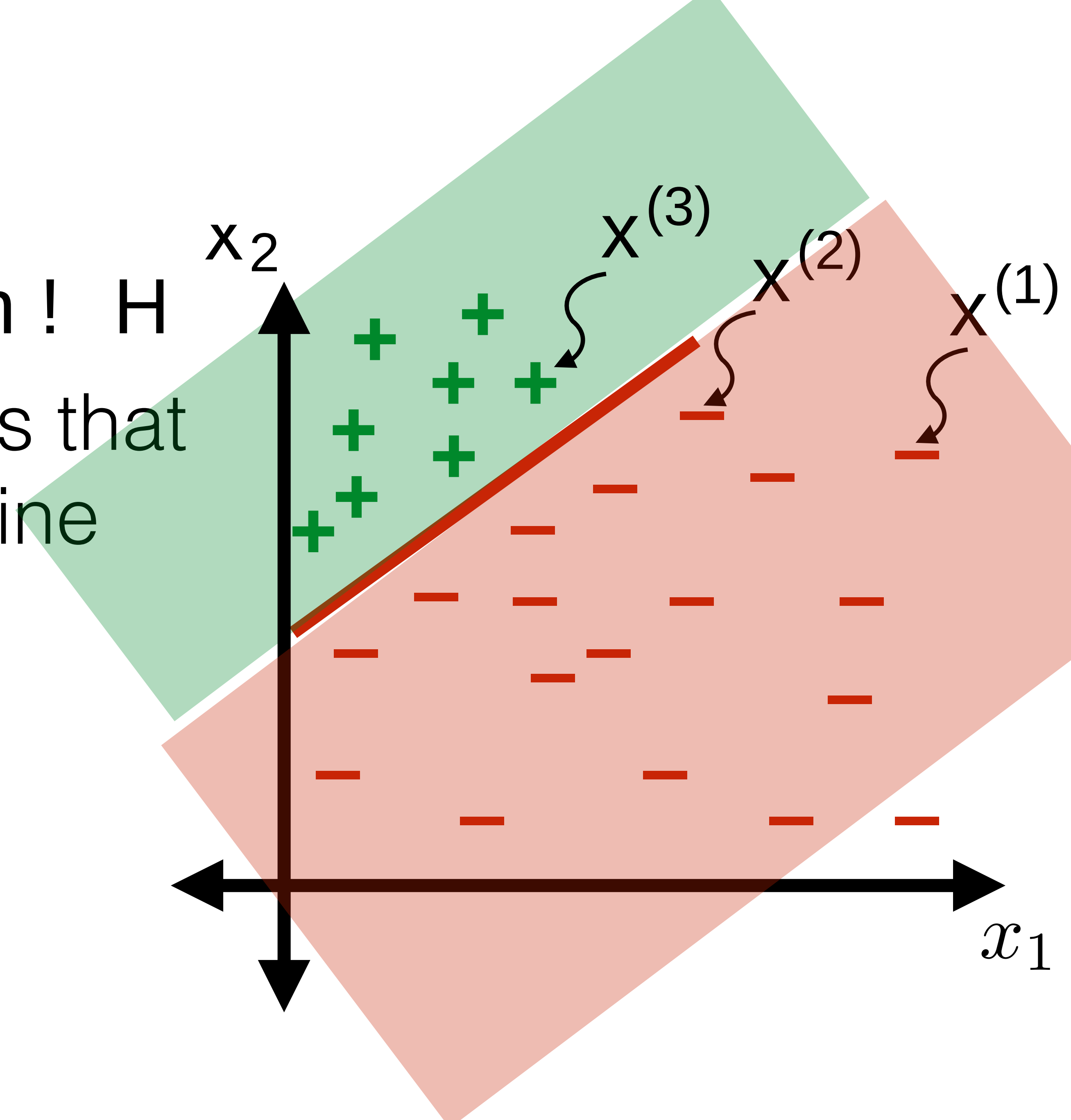

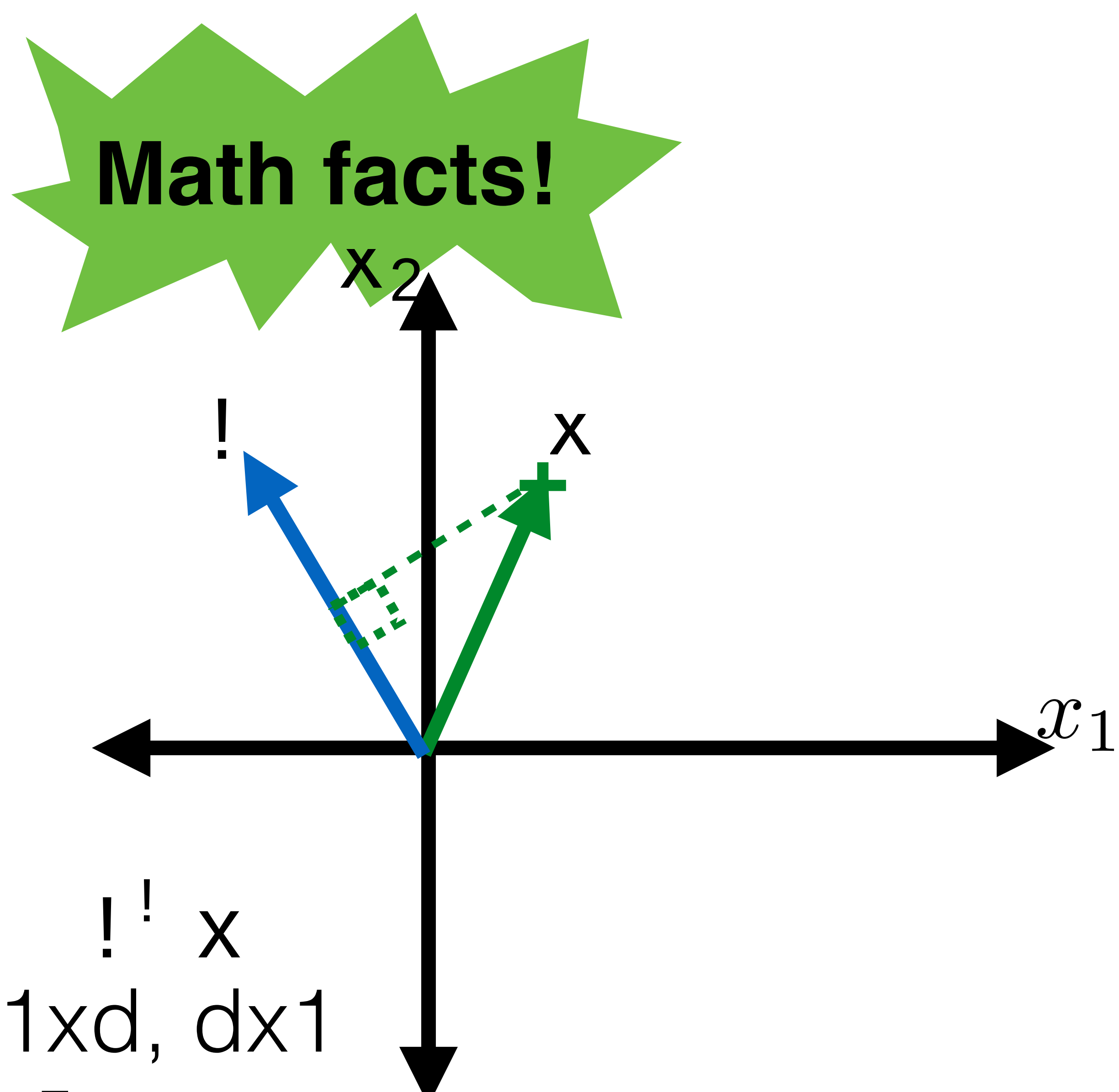

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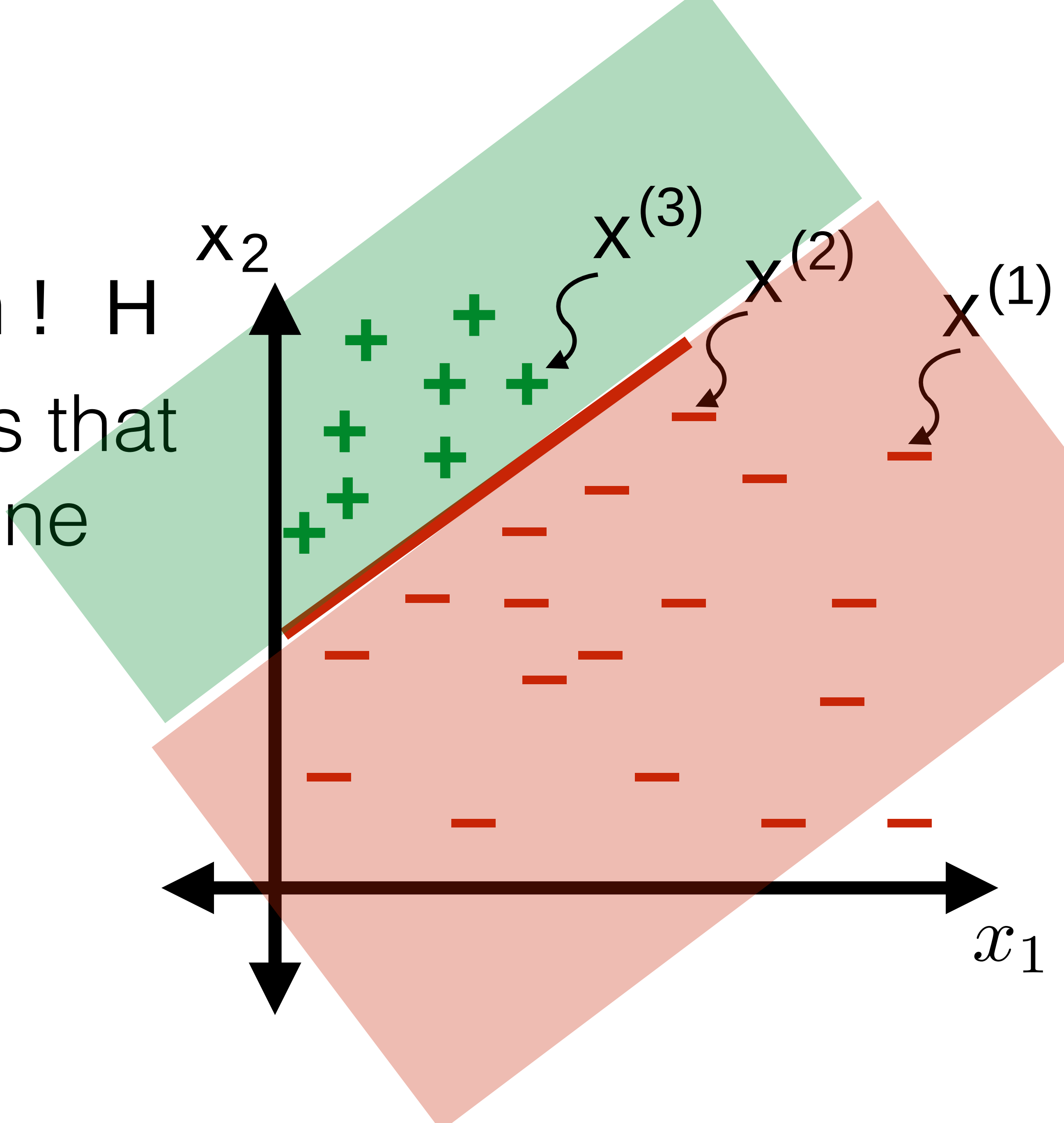

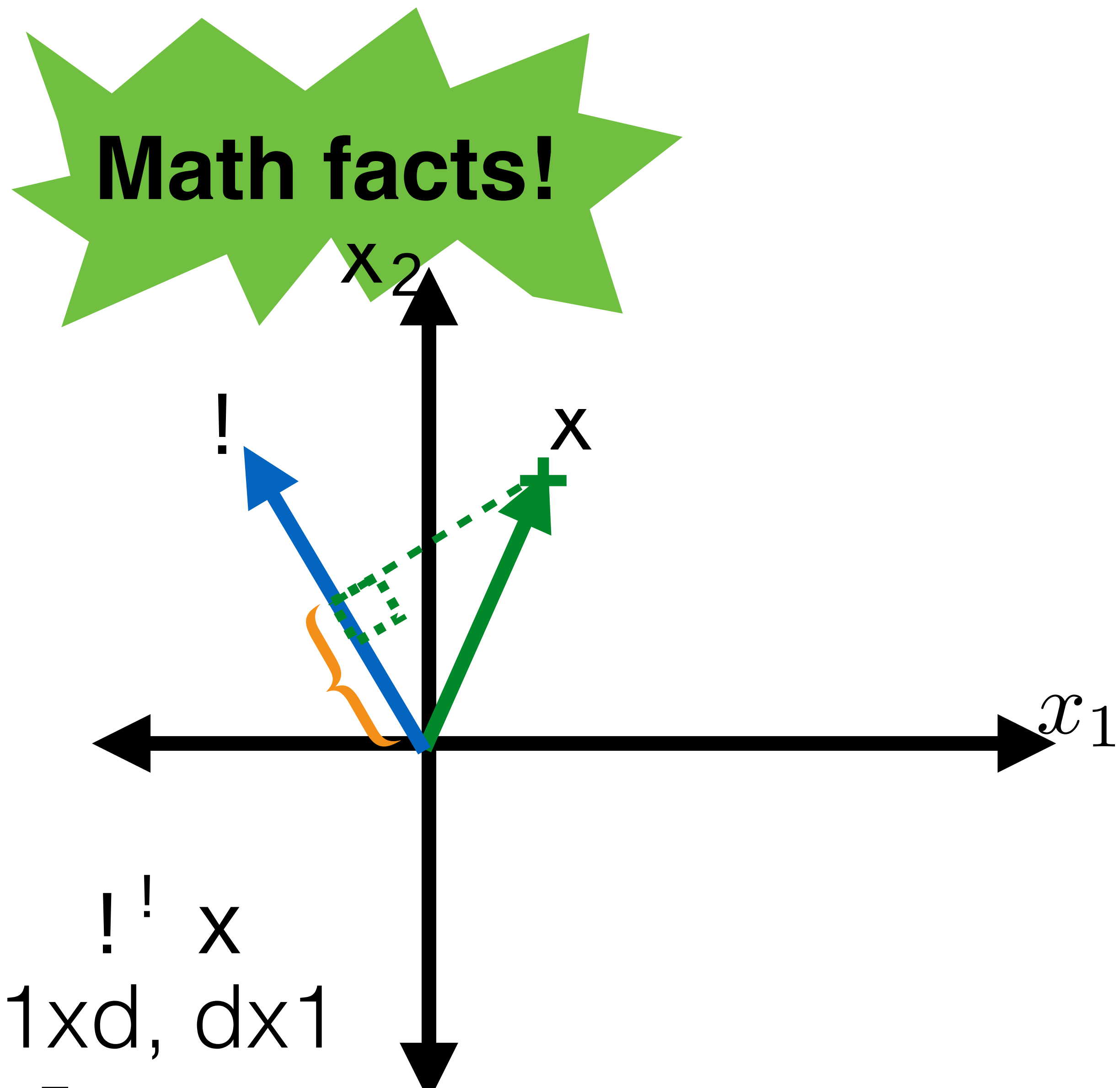

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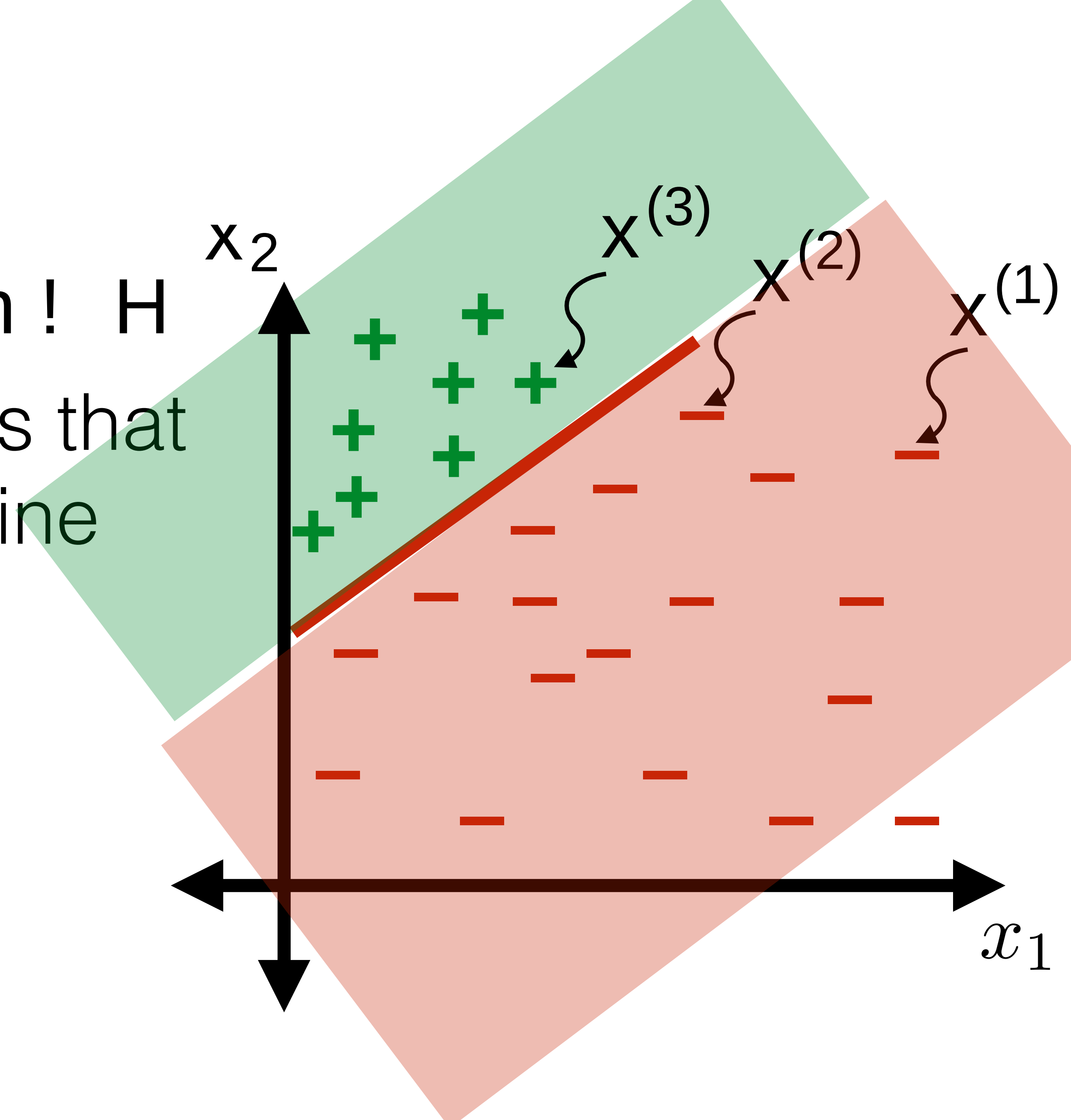

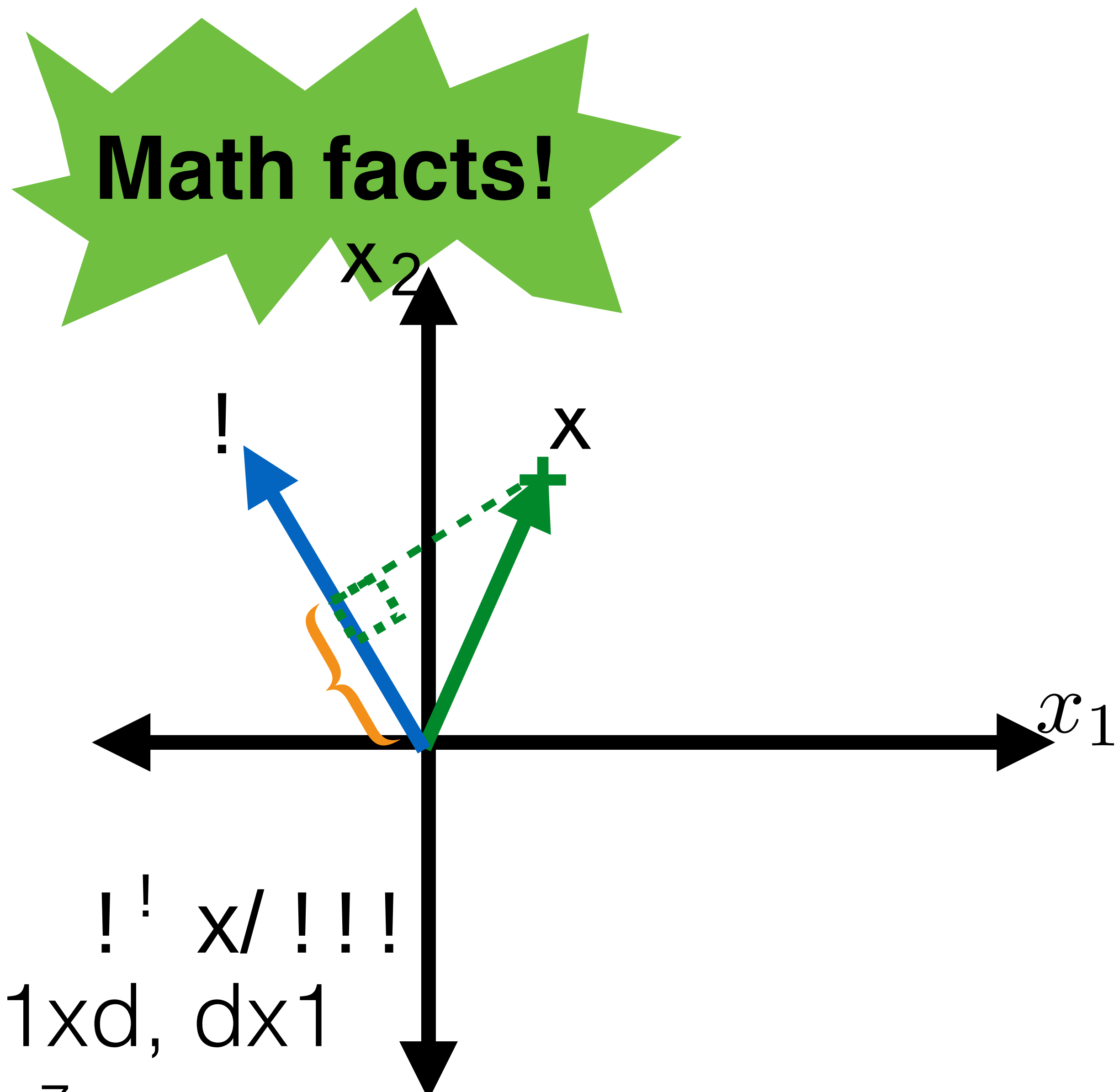

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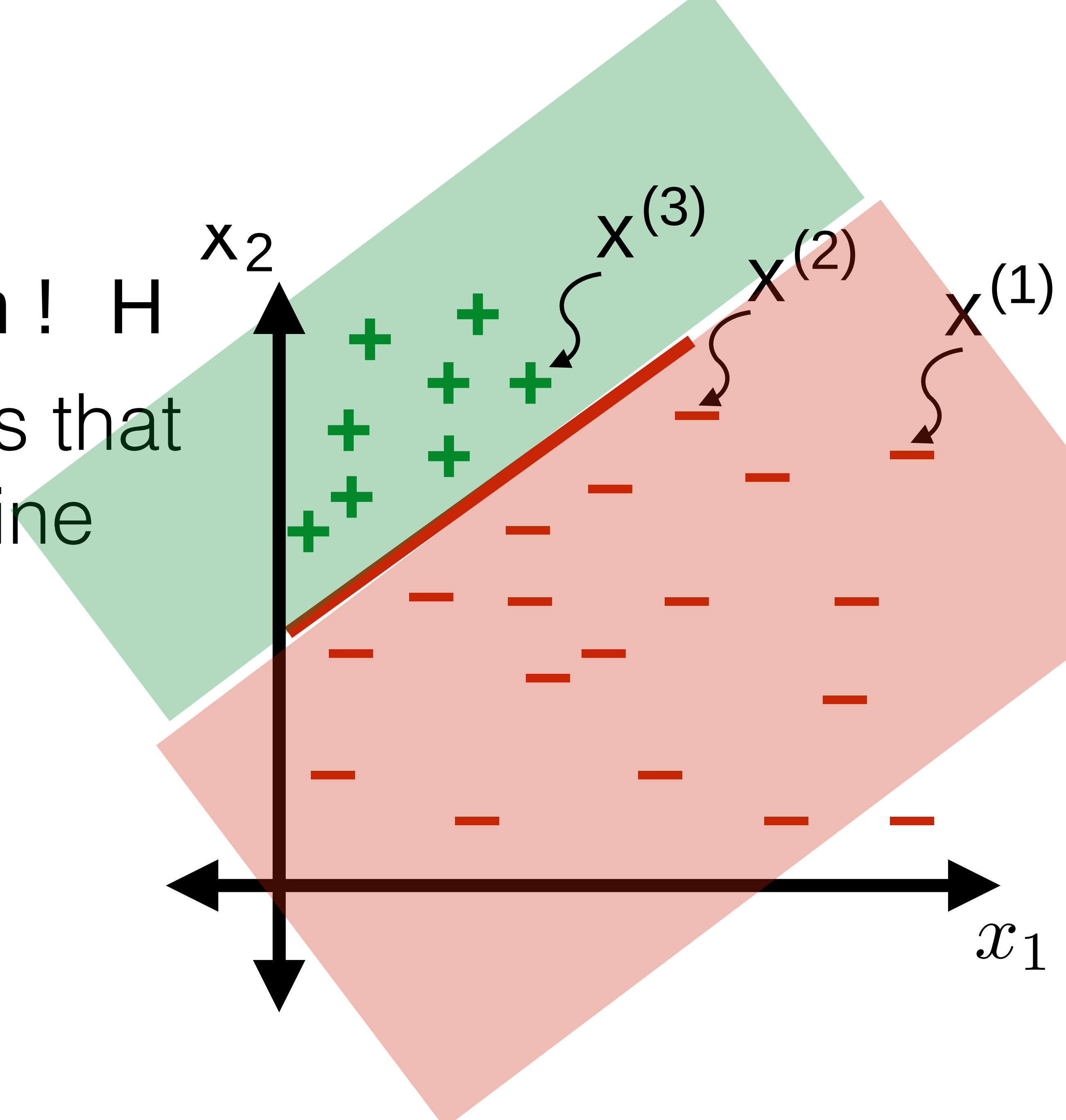

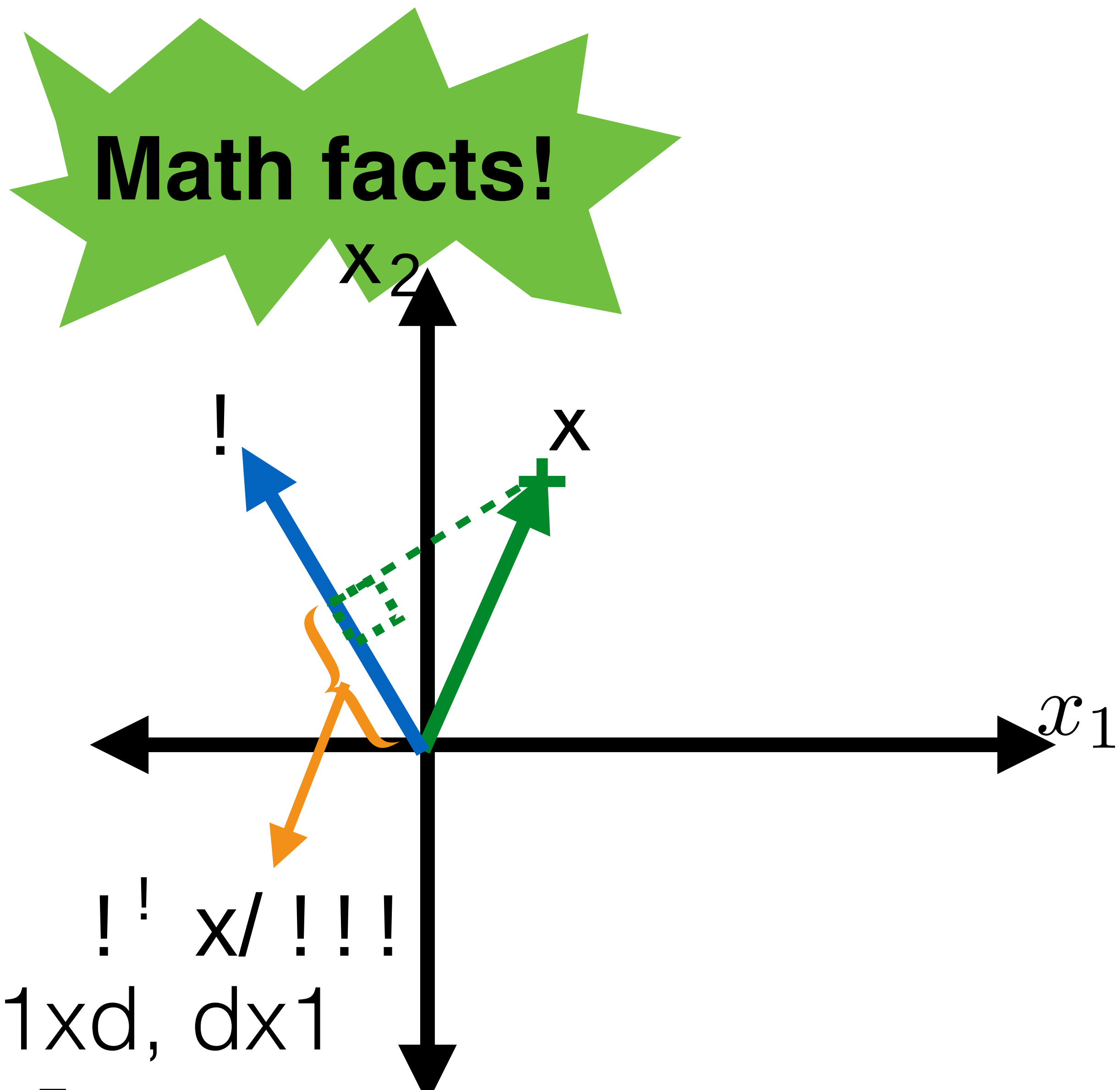

! ! x/ ! ! !
1xd, dx1

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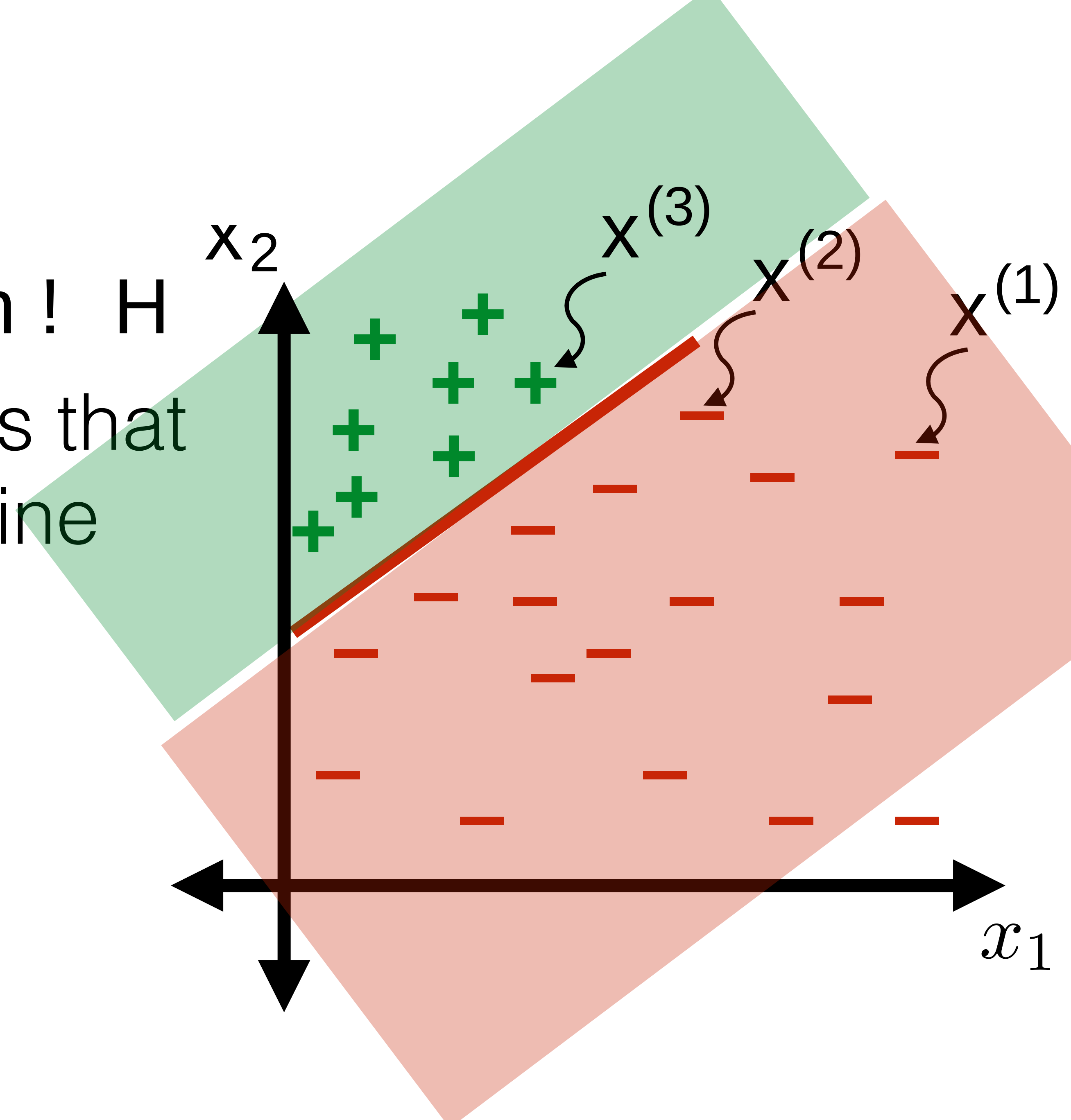

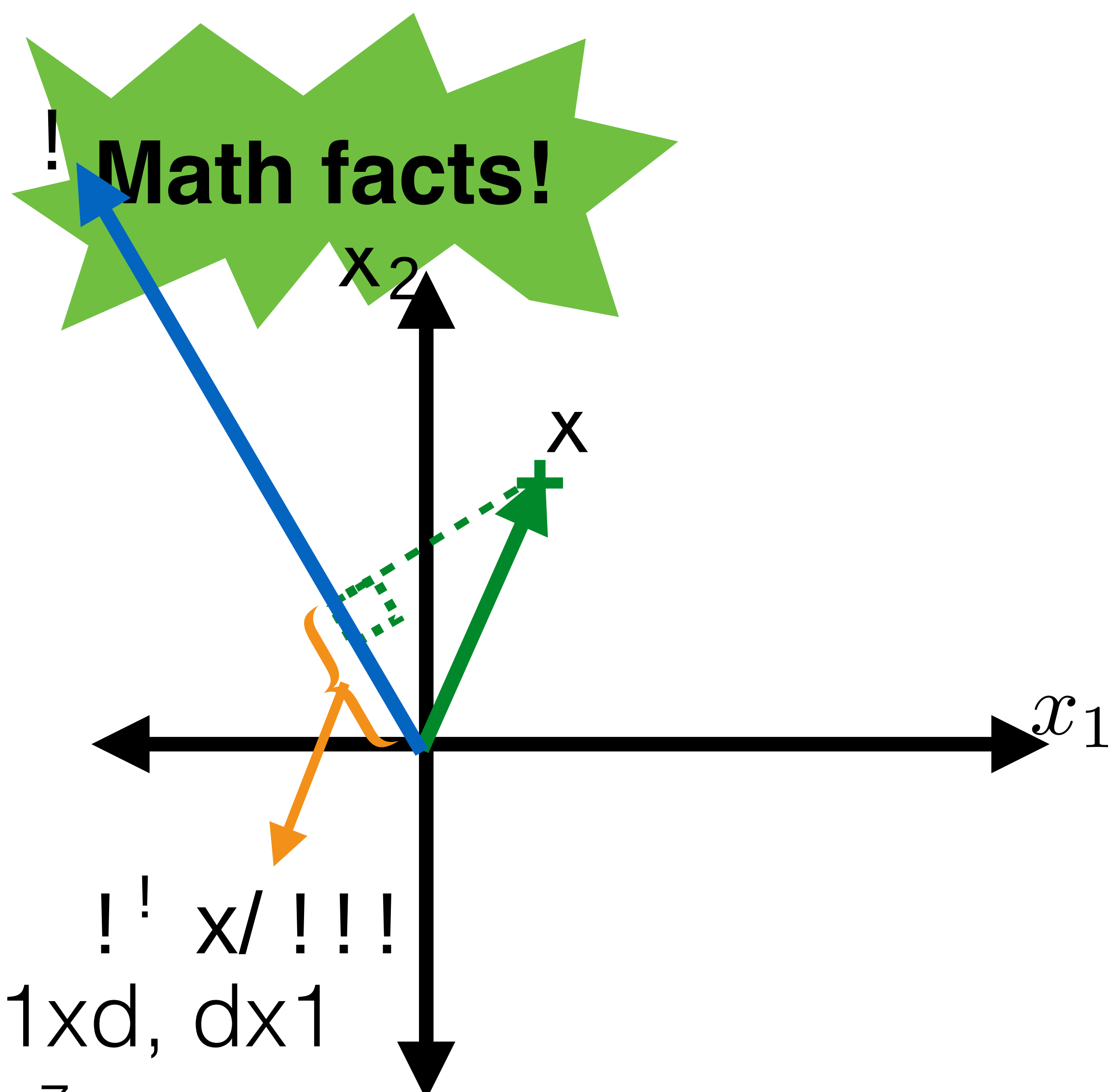

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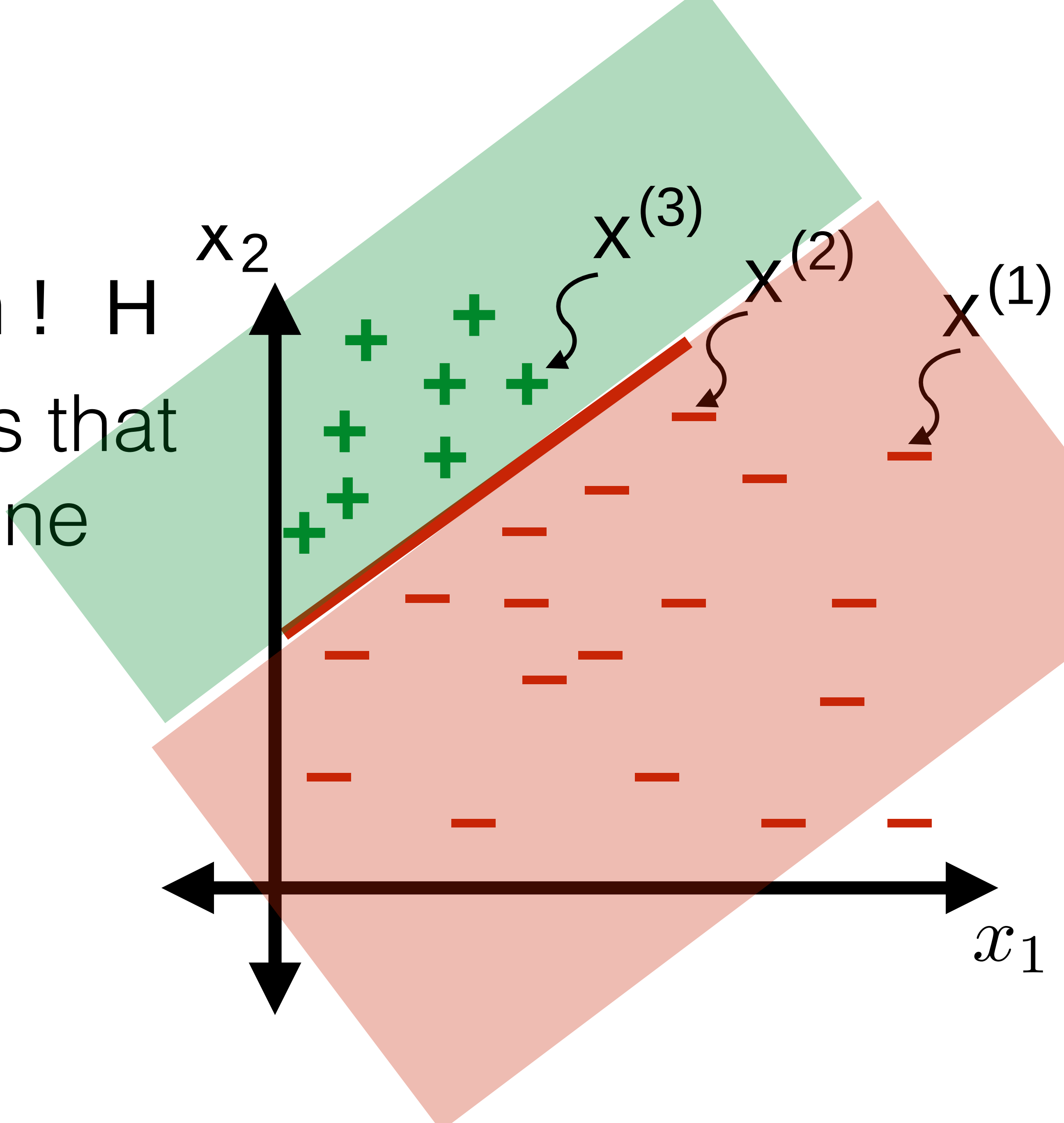

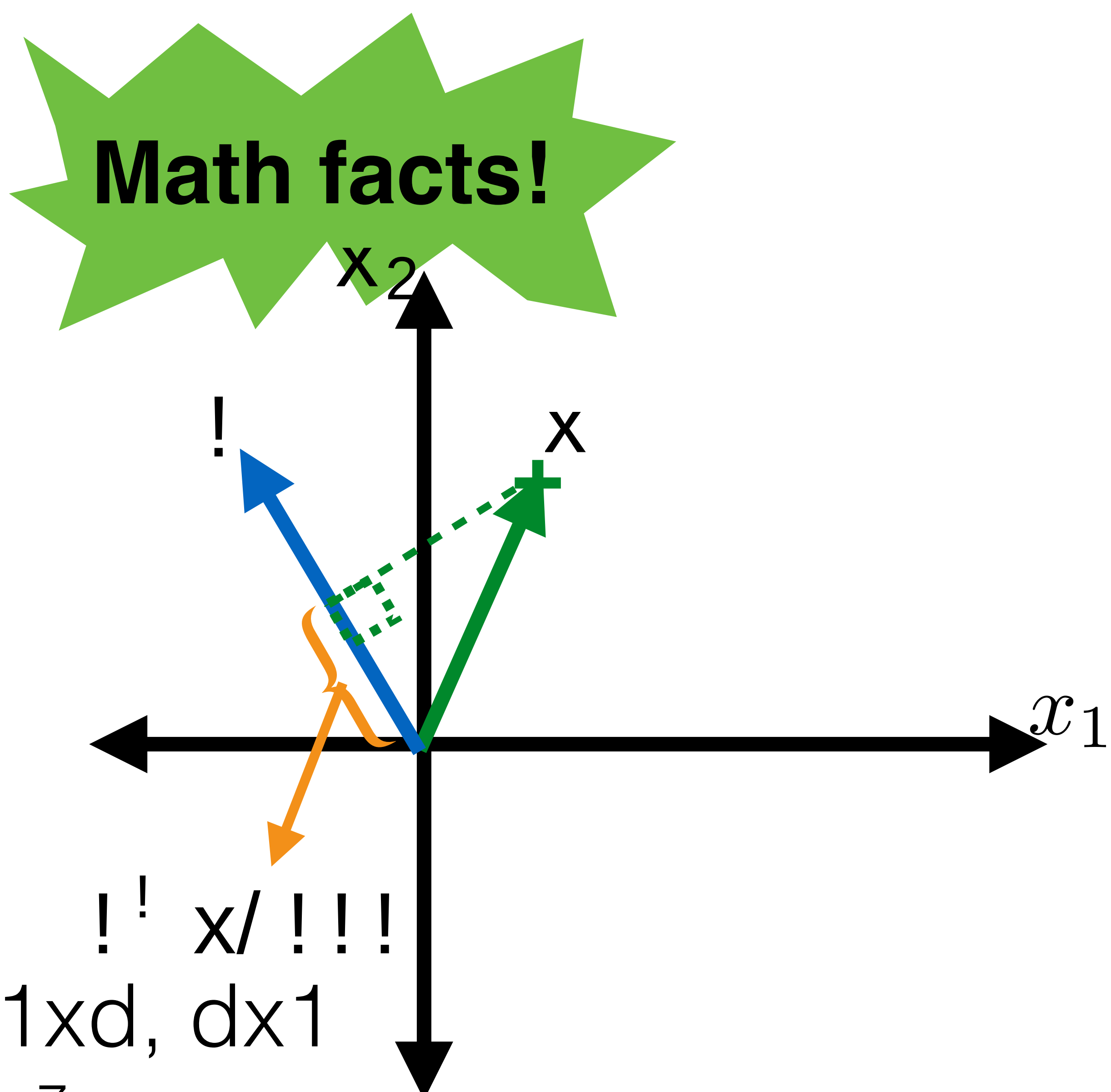

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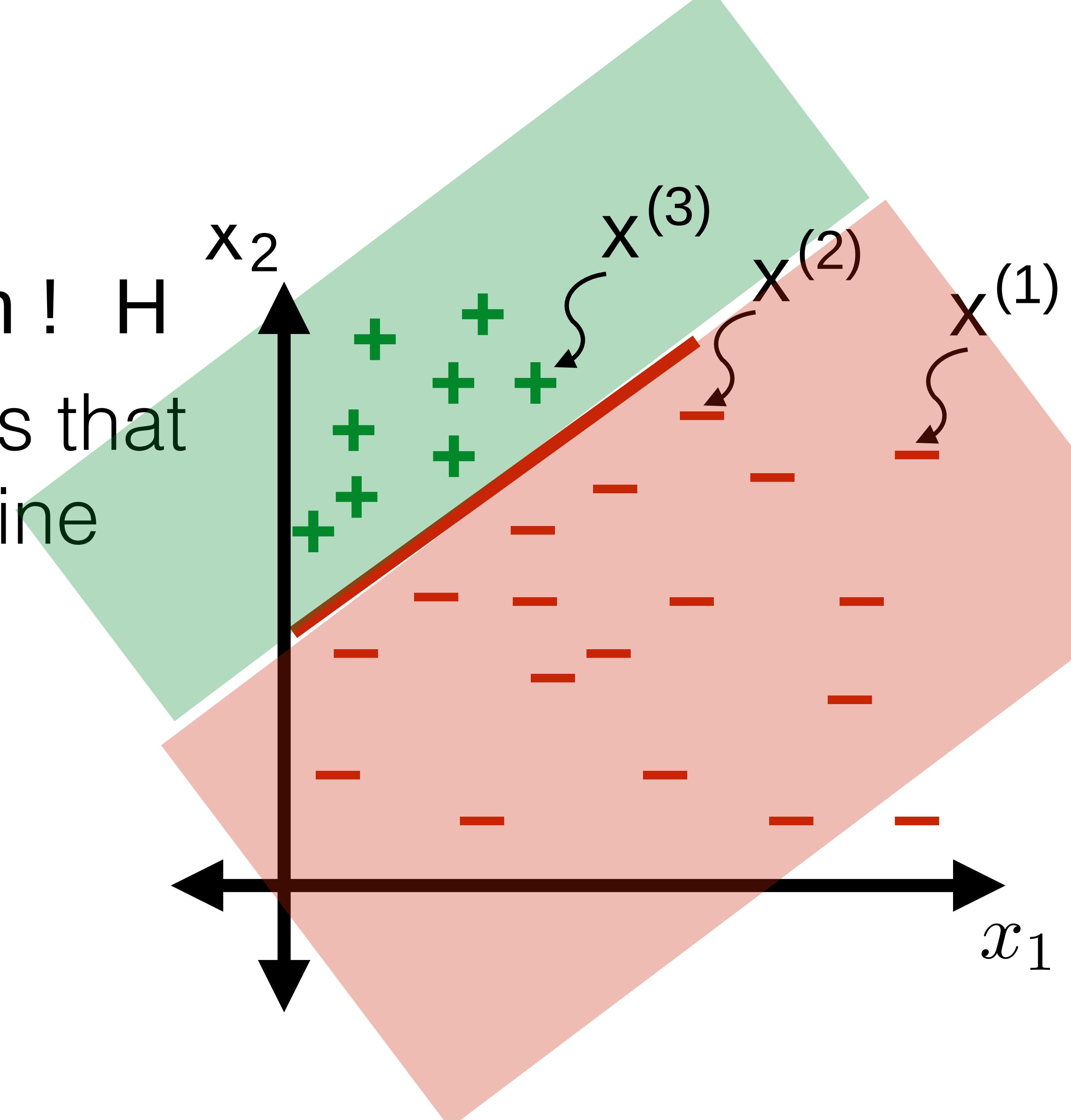
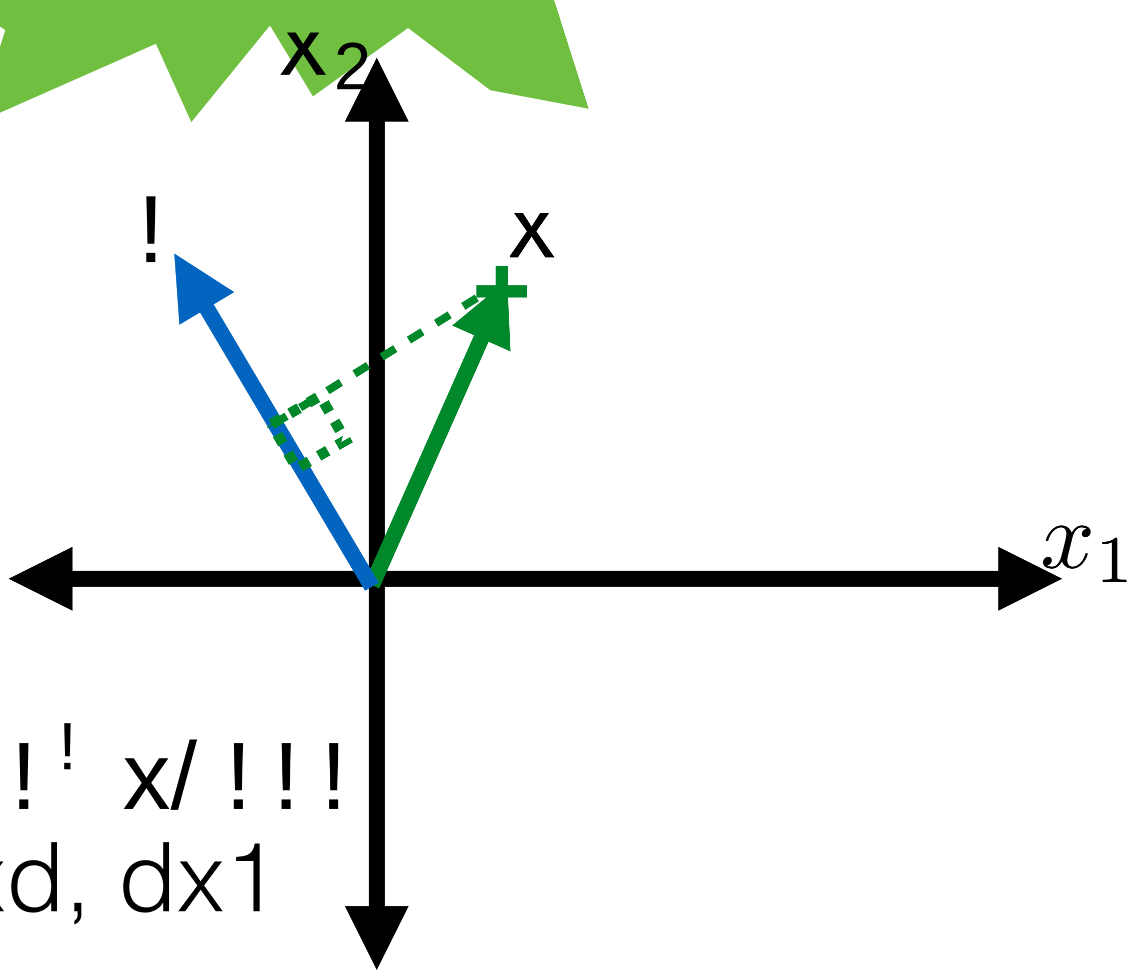


Math facts!



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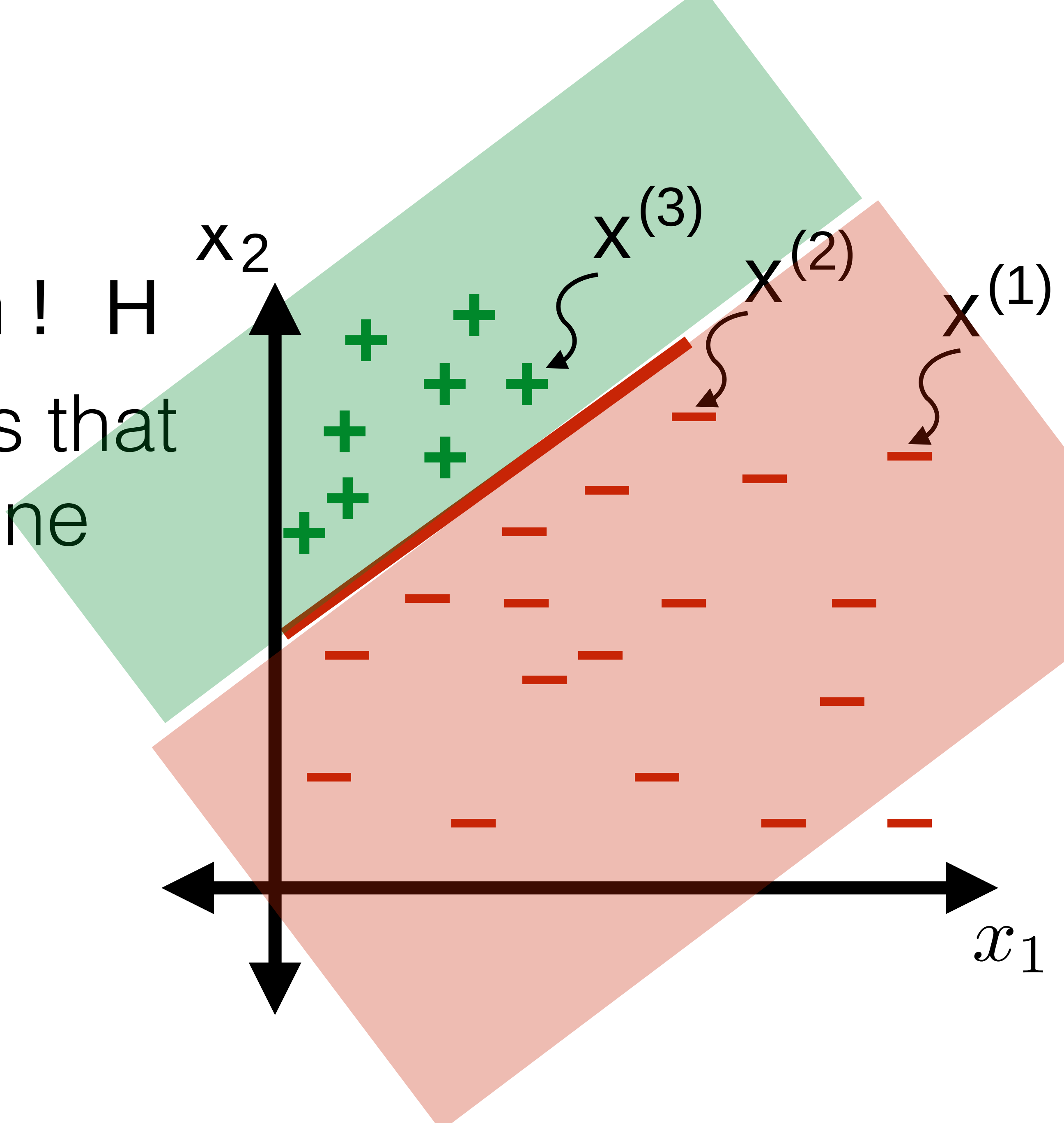

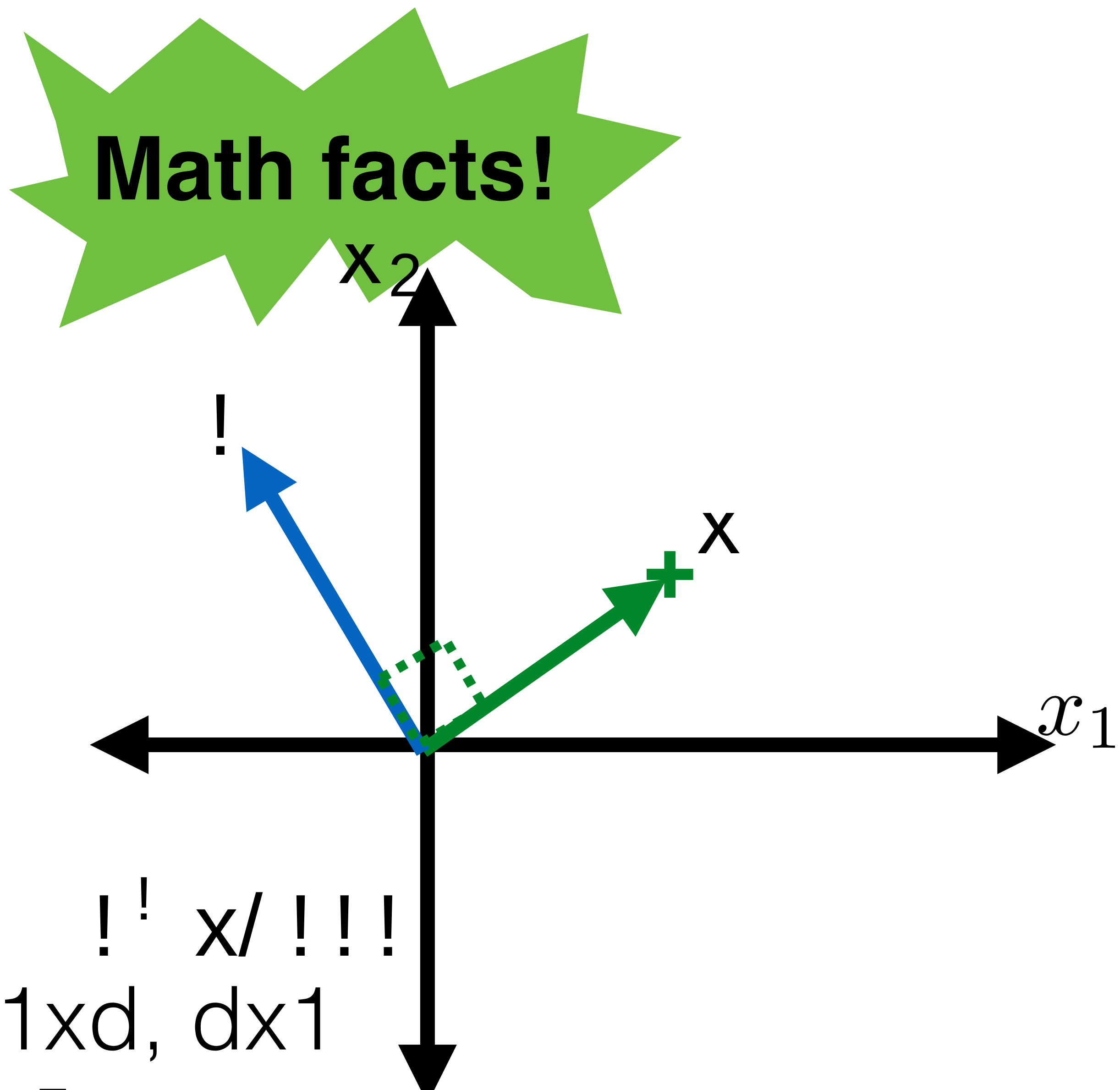

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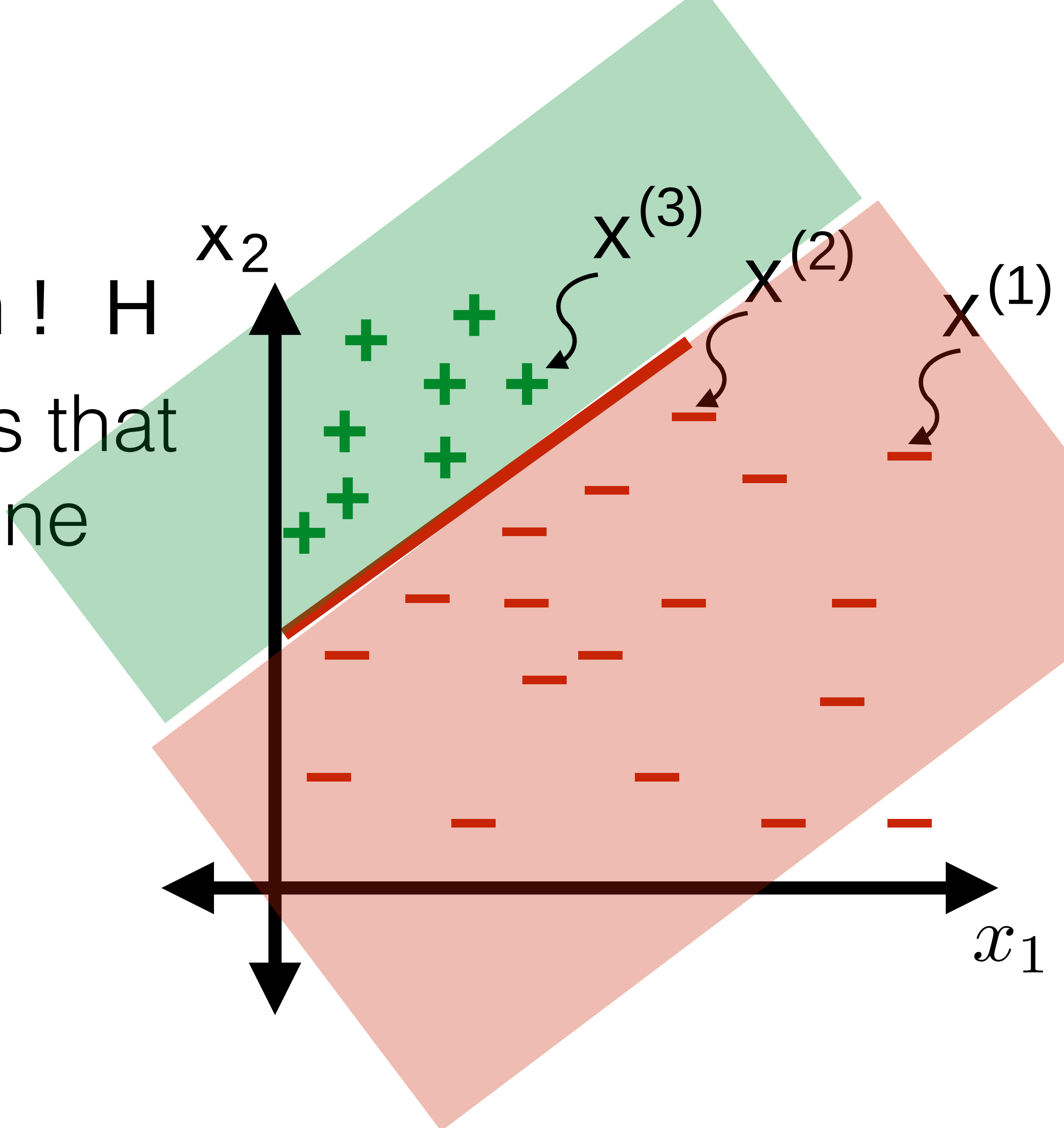

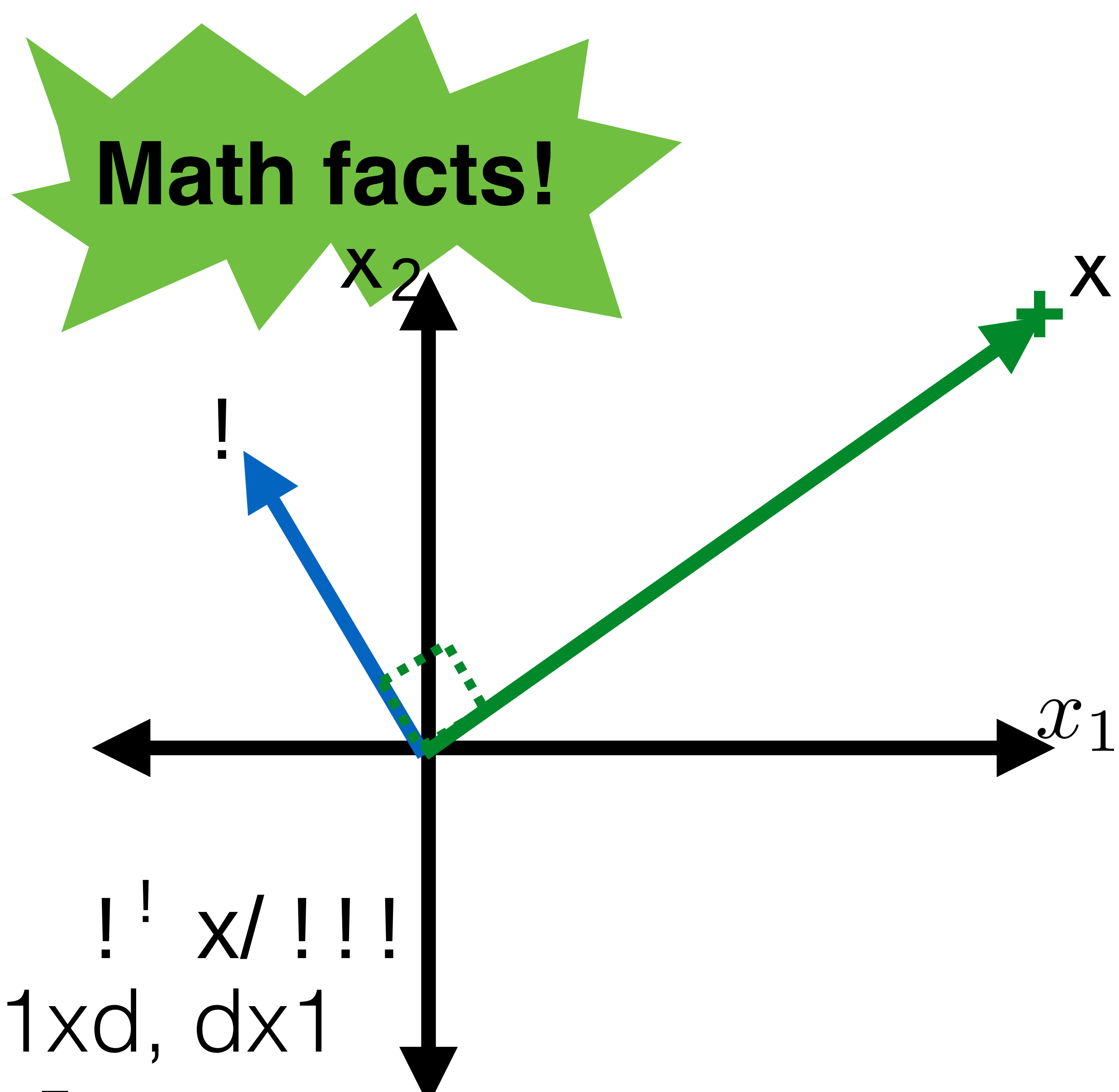

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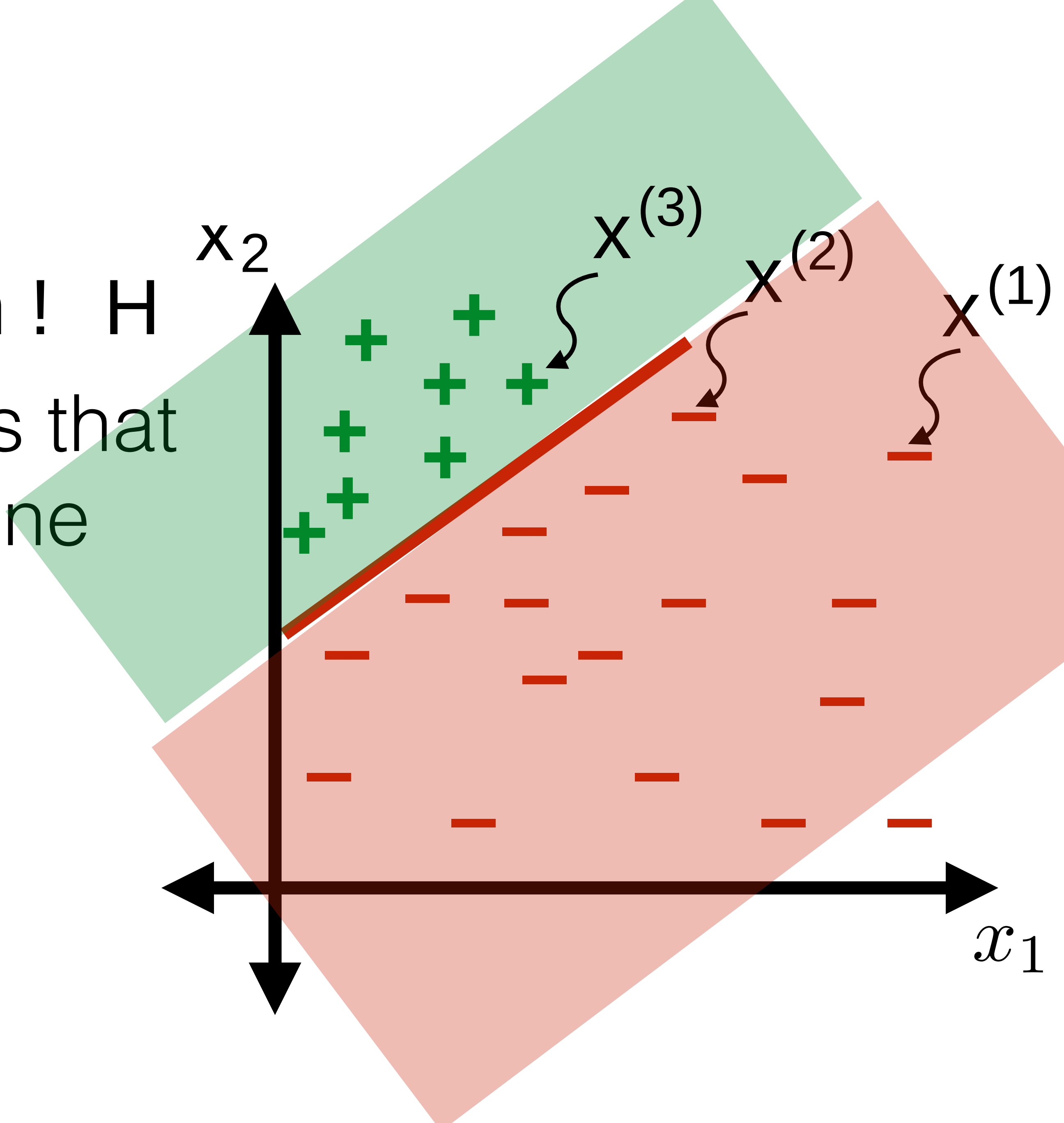

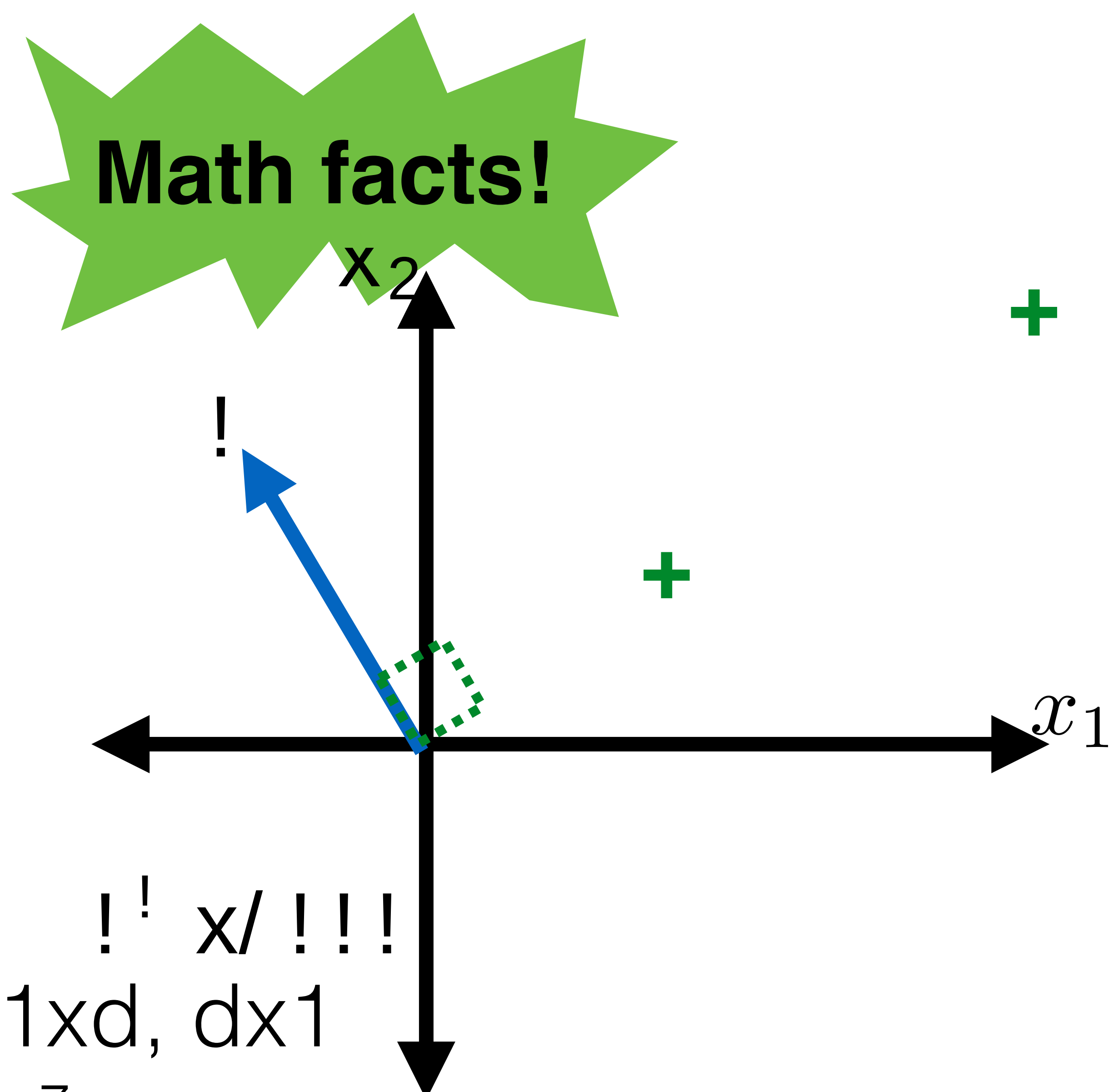

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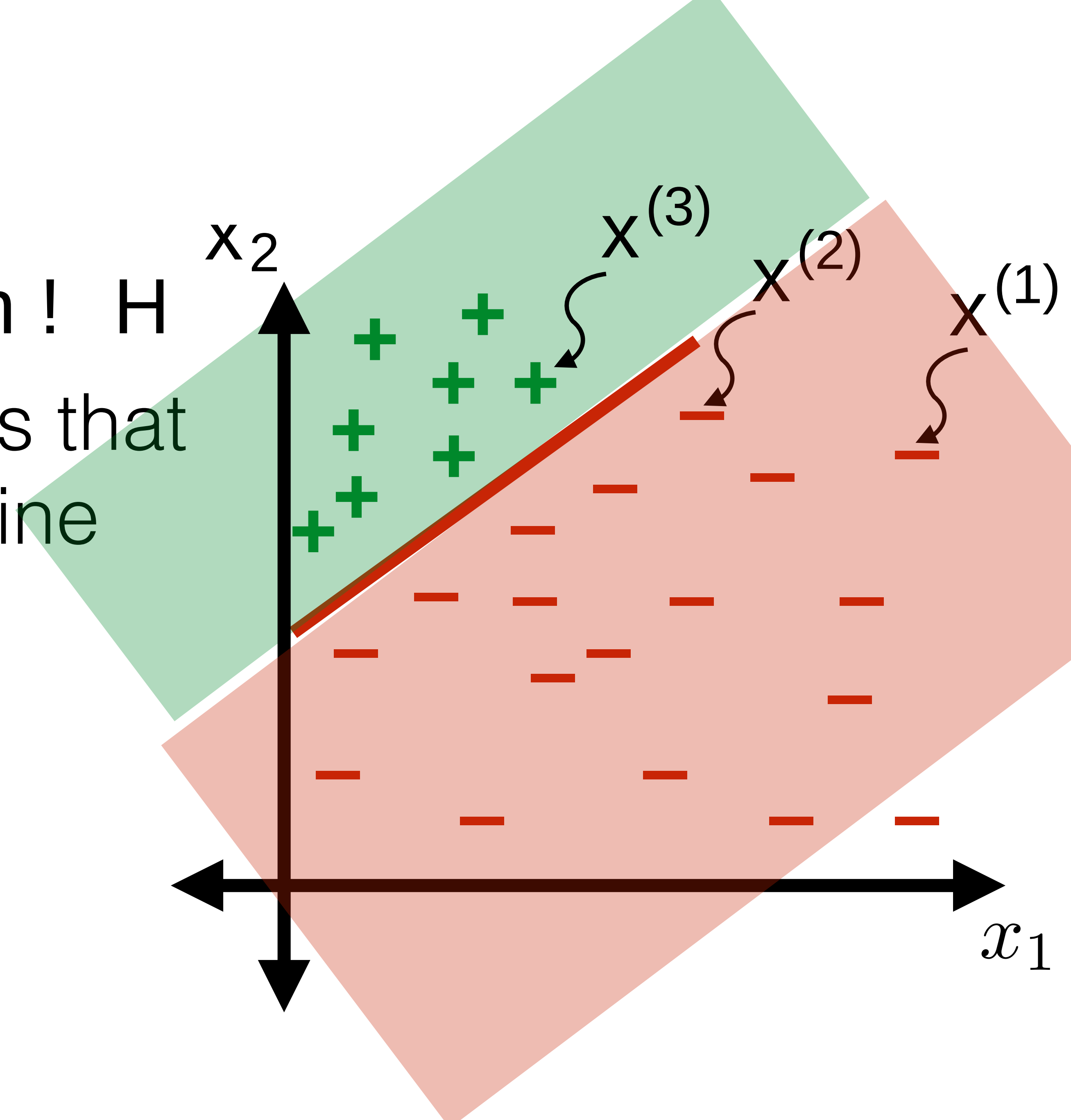

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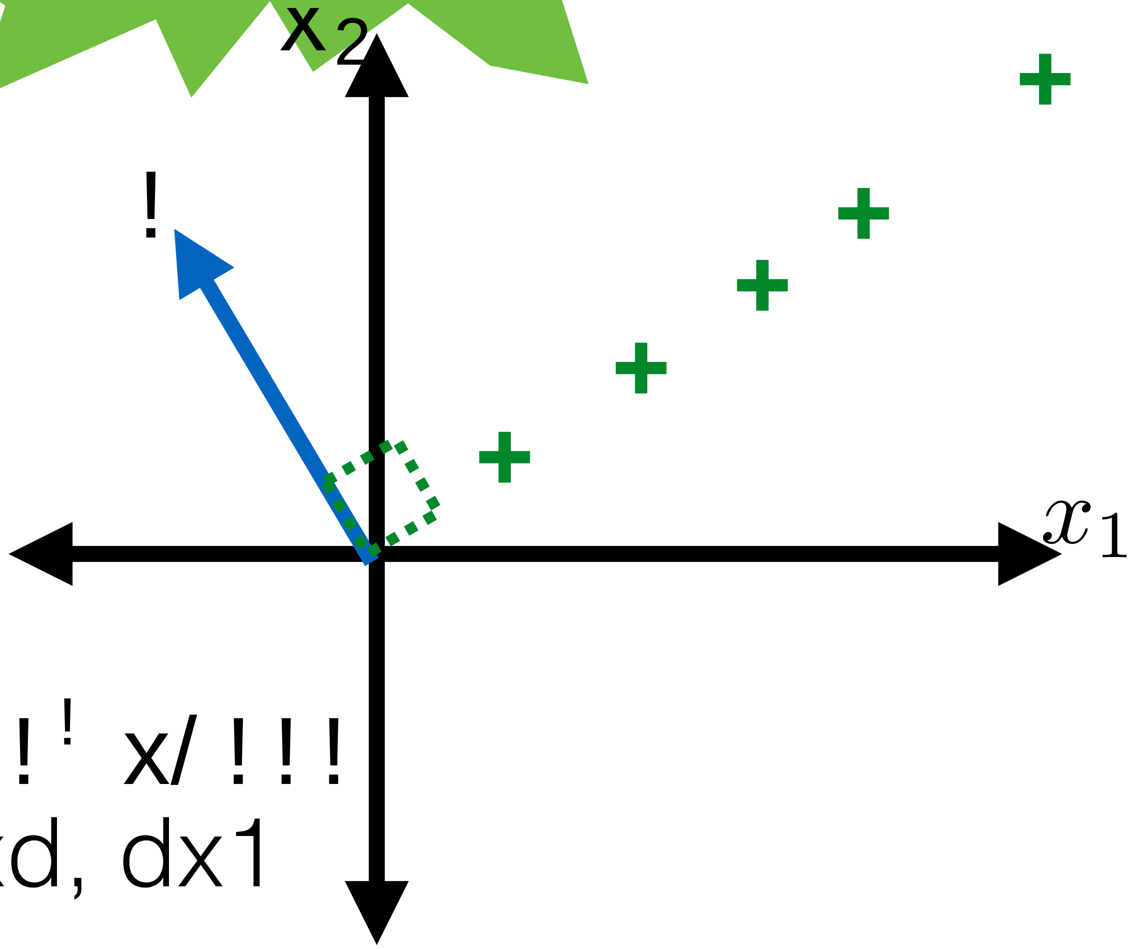

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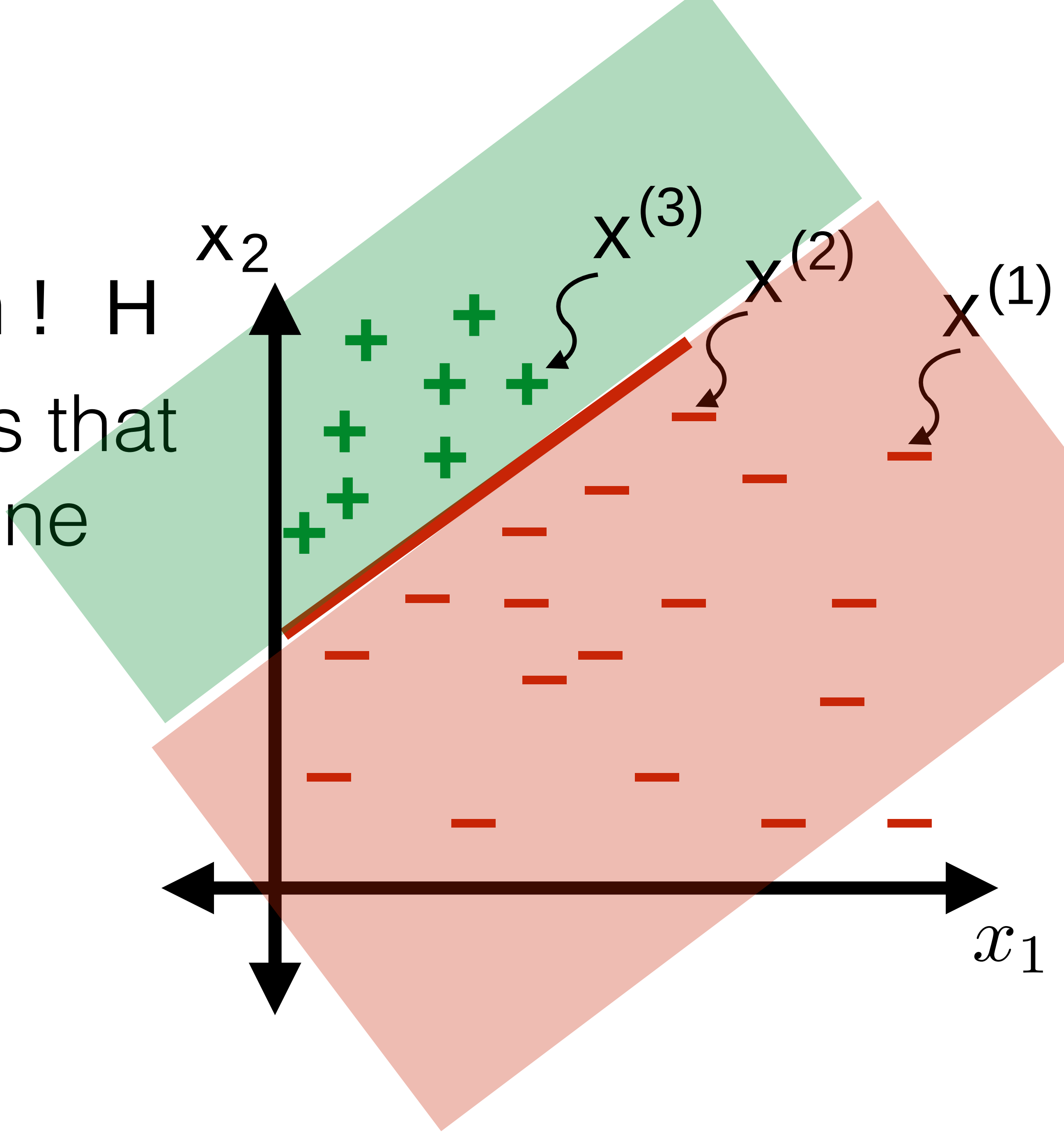

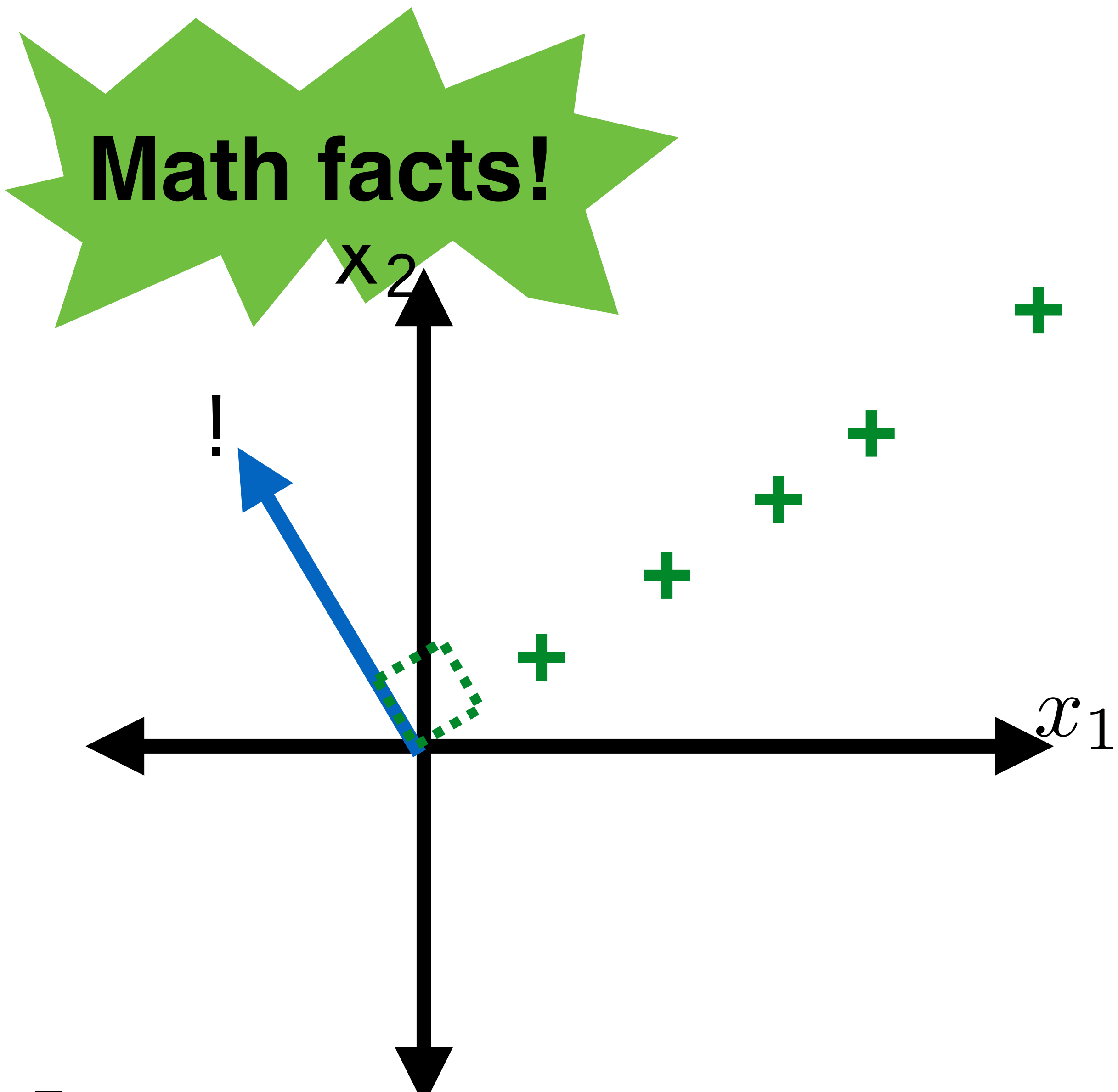

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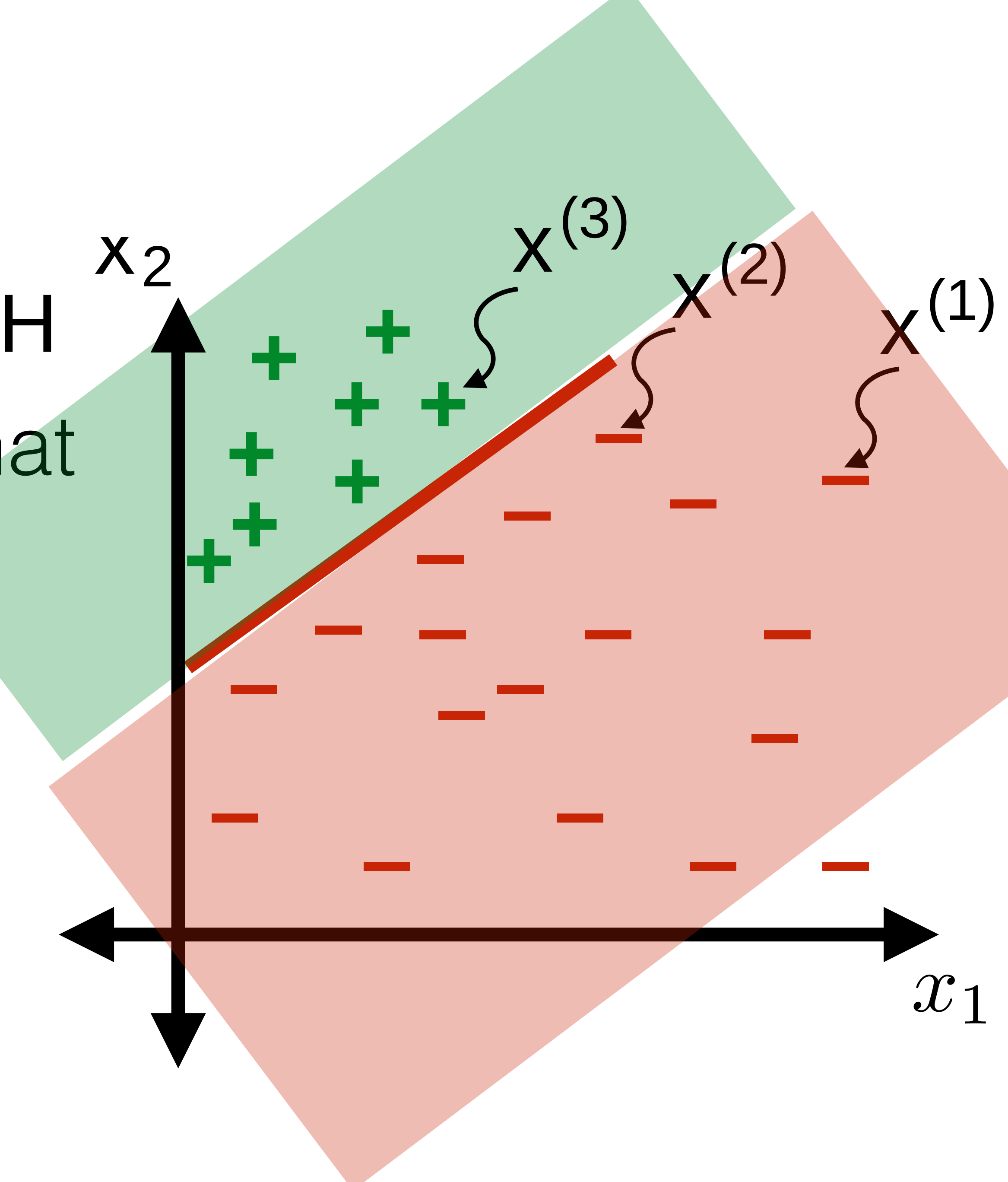

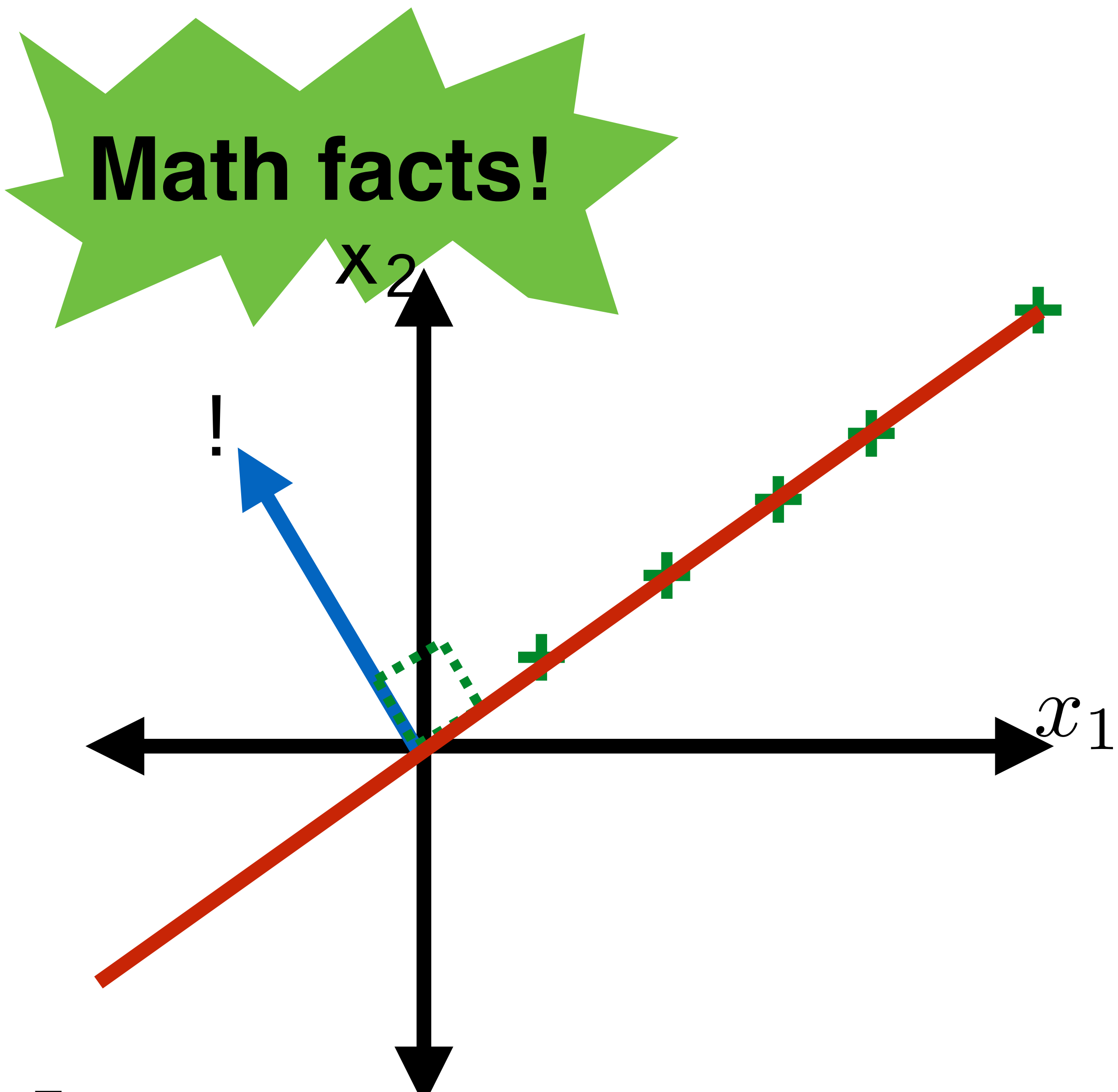

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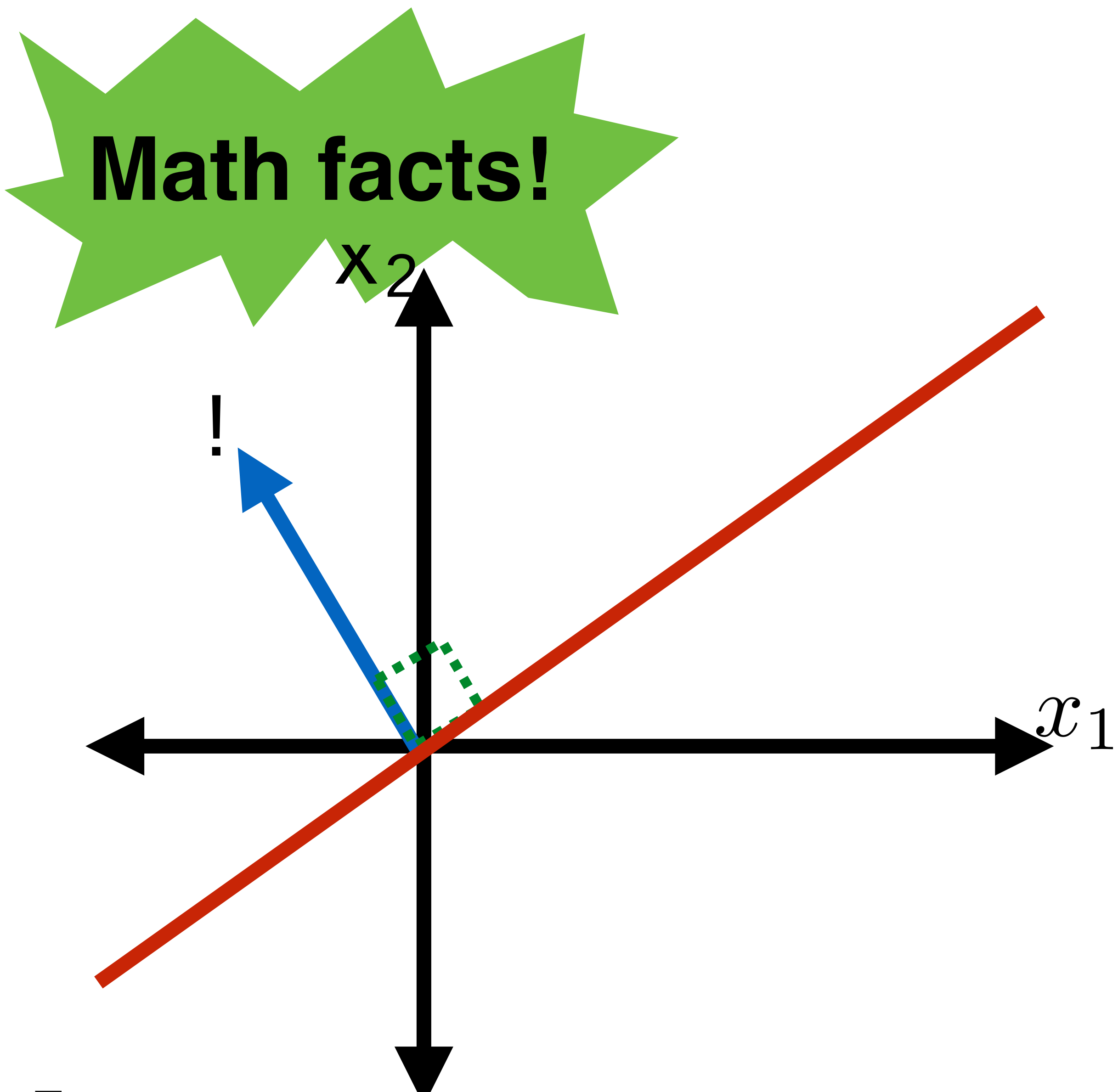

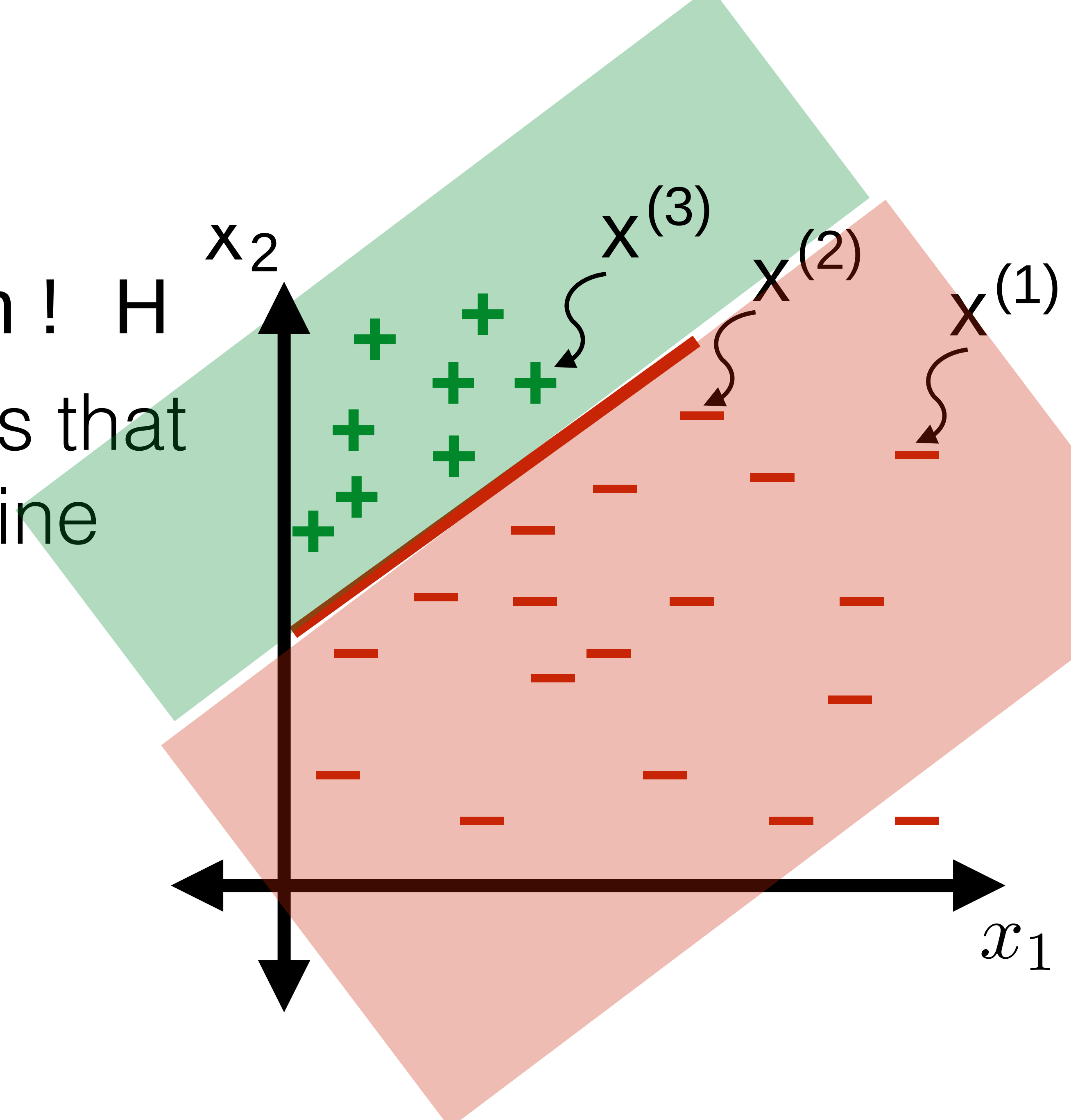

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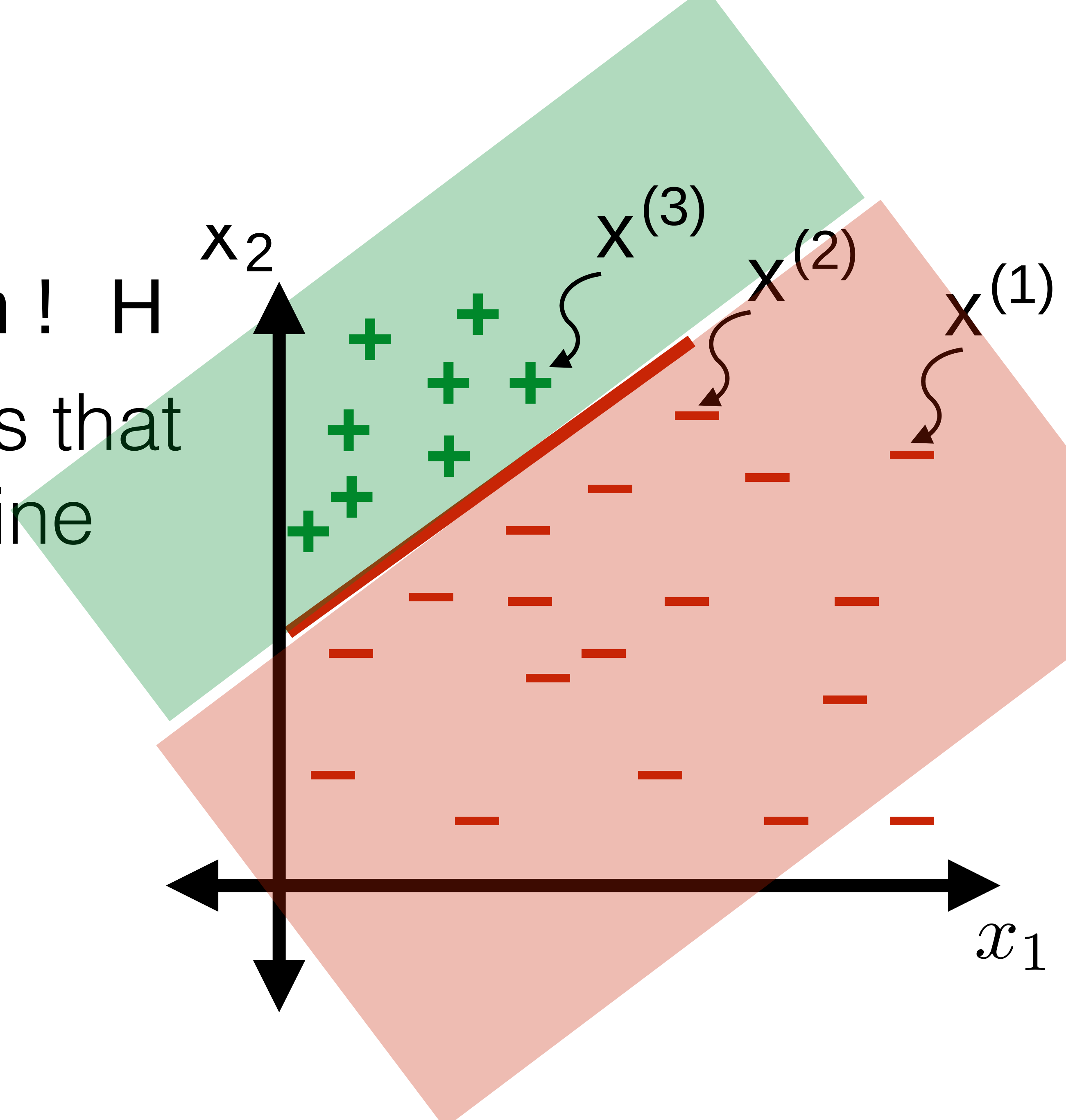

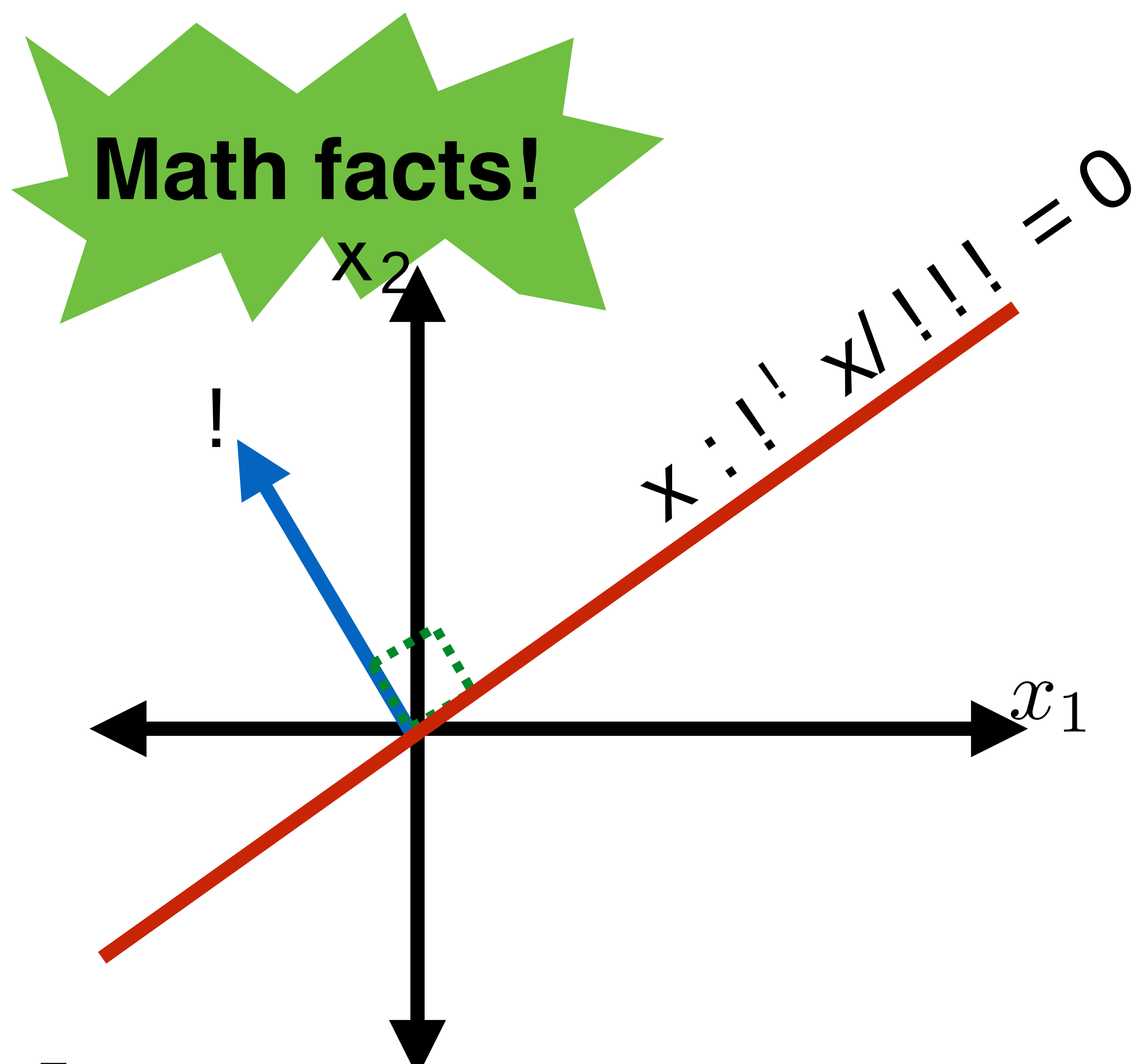

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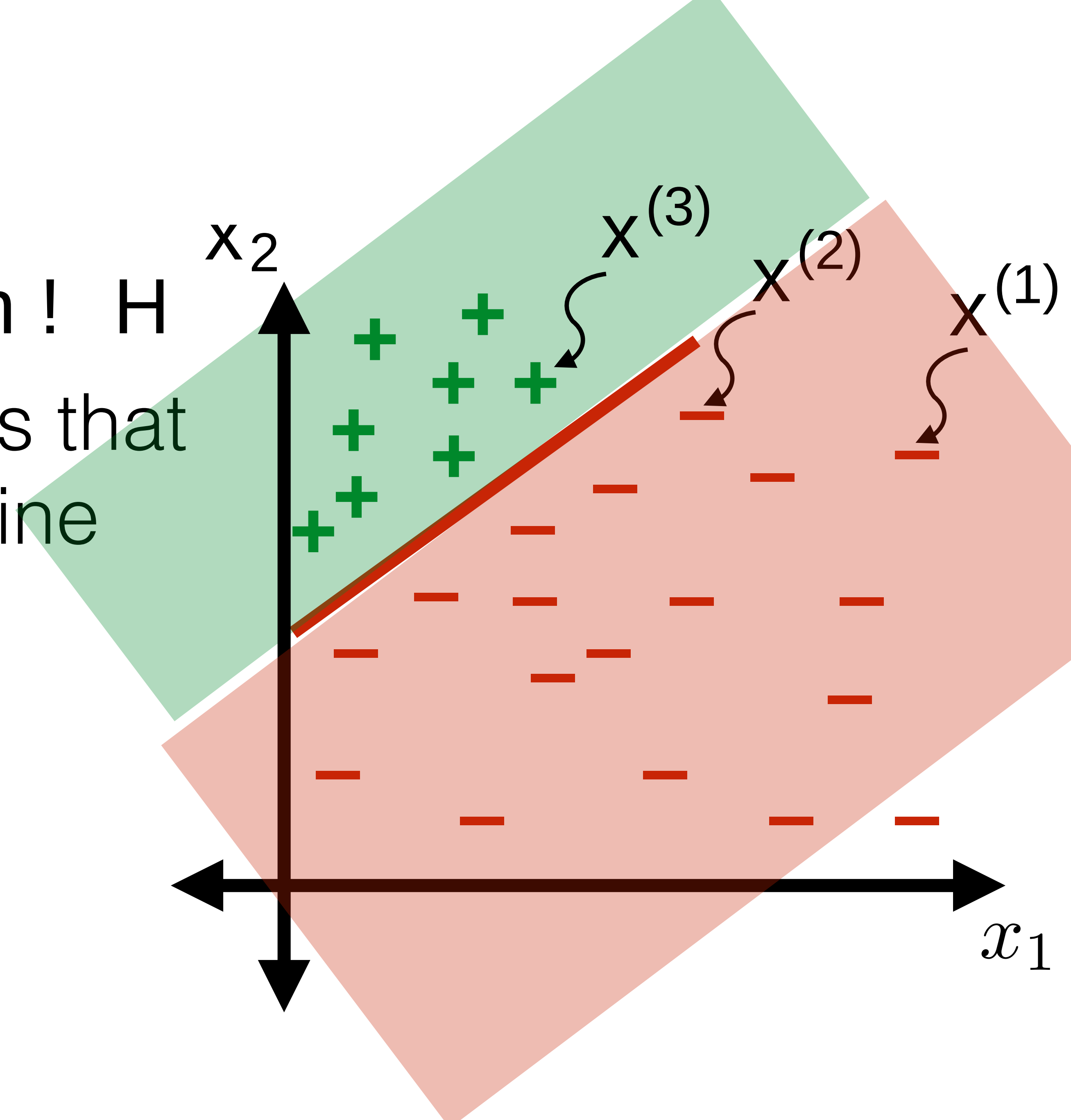

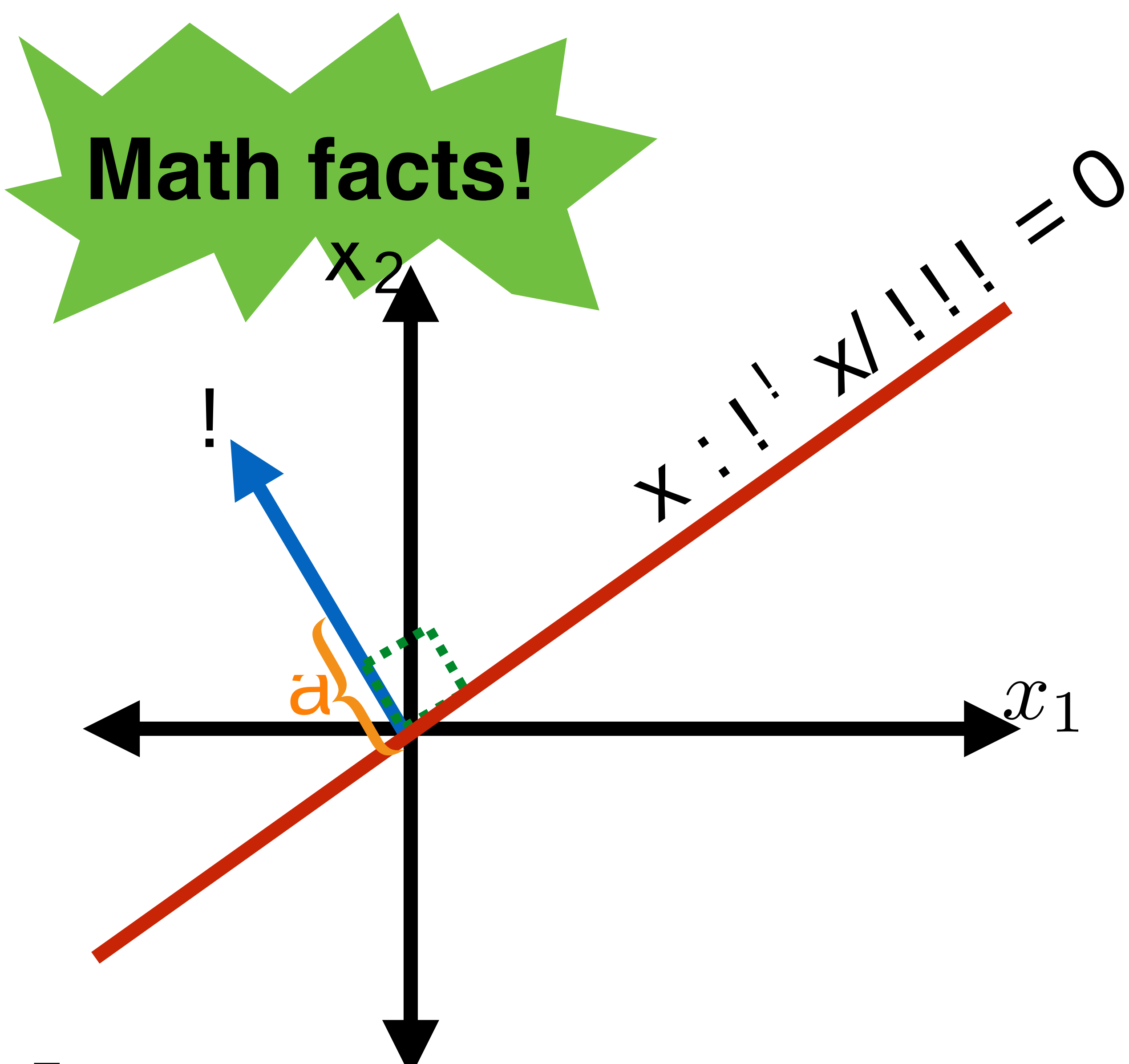

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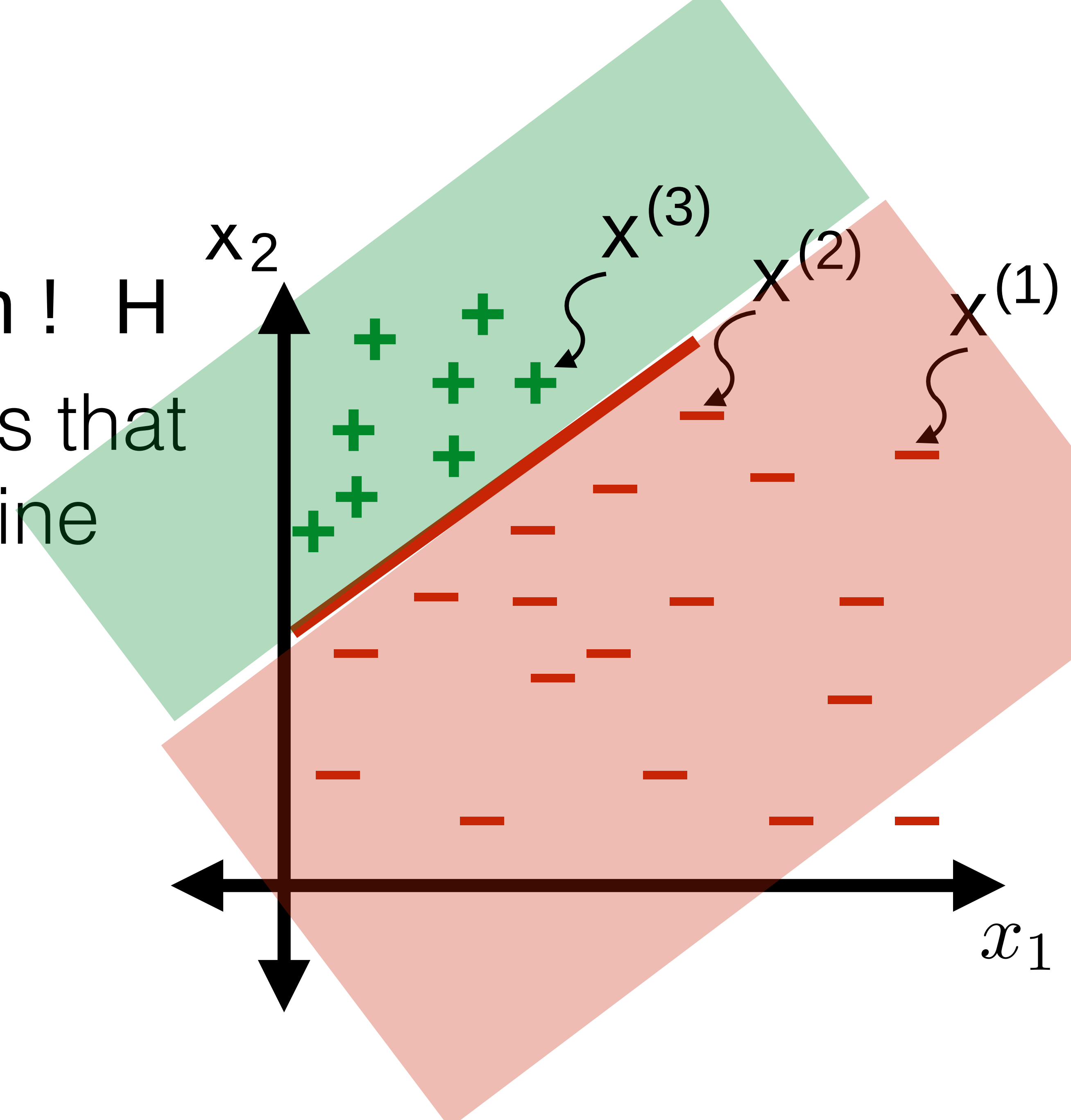

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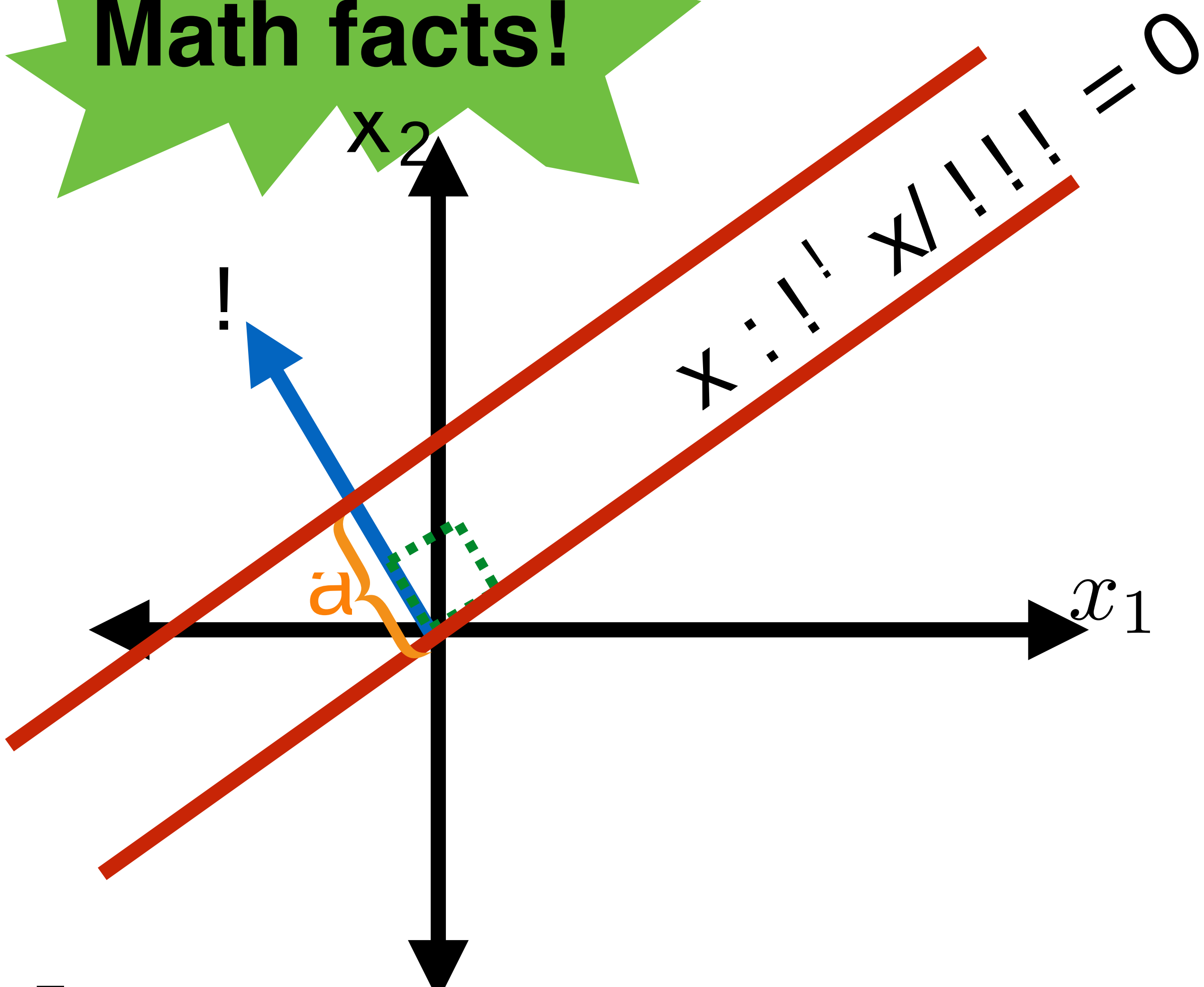

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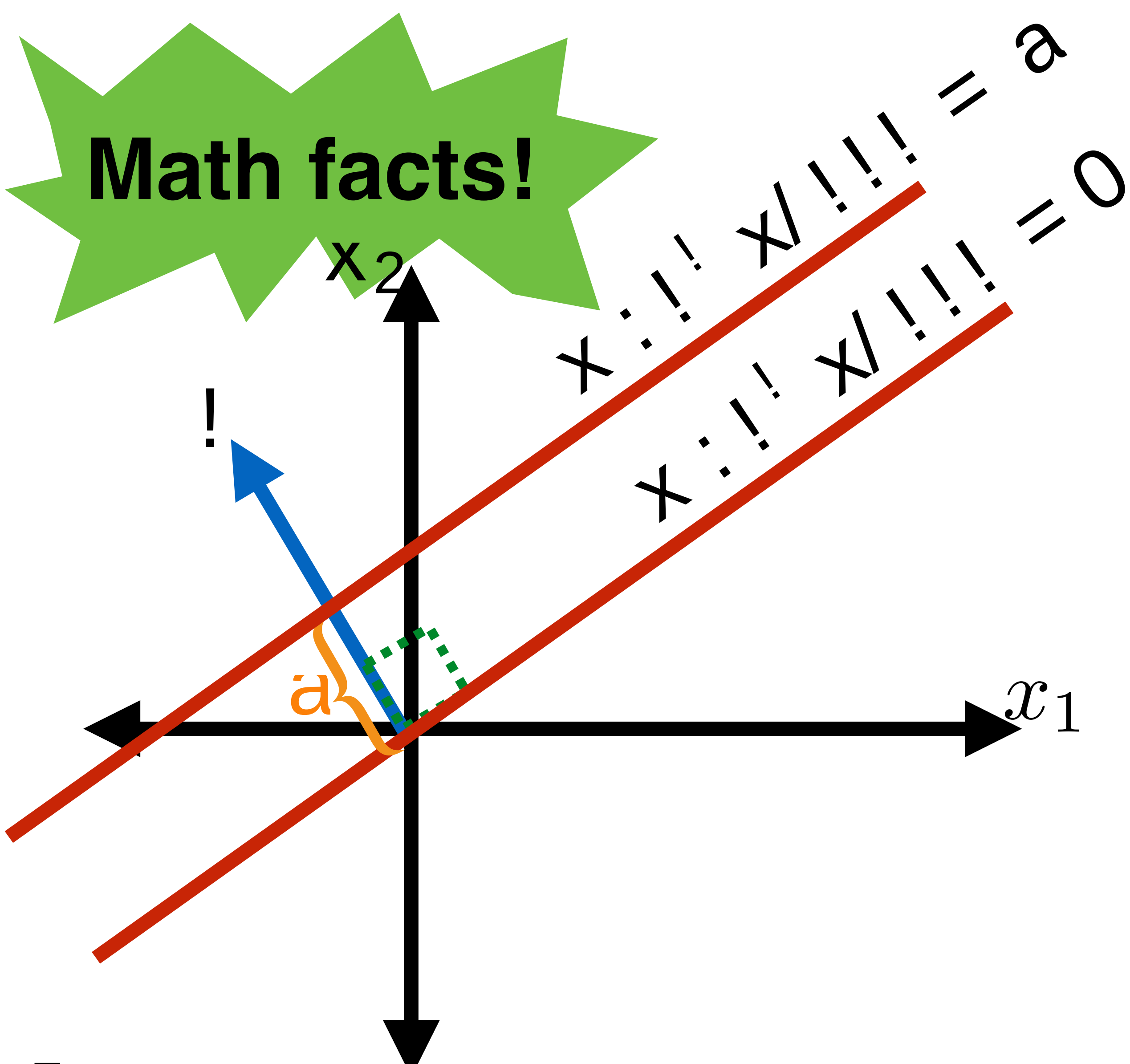

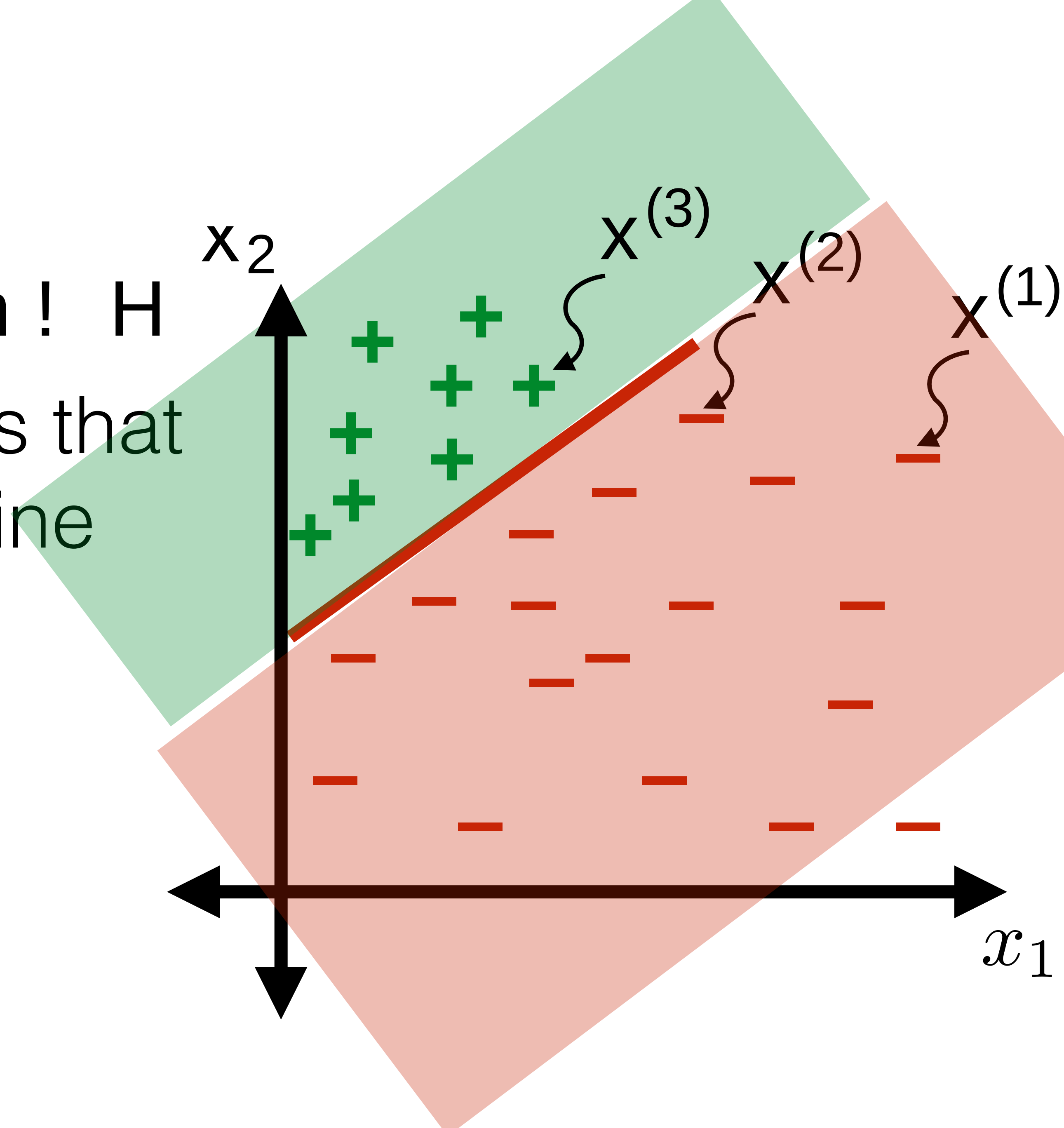

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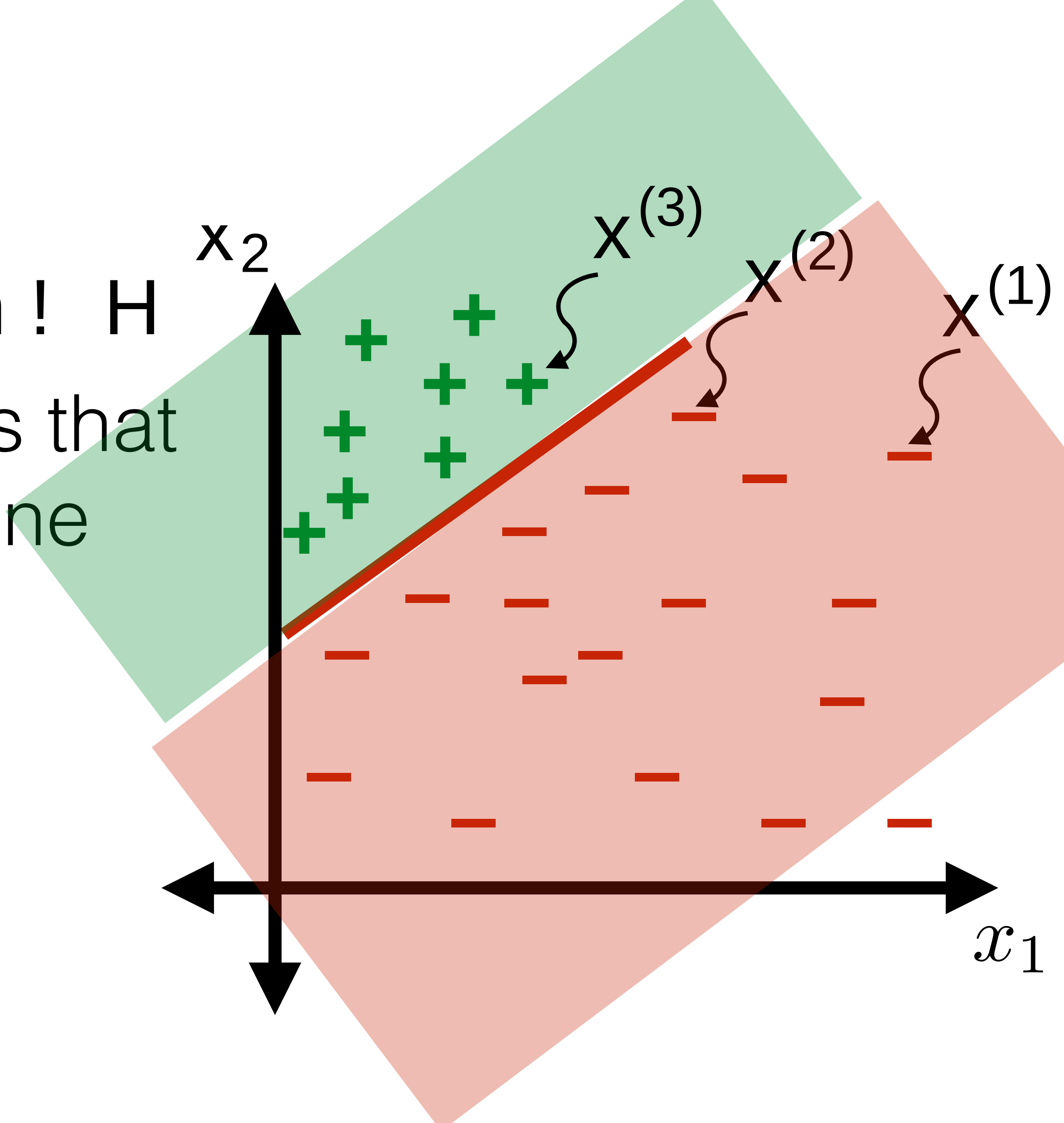

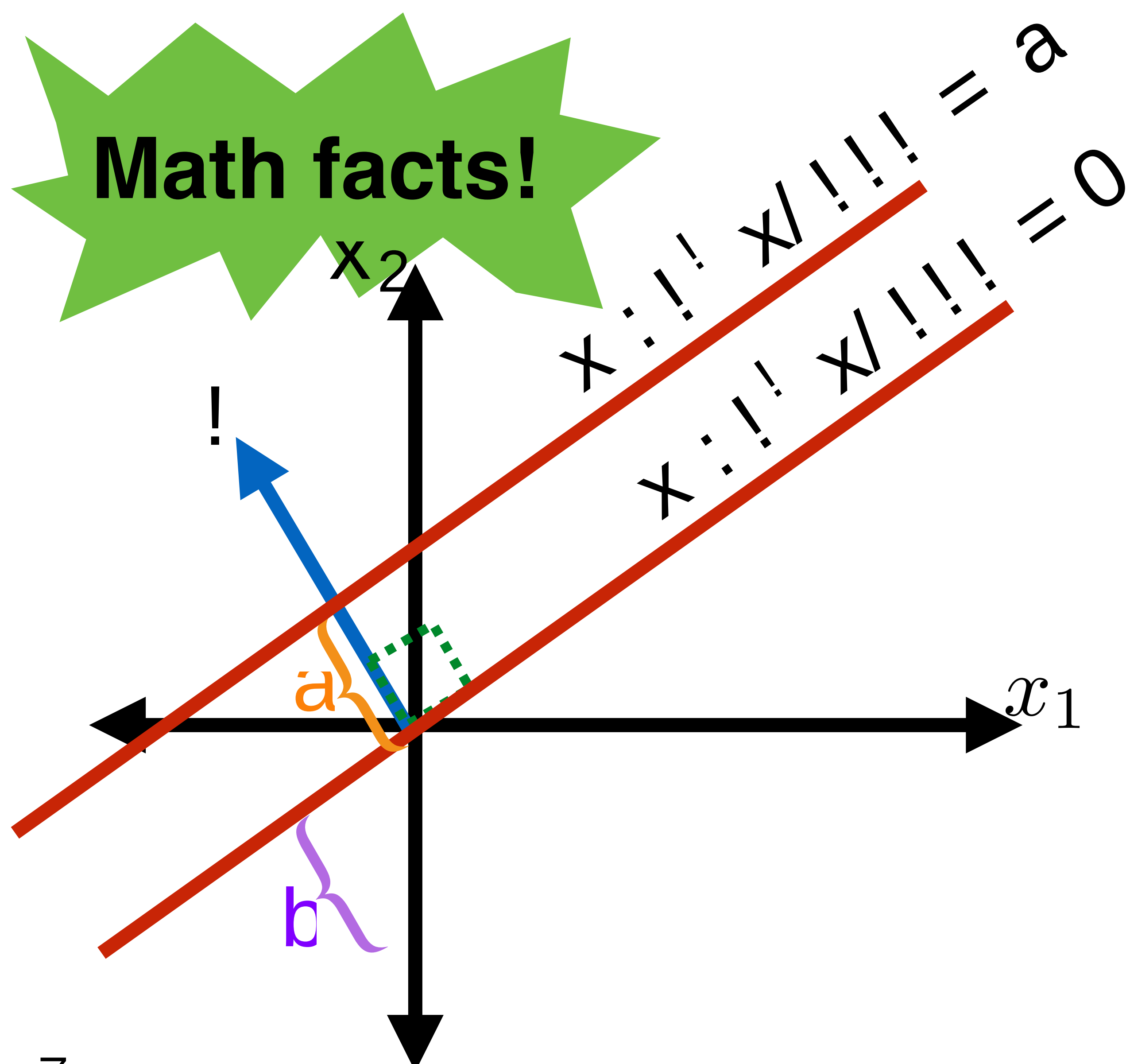

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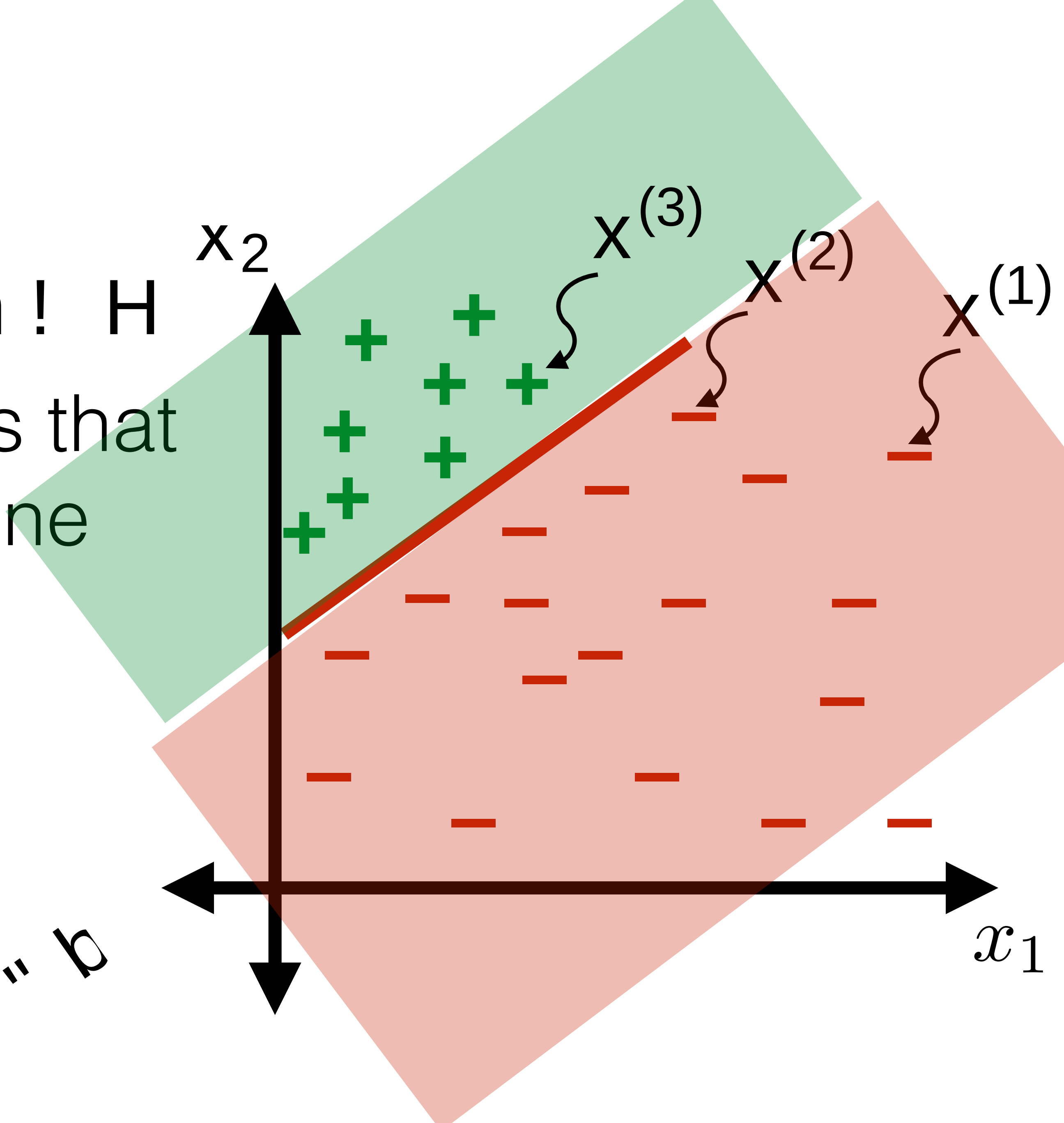

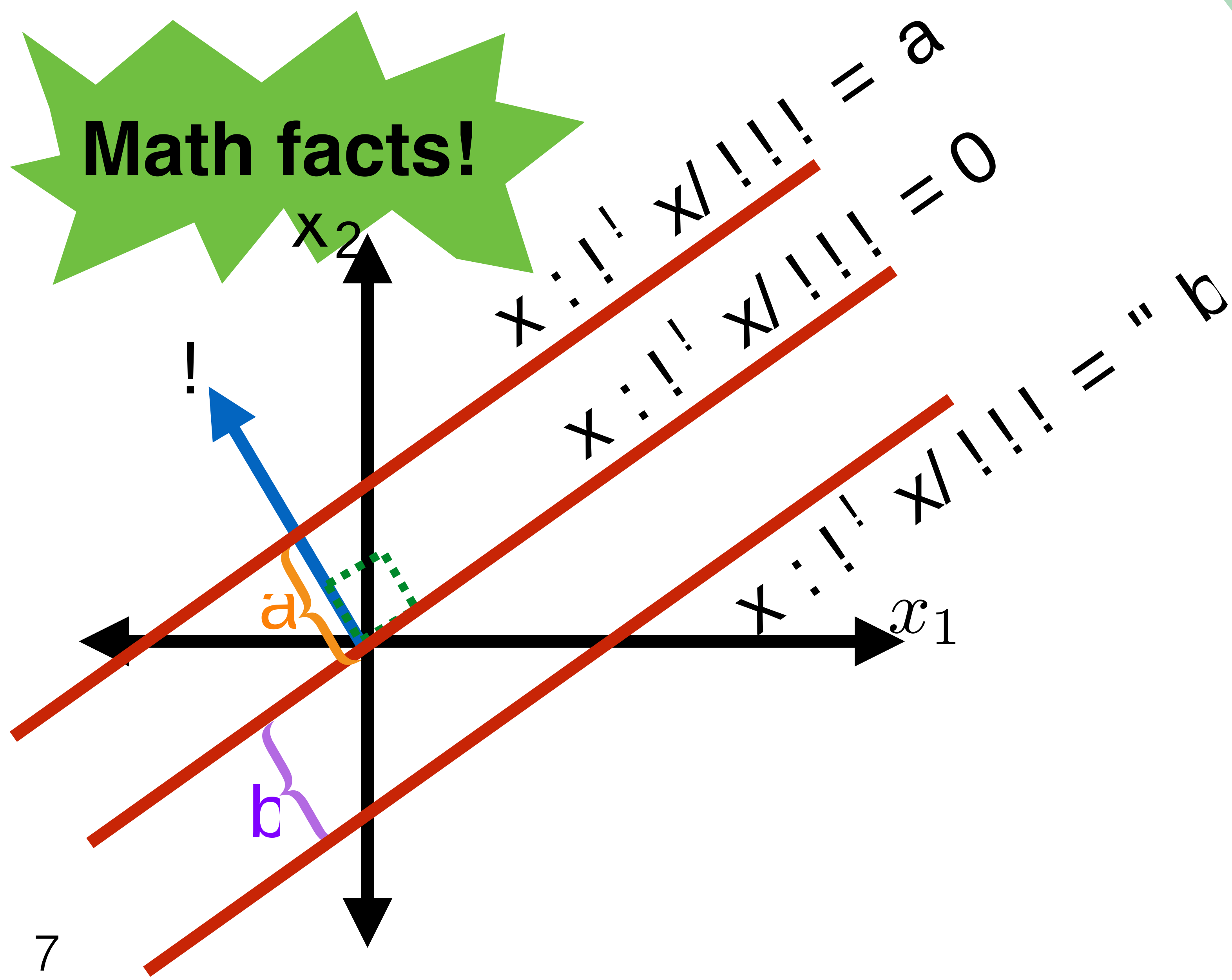

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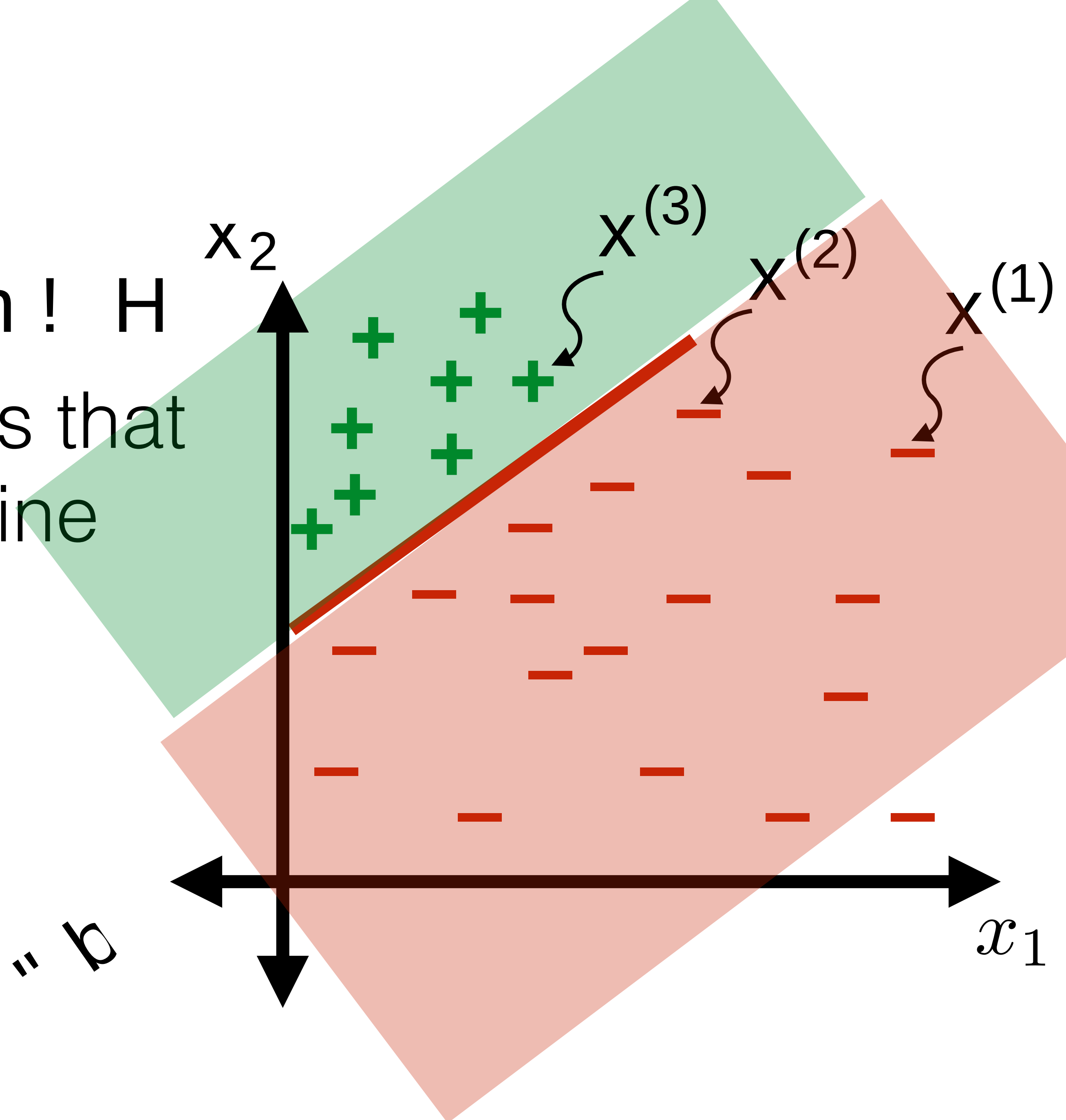

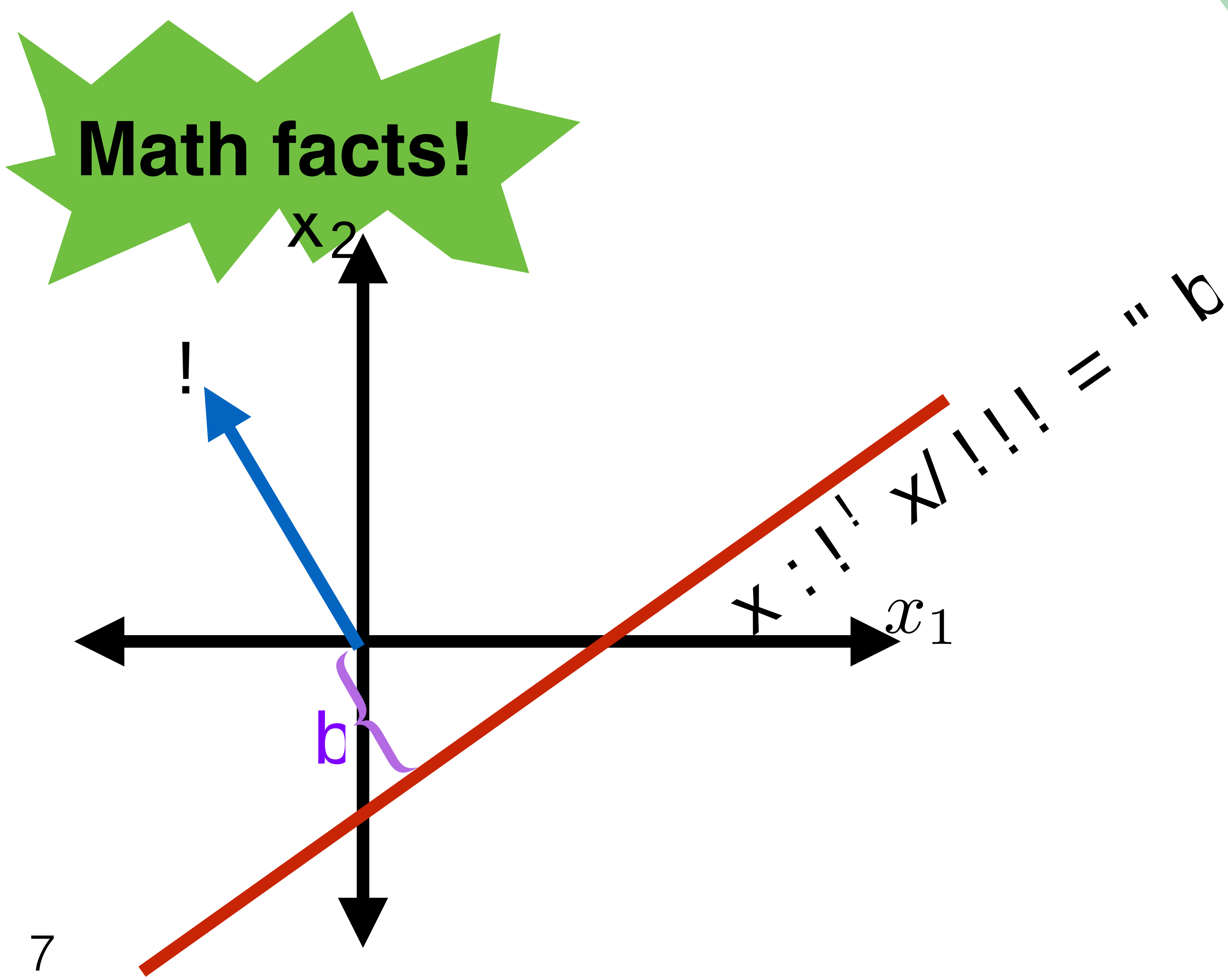

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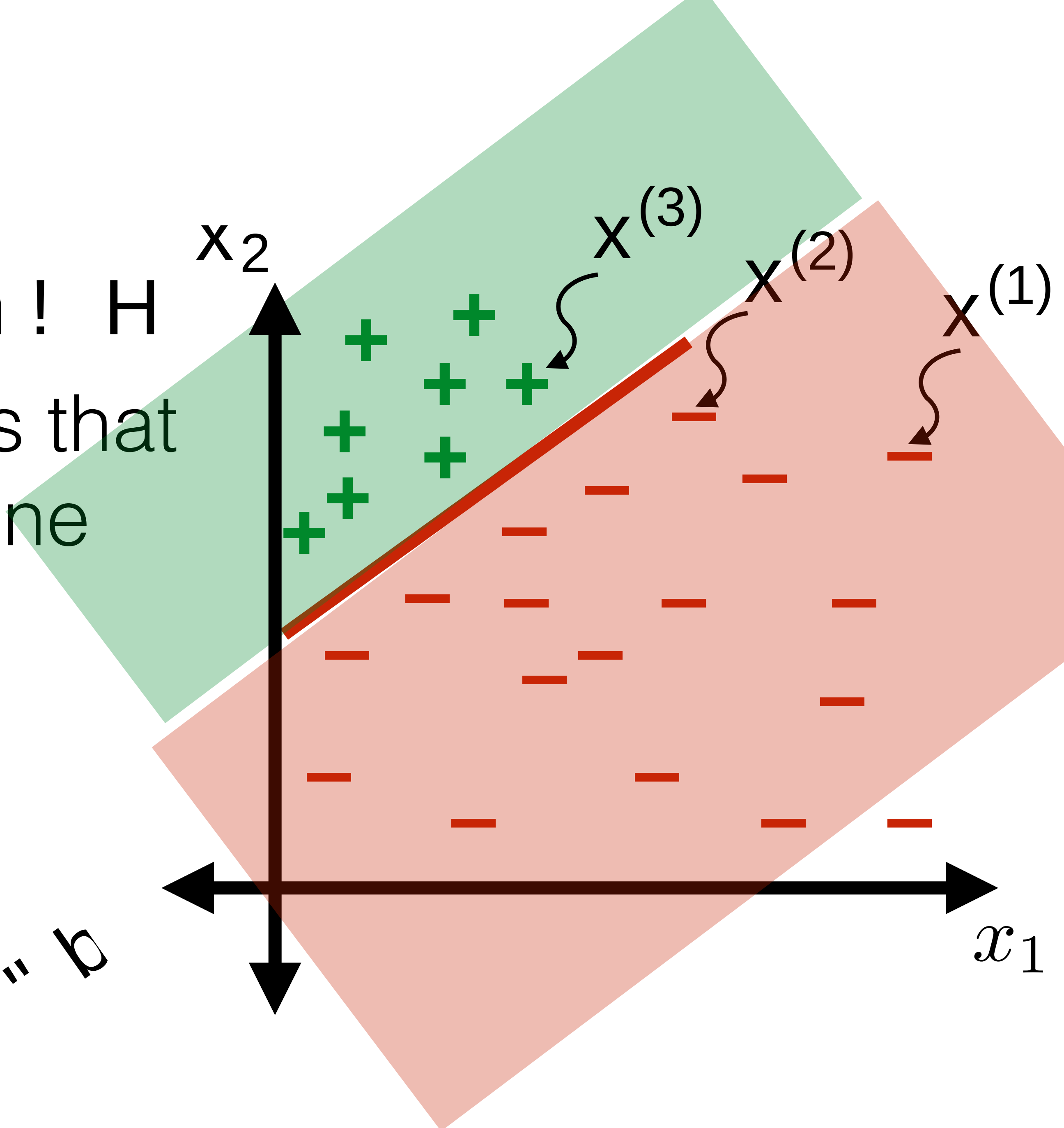

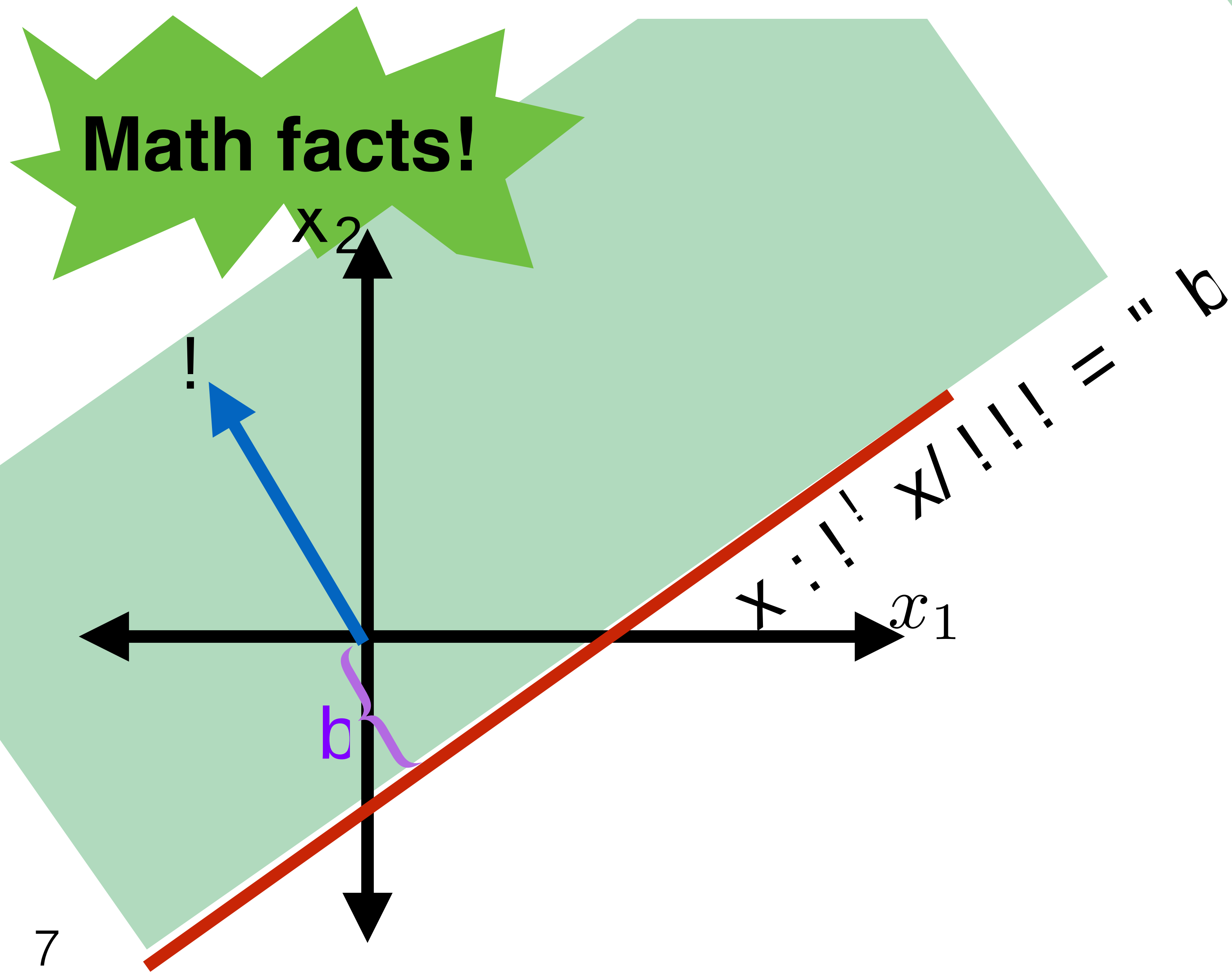

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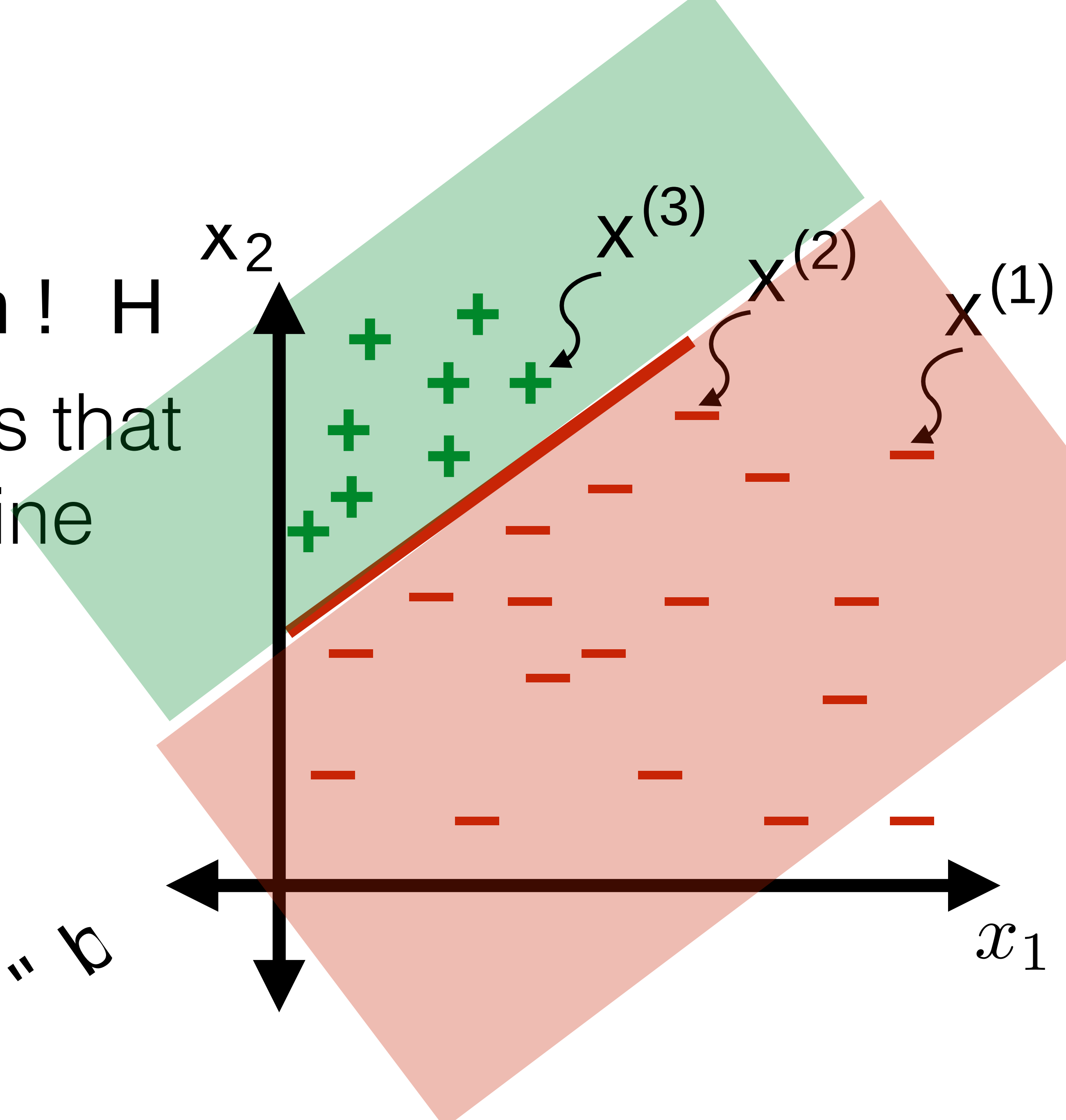

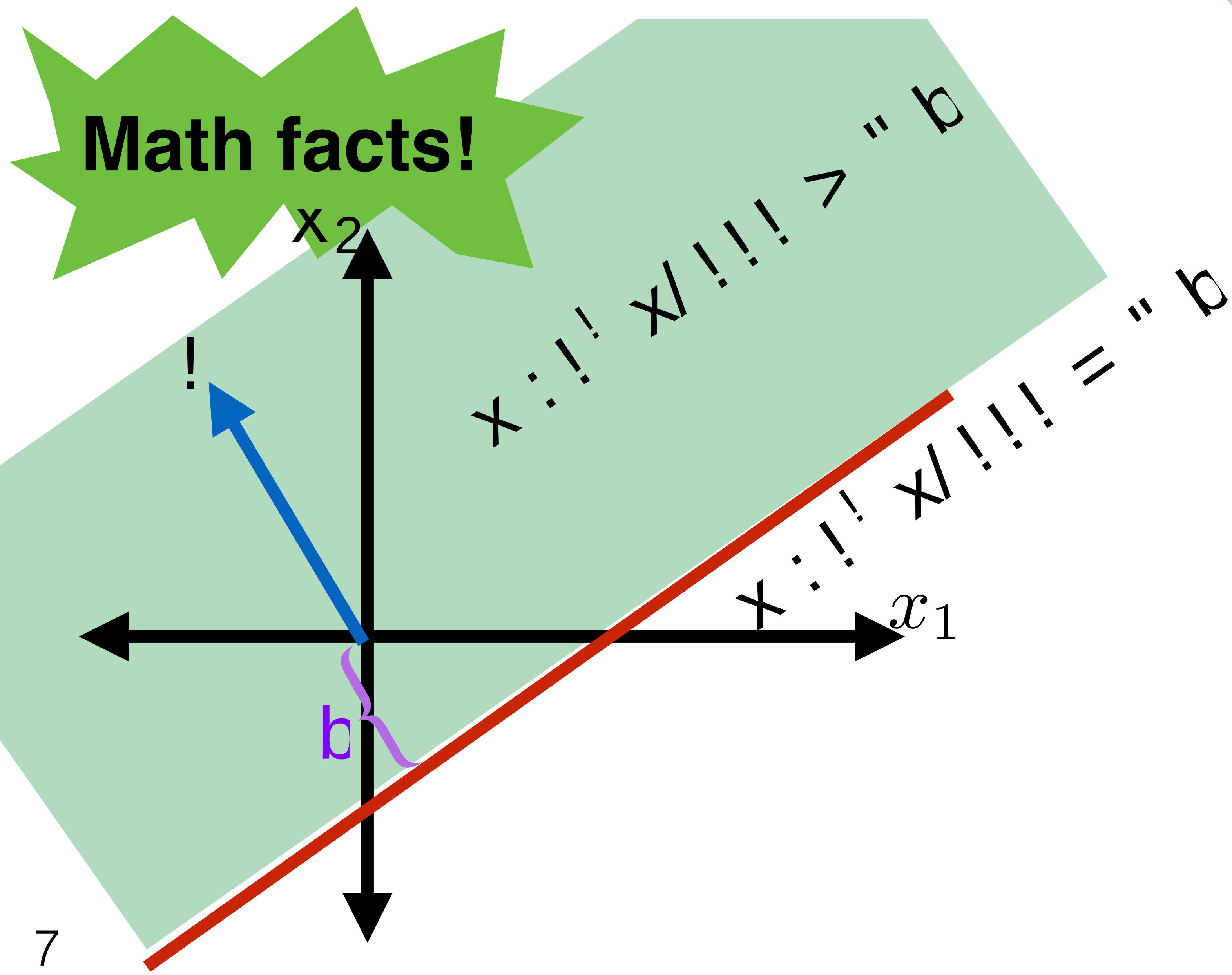

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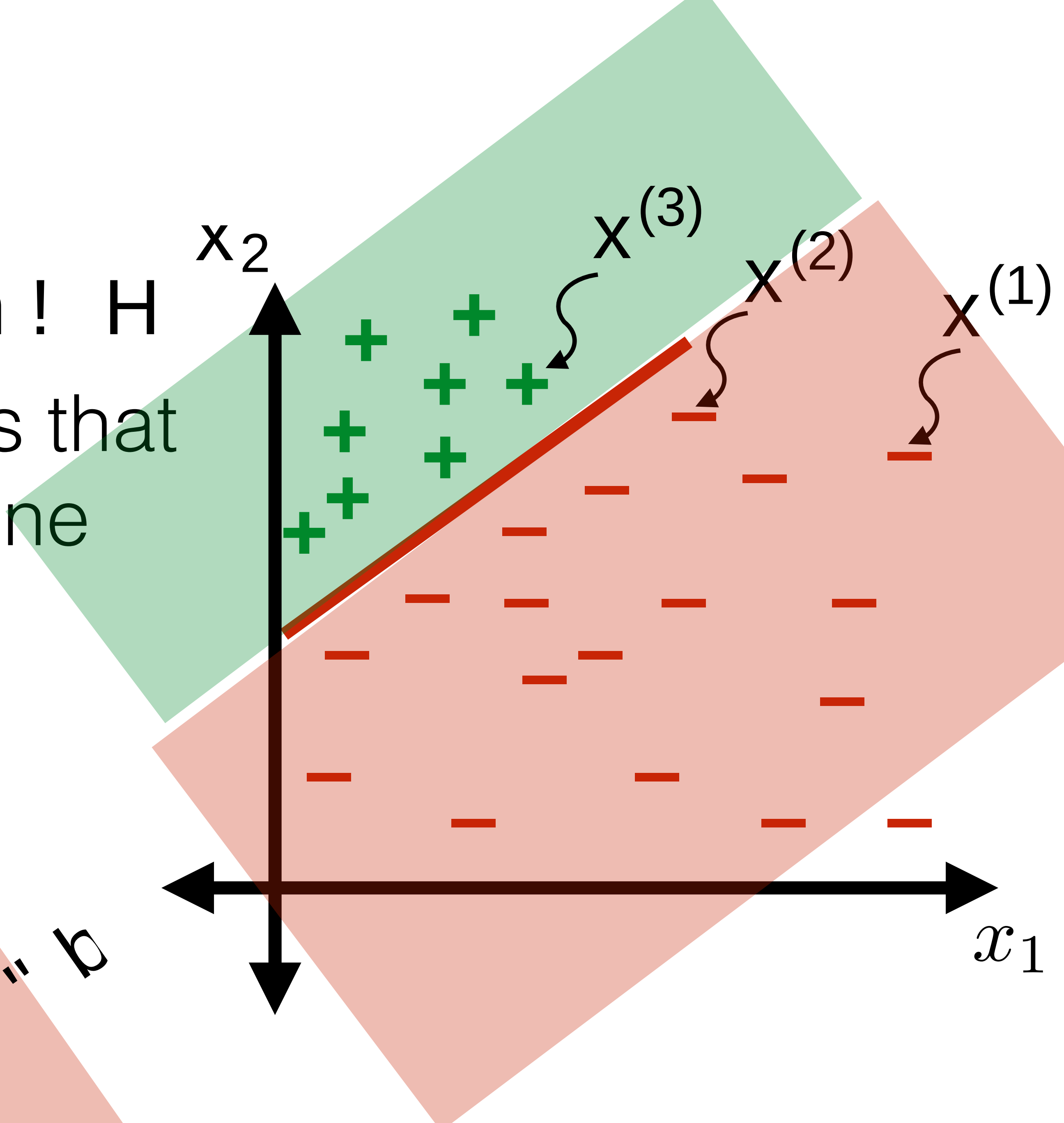

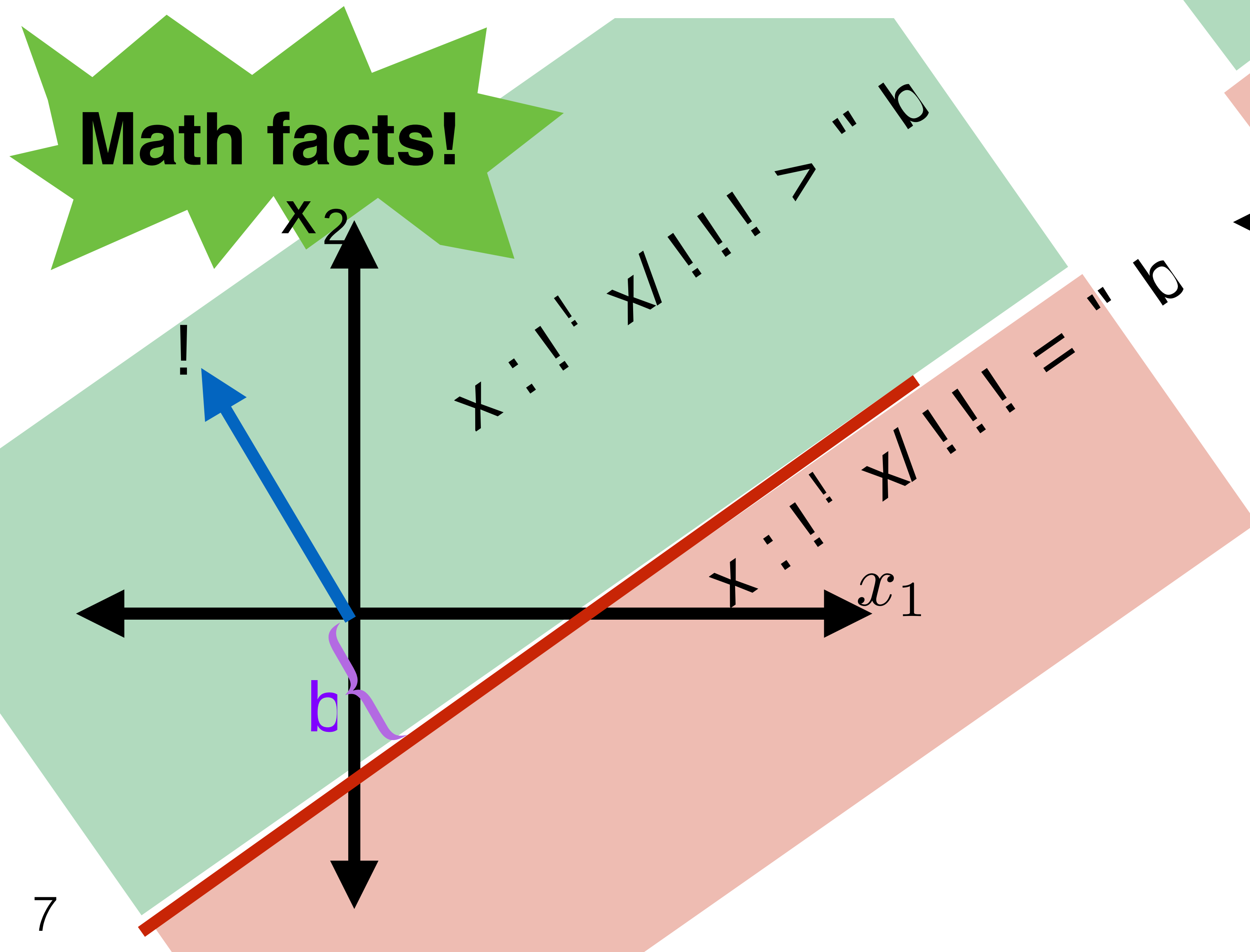

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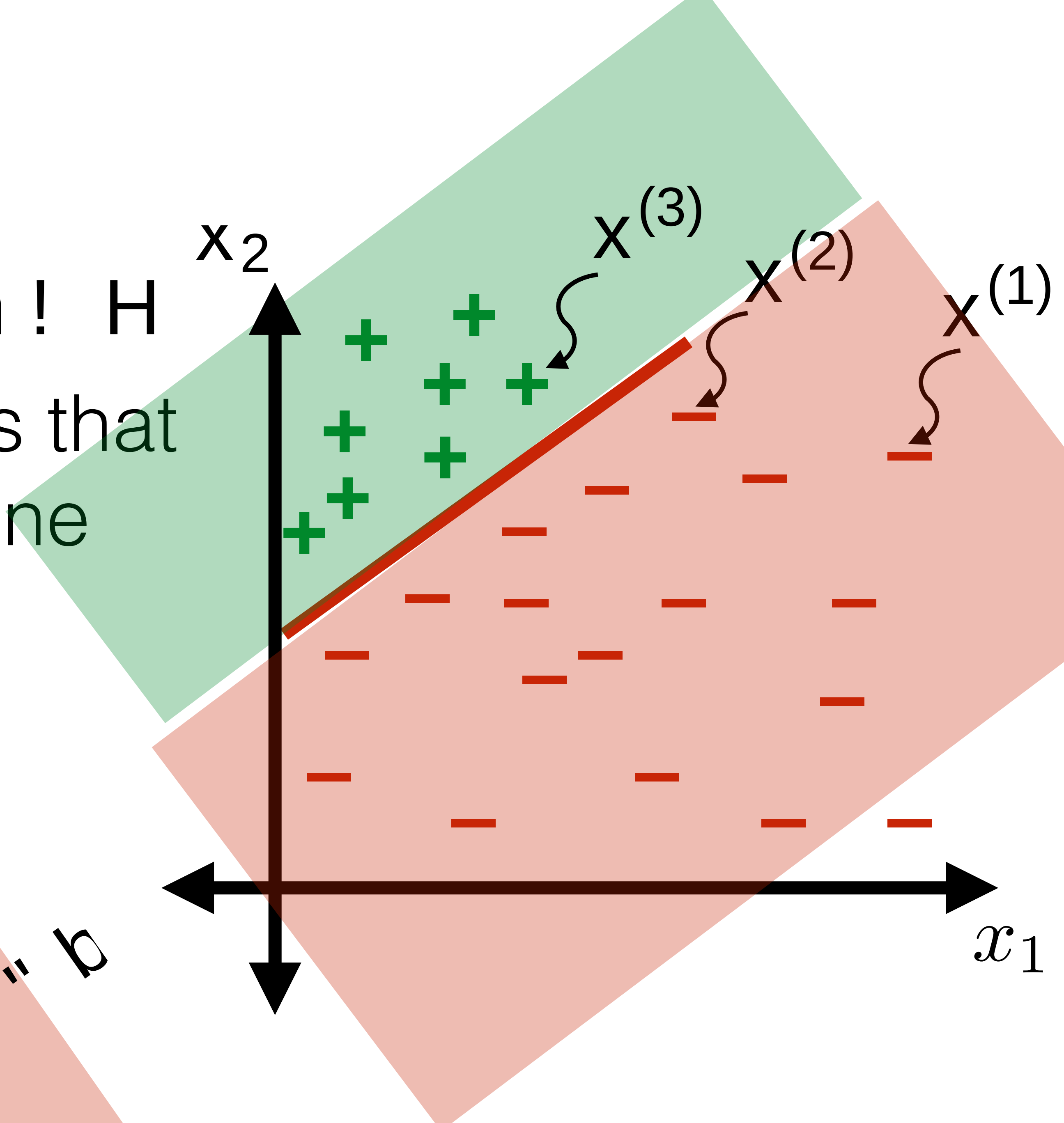

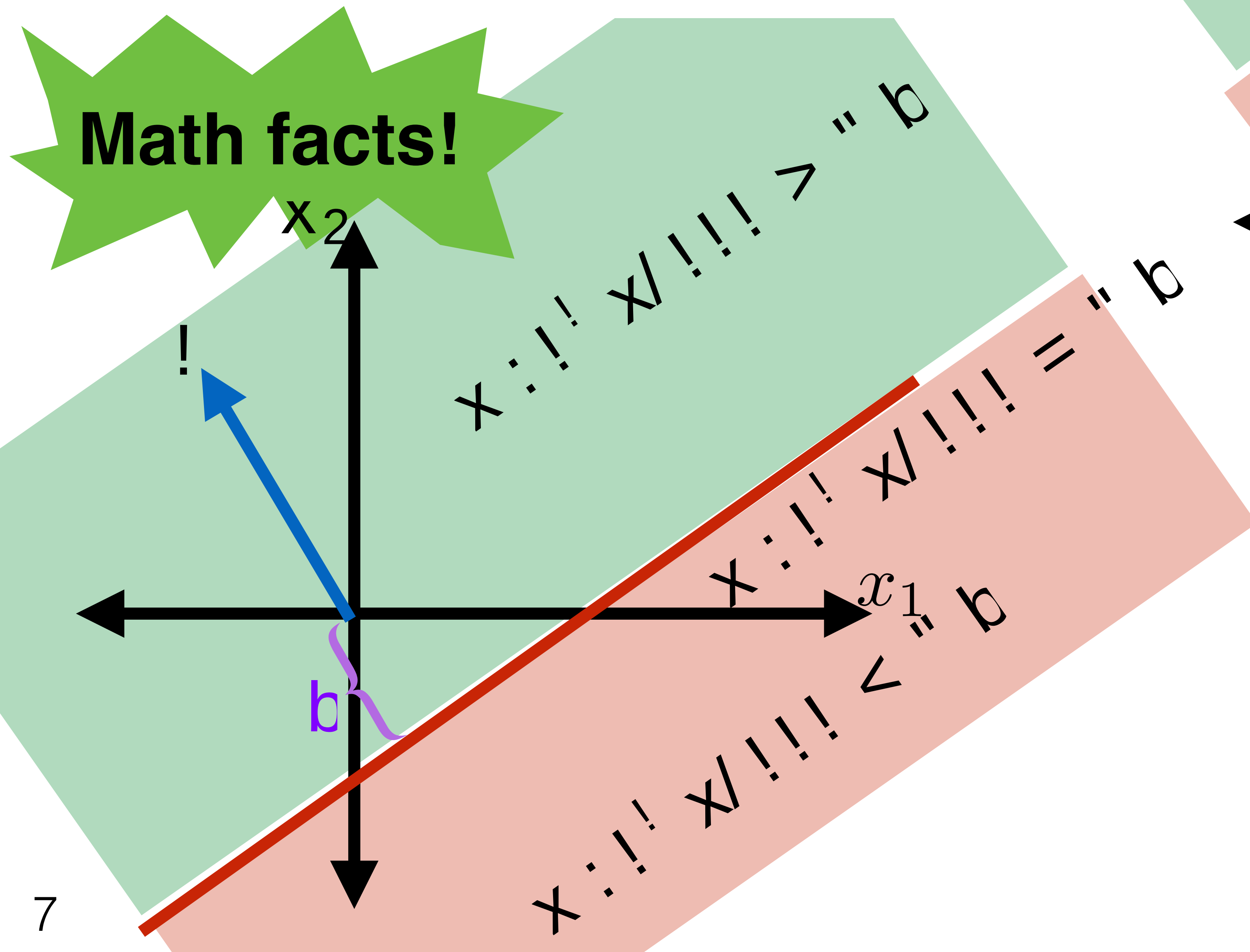

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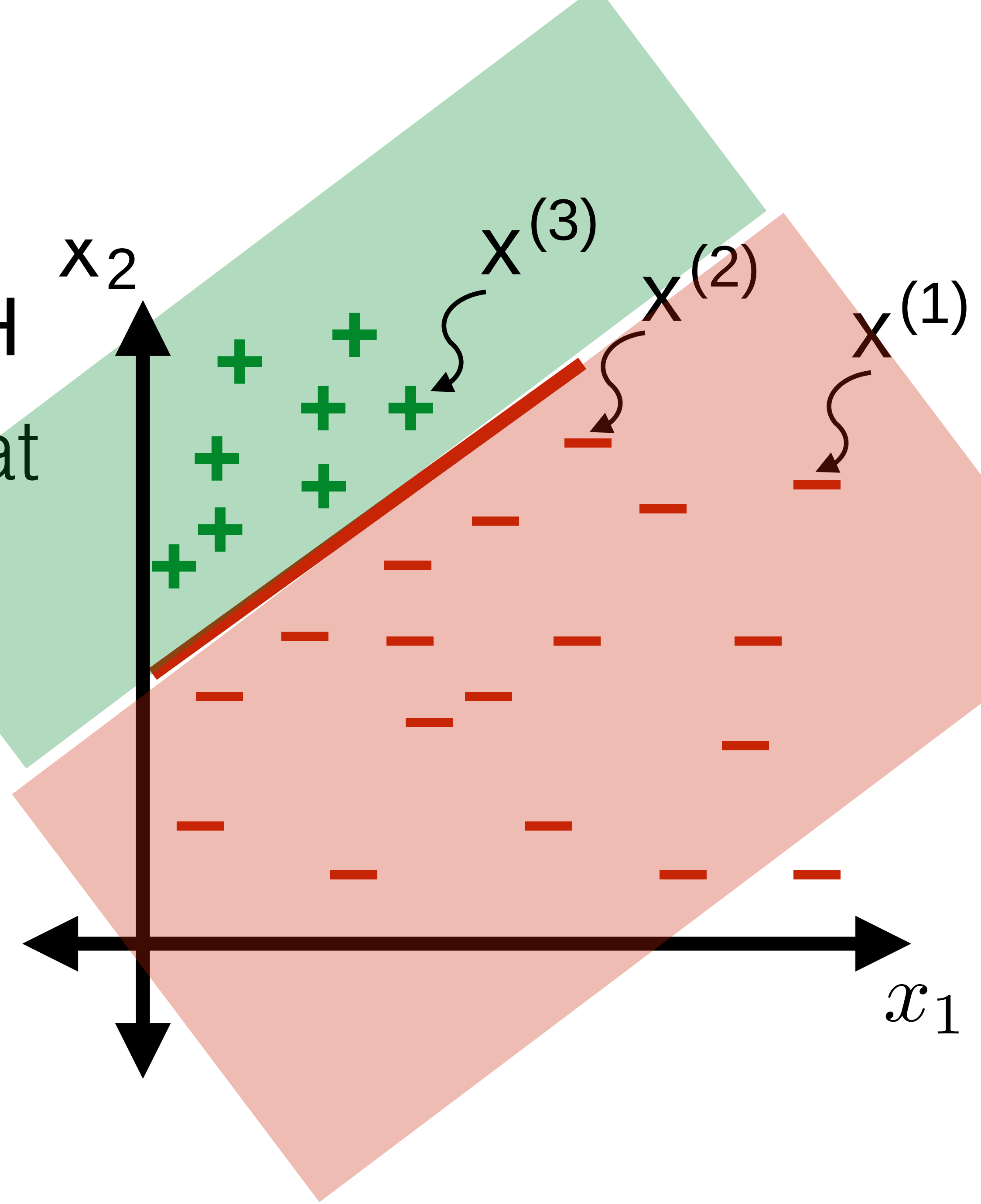

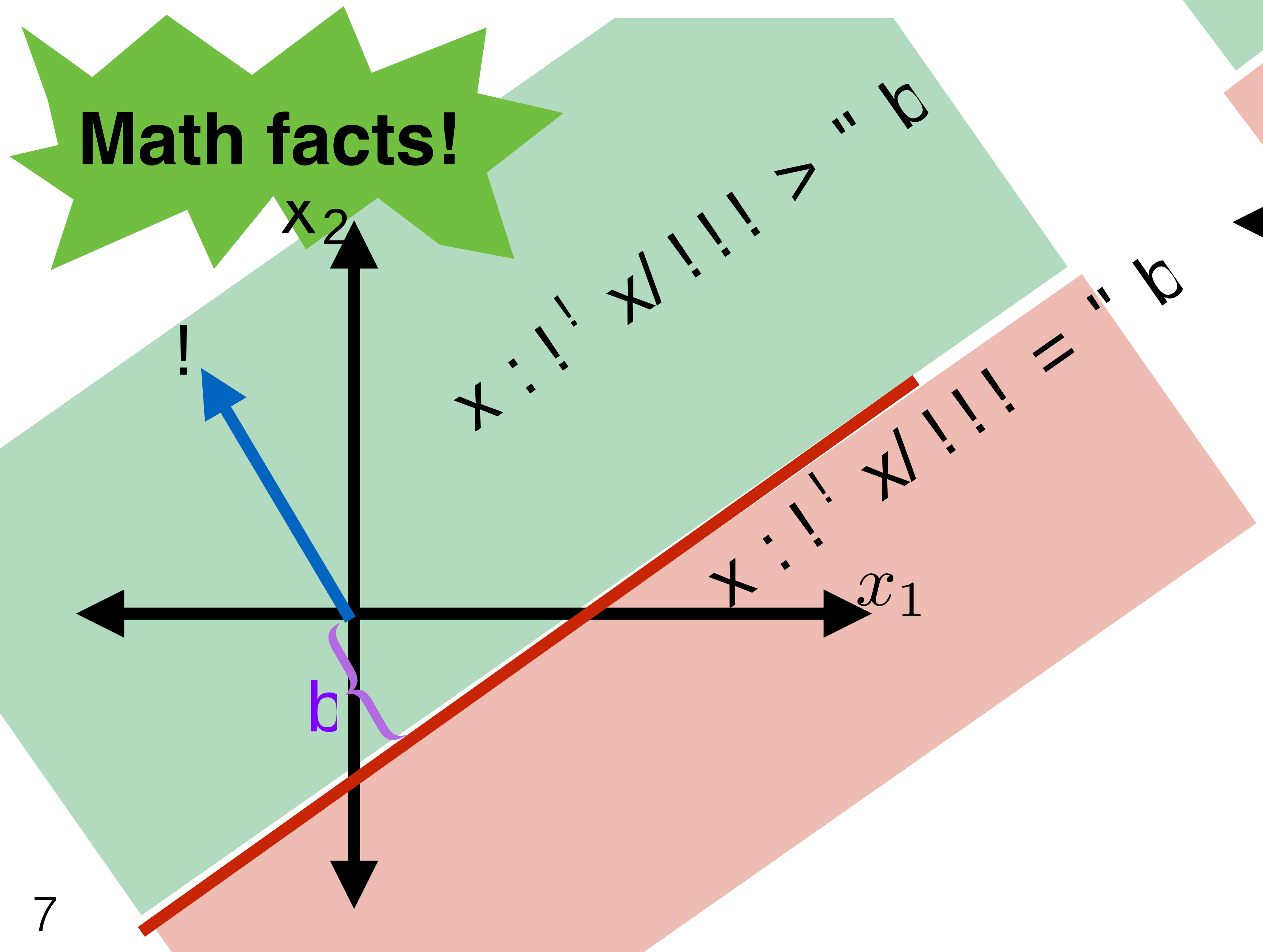

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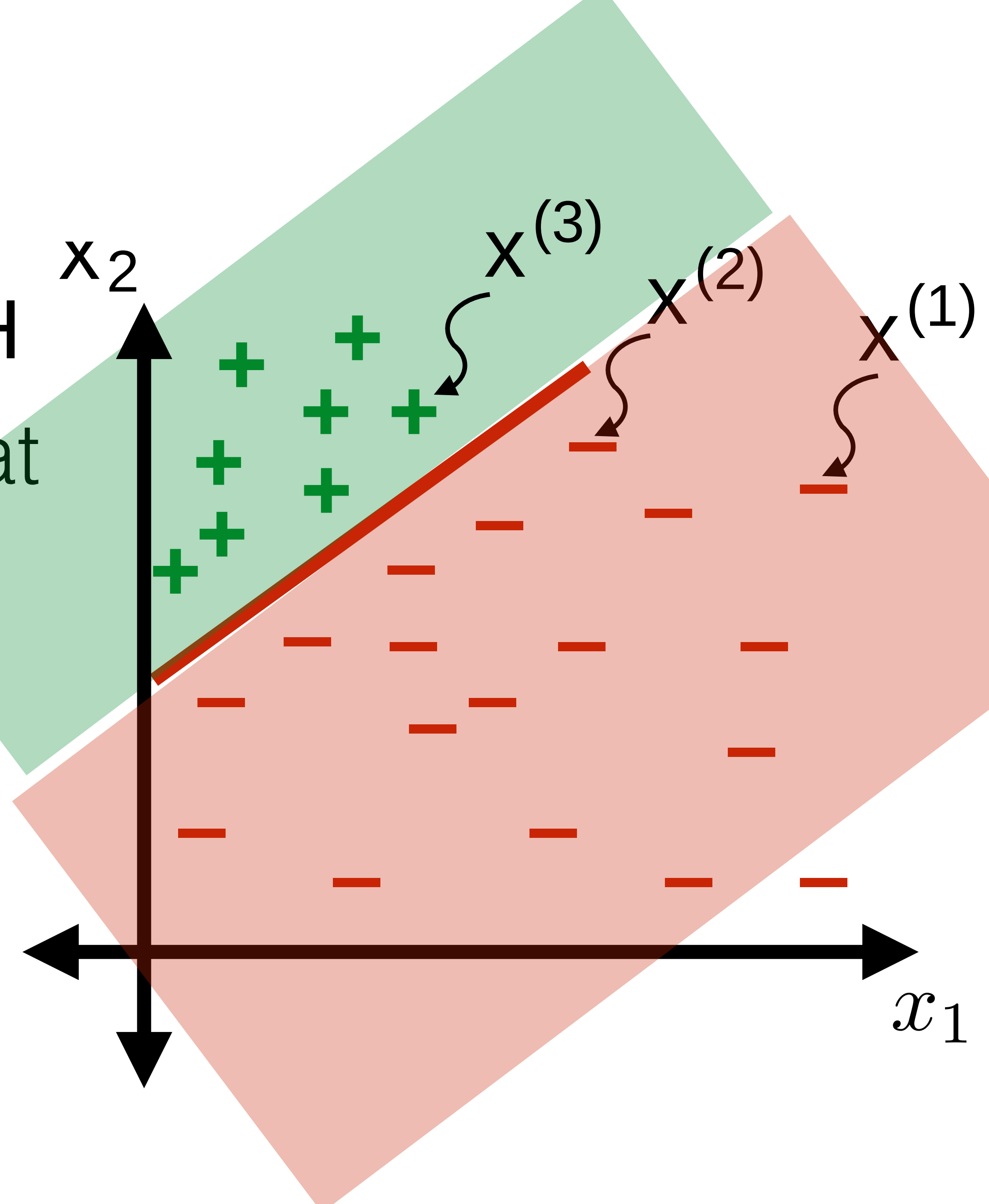

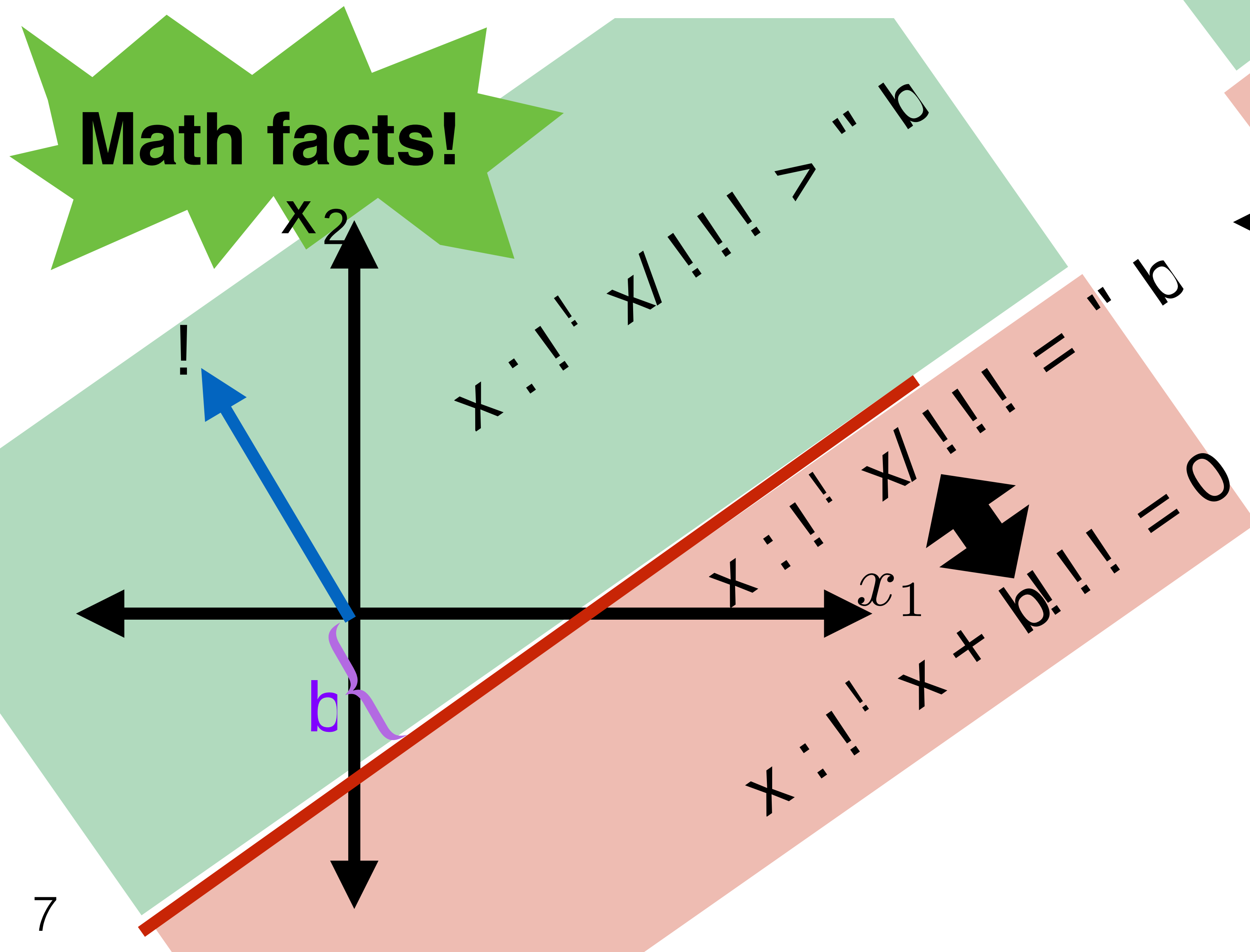

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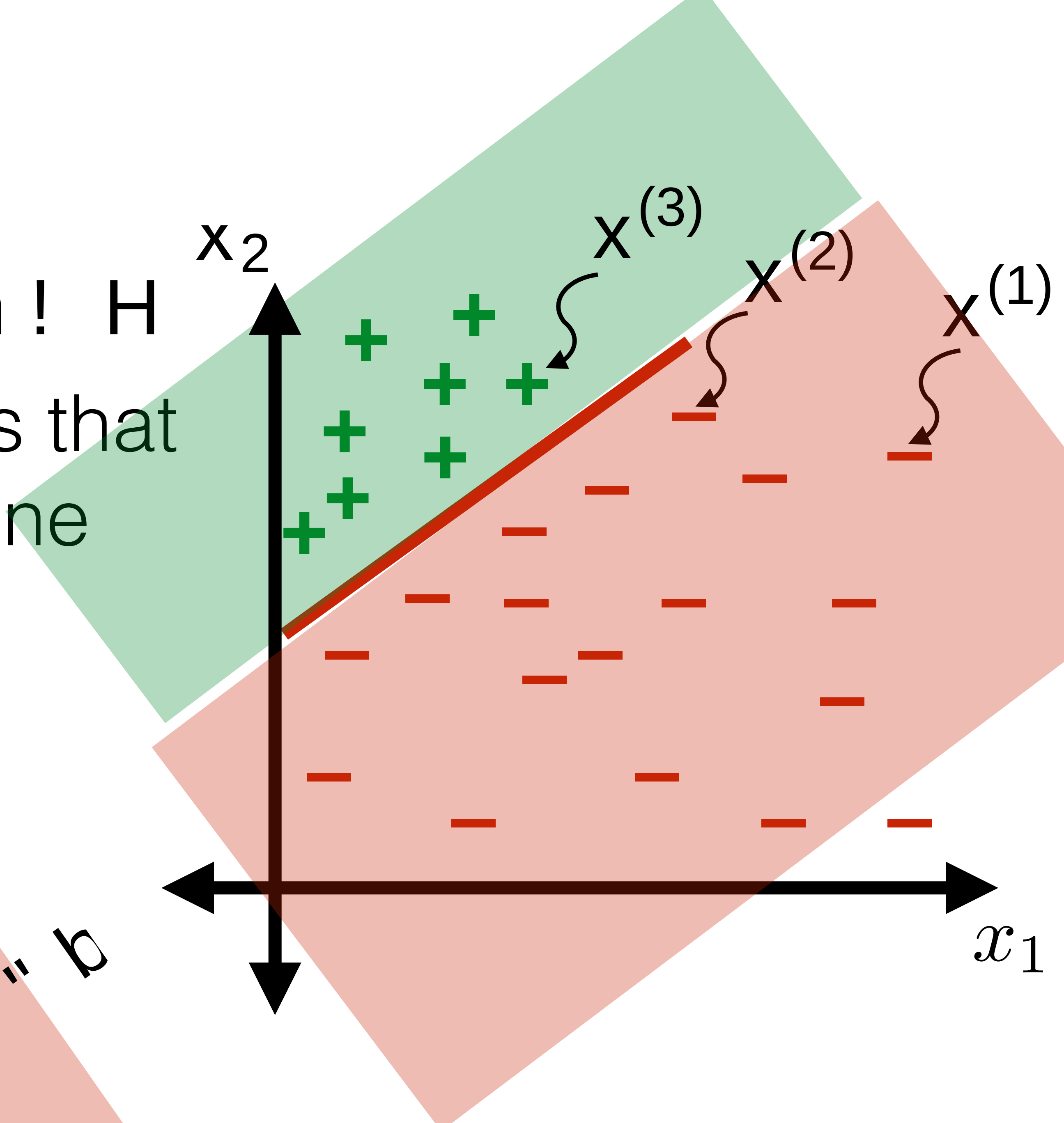

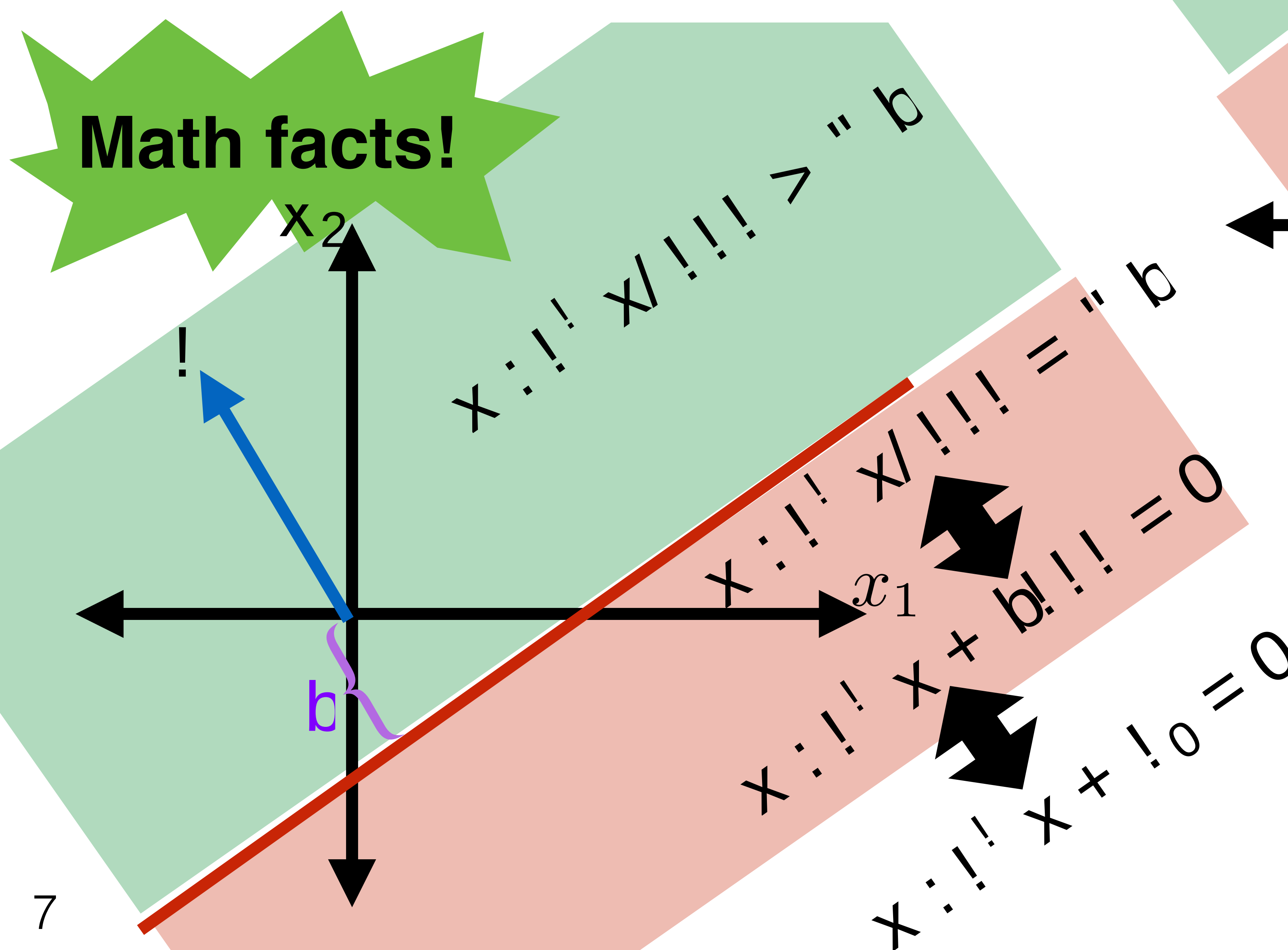

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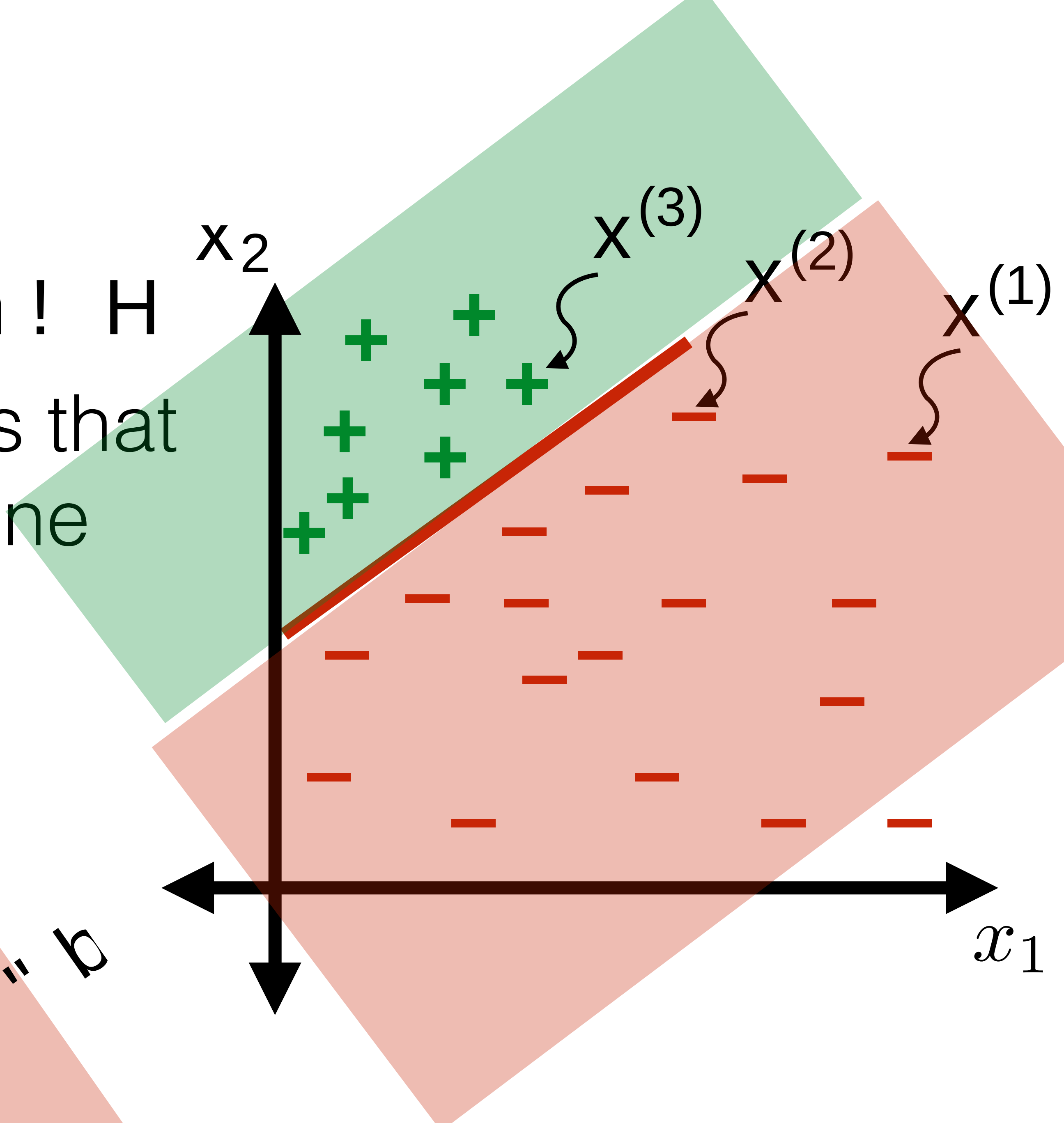

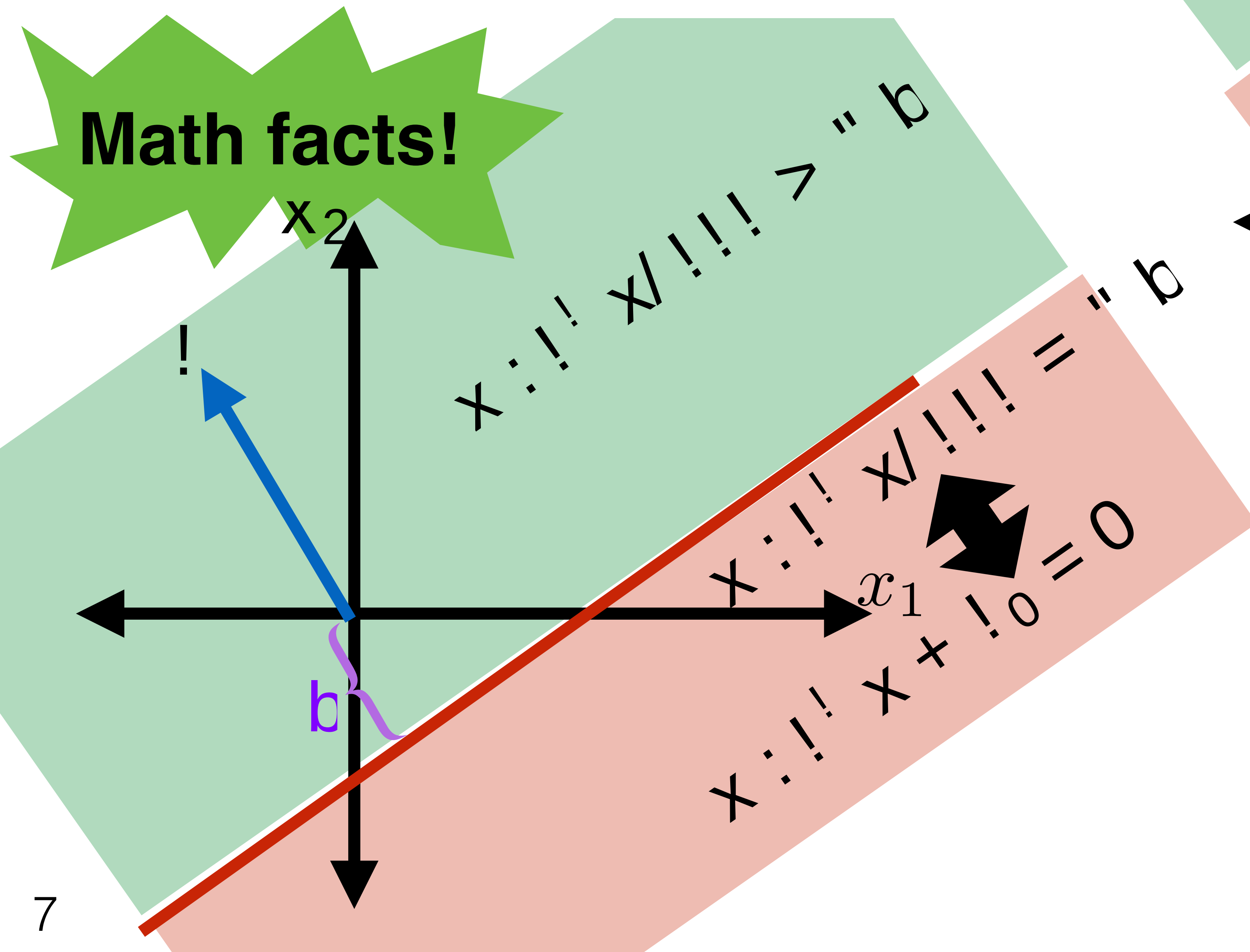

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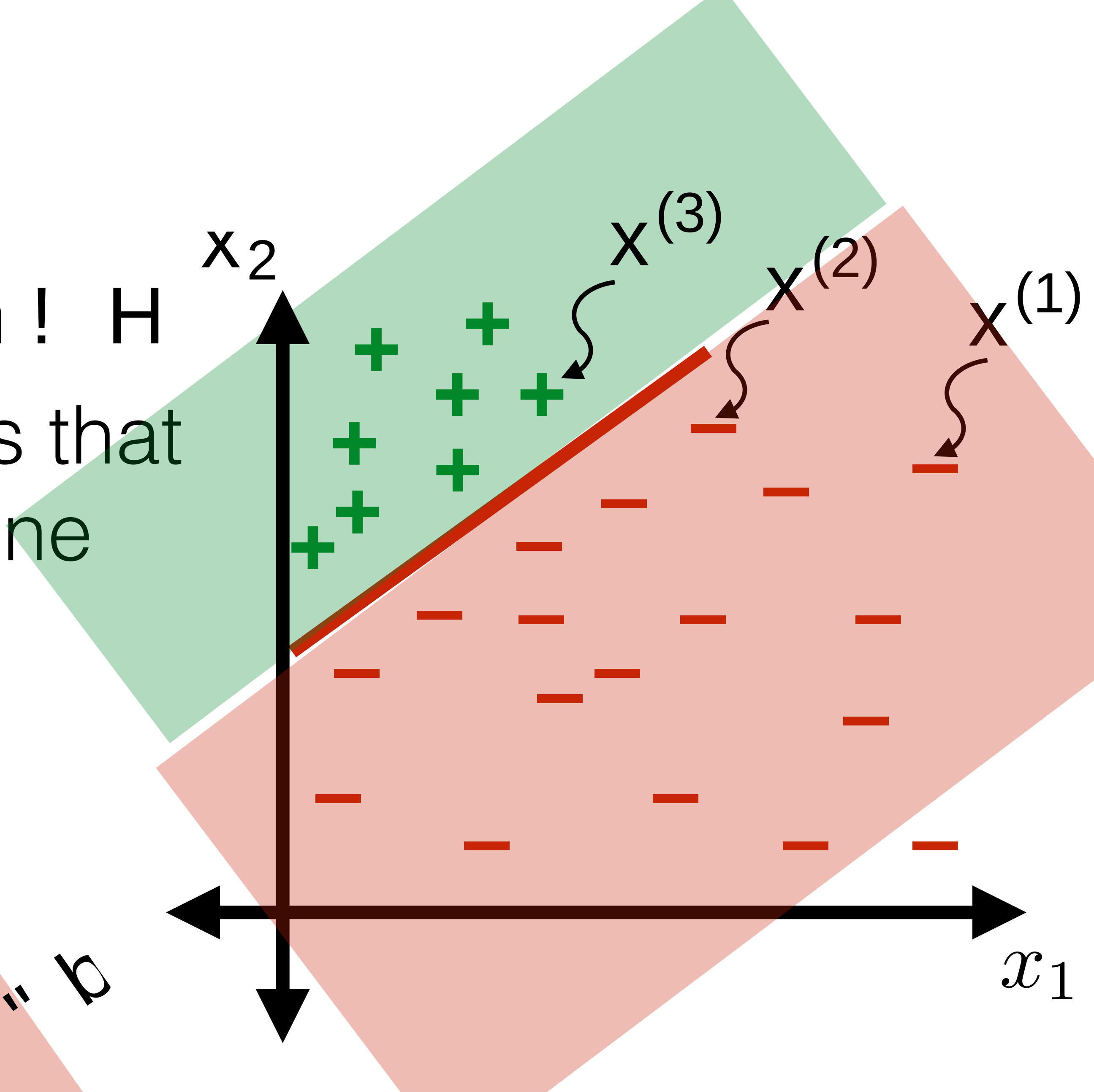

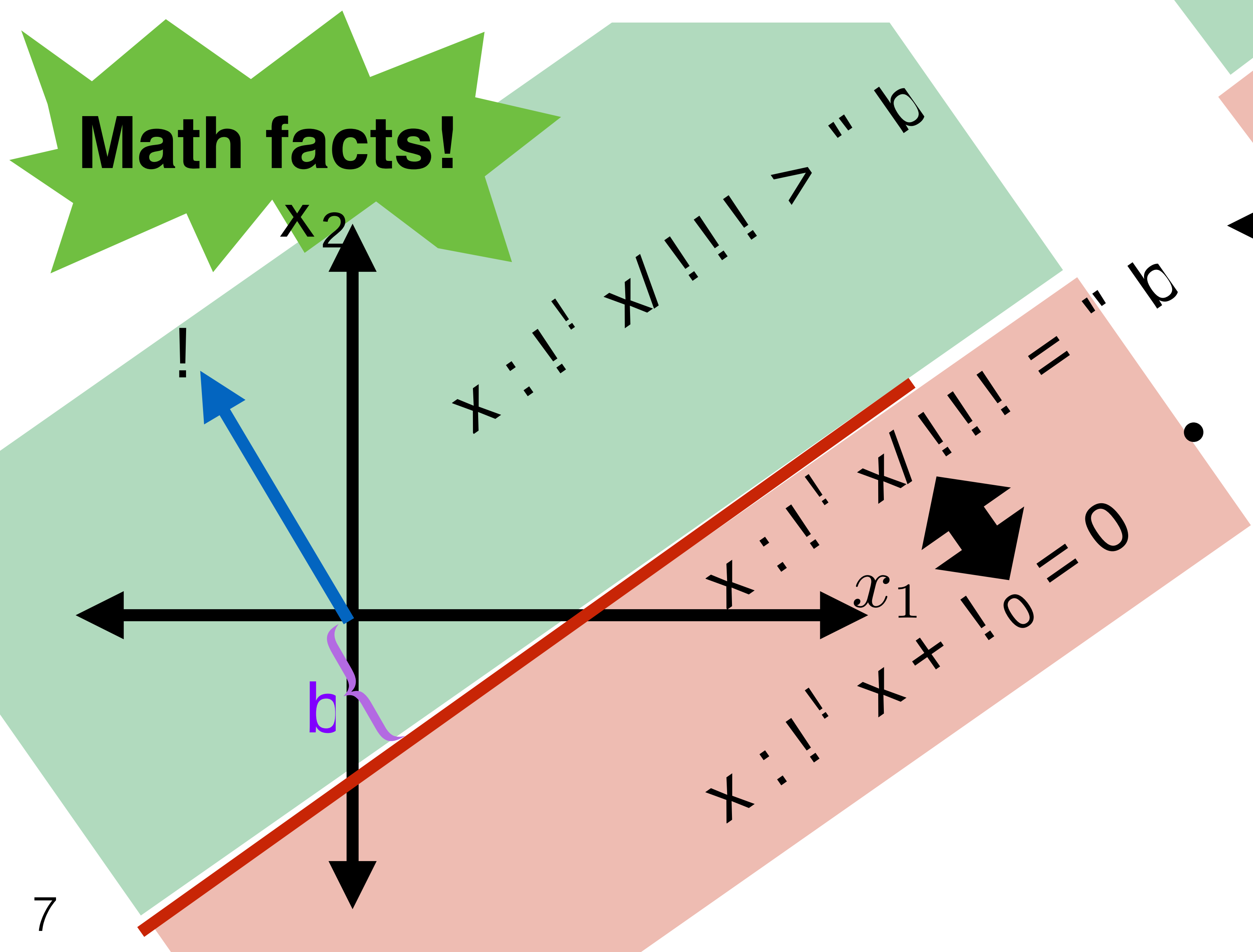

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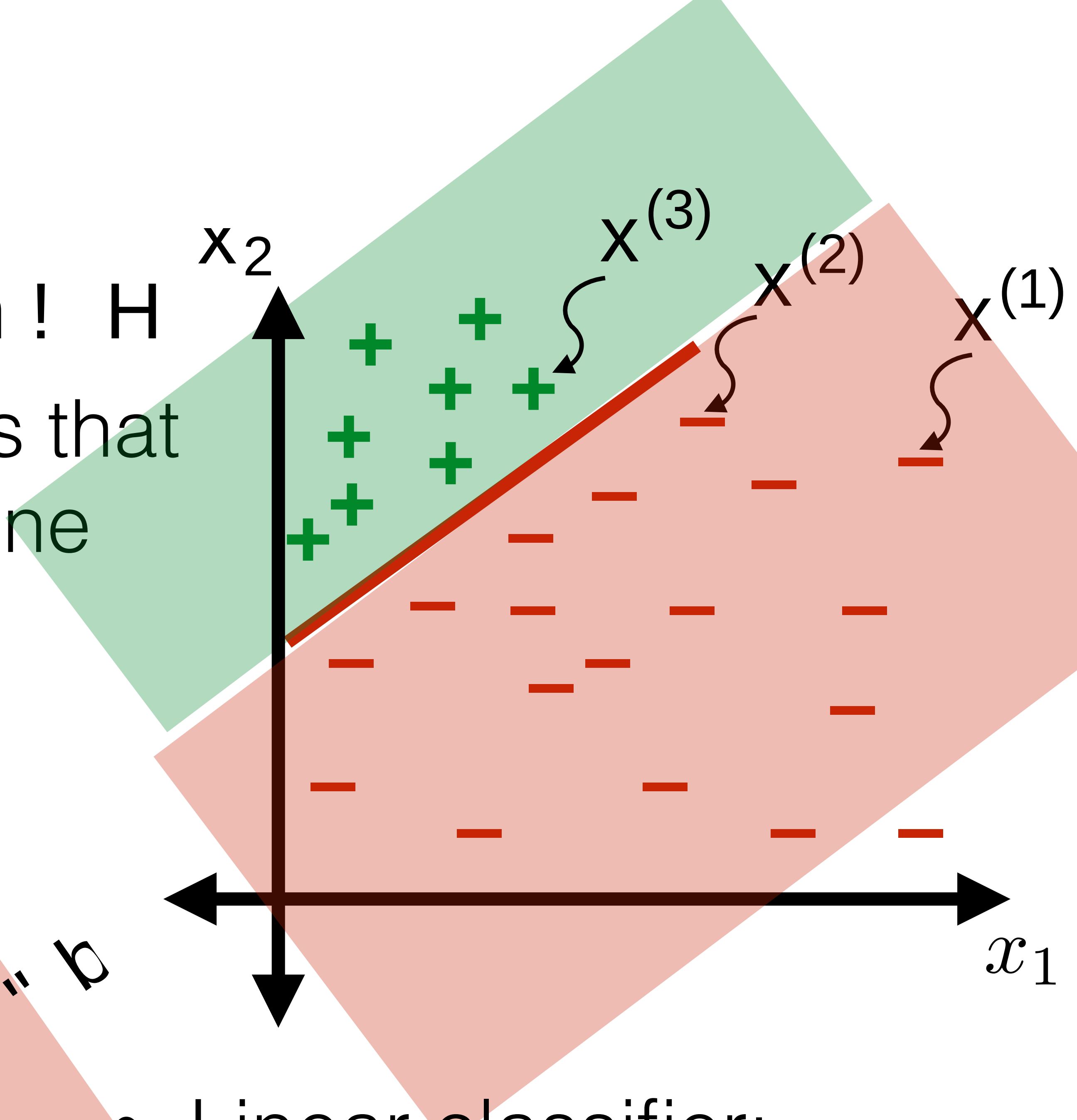

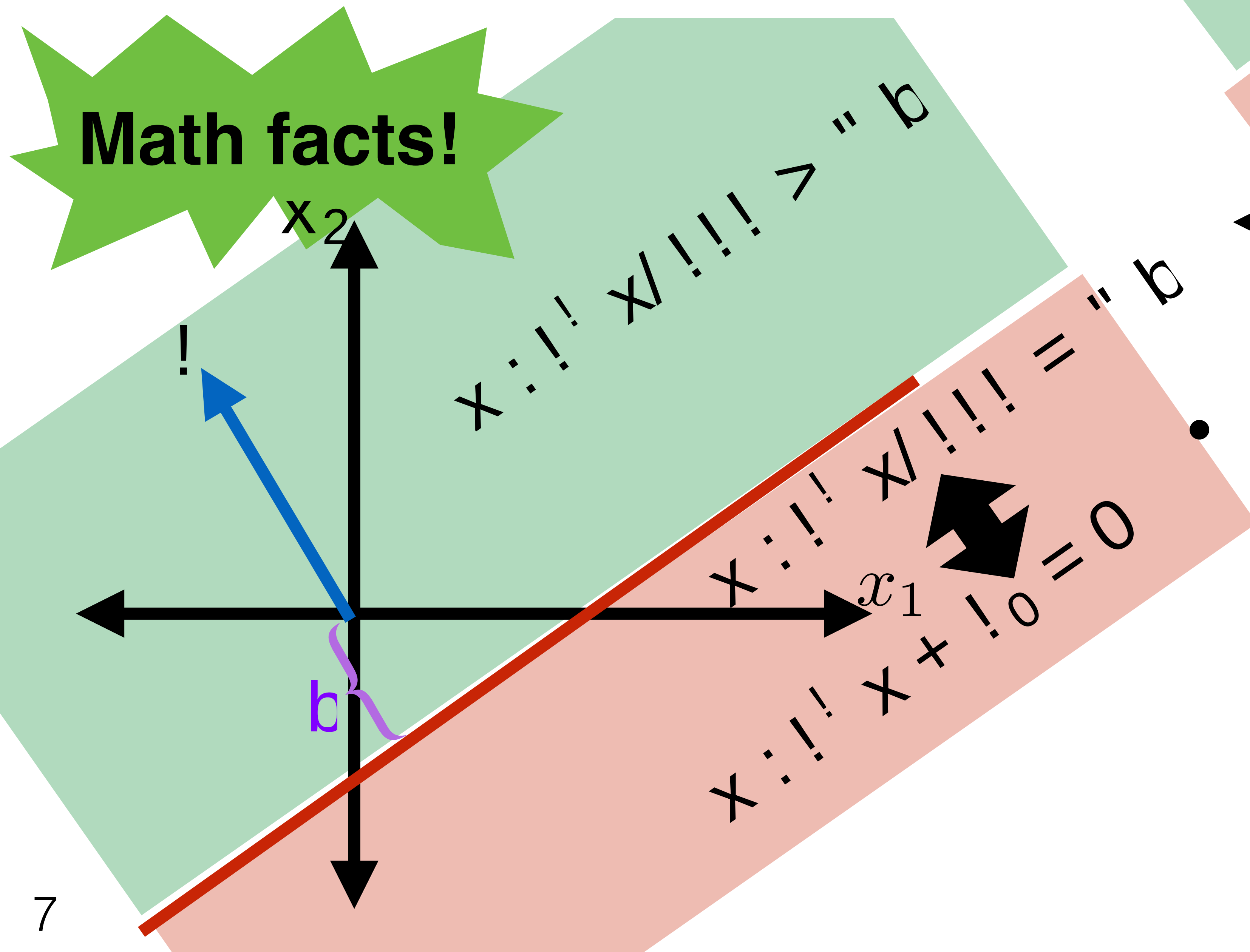

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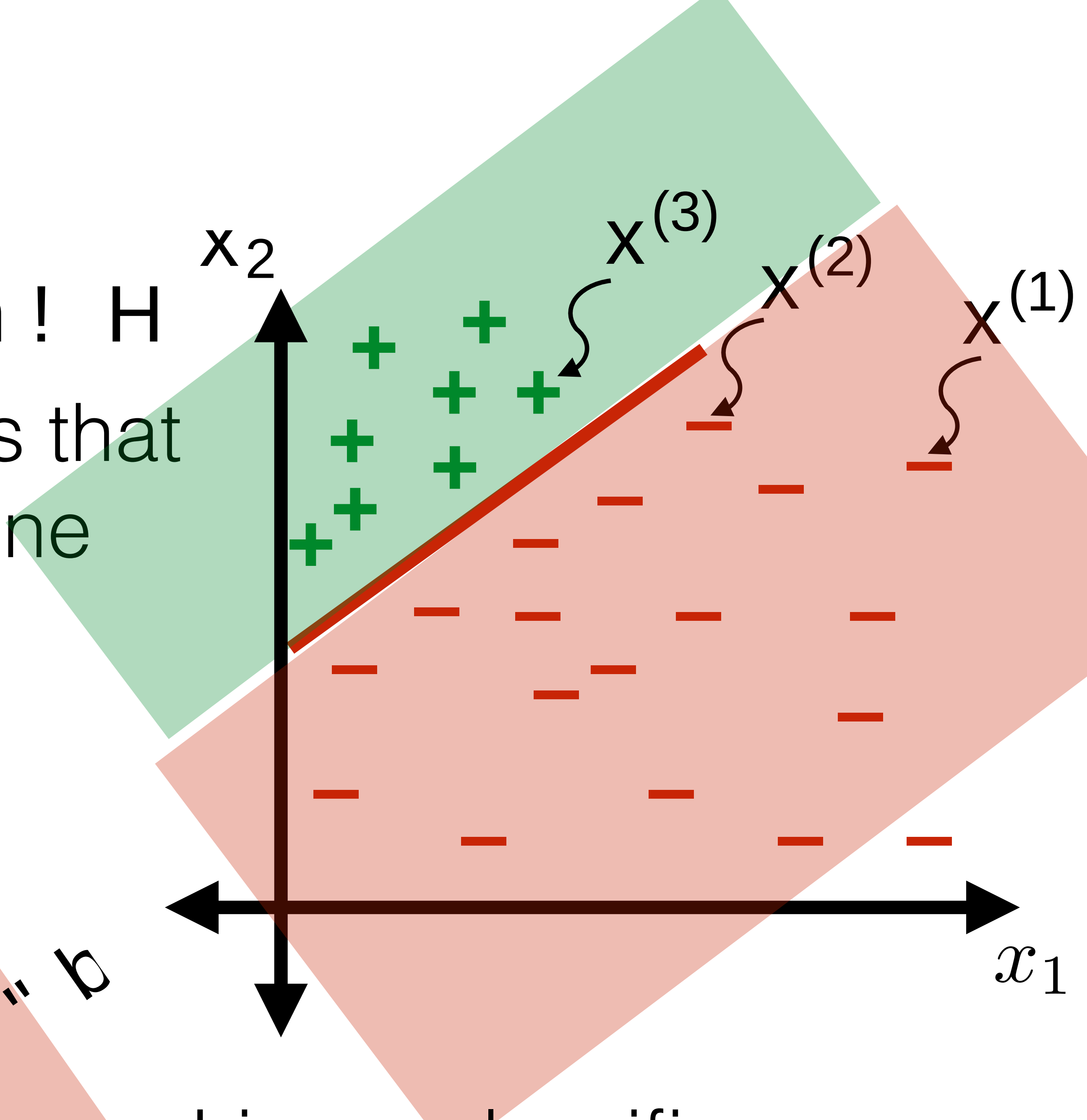
  h(x) = sign(! ! x + ! $_0$)

Linear classifiers



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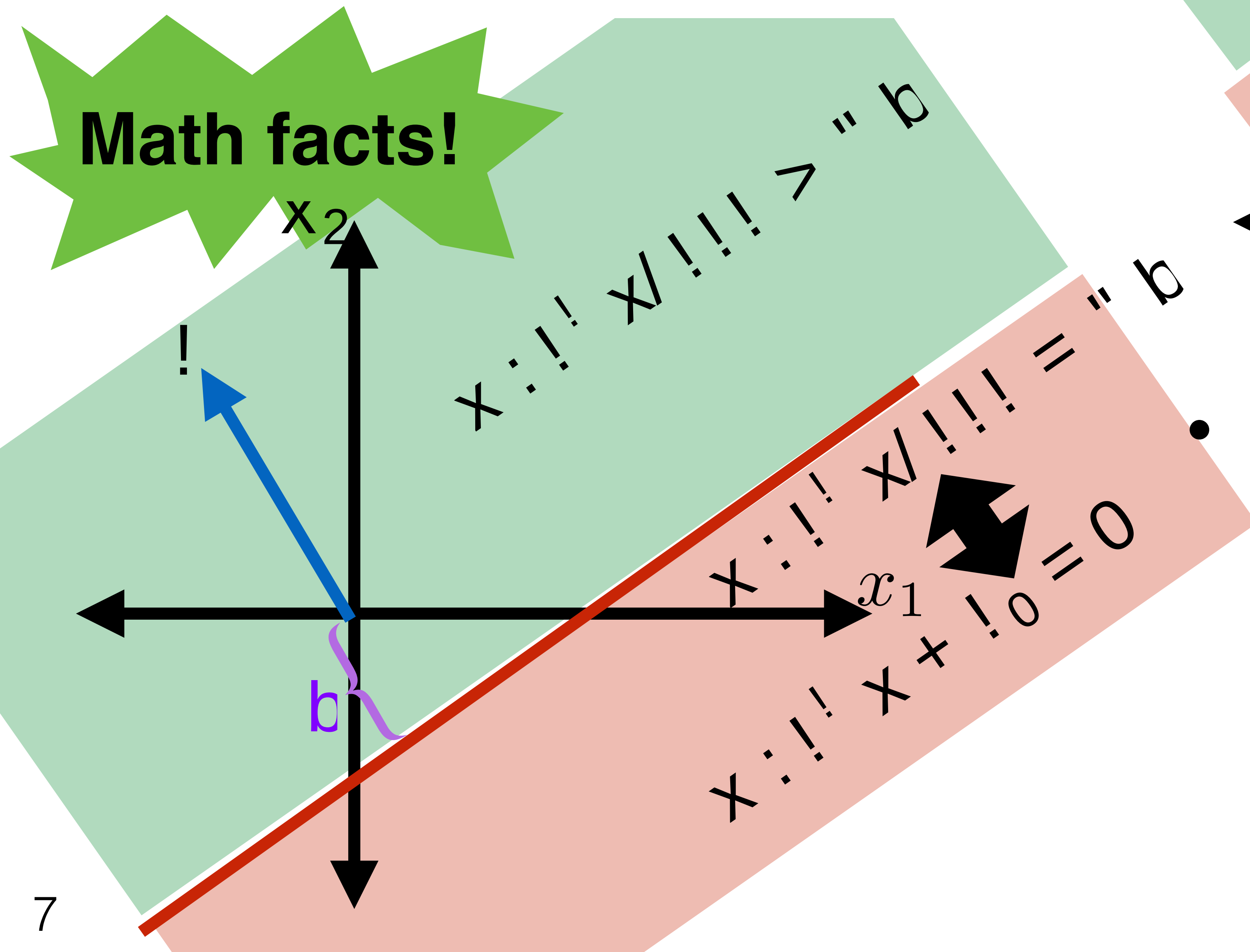

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$$h(x) = \text{sign}(!^{!}\ x + !_0)$$

$$= \begin{cases} +1 \text{ if } !^{!}\ x + !_0 > 0 \\ !\ 1 \text{ if } !^{!}\ x + !_0 < 0 \end{cases}$$

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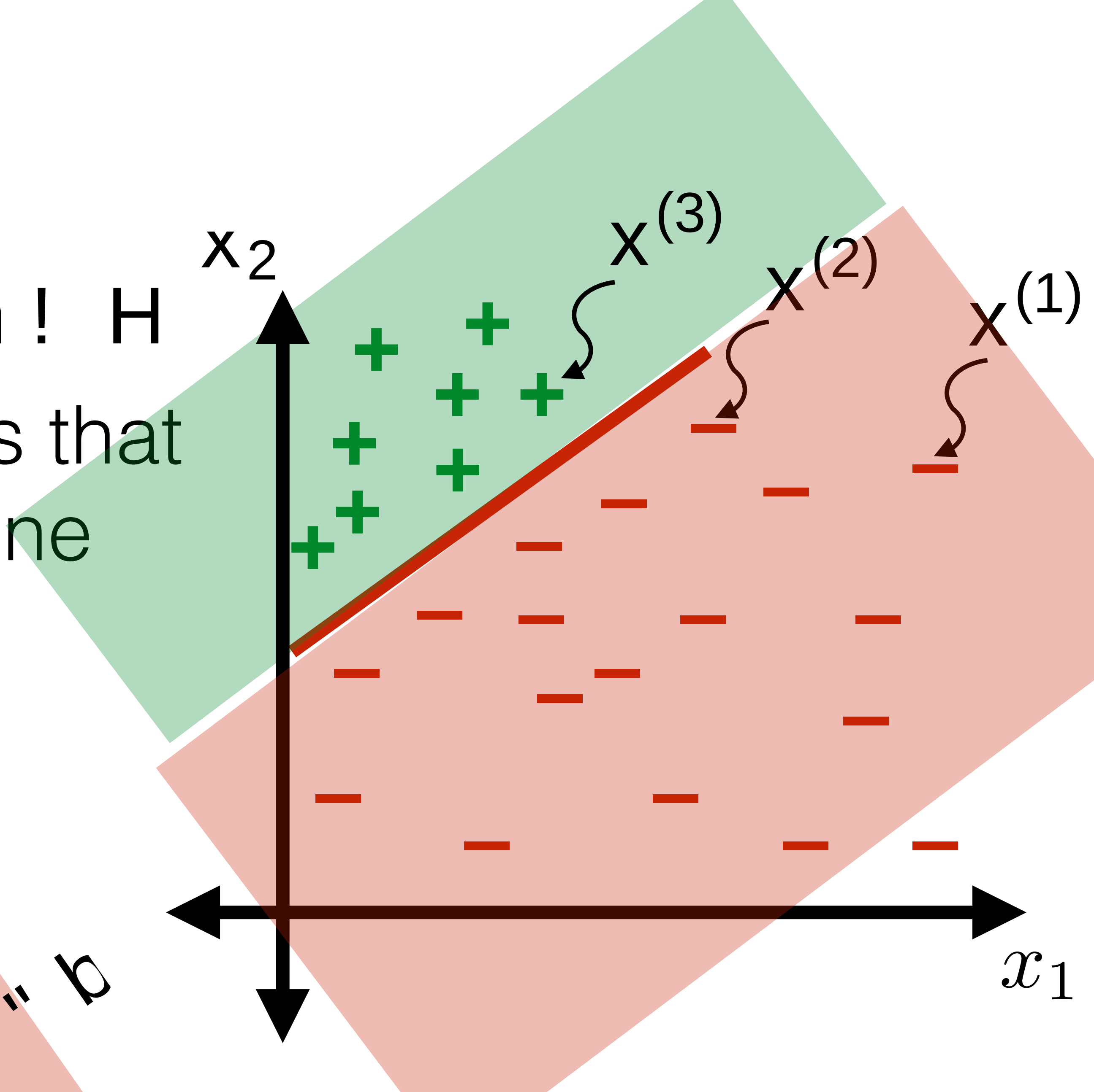

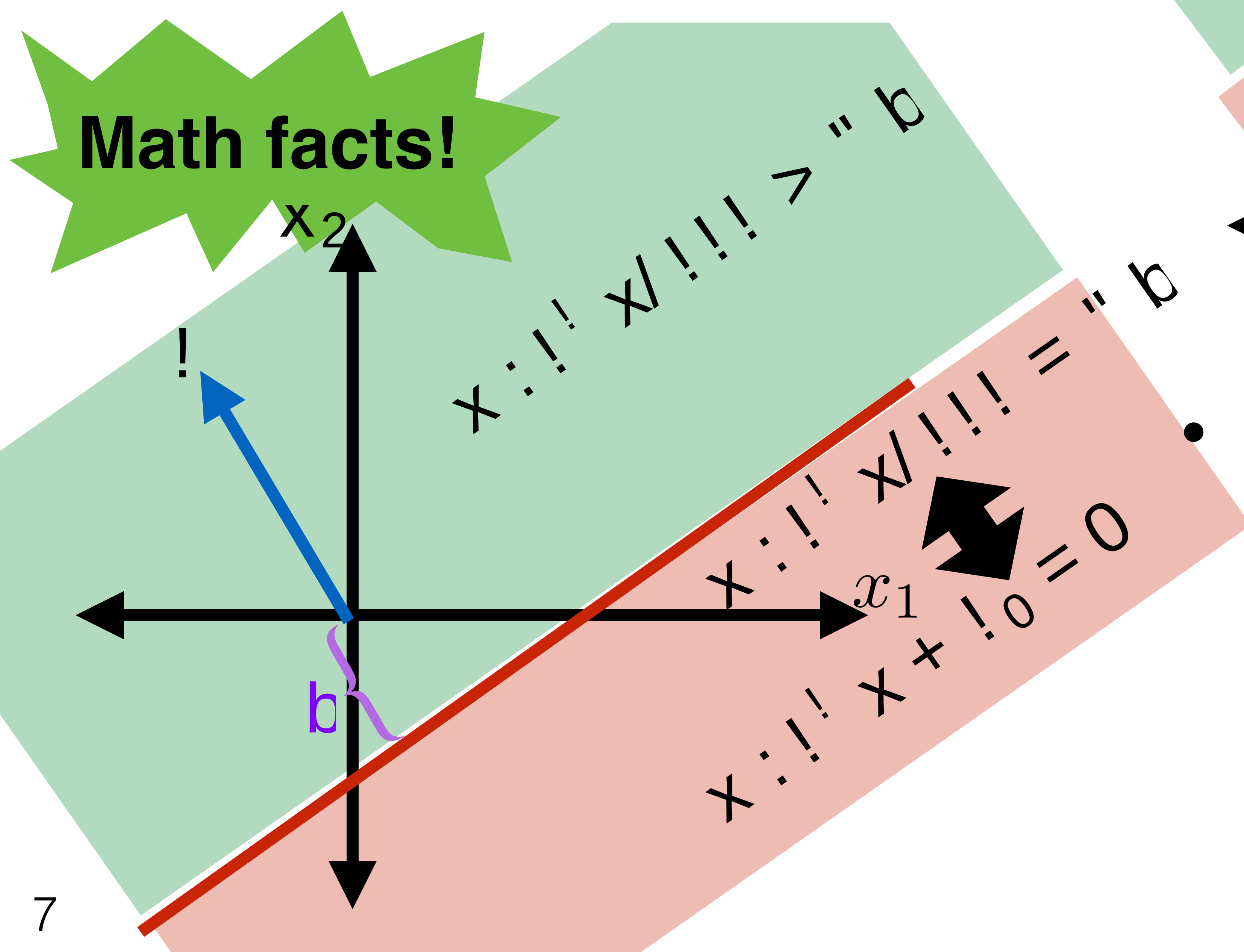

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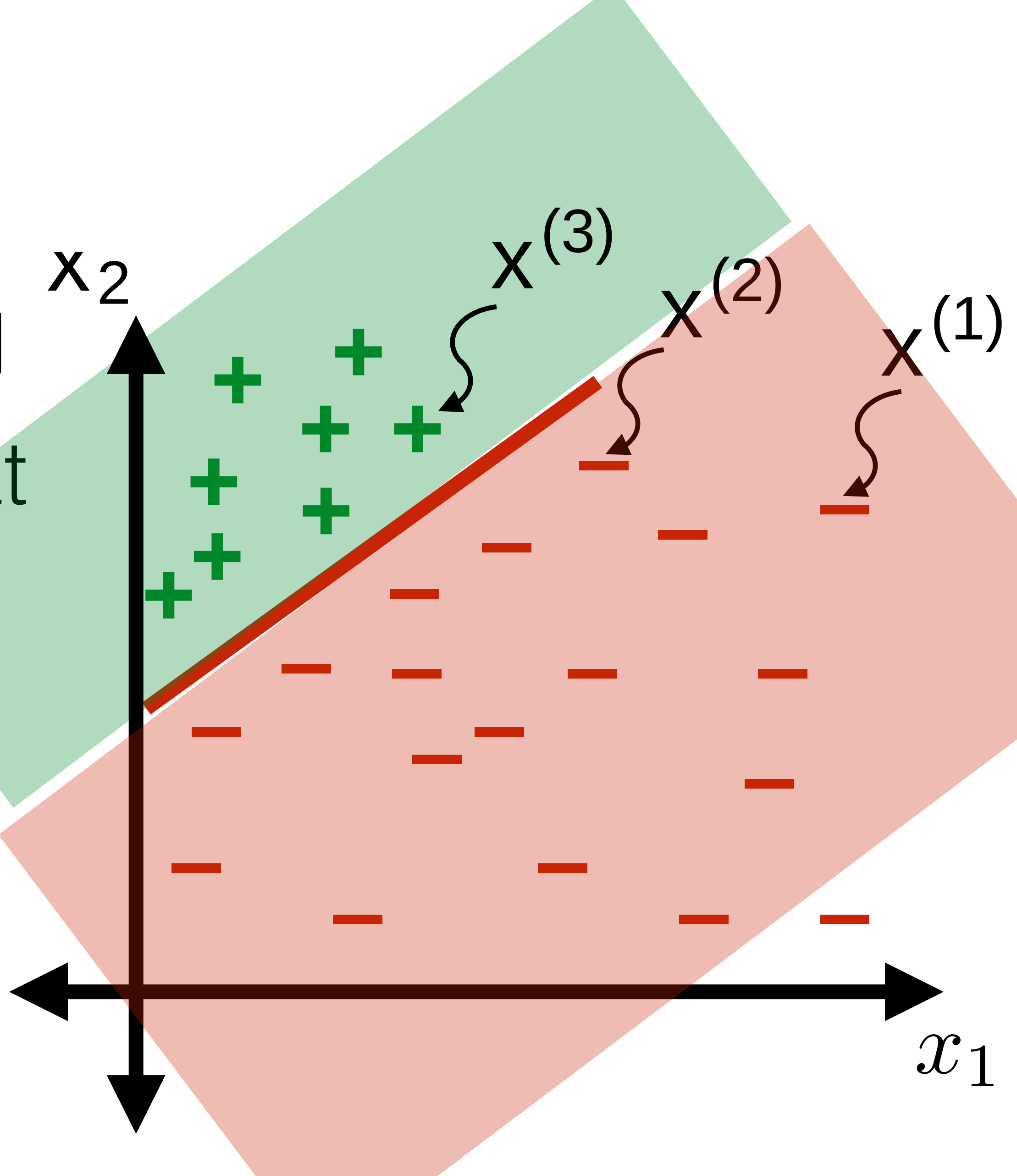

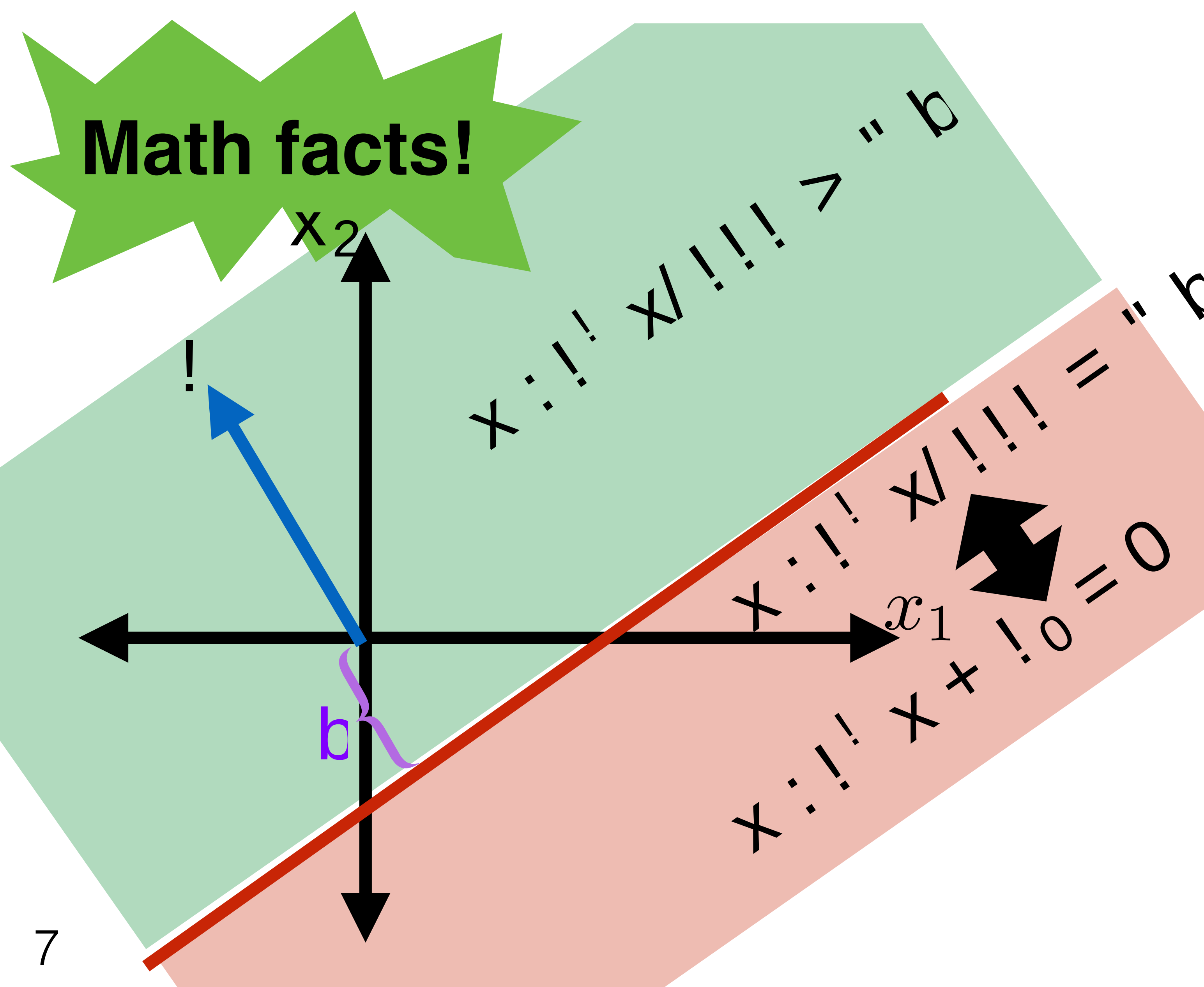

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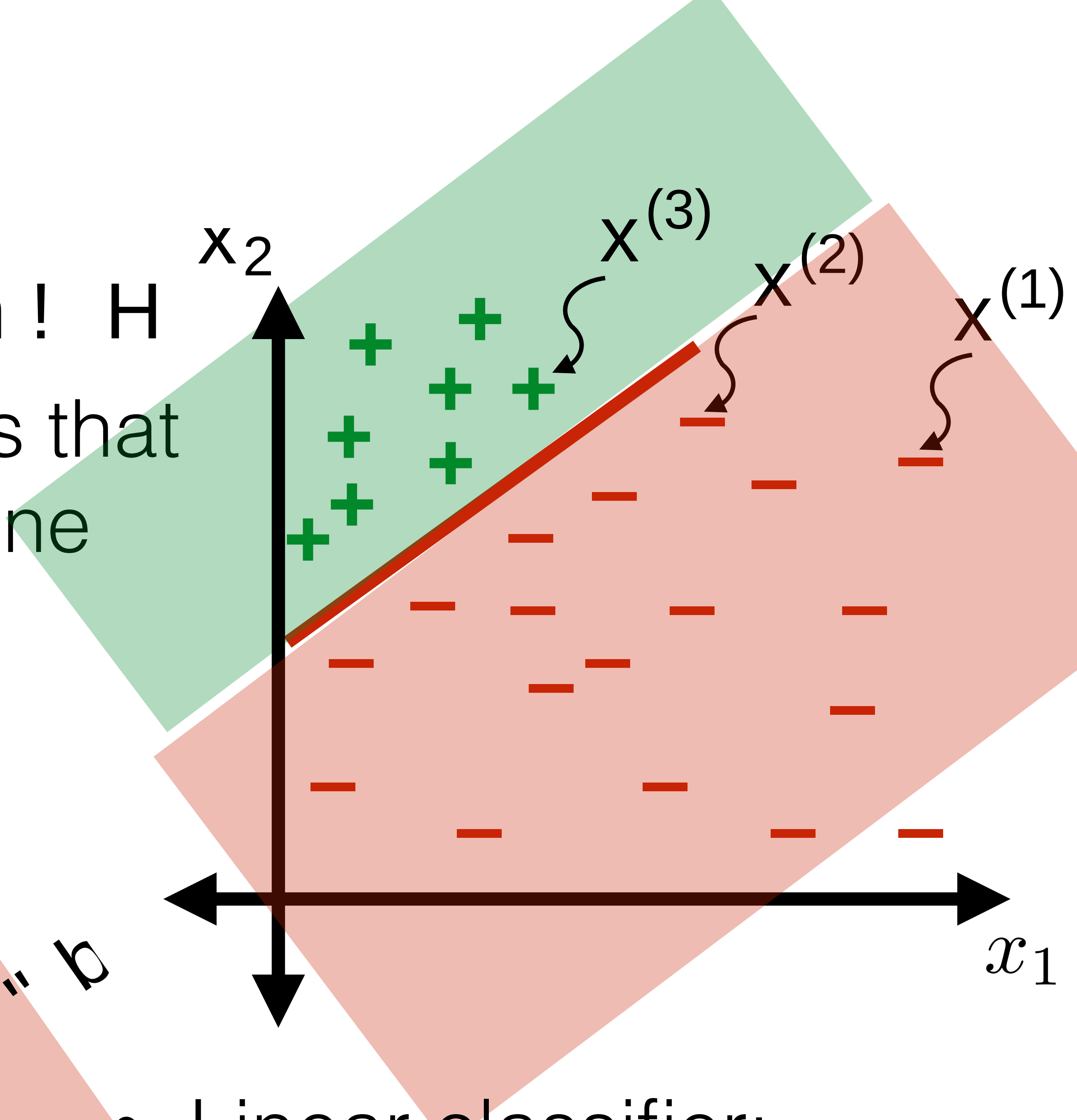

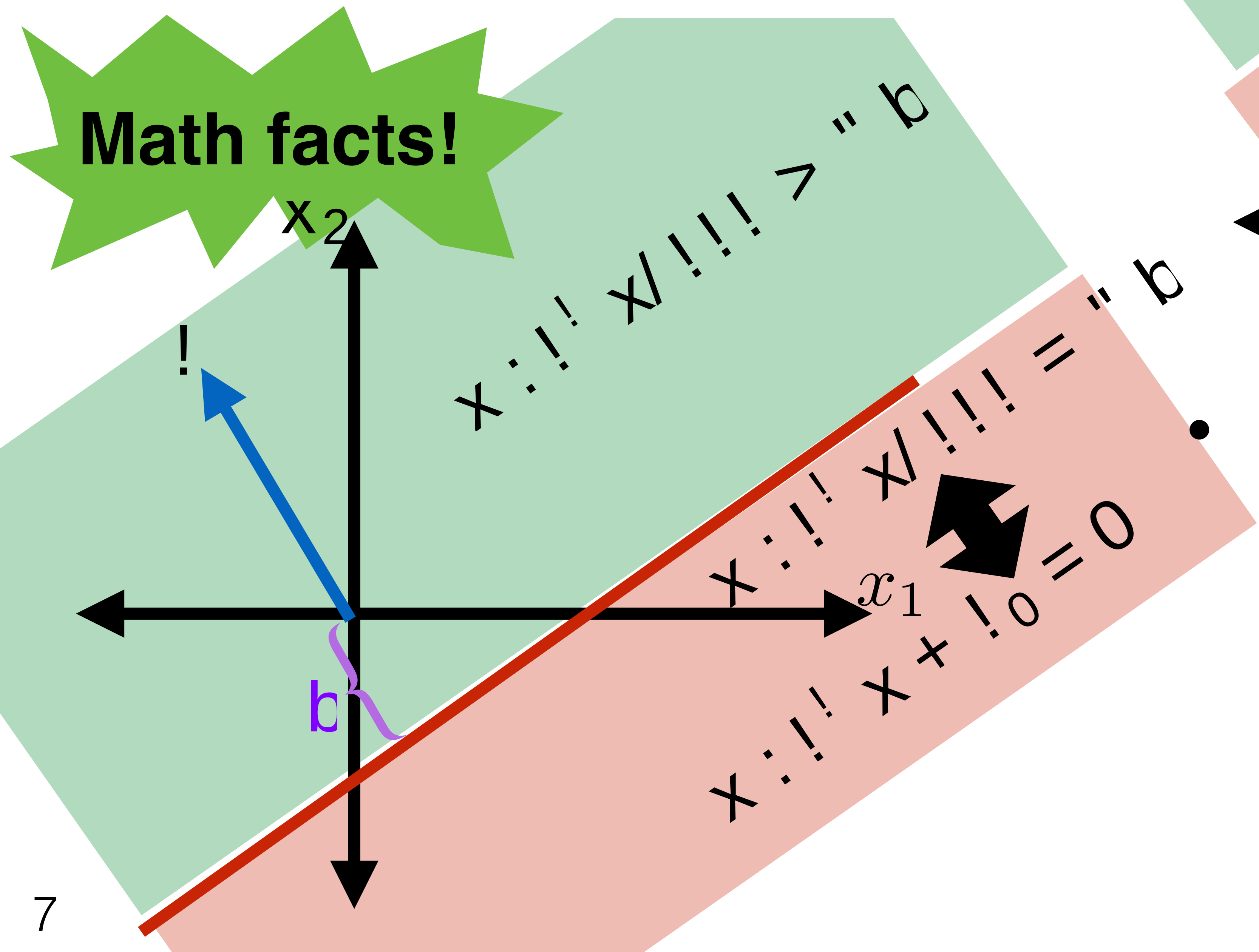

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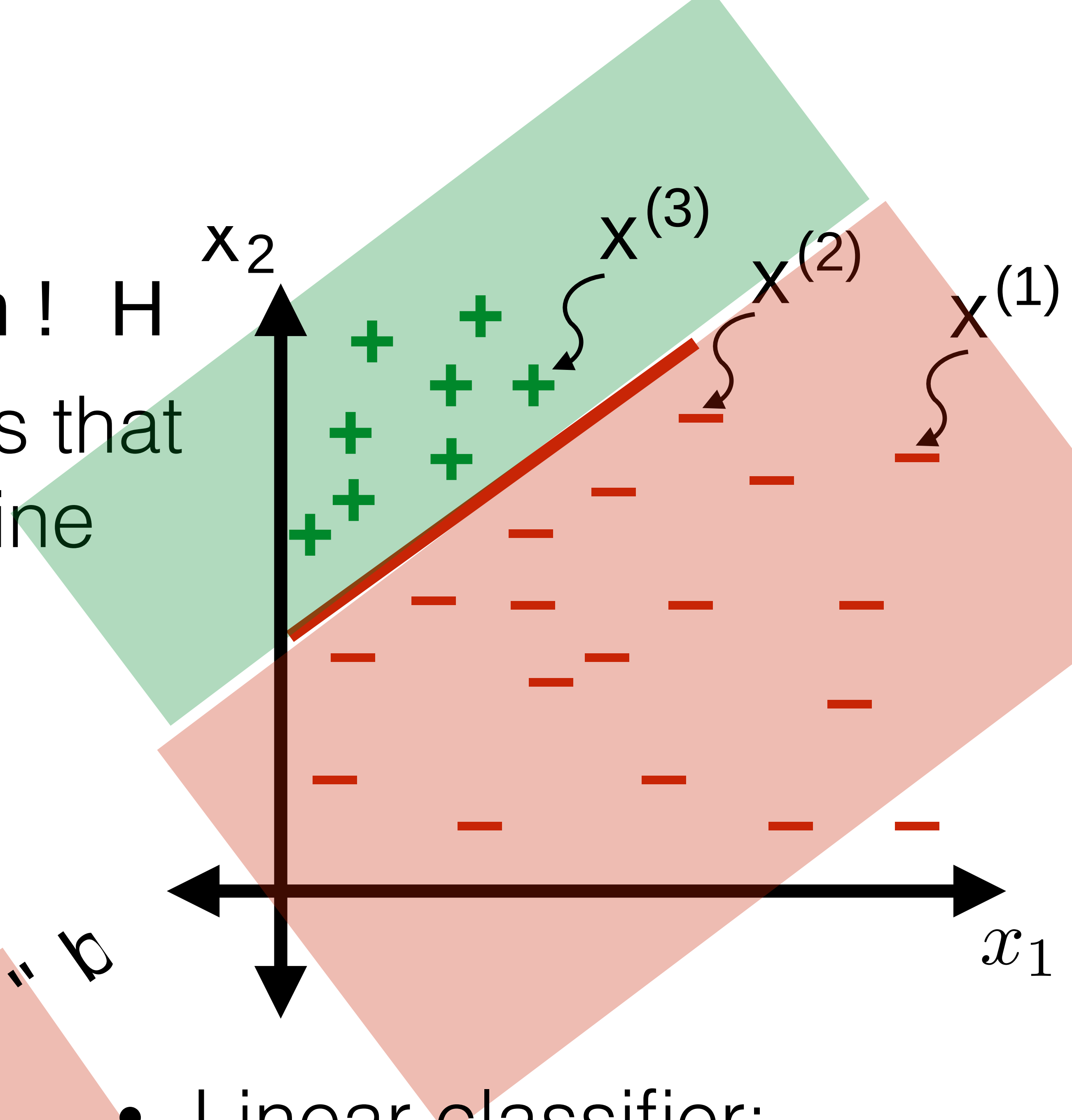

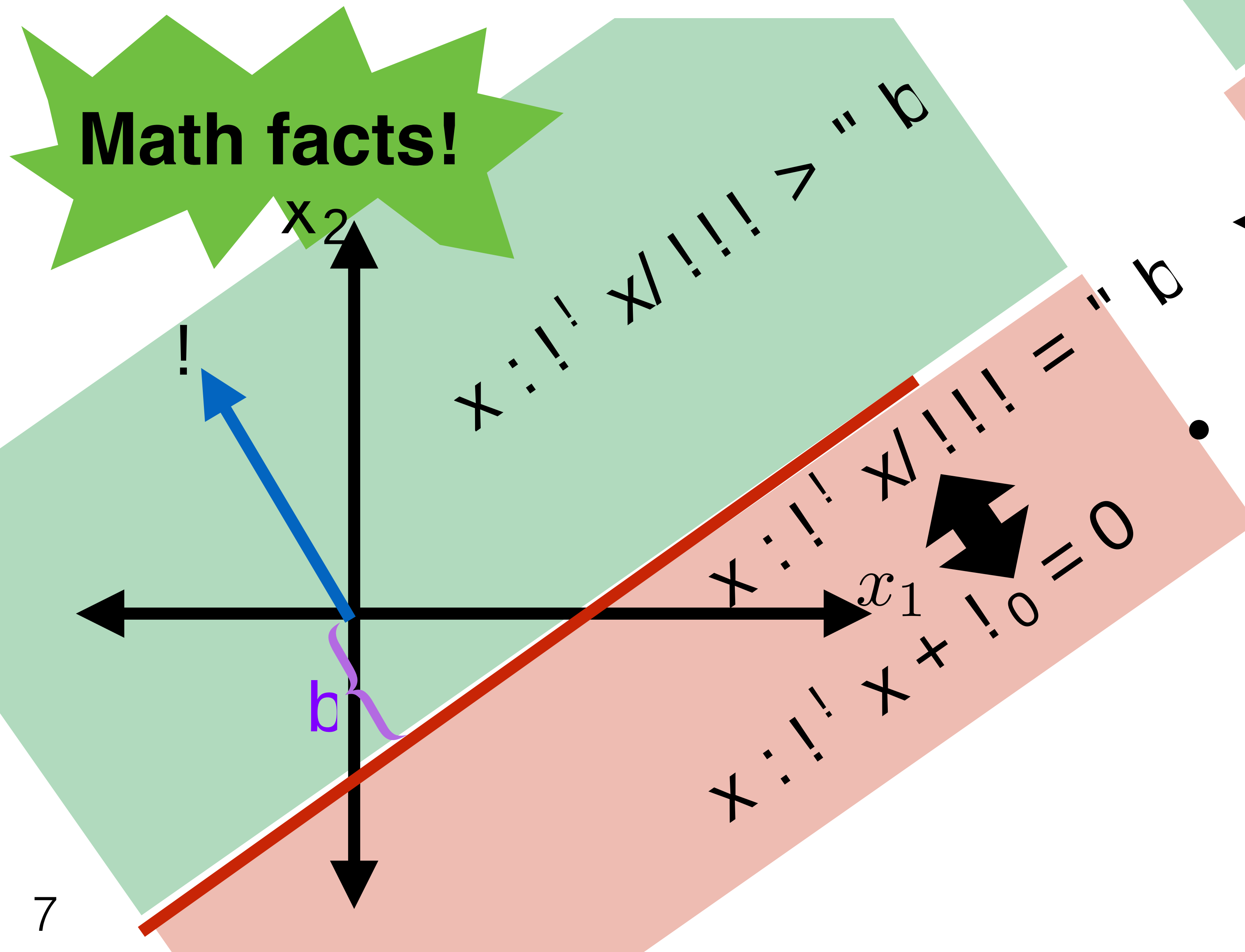

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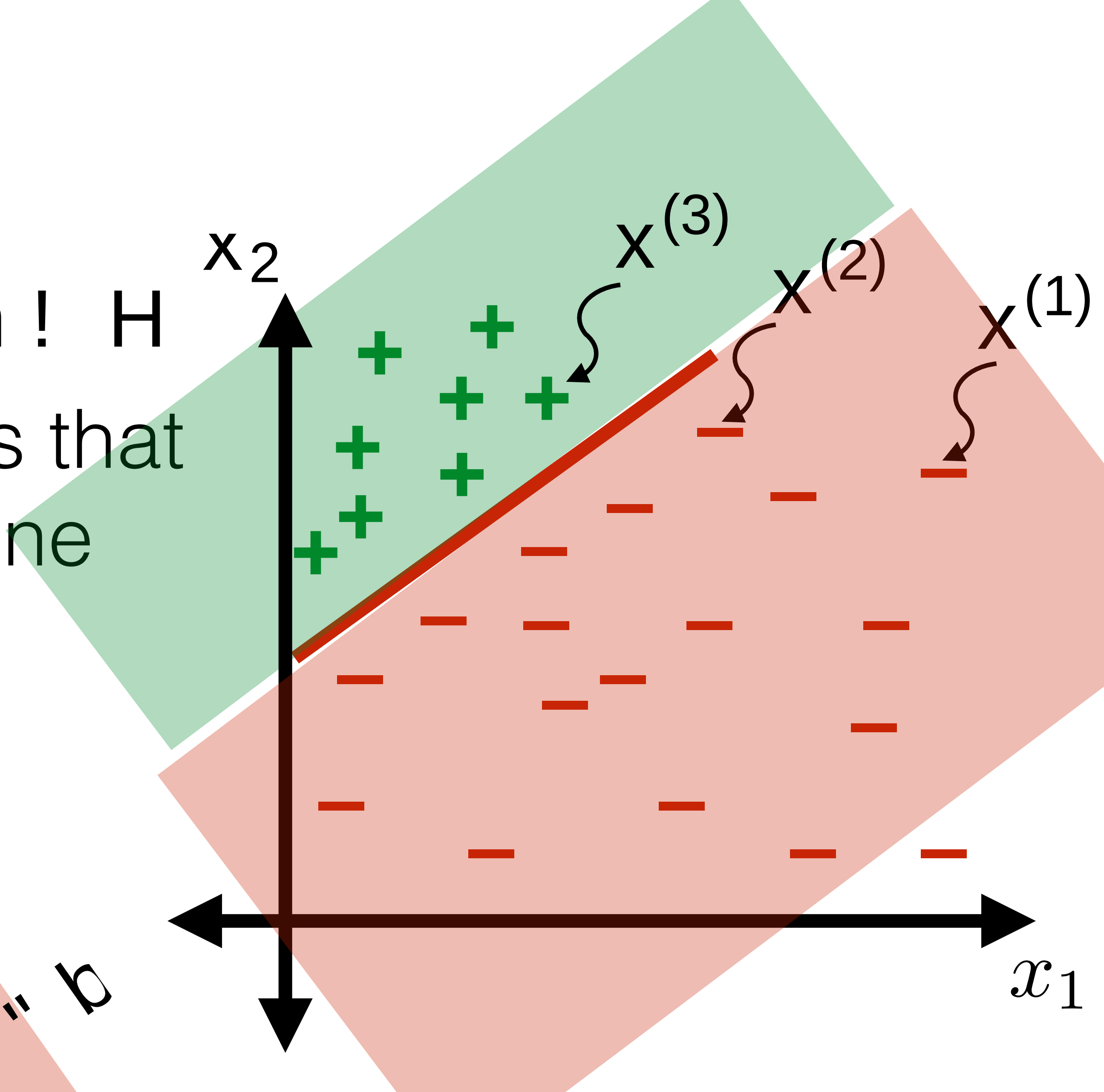

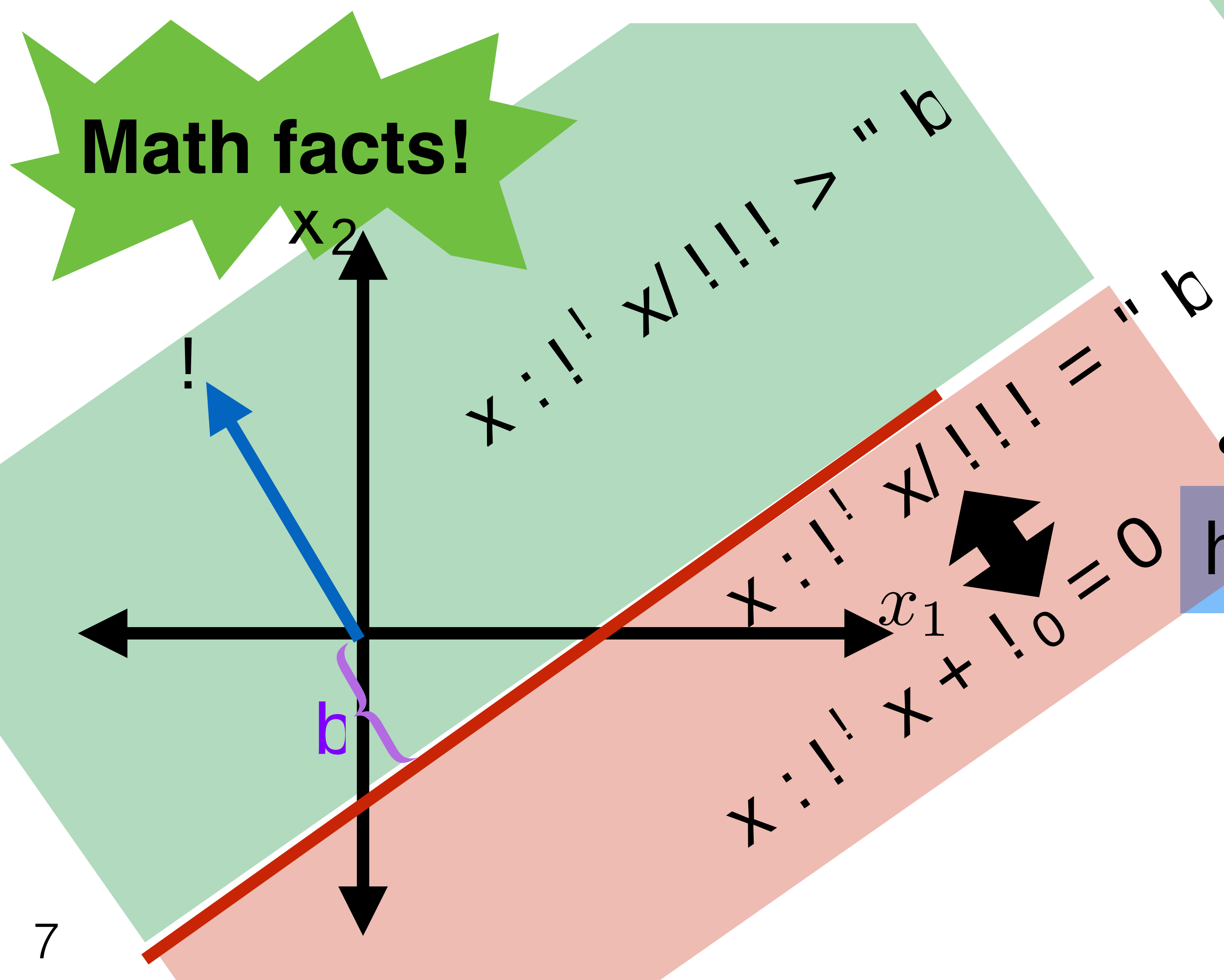

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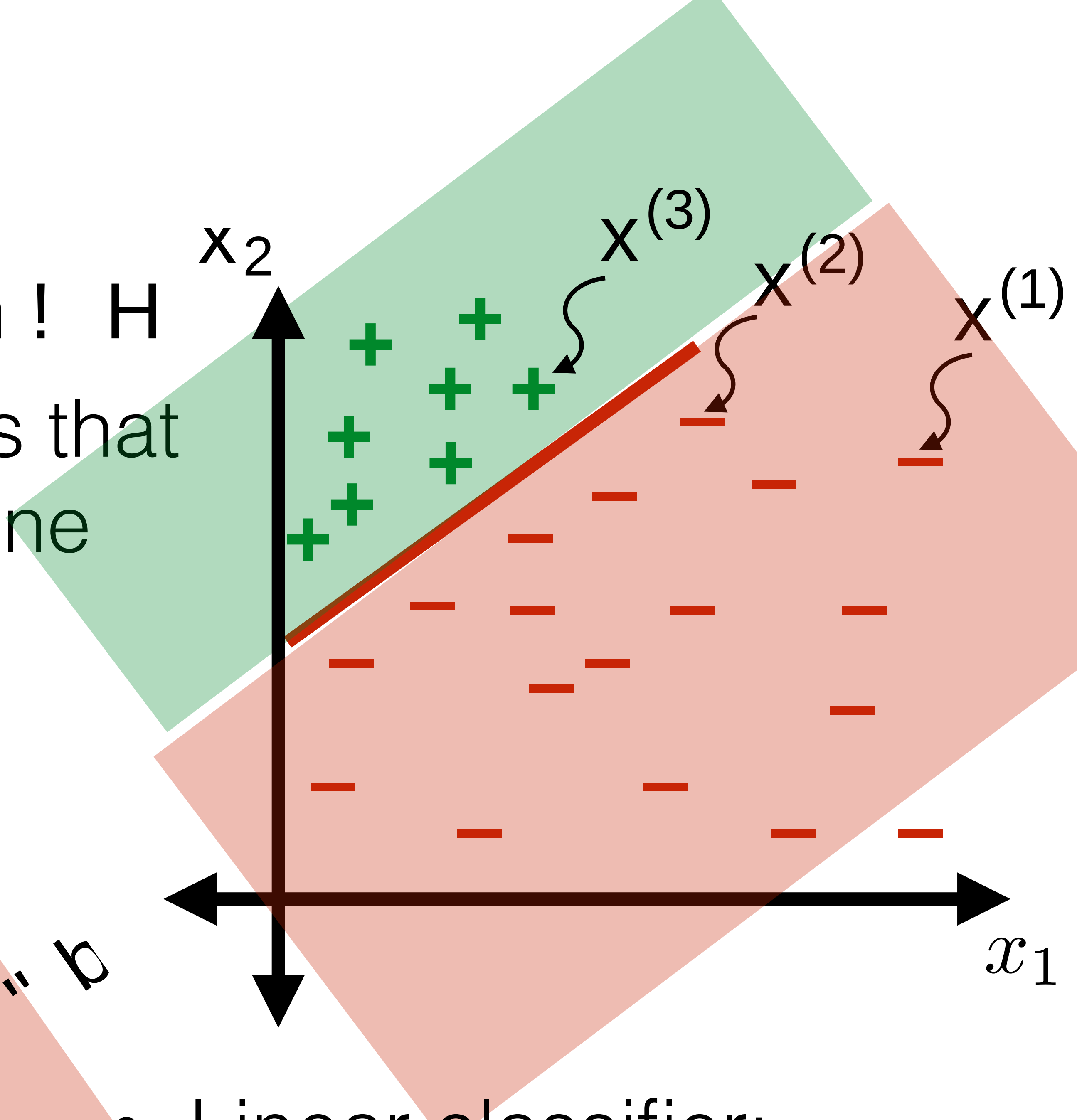

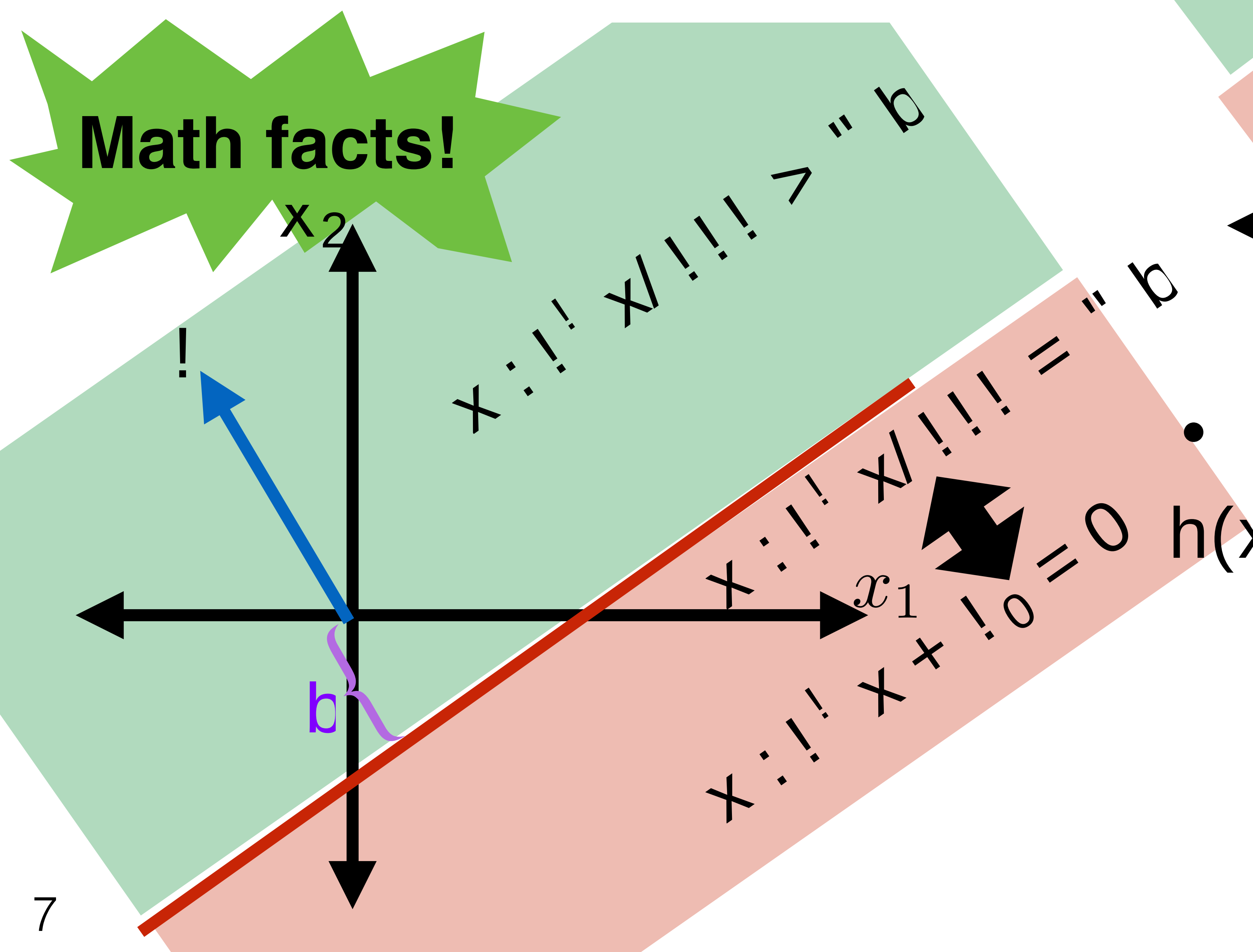

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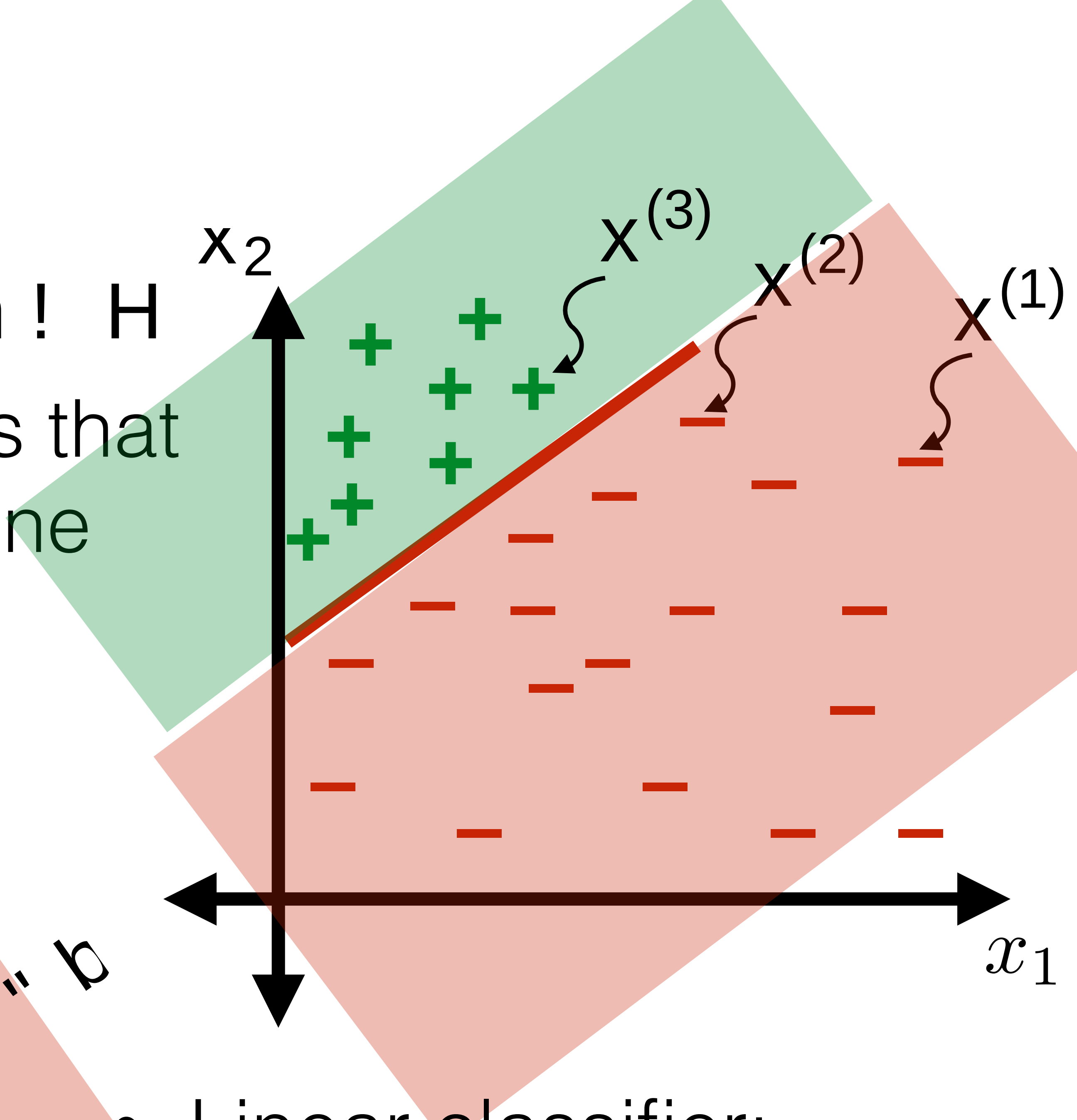

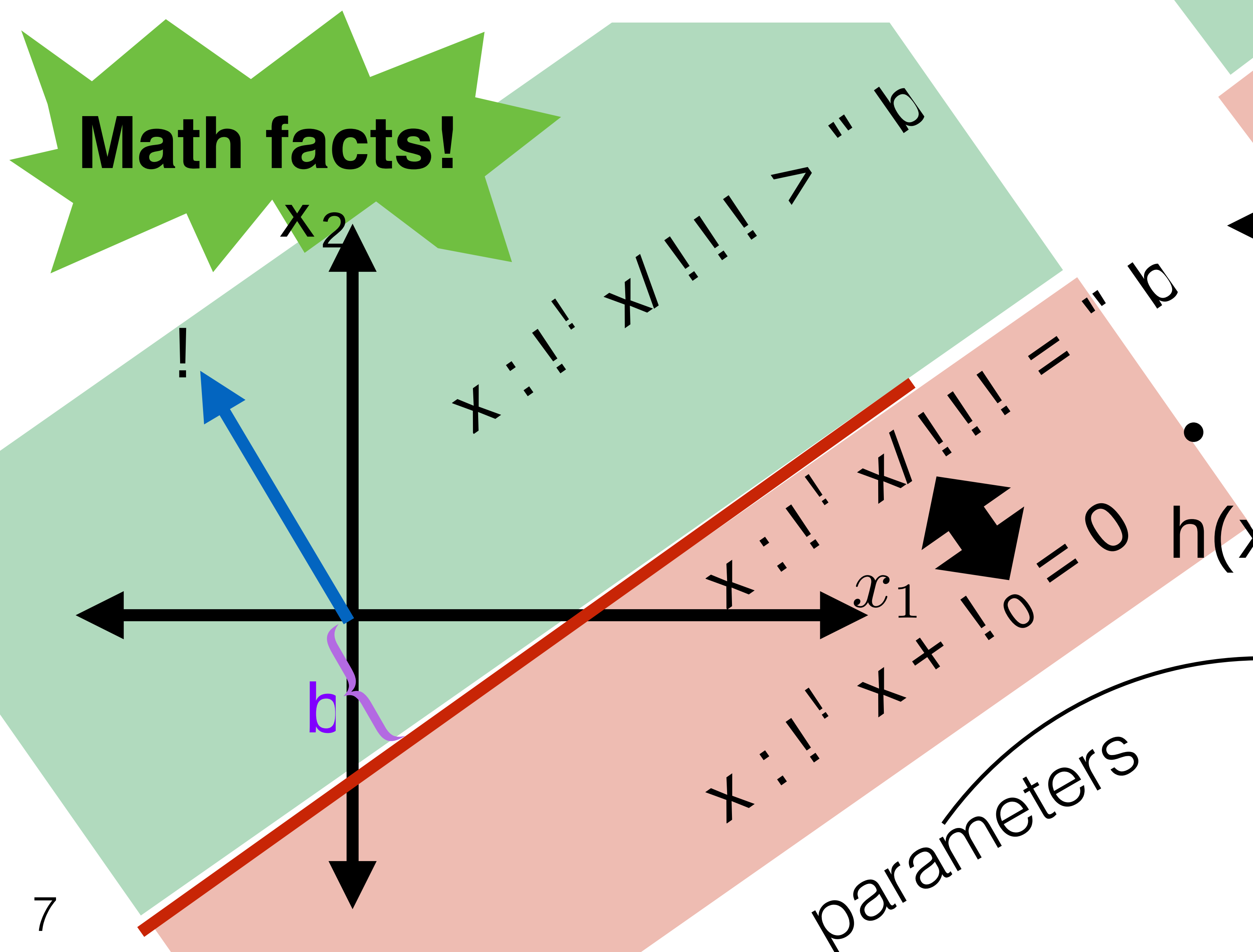

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parameters

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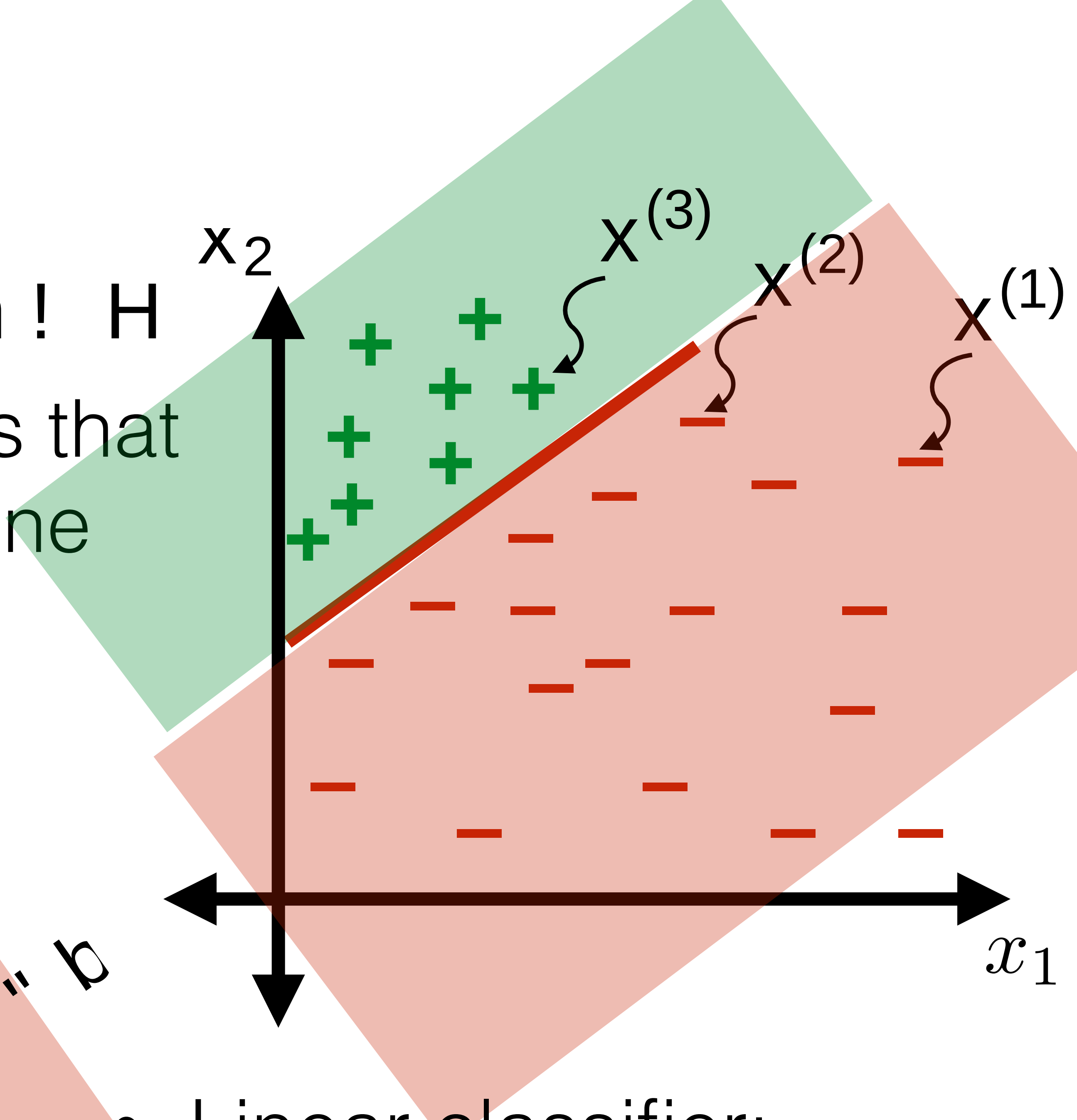

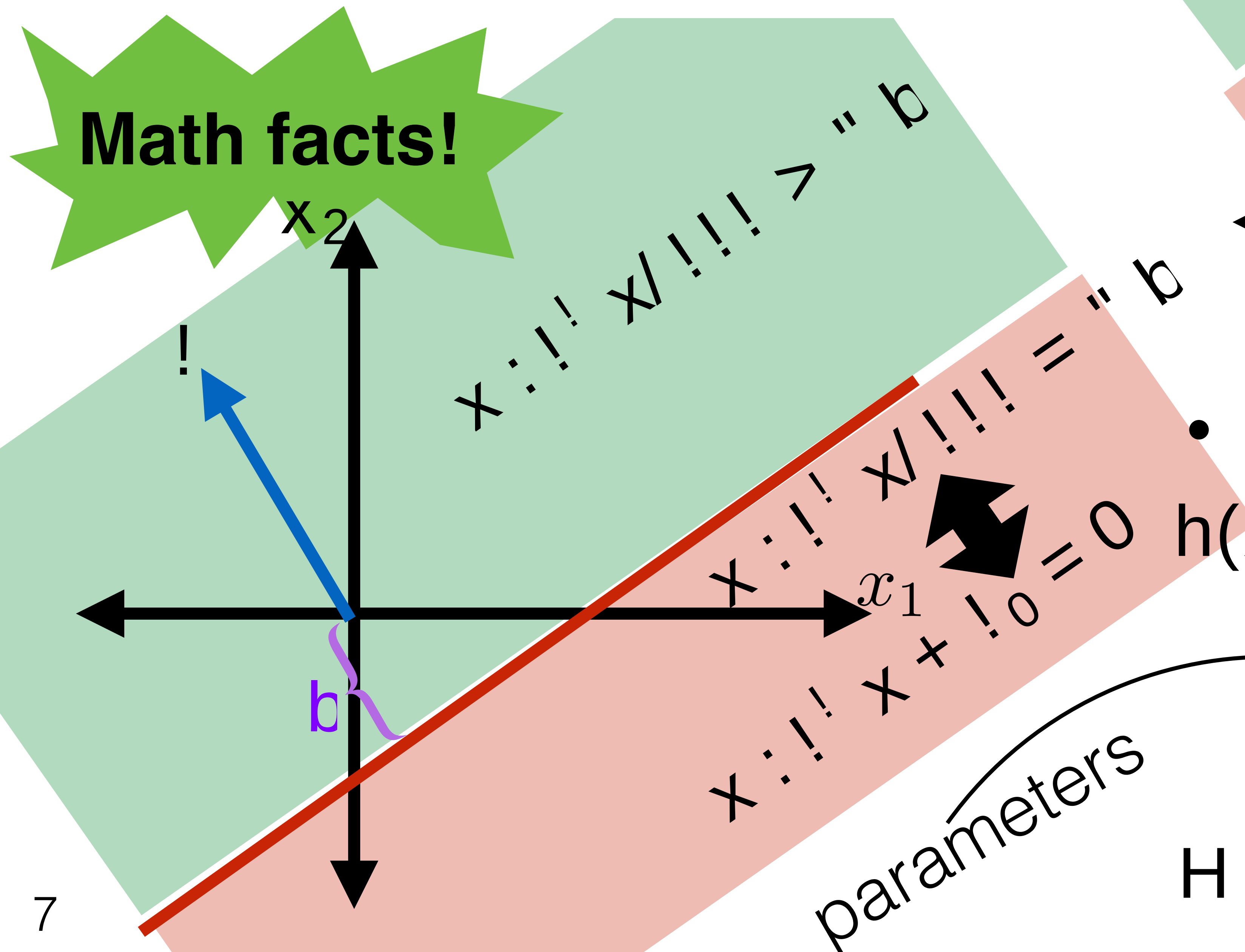

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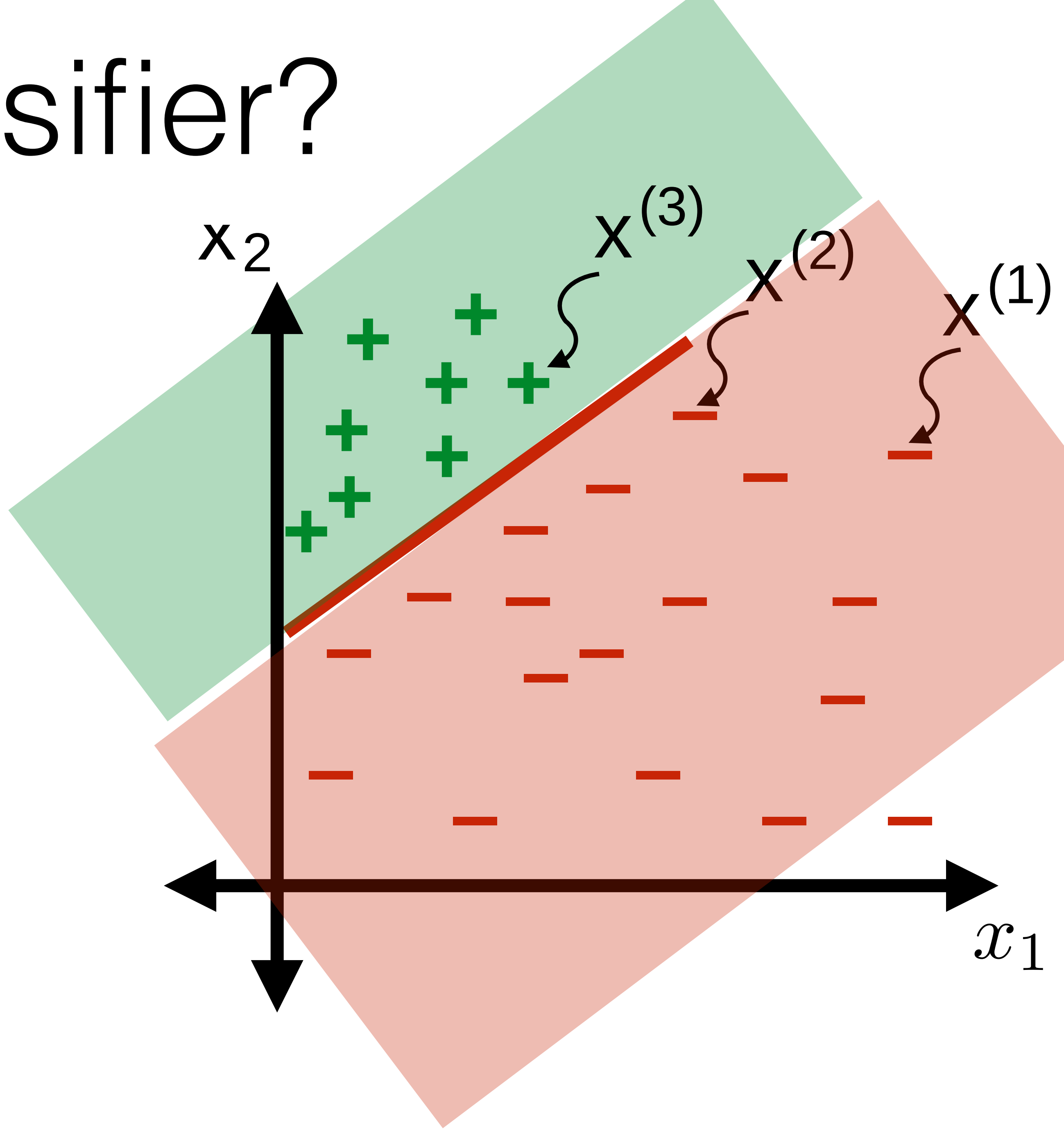
H = set of all such h

How good is a classifier?



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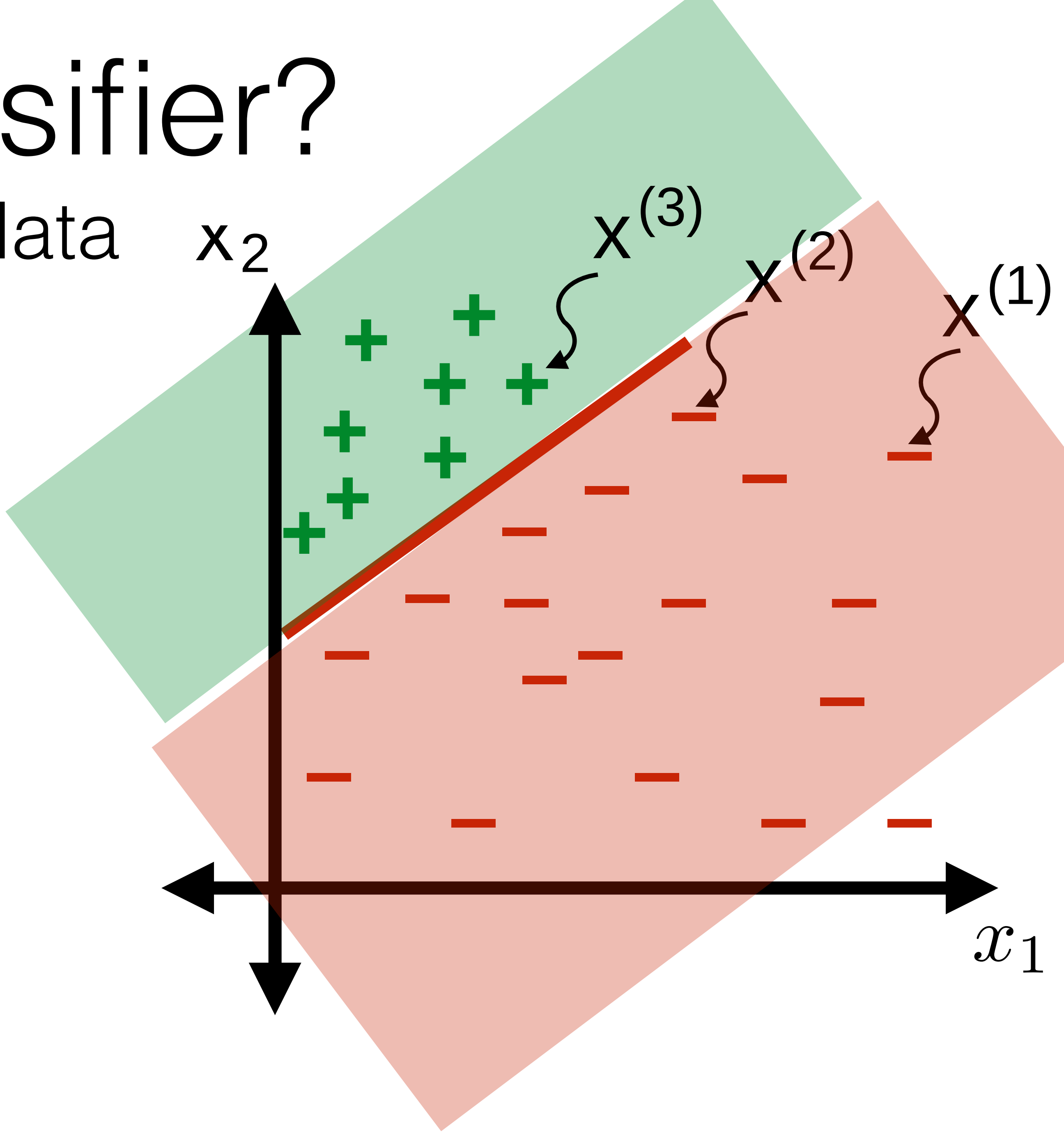
- Should predict well on future data



How good is a classifier?

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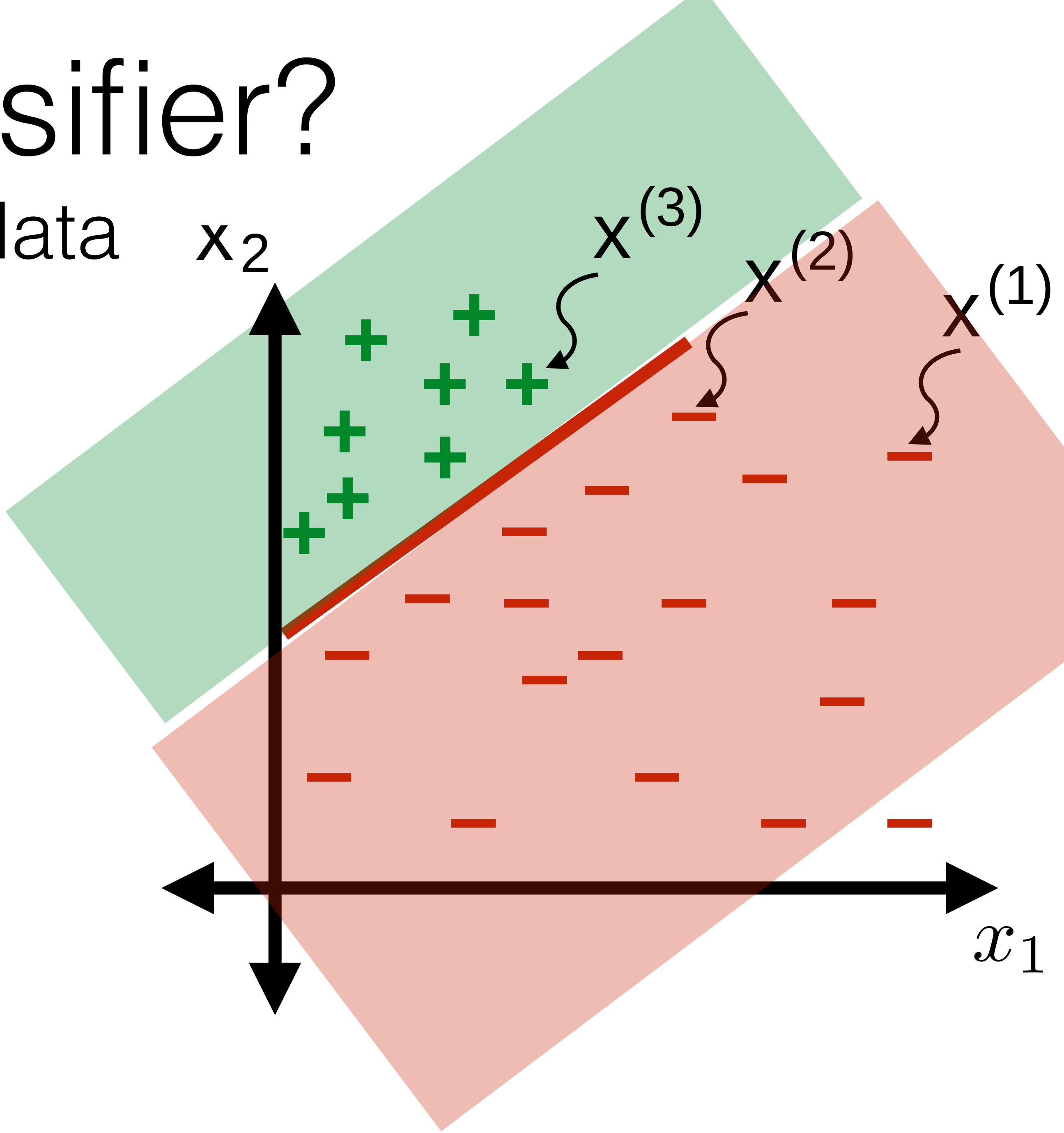
- How good is a classifier at a single point?



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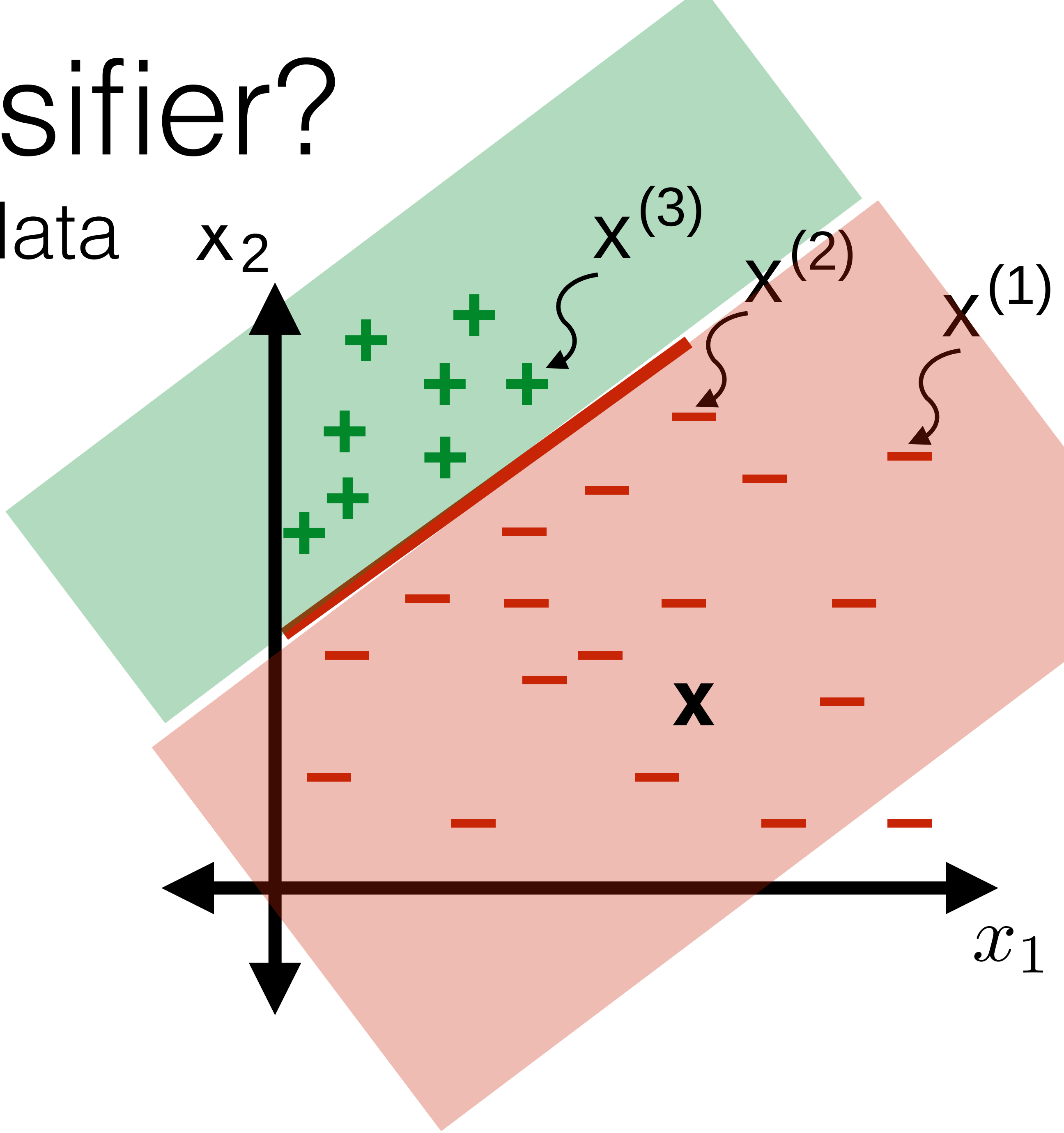

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- Should predict well on future data
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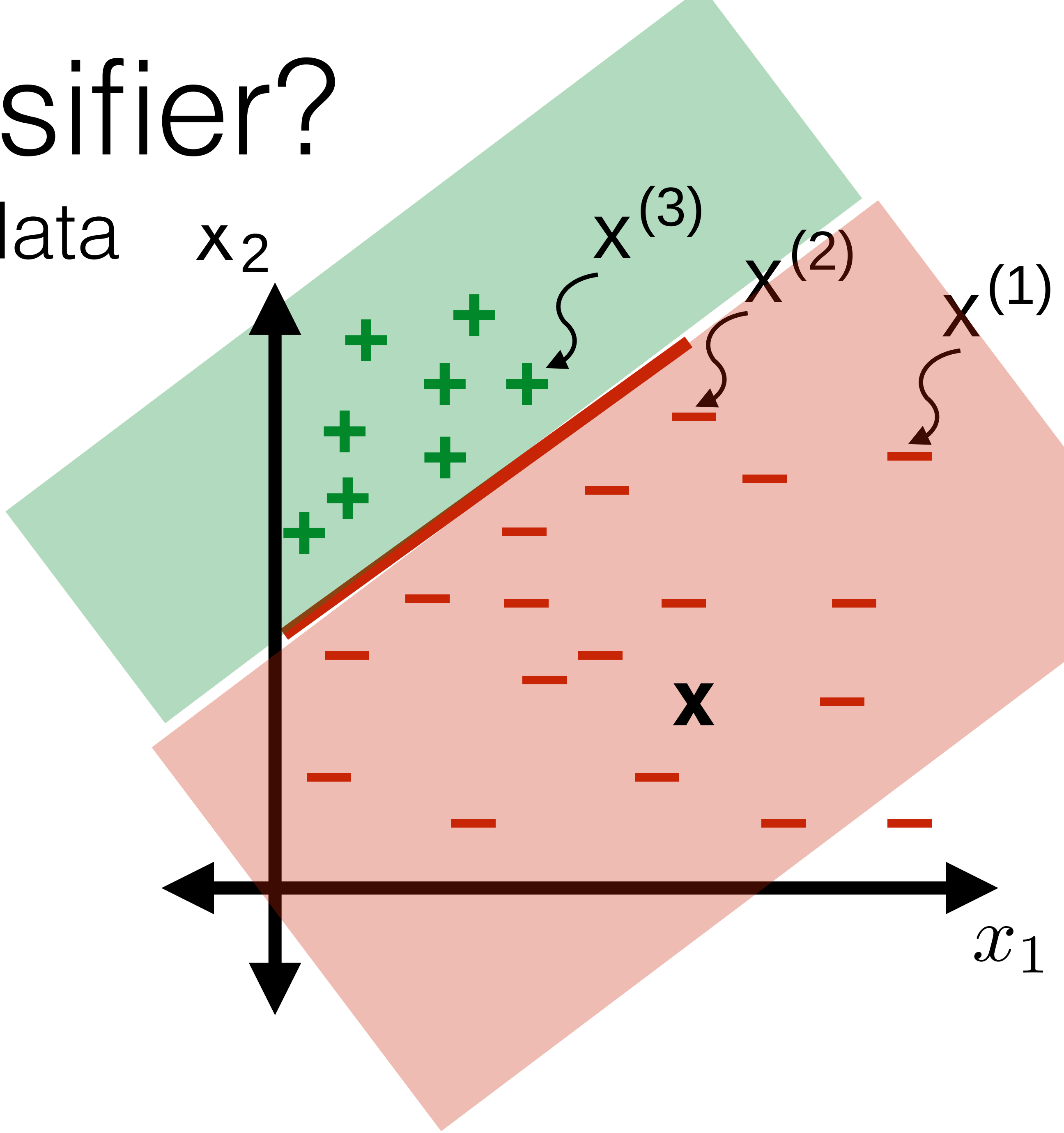

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g: guess,
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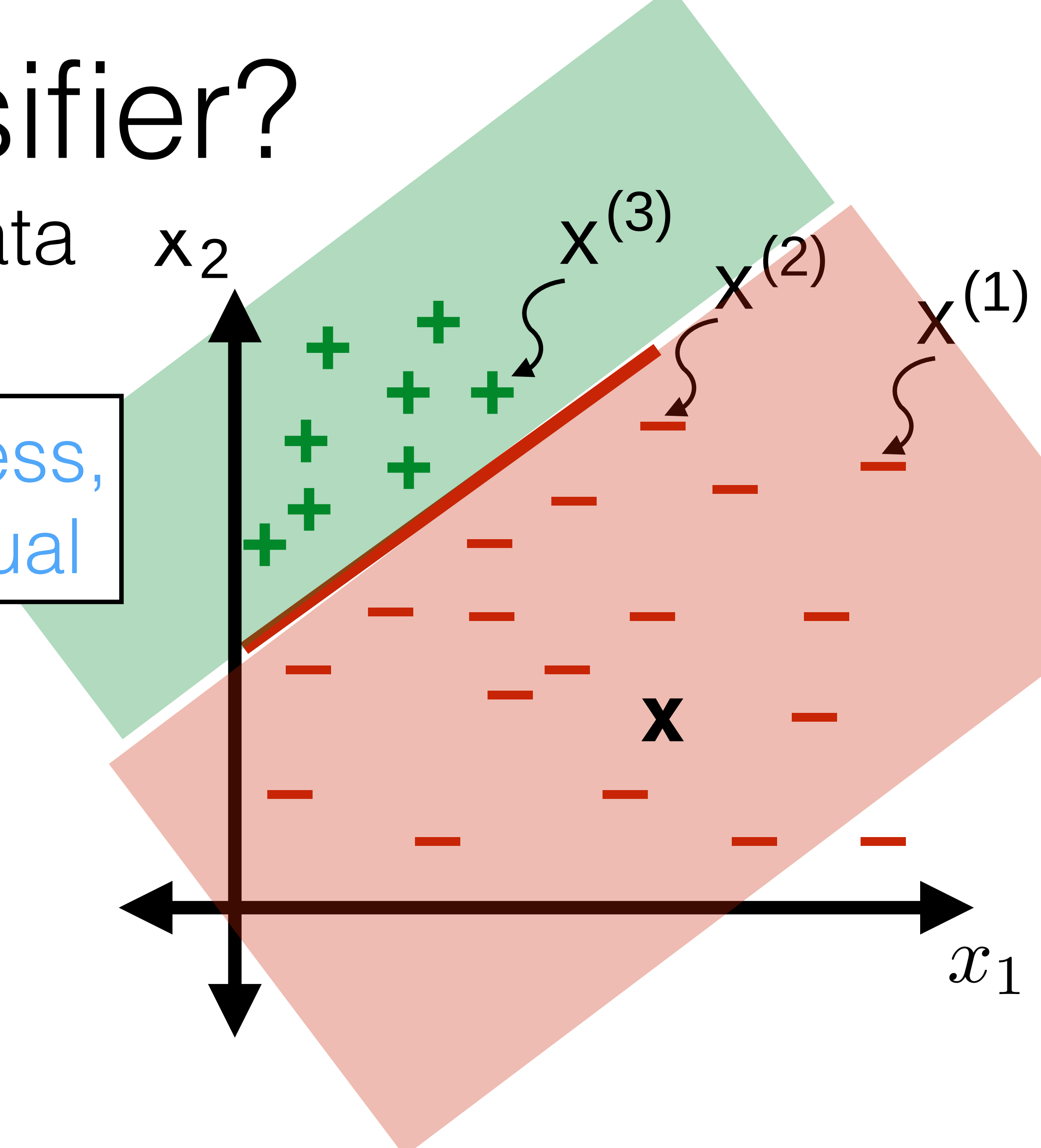

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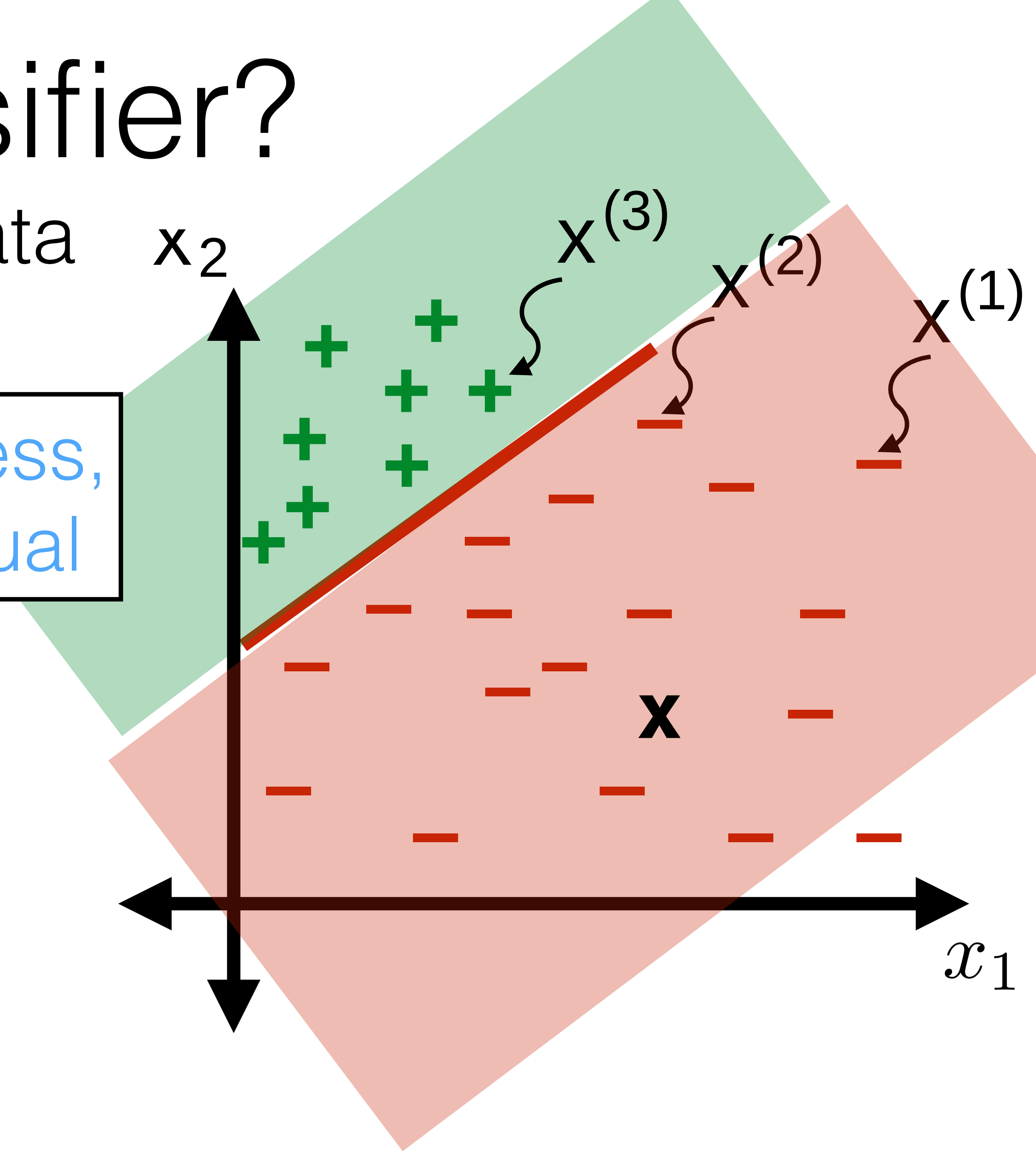
  - Example: 0-1 loss



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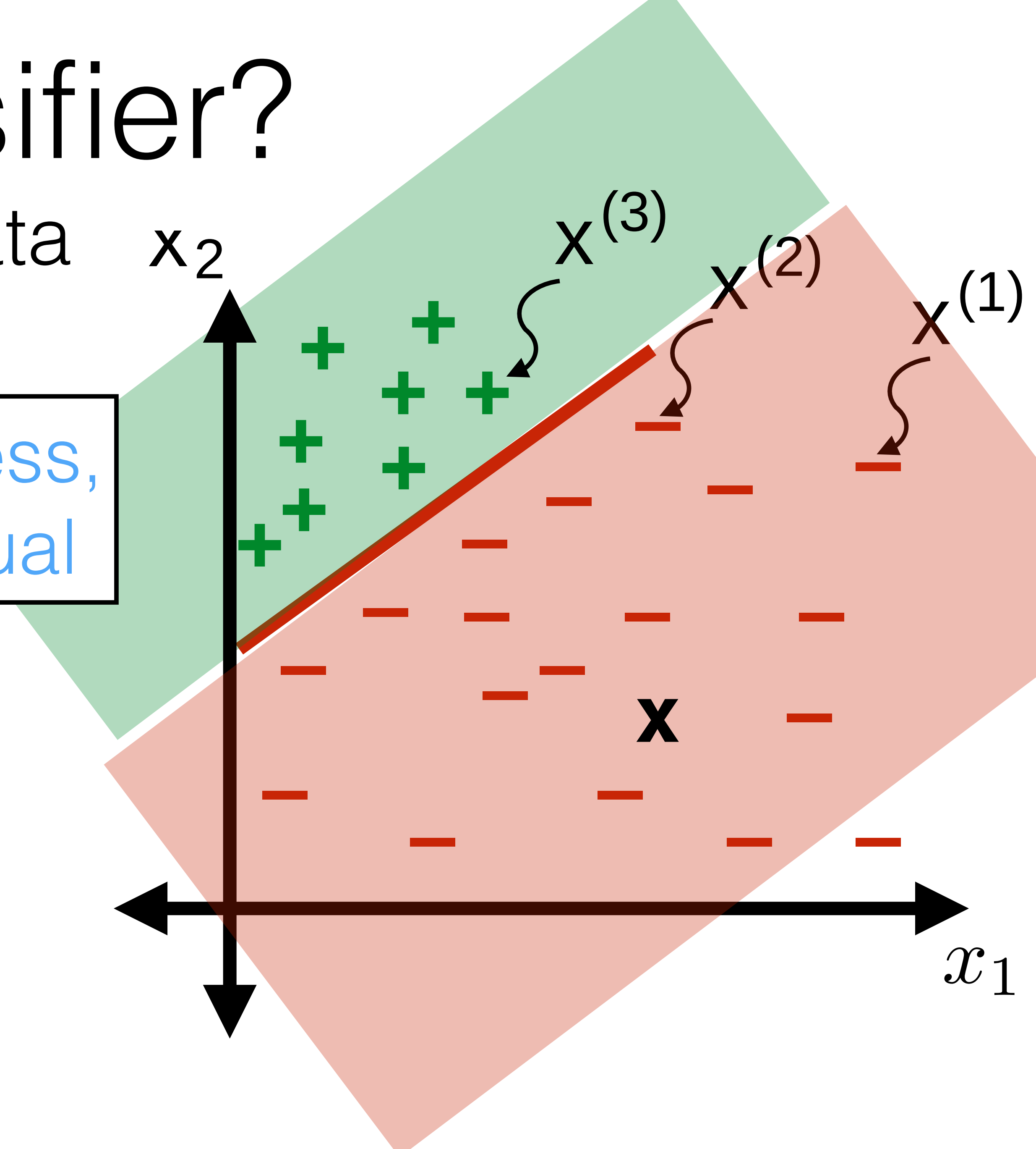
$$L(g, a) = \begin{cases} 0 & \text{if } g = a \\ 1 & \text{else} \end{cases}$$



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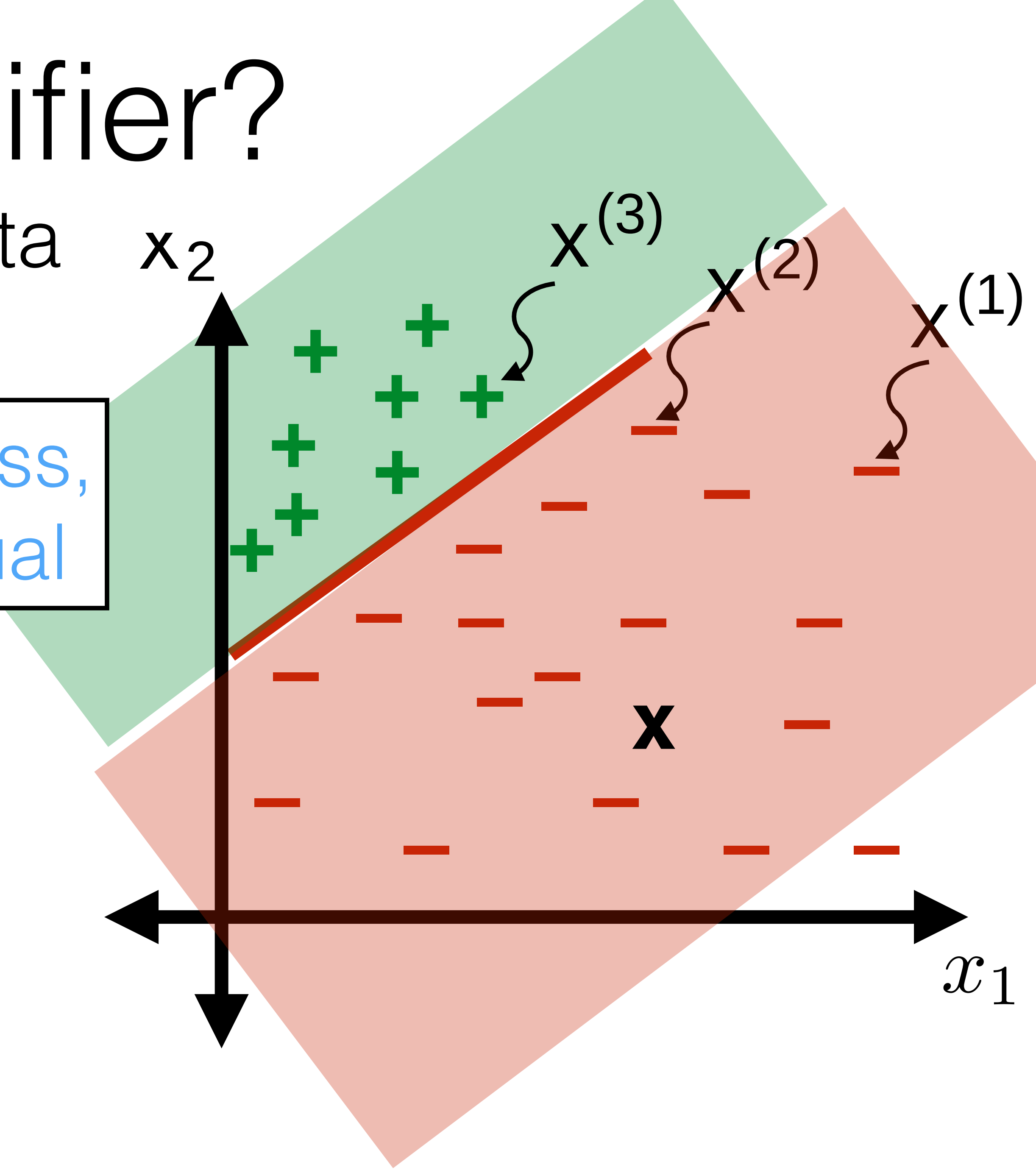
$$L(g, a) = \begin{cases} 0 & \text{if } g = a \\ 1 & \text{else} \end{cases}$$

  - Example: asymmetric loss



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- Should predict well on future data
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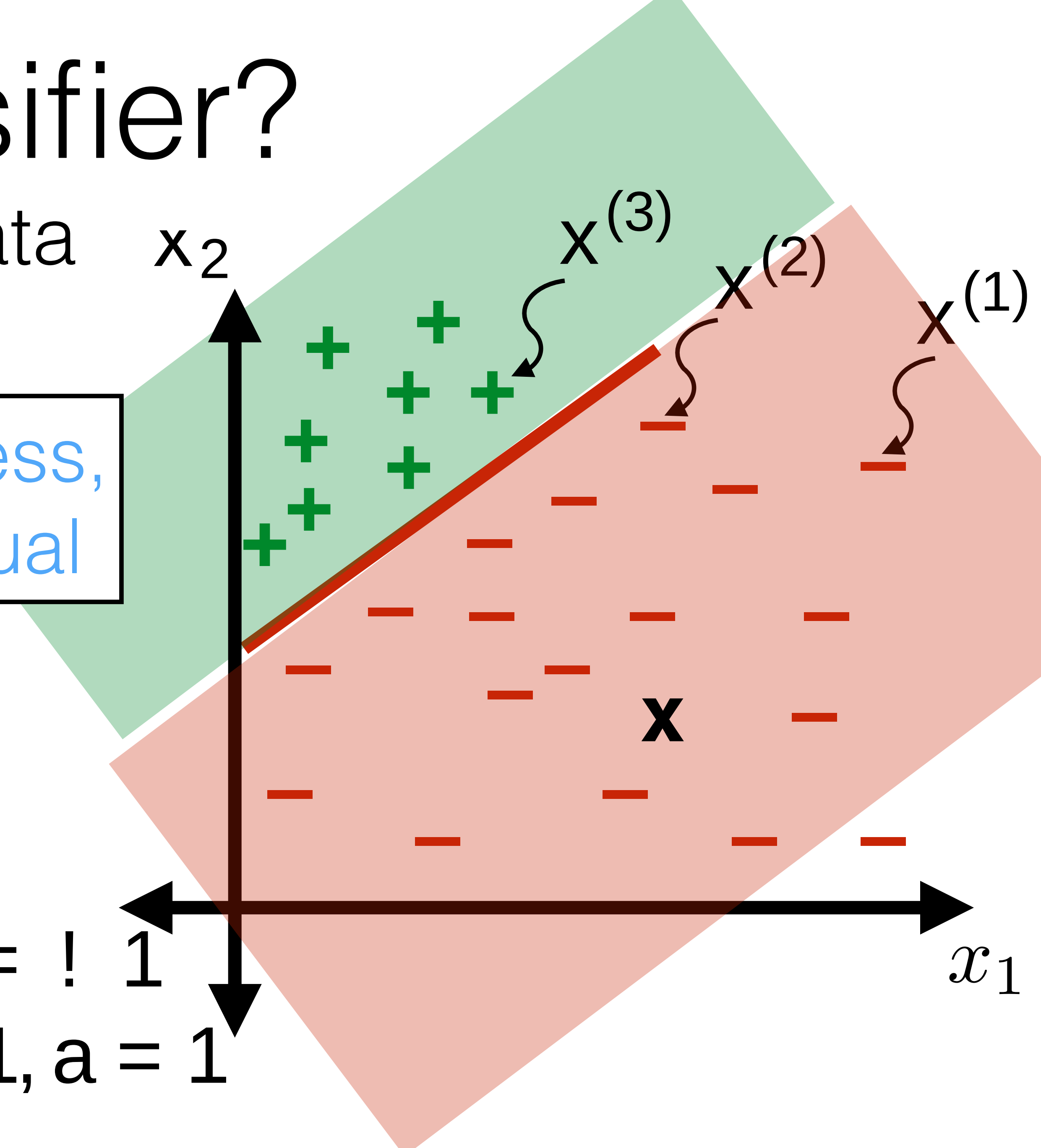
g: guess,
a: actual

  - Example: 0-1 loss

$$L(g, a) = \begin{cases} 0 \text{ if } g = a \\ 1 \text{ else} \end{cases}$$

  - Example: asymmetric loss

$$L(g, a) = \begin{cases} 1 \text{ if } g = 1, a \neq 1 \\ 100 \text{ if } g \neq 1, a = 1 \\ 0 \text{ else} \end{cases}$$



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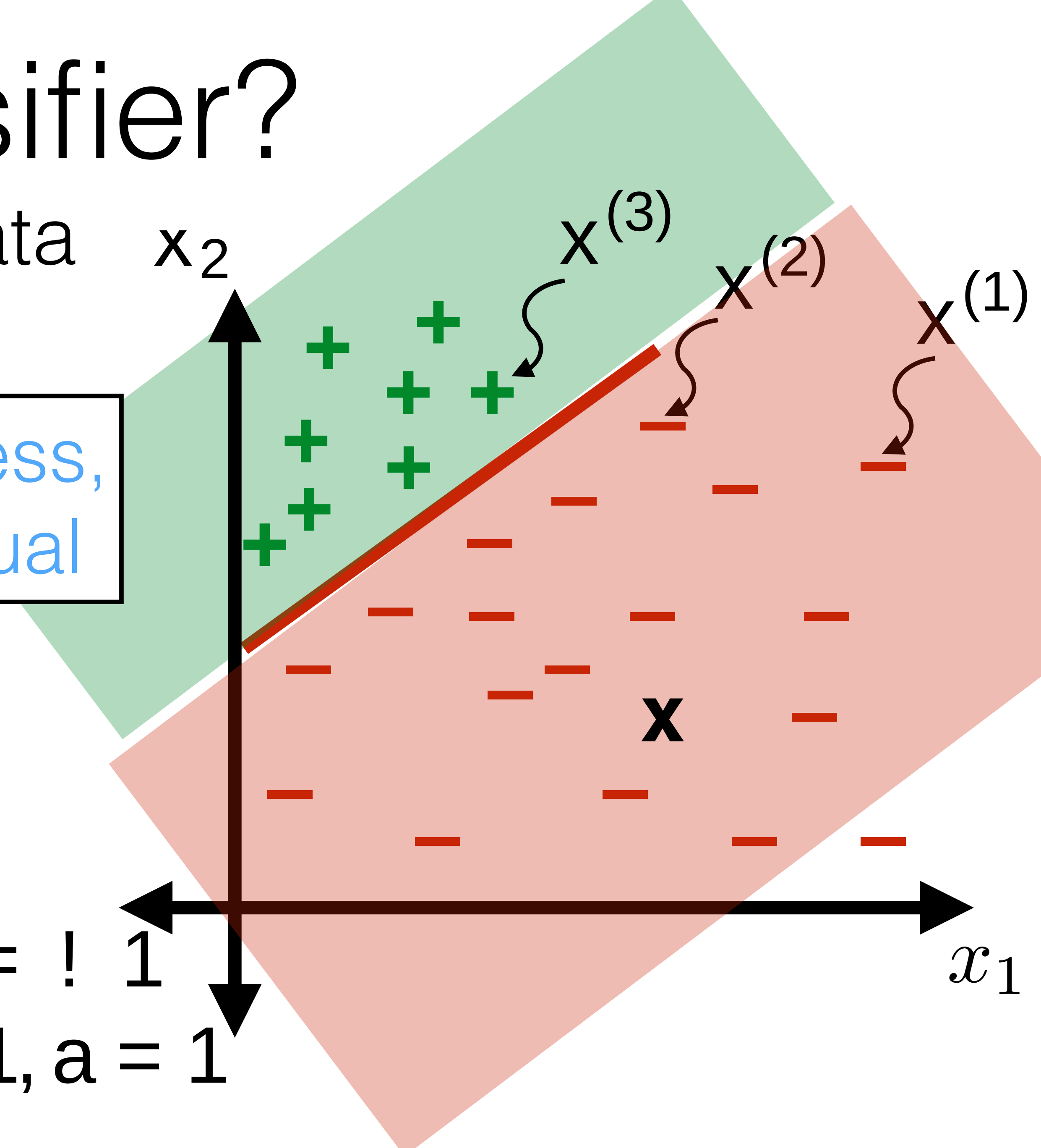
a: actual



  - Example: 0-1 loss

$$L(g, a) = \begin{cases} 0 \text{ if } g = a \\ 1 \text{ else} \end{cases}$$

  - Example: asymmetric loss

$$L(g, a) = \begin{cases} 1 \text{ if } g = 1, a = -1 \\ 100 \text{ if } g = -1, a = 1 \\ 0 \text{ else} \end{cases}$$

- Test error (n' new points):

How good is a classifier?

- Should predict well on future data
- How good is a classifier at a single point? Loss $L(g, a)$

g: guess,
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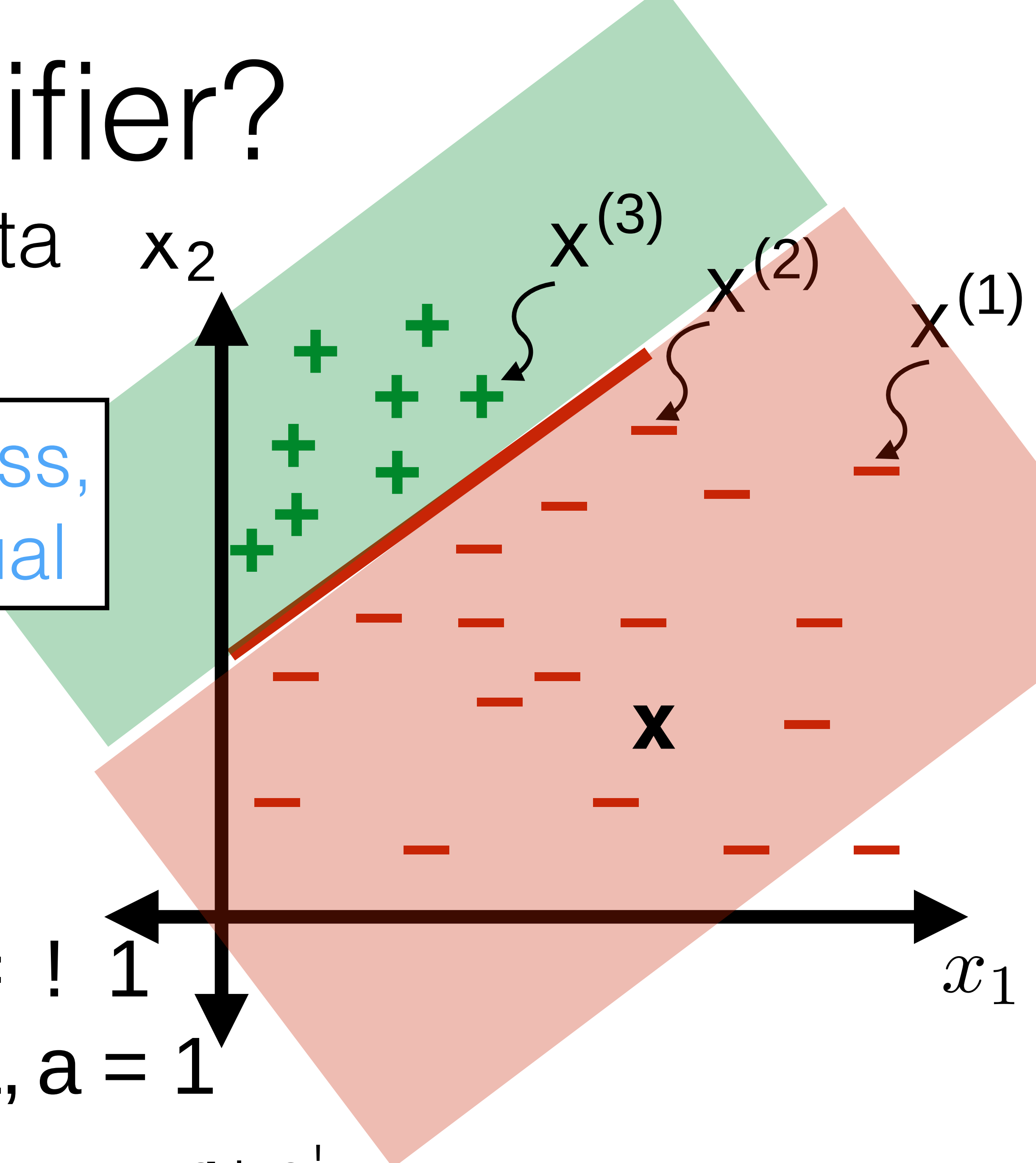

- Test error (n' new points): $E(h) = \frac{1}{n'} \sum_{i=n+1}^{n+n'} L(h(x^{(i)}), y^{(i)})$

How good is a classifier?

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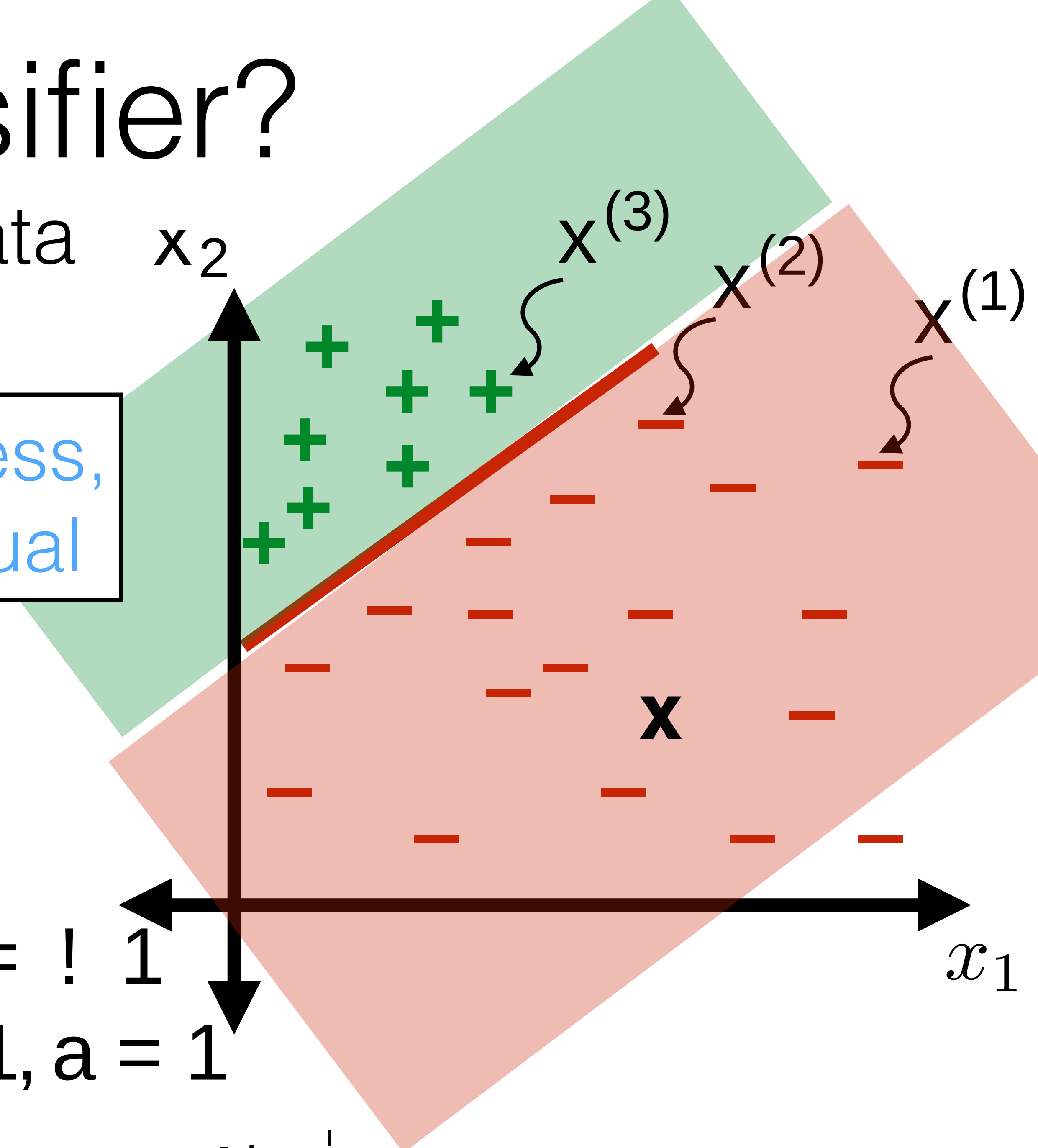

- Test error (n' new points): $E(h) = \frac{1}{n'} \sum_{i=n+1}^{n+n'} L(h(x^{(i)}), y^{(i)})$
- Training error:

How good is a classifier?

- Should predict well on future data
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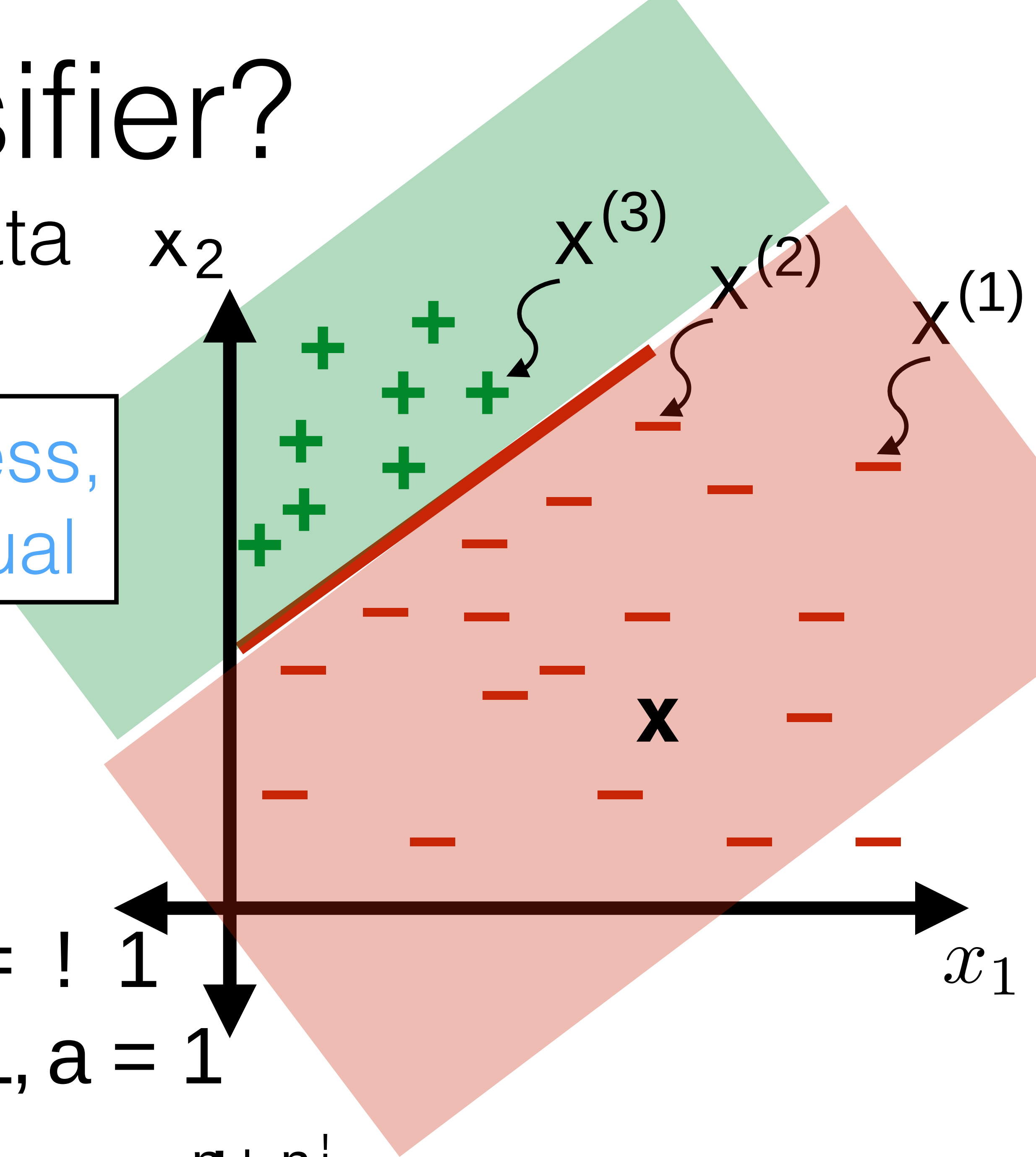
$$L(g,a) = \begin{cases} 0 \text{ if } g = a \\ 1 \text{ else} \end{cases}$$

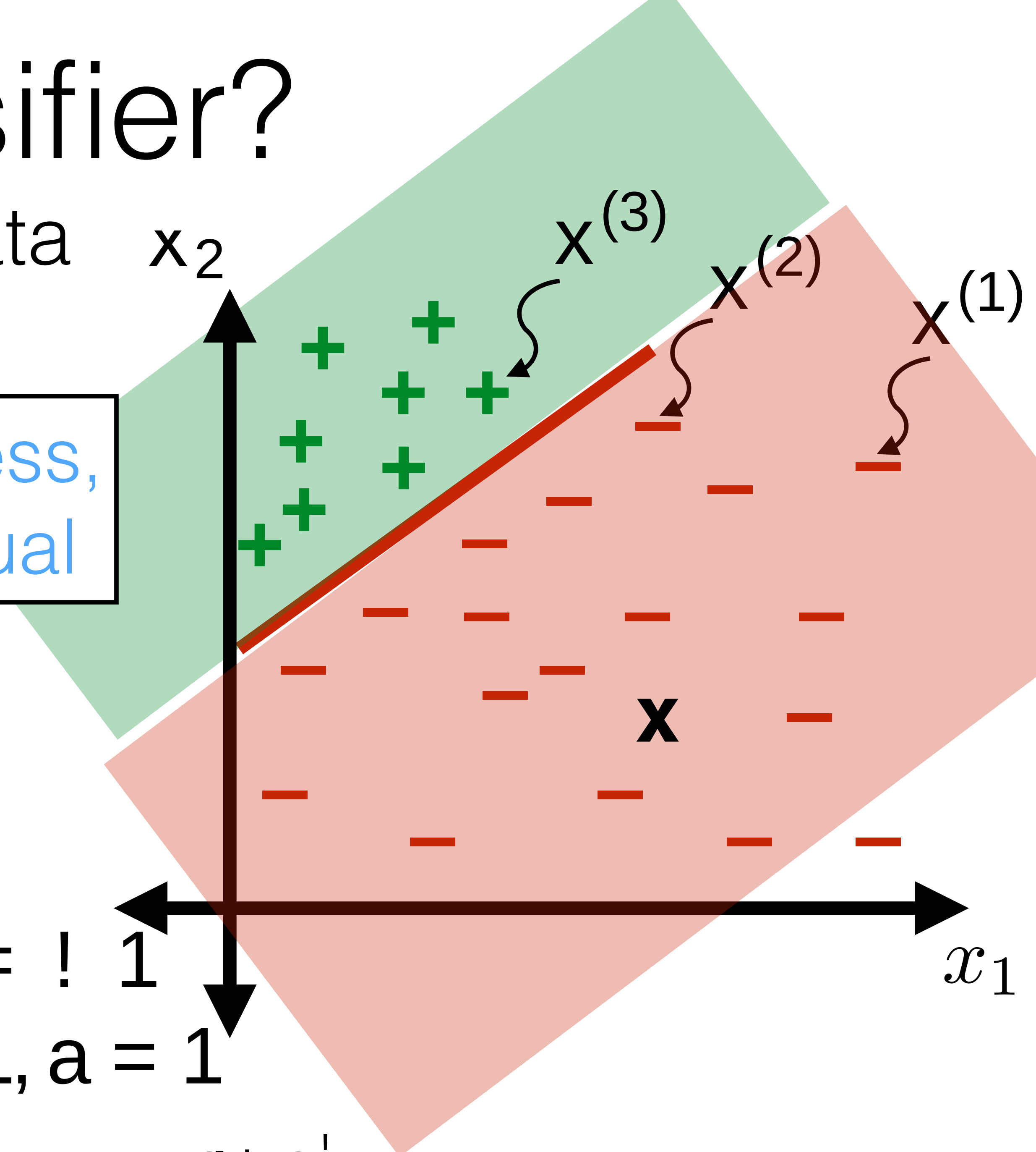
  - Example: asymmetric loss

$$L(g,a) = \begin{cases} 1 \text{ if } g = 1, a \neq 1 \\ 100 \text{ if } g \neq 1, a = 1 \\ 0 \text{ else} \end{cases}$$



- Test error (n' new points): $E(h) = \frac{1}{n'} \sum_{i=n+1}^{n+n'} L(h(x^{(i)}), y^{(i)})$
- Training error: $E_n(h) = \frac{1}{n} \sum_{i=1}^{n} L(h(x^{(i)}), y^{(i)})$

How good is a classifier?



- Should predict well on future data
- How good is a classifier at a single point? Loss $L(g, a)$

g: guess,
a: actual

  - Example: 0-1 loss

$$L(g,a) = \begin{cases} 0 & \text{if } g = a \\ 1 & \text{else} \end{cases}$$

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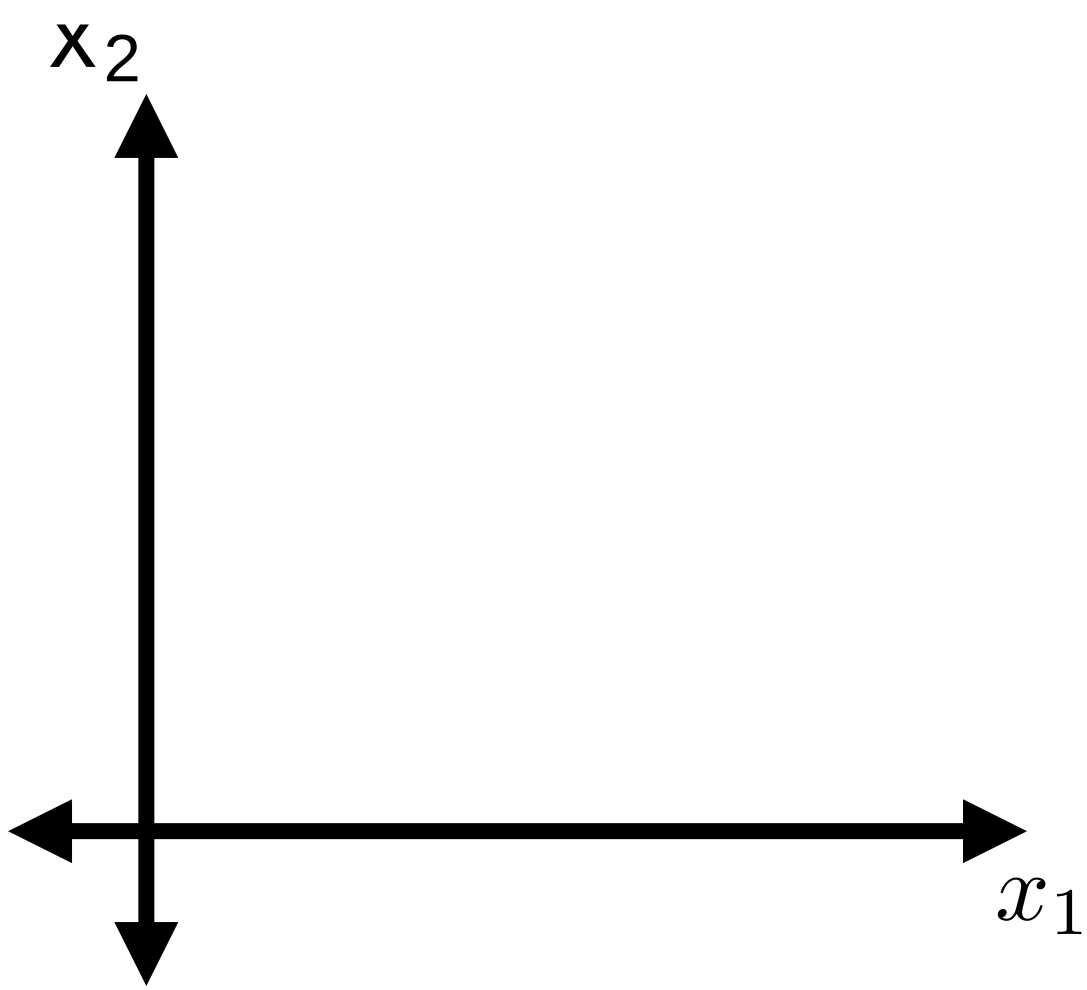
$$L(g,a) = \begin{cases} 1 & \text{if } g = 1, a = -1 \\ 100 & \text{if } g = -1, a = 1 \\ 0 & \text{else} \end{cases}$$

- Test error (n' new points): $E(h) = \frac{1}{n'} \sum_{i=n+1}^{n+n'} L(h(x^{(i)}), y^{(i)})$
- Training error: $E_n(h) = \frac{1}{n} \sum_{i=1}^{n} L(h(x^{(i)}), y^{(i)})$
- Prefer h to $\tilde{h}$ if $E_n(h) < E_n(\tilde{h})$

Learning a classifier

- Have data; have hypothesis class
- Want to choose a good classifier
    - Recall: $x \rightarrow \boxed{h} \rightarrow y$



Learning a classifier

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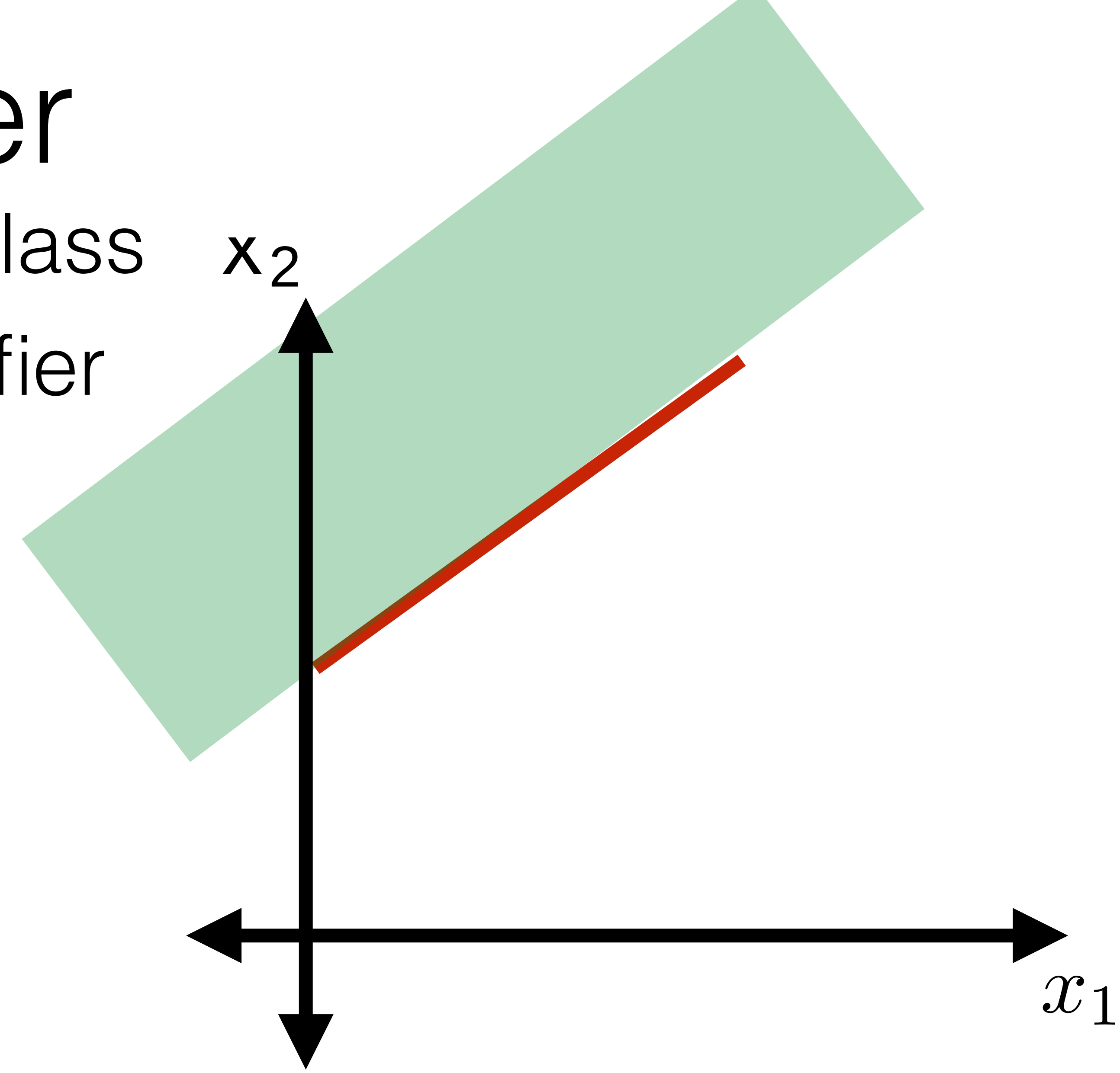

Learning a classifier

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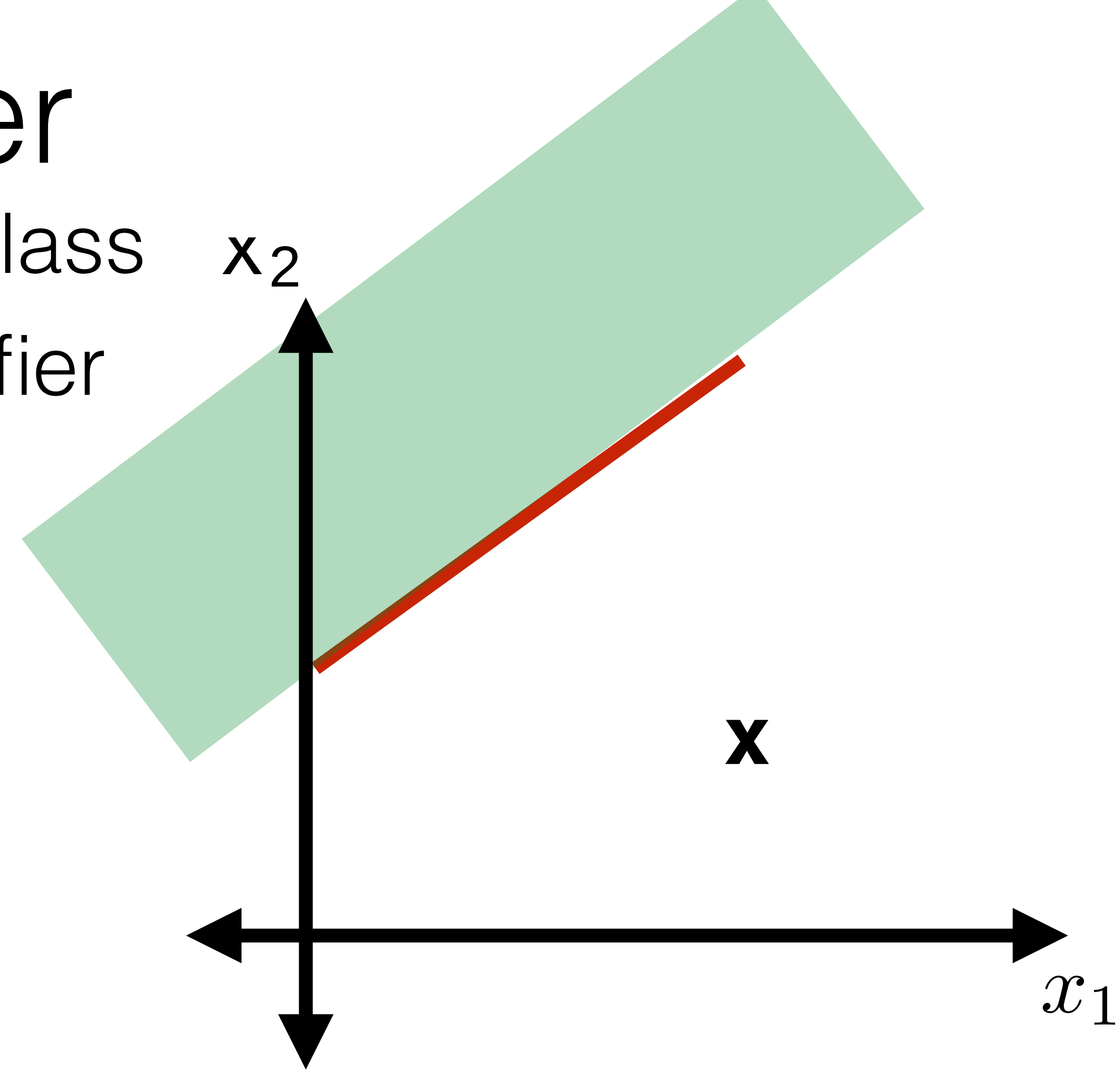

Learning a classifier

- Have data; have hypothesis class
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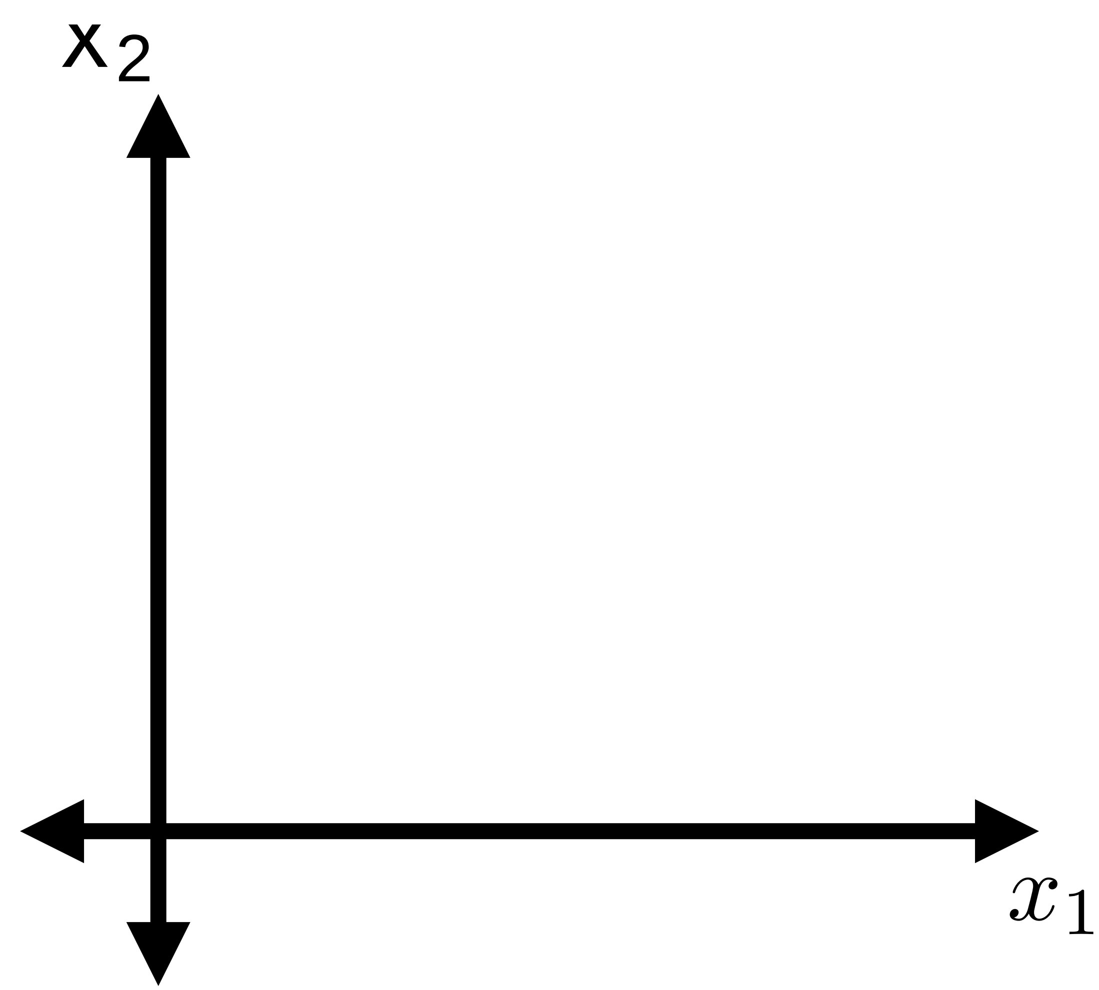
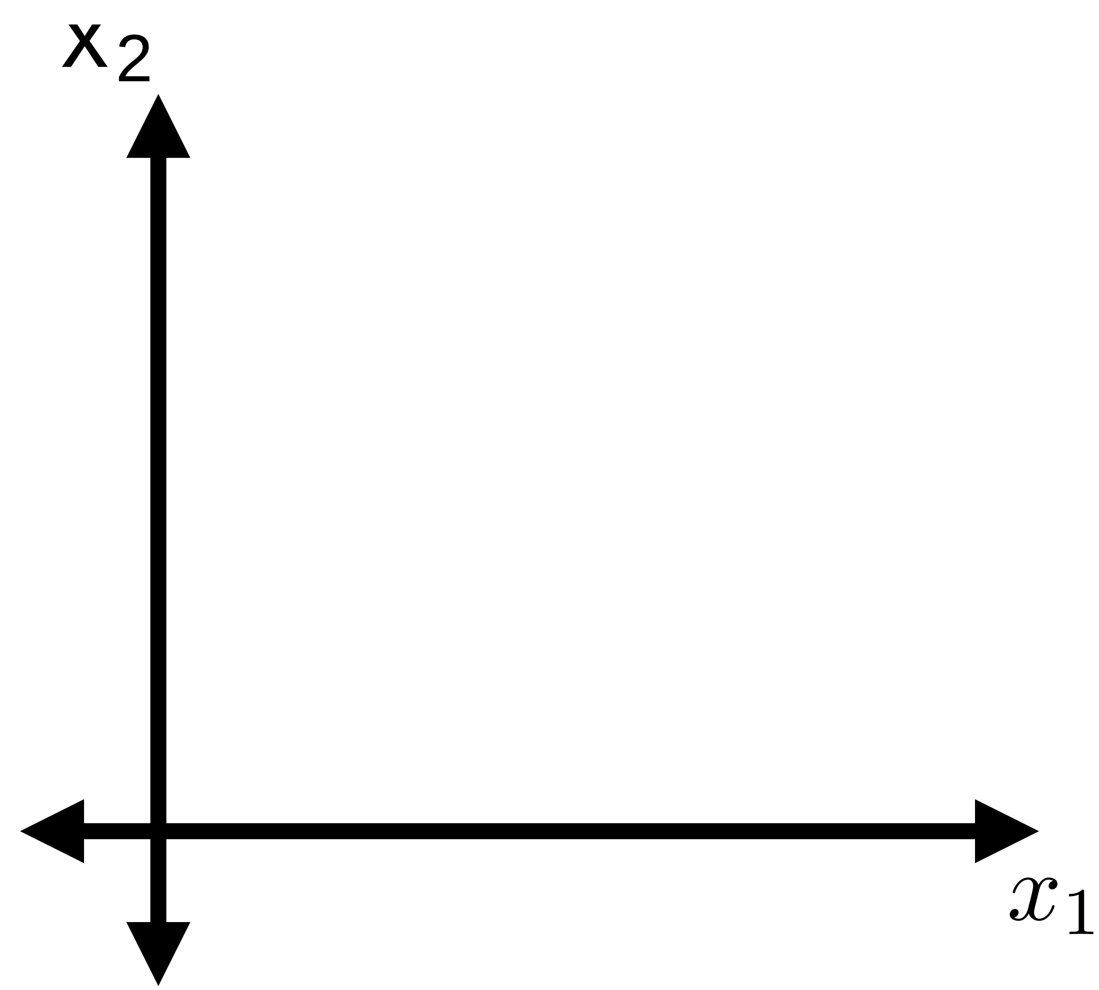
  - Recall: $x \rightarrow \boxed{h} \rightarrow y$



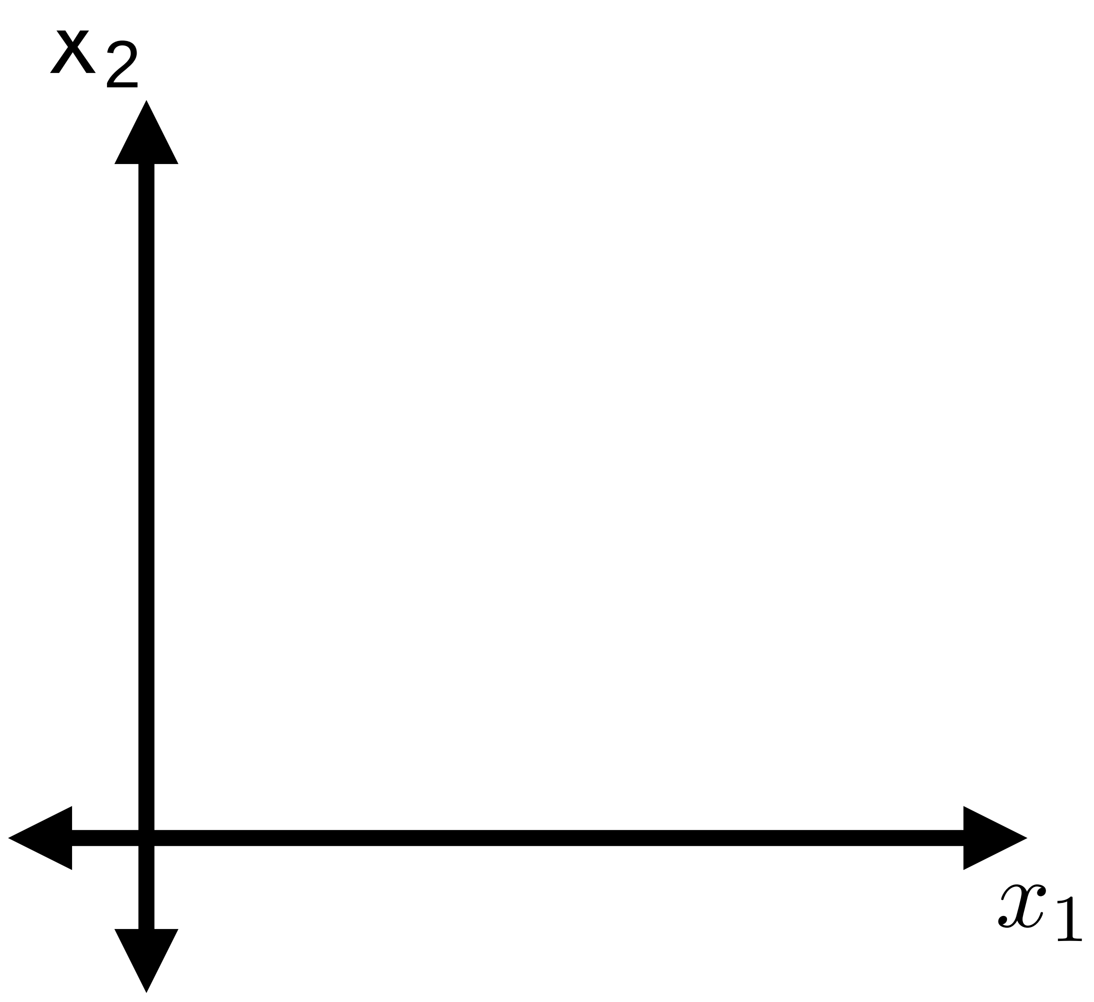
Learning a classifier

- Have data; have hypothesis class
- Want to choose a good classifier
    - Recall: $x \rightarrow \boxed{h} \rightarrow y$
    - New:



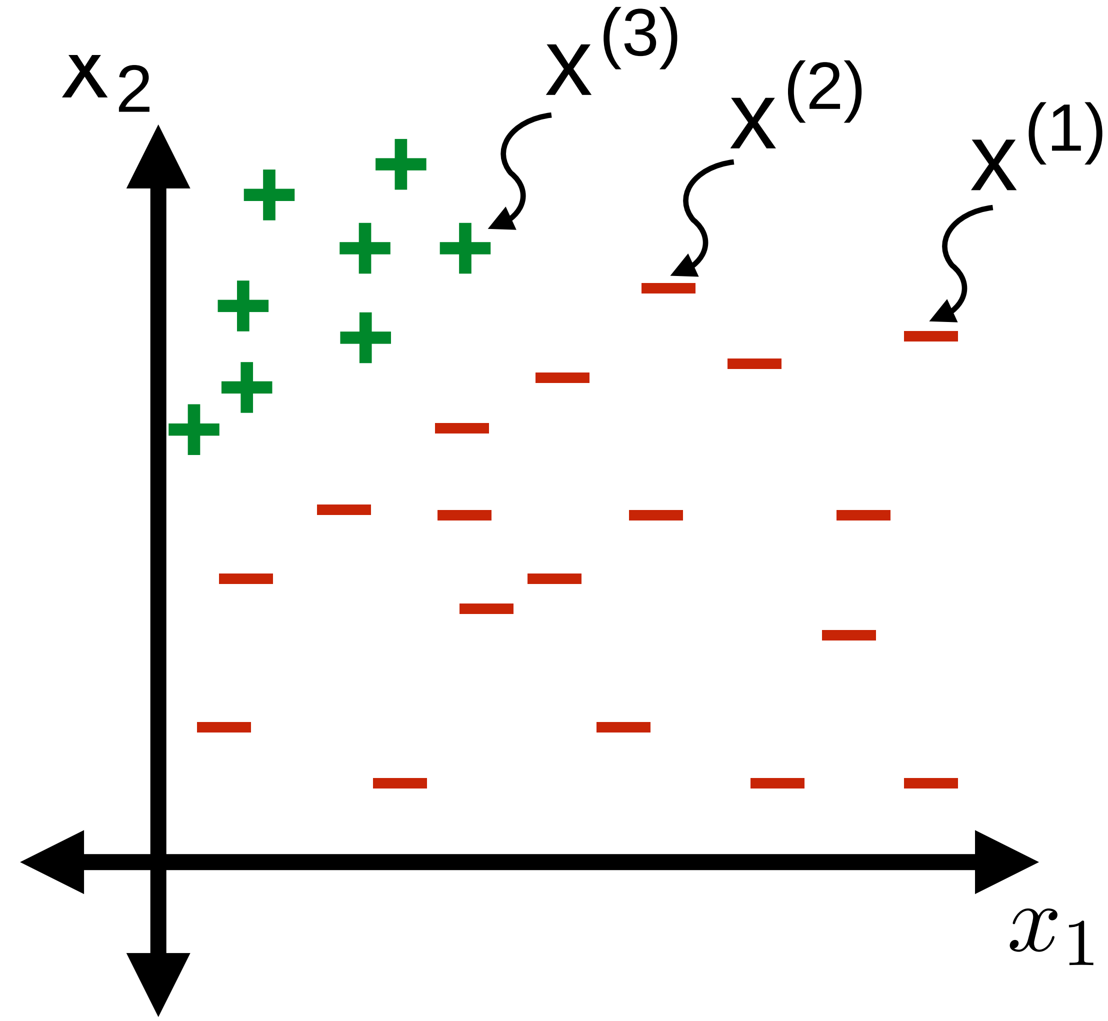
Learning a classifier

- Have data; have hypothesis class
- Want to choose a good classifier
  - Recall: x → h → y
  - New: D_n → learning algorithm → h



Learning a classifier

- Have data; have hypothesis class
- Want to choose a good classifier
  - Recall: $x \rightarrow \boxed{h} \rightarrow y$
  - New: $D_n \rightarrow \boxed{\text{learning algorithm}} \rightarrow h$



Learning a classifier

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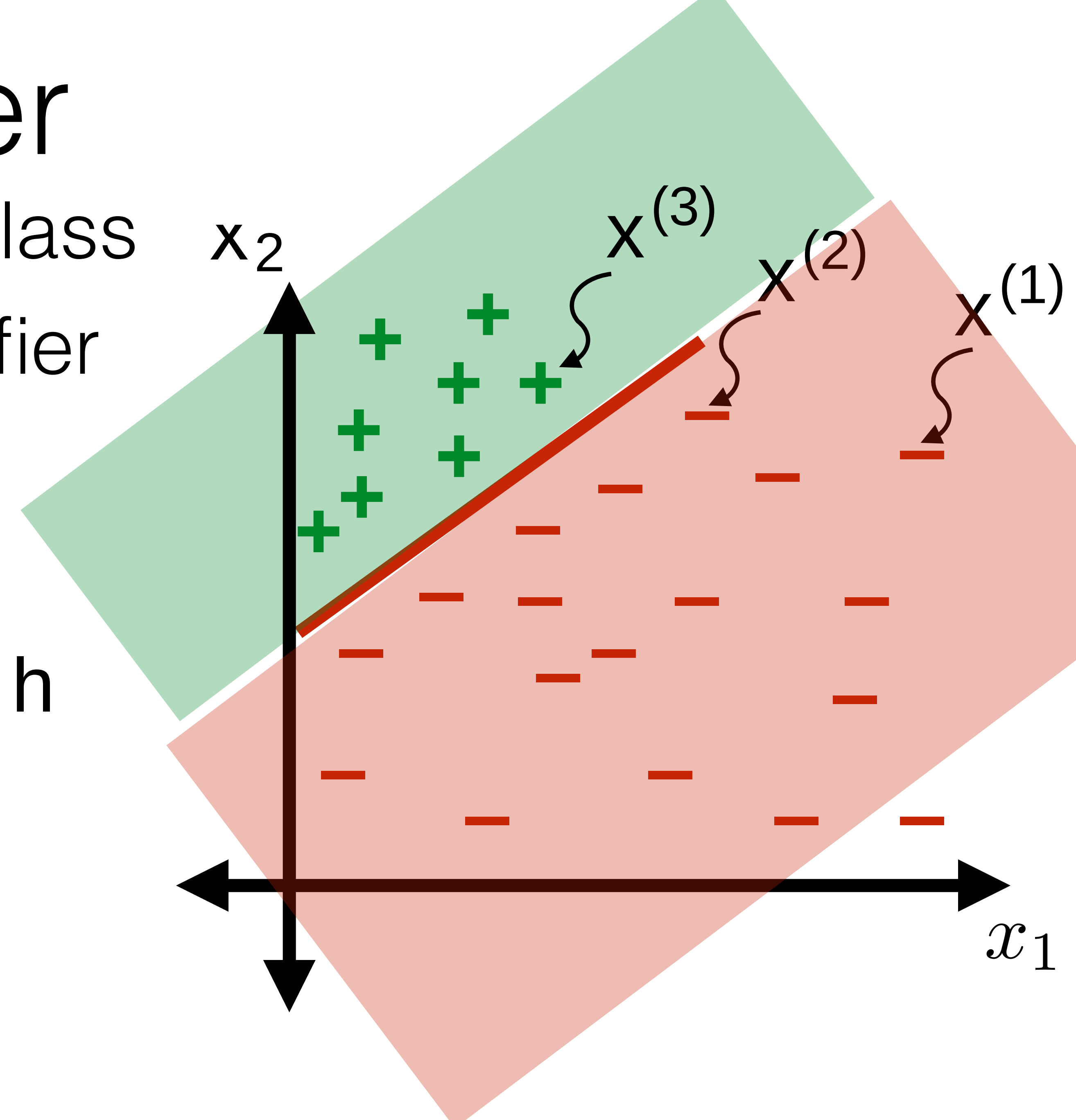

Learning a classifier

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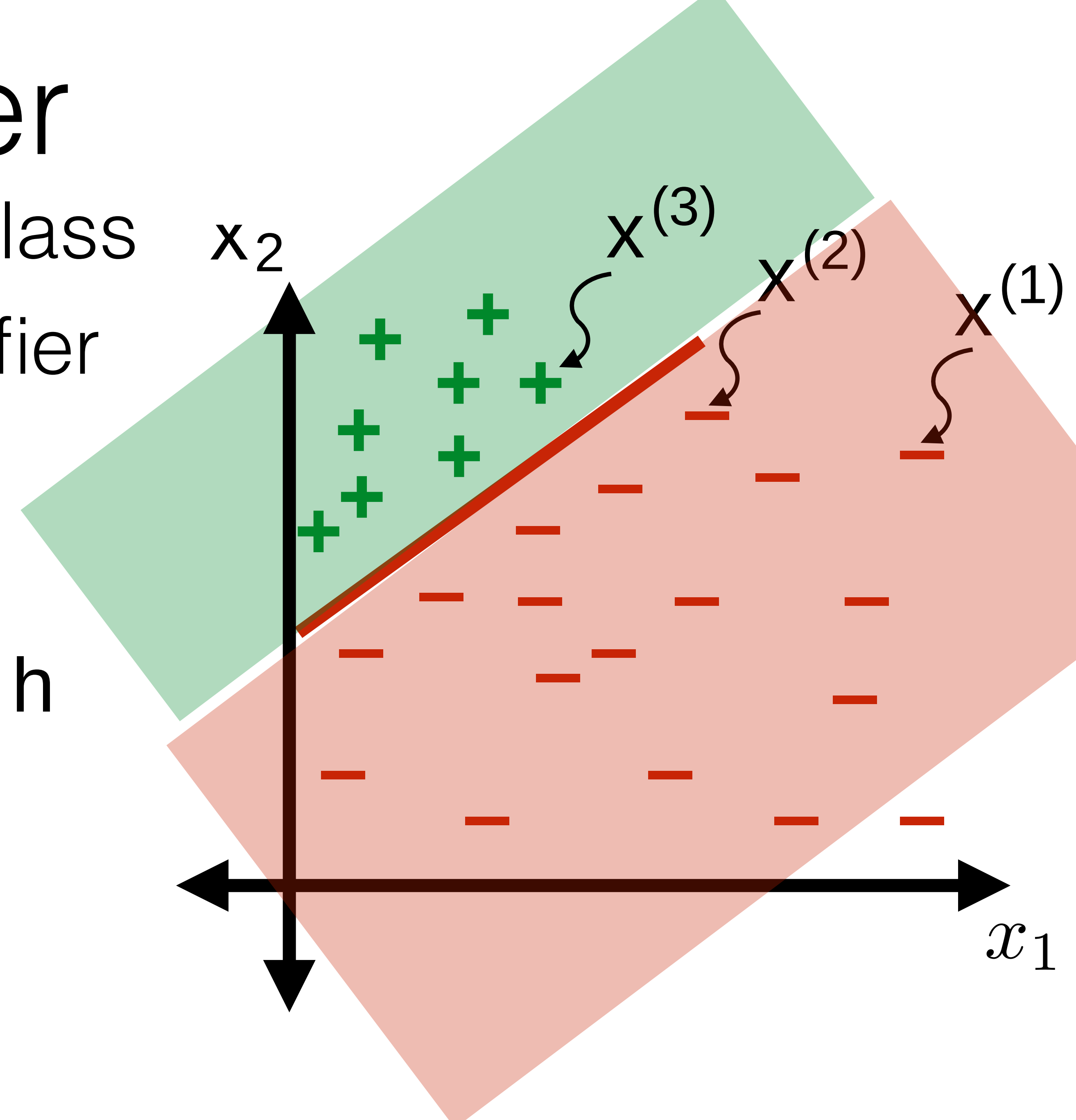
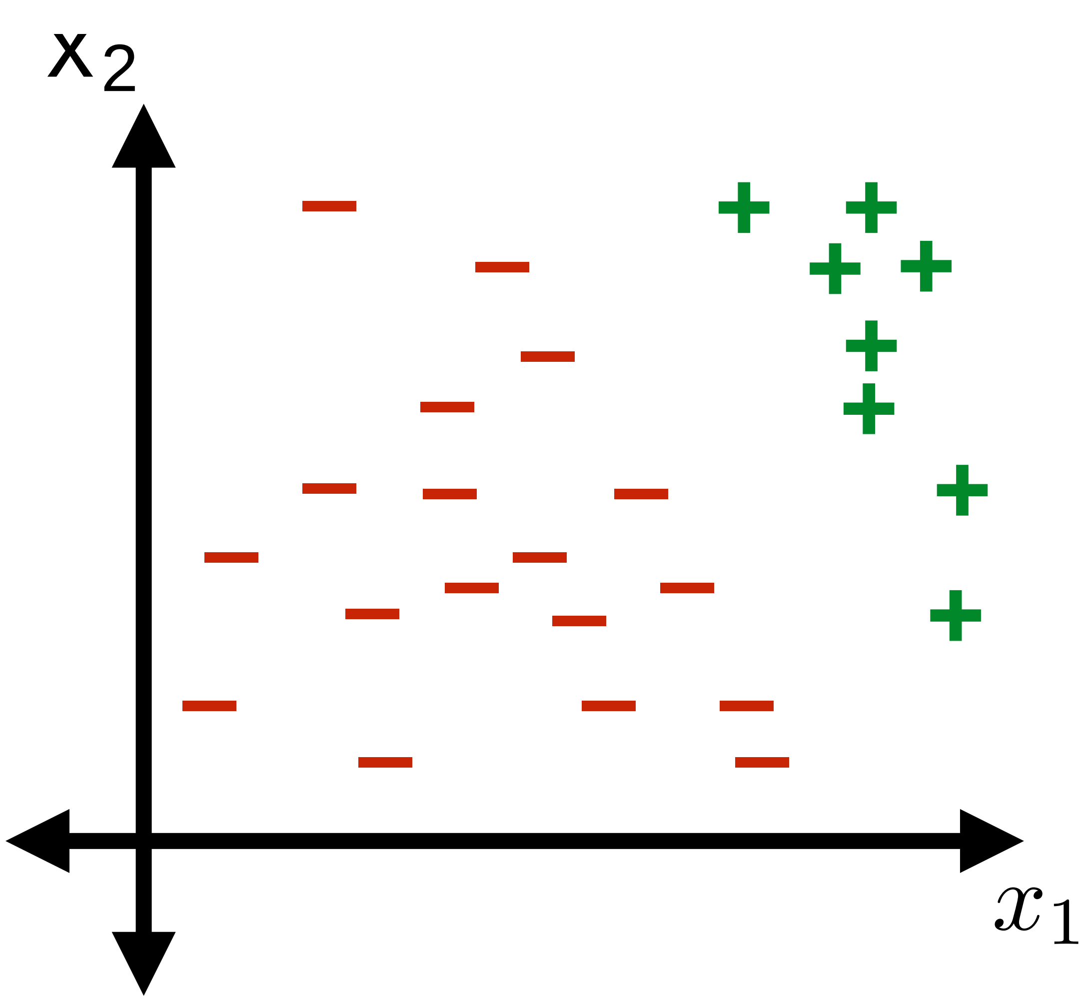
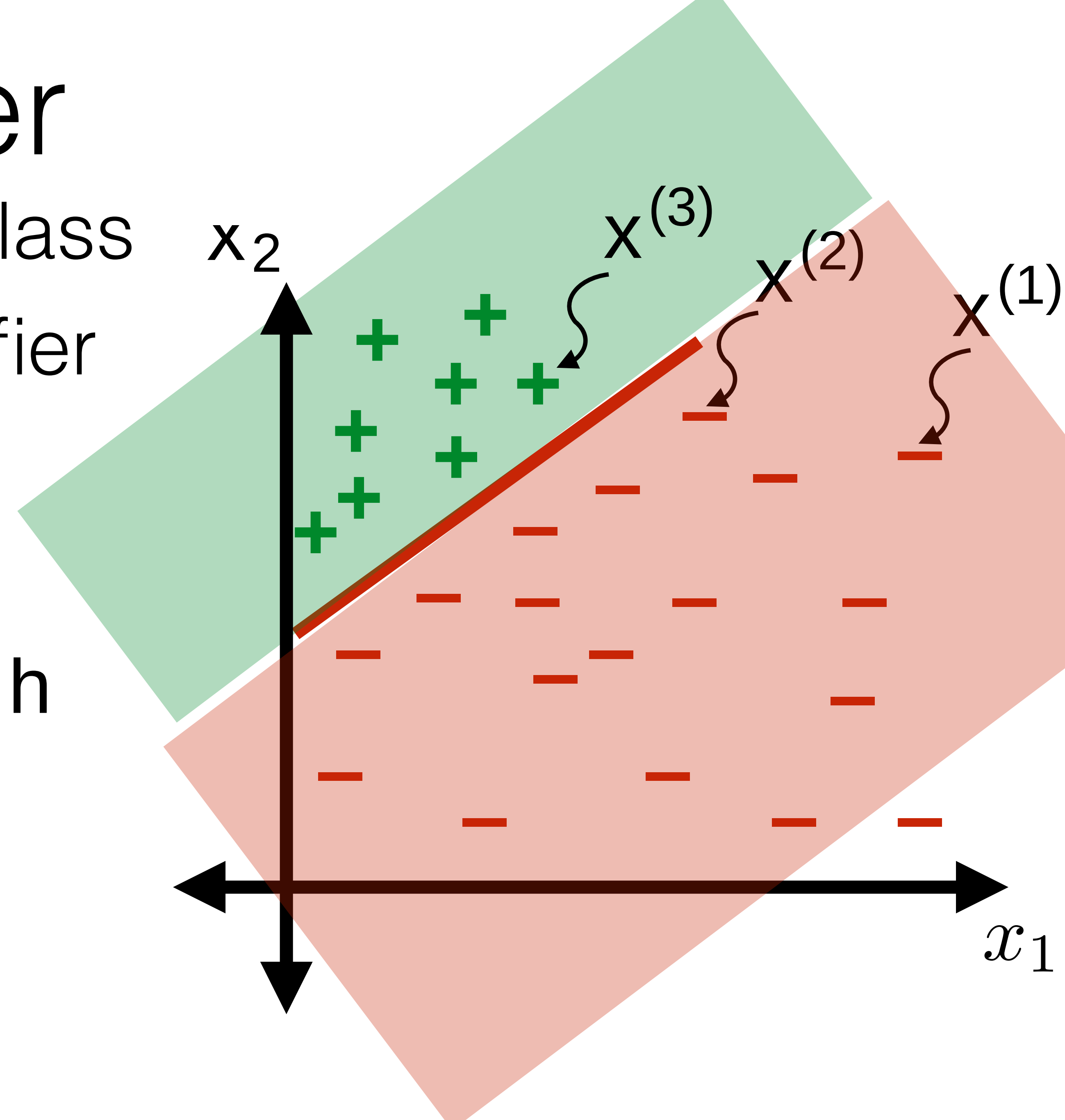
- Want to choose a good classifier
  - Recall: $x \rightarrow \boxed{h} \rightarrow y$
  - New: $D_n \rightarrow \boxed{\text{learning algorithm}} \rightarrow h$

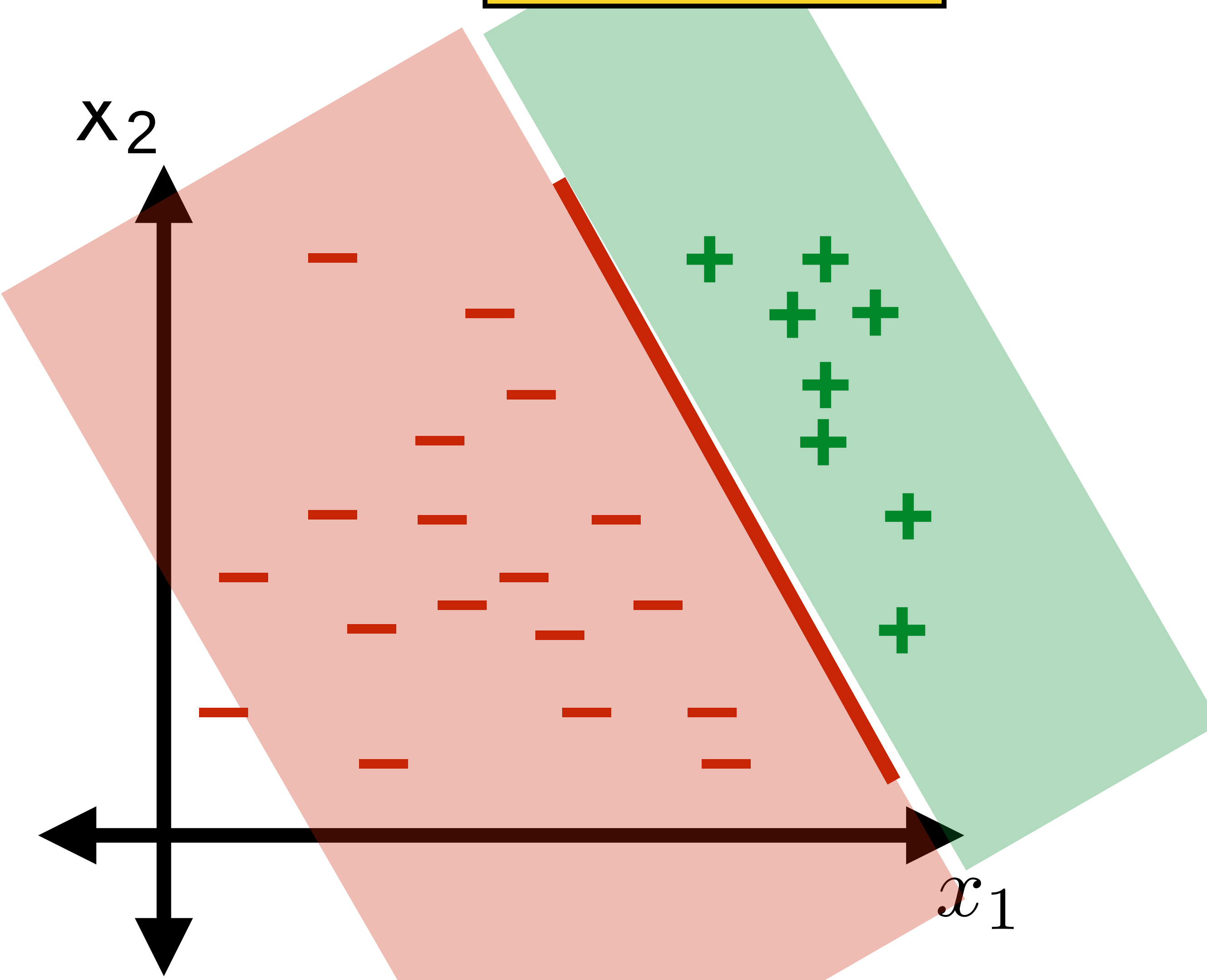




Learning a classifier

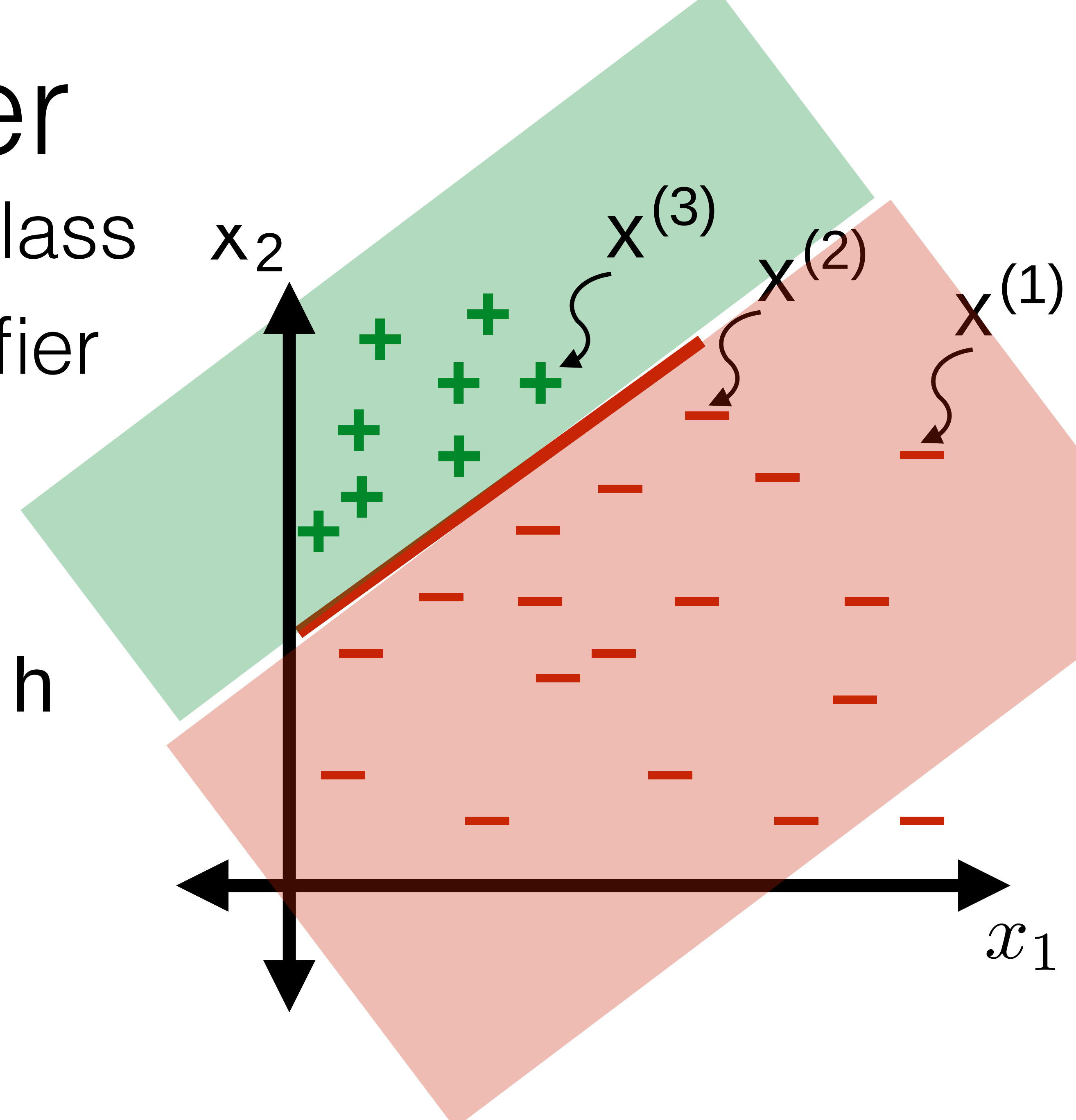
- Have data; have hypothesis class
- Want to choose a good classifier
  - Recall: x → h → y
  - New:
    D_n → learning algorithm → h





Learning a classifier

- Have data; have hypothesis class
- Want to choose a good classifier
    - Recall: $x \rightarrow \boxed{h} \rightarrow y$
    - New: $D_n \rightarrow \boxed{\text{learning algorithm}} \rightarrow h$



Learning a classifier

- Have data; have hypothesis class
- Want to choose a good classifier
  - Recall: x → h → y
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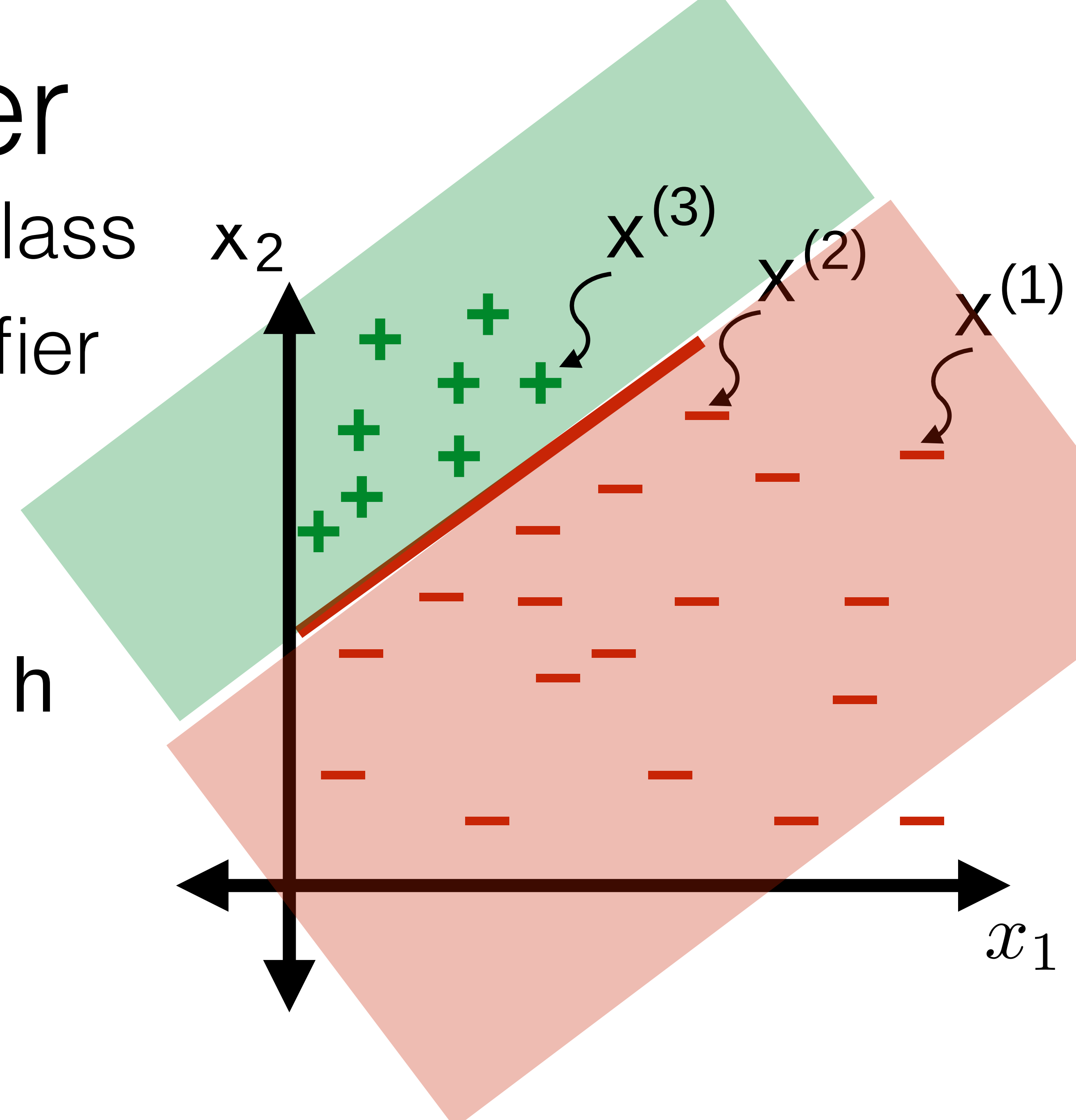
- Example:



Learning a classifier

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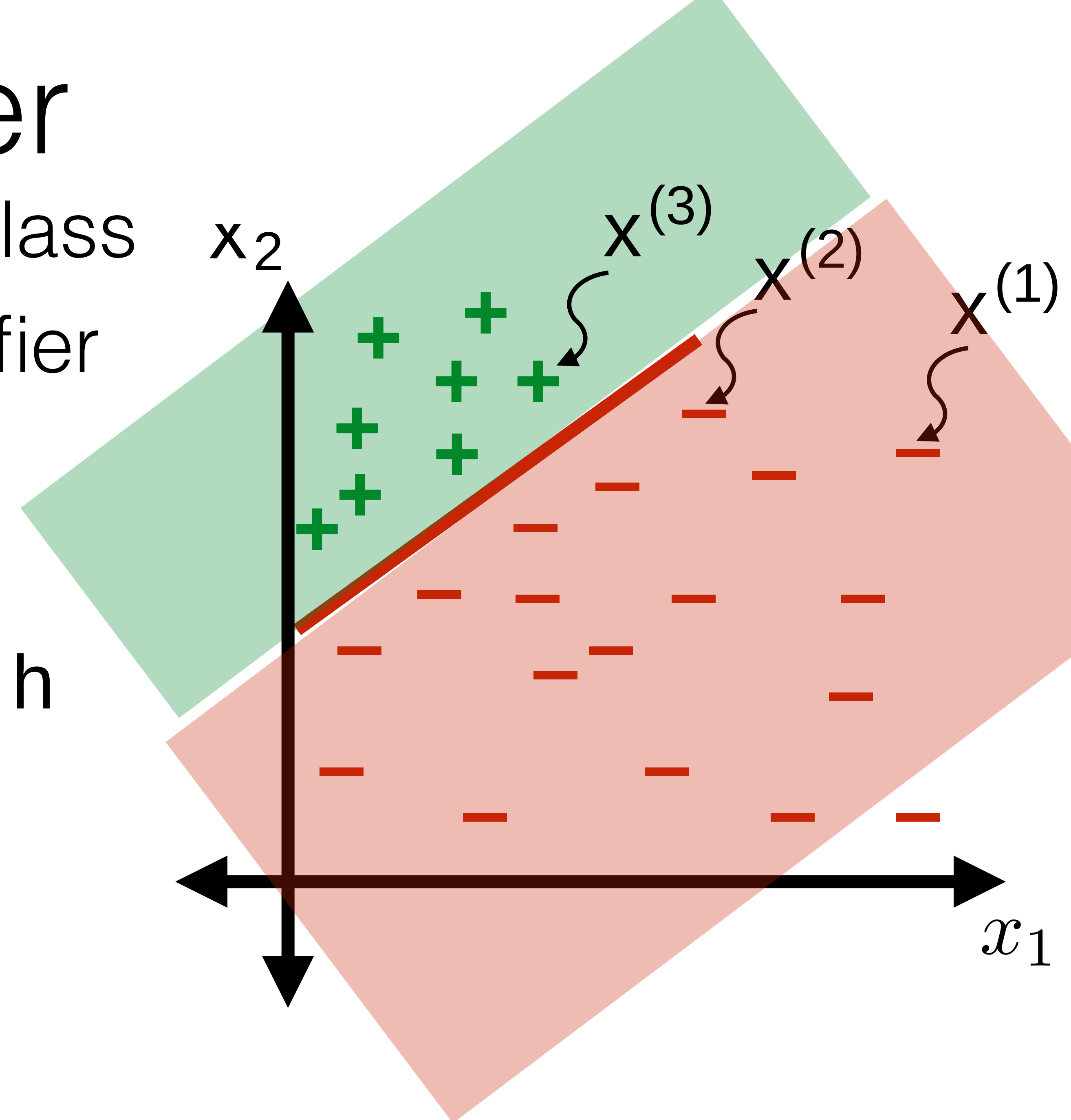
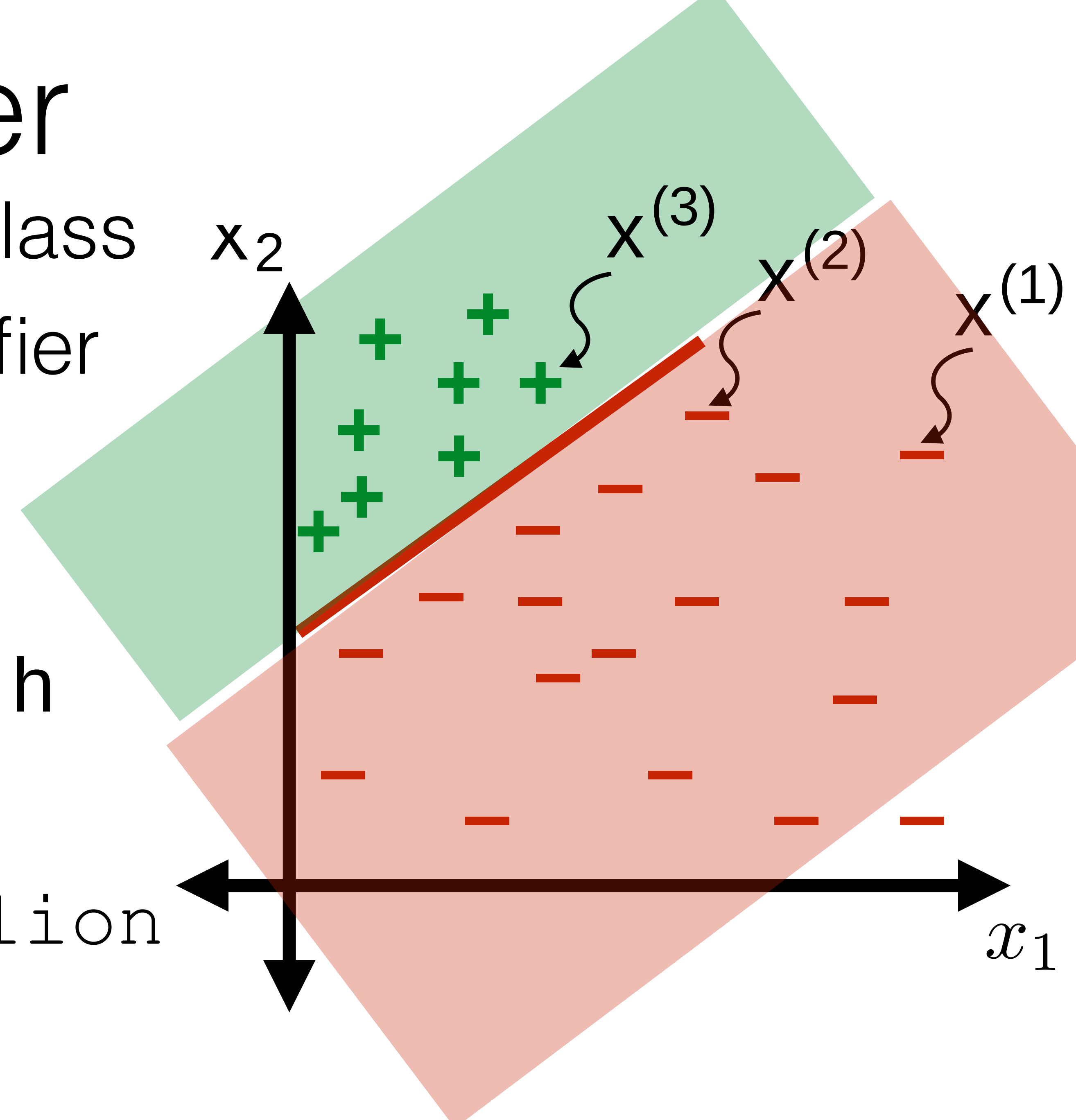


Learning a classifier

- Have data; have hypothesis class
- Want to choose a good classifier
  - Recall: $x \rightarrow$ h $\rightarrow$ y
  - New: $D_n \rightarrow$ learning algorithm $\rightarrow$ h
- Example:

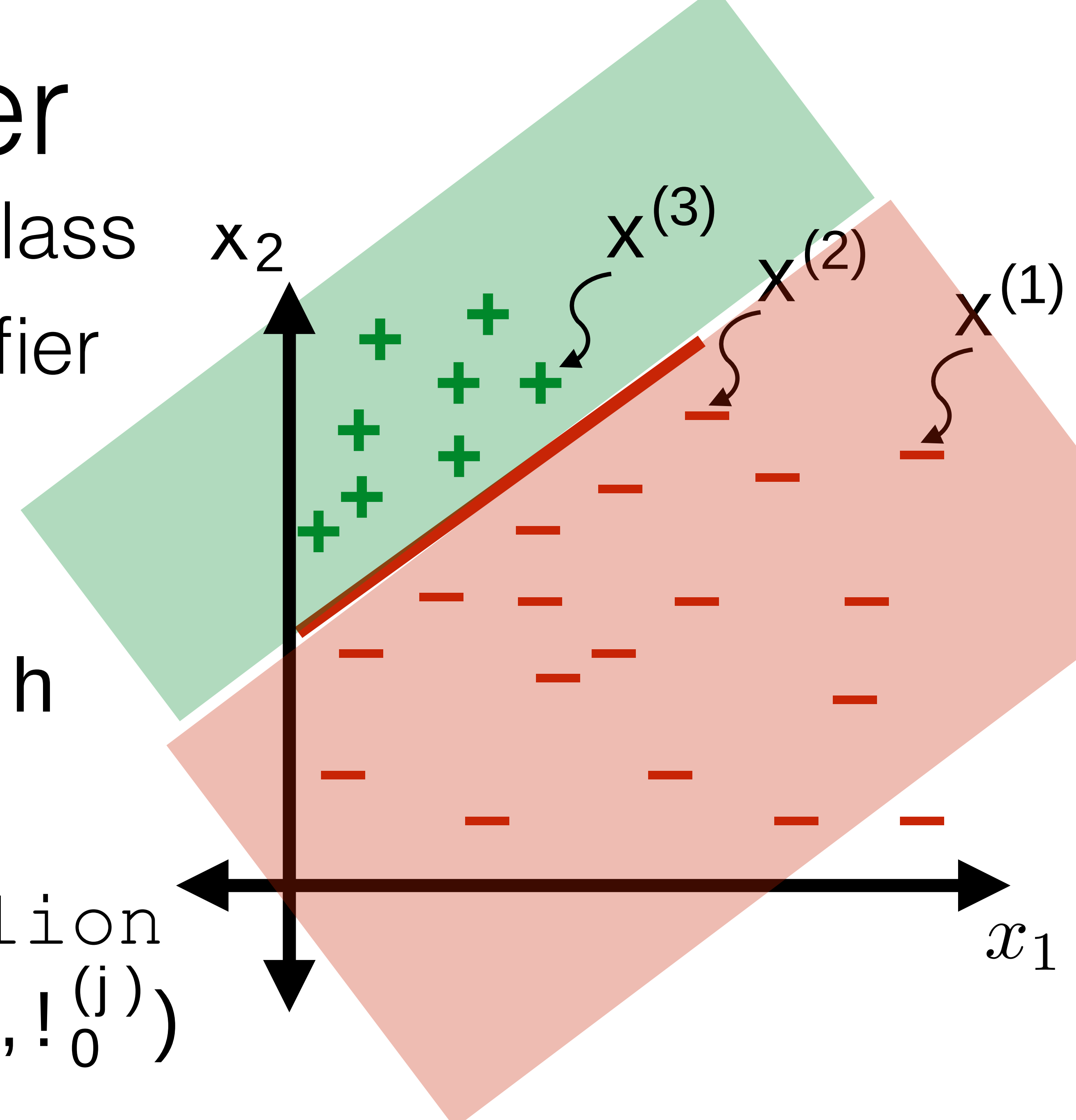
```
for j = 1, …, 1 trillion
```



Learning a classifier

- Have data; have hypothesis class
- Want to choose a good classifier
  - Recall: x → h → y
  - New: D_n → learning algorithm → h
- Example:

```
for j = 1, …, 1 trillion
  Randomly sample (!^(j), !_0^(j))
```



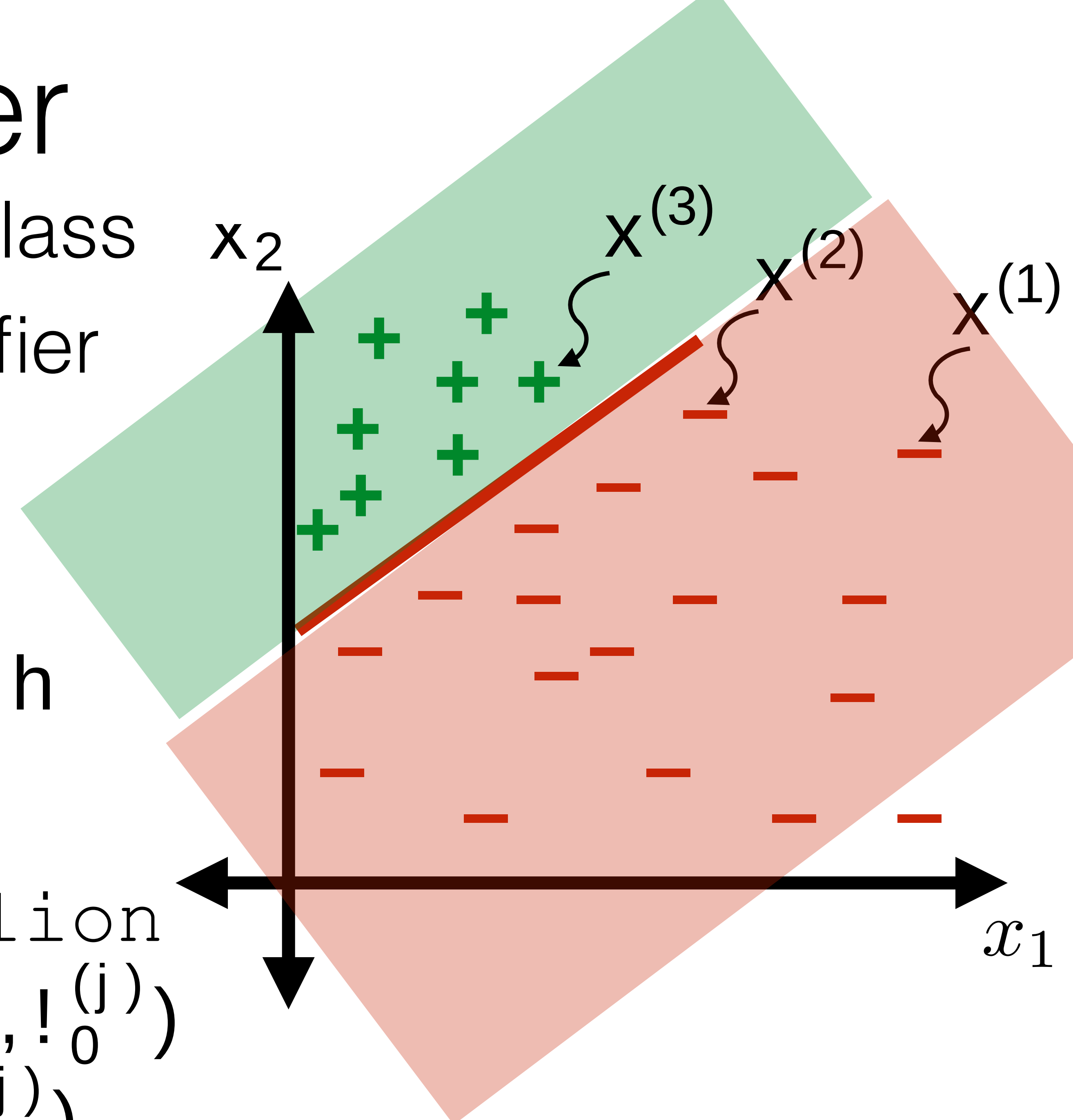
Learning a classifier

- Have data; have hypothesis class
- Want to choose a good classifier
  - Recall: $x \rightarrow \boxed{h} \rightarrow y$
  - New: $D_n \rightarrow \boxed{\text{learning algorithm}} \rightarrow h$
- Example:

```
for j = 1, …, 1 trillion
  Randomly sample (!(j), !0(j))
  Set h(j)(x) = h(x; !(j), !0(j))
```

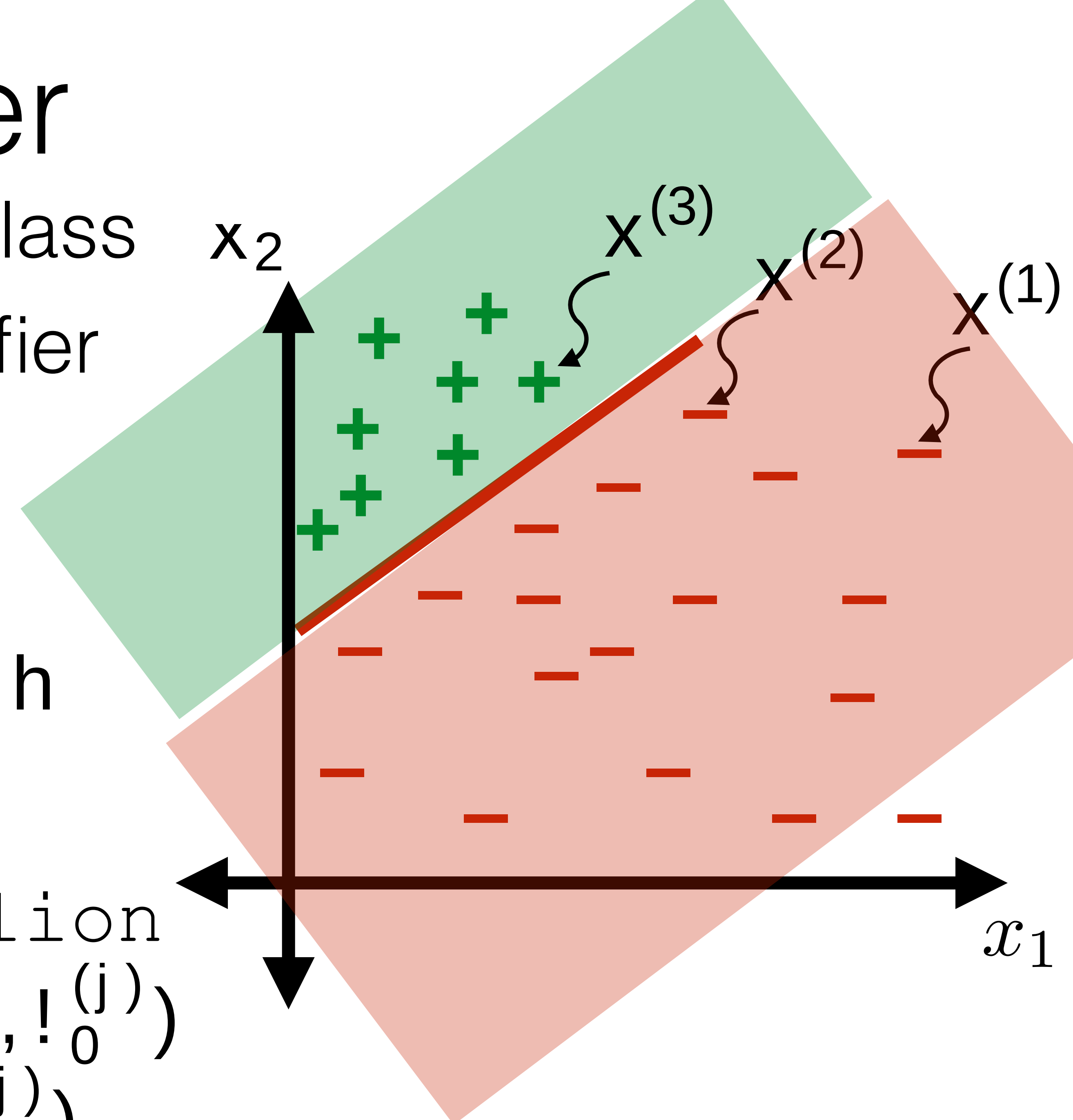
$\text{Randomly sample } (!^{(j)}, !_0^{(j)})$

$\text{Set } h^{(j)}(x) = h(x; !^{(j)}, !_0^{(j)})$



Learning a classifier

- Have data; have hypothesis class
- Want to choose a good classifier
  - Recall: $x \rightarrow$ **h** $\rightarrow$ y
  - New: $D_n \rightarrow$ **learning algorithm** $\rightarrow$ h



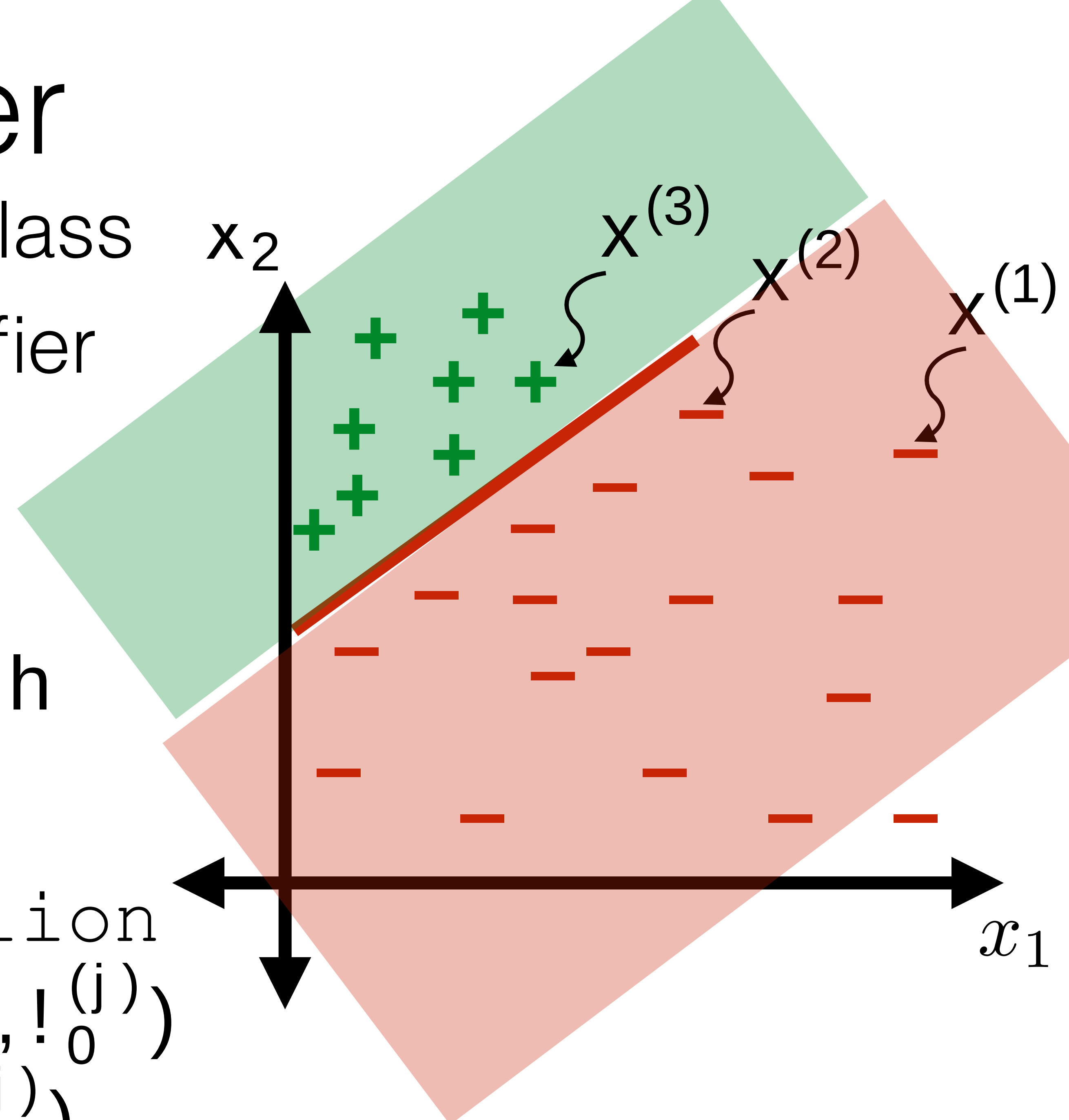
- Example:

```
for j = 1, …, 1 trillion
  Randomly sample (!^(j), !_0^(j))
  Set h^(j)(x) = h(x; !^(j), !_0^(j))
```

Learning a classifier

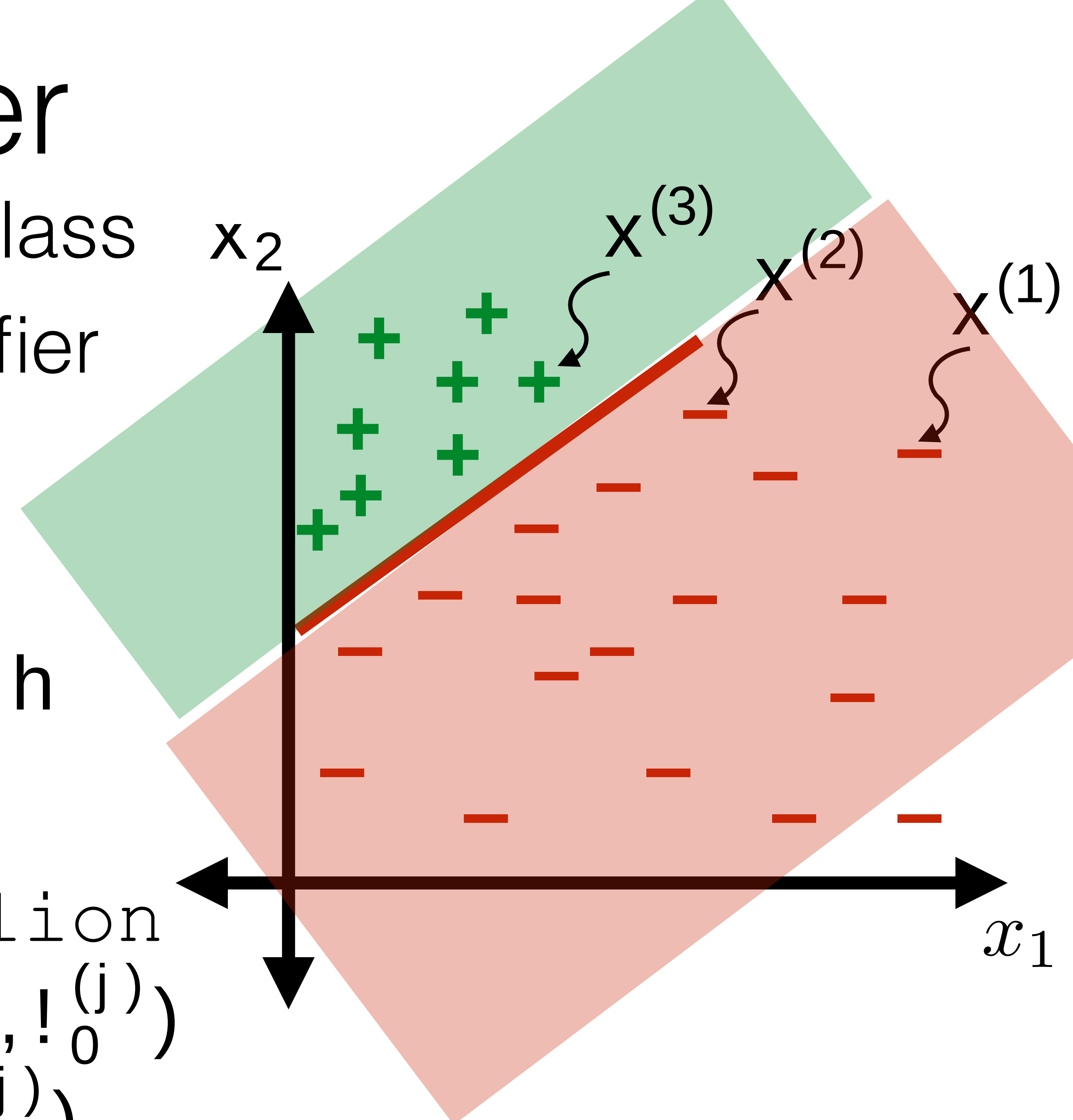
- Have data; have hypothesis class
- Want to choose a good classifier
  - Recall: $x \rightarrow$ h $\rightarrow$ y
  - New: $D_n \rightarrow$ learning algorithm $\rightarrow$ h
- Example:

```
for j = 1, …, 1 trillion
  Randomly sample (!(j),!0(j))
  Set h(j)(x) = h(x;!(j),!0(j))
Ex_learning_alg
```



Learning a classifier

- Have data; have hypothesis class
- Want to choose a good classifier
  - Recall: $x \rightarrow$ h $\rightarrow$ y
  - New: $D_n \rightarrow$ learning algorithm $\rightarrow$ h

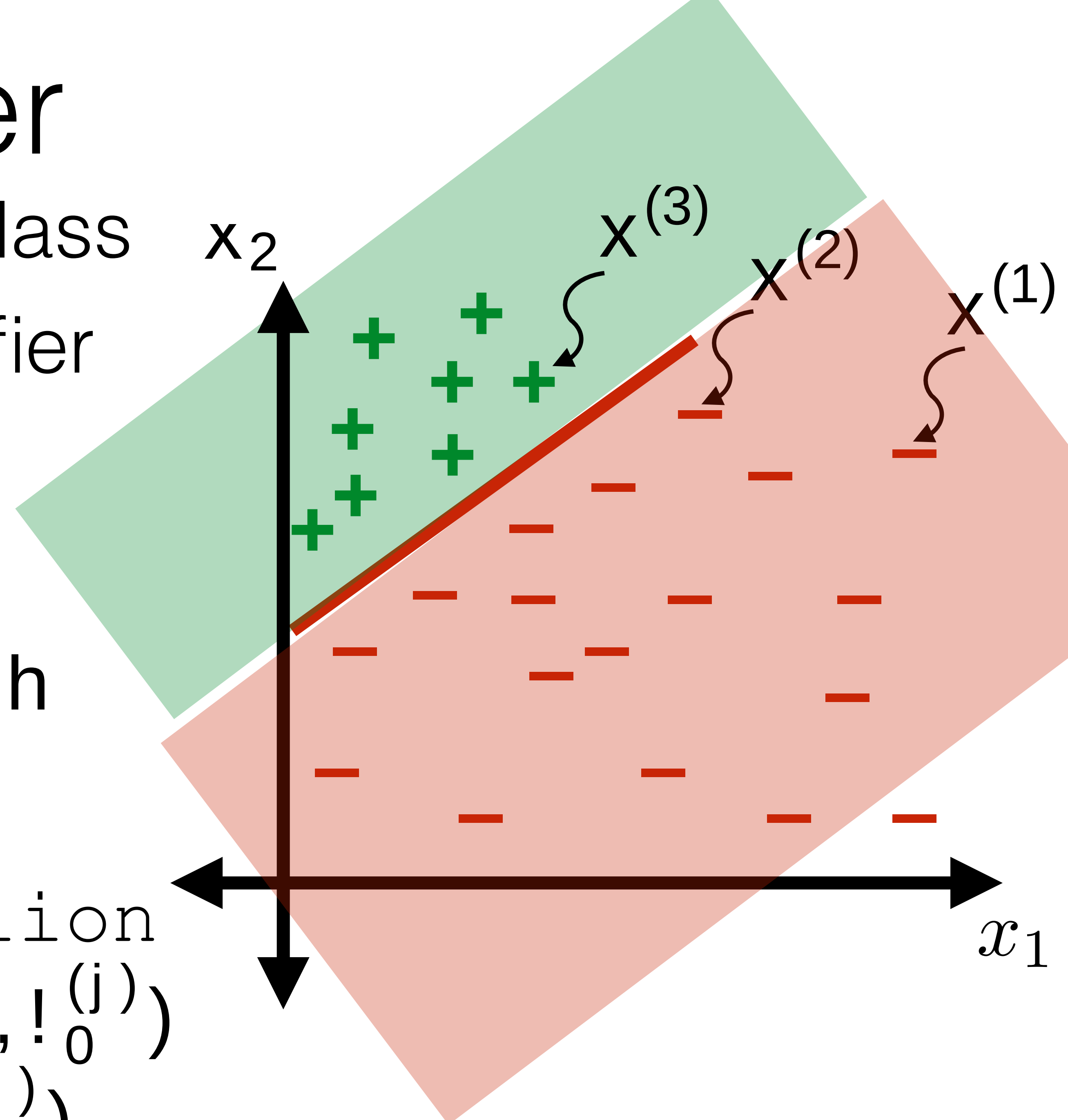


- Example:

```
for j = 1, …, 1 trillion
  Randomly sample (!^(j), !_0^(j))
  Set h^(j)(x) = h(x; !^(j), !_0^(j))
Ex_learning_alg( D_n )
```

Learning a classifier

- Have data; have hypothesis class
- Want to choose a good classifier
  - Recall: $x \rightarrow$ h $\rightarrow$ y
  - New: $D_n \rightarrow$ learning algorithm $\rightarrow$ h



- Example:

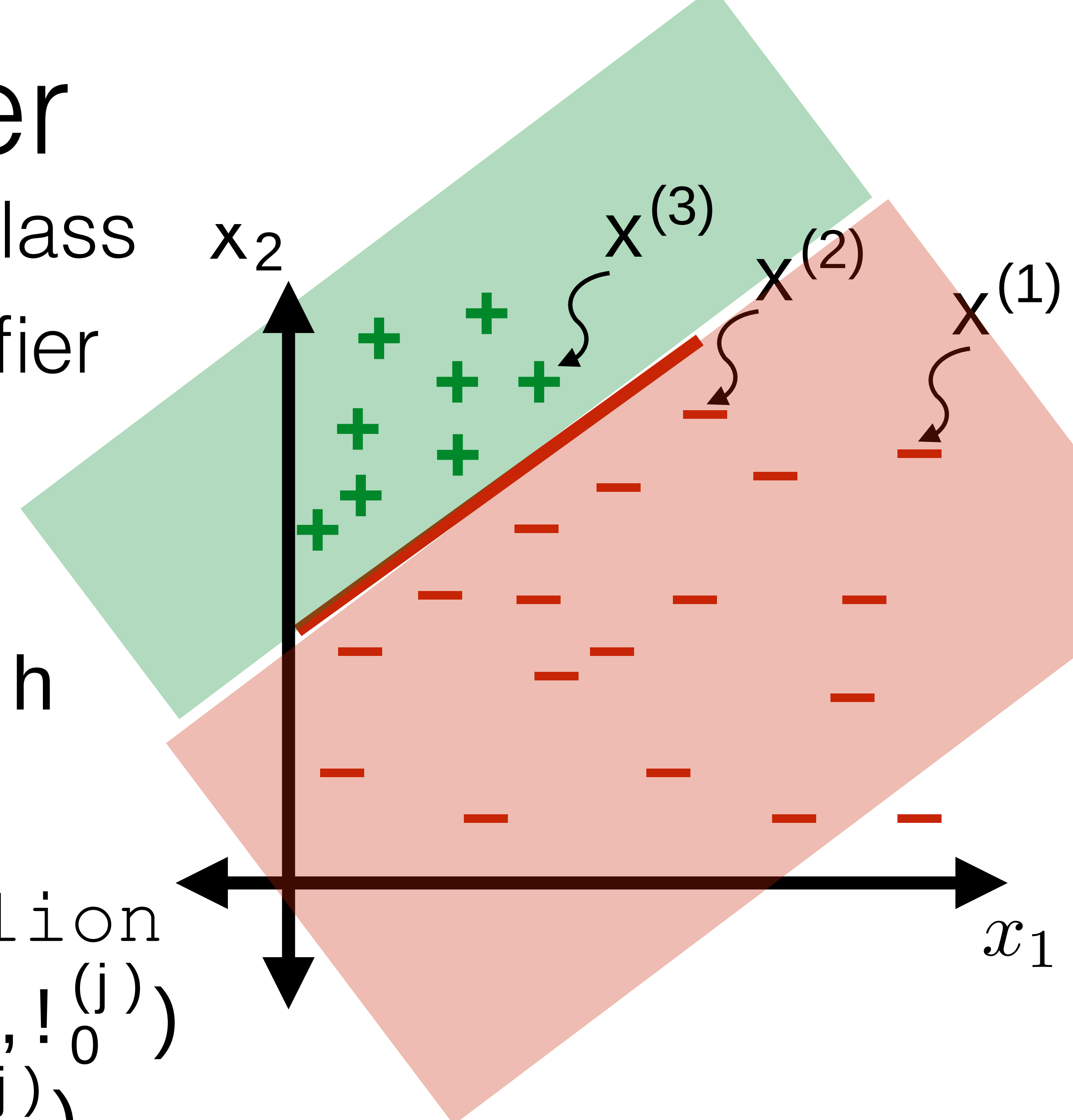
```
for j = 1, …, 1 trillion
   Randomly sample (!(j), !0(j))
   Set h(j)(x) = h(x; !(j), !0(j))
Ex_learning_alg( Dn ; k < 1 trillion)
```

Learning a classifier

- Have data; have hypothesis class
- Want to choose a good classifier
  - Recall: $x \rightarrow$ h $\rightarrow$ y
  - New: $D_n \rightarrow$ learning algorithm $\rightarrow$ h
- Example:

for j = 1, …, 1 trillion
  Randomly sample $(!^{(j)}, !_0^{(j)})$
  Set $h^{(j)}(x) = h(x; !^{(j)}, !_0^{(j)})$
Ex_learning_alg(D_n ; k < 1 trillion)

hyperparameter

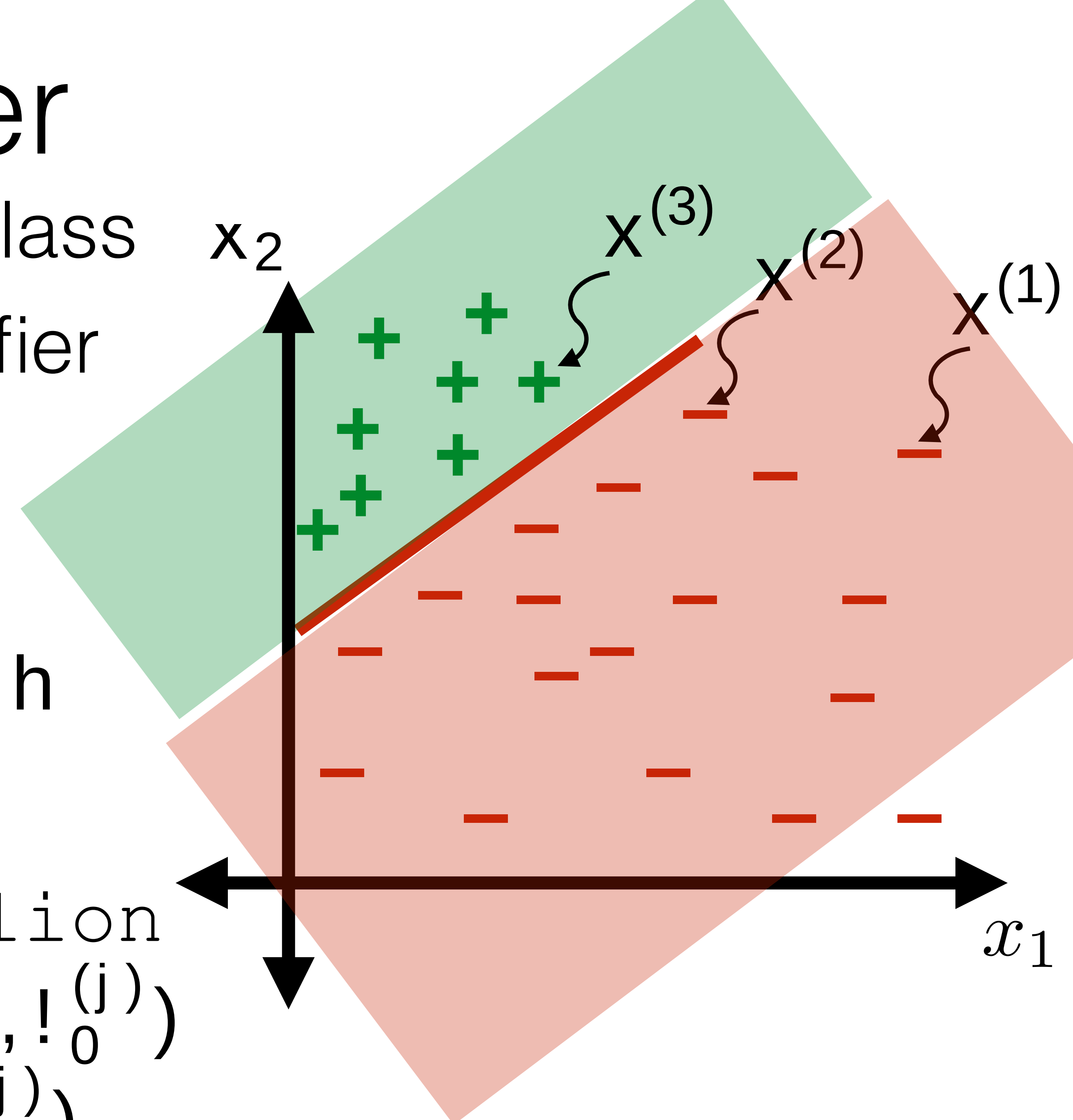


Learning a classifier

- Have data; have hypothesis class
- Want to choose a good classifier
  - Recall: x → h → y
  - New: D_n → learning algorithm → h
- Example:

```
for j = 1, …, 1 trillion
  Randomly sample (!^(j), !_0^(j))
  Set h^(j)(x) = h(x; !^(j), !_0^(j))
Ex_learning_alg( D_n ; k < 1 trillion)
  Set j^! = argmin_{j " {1,…,k}} E_n(h^(j))
```

hyperparameter



Learning a classifier

- Have data; have hypothesis class
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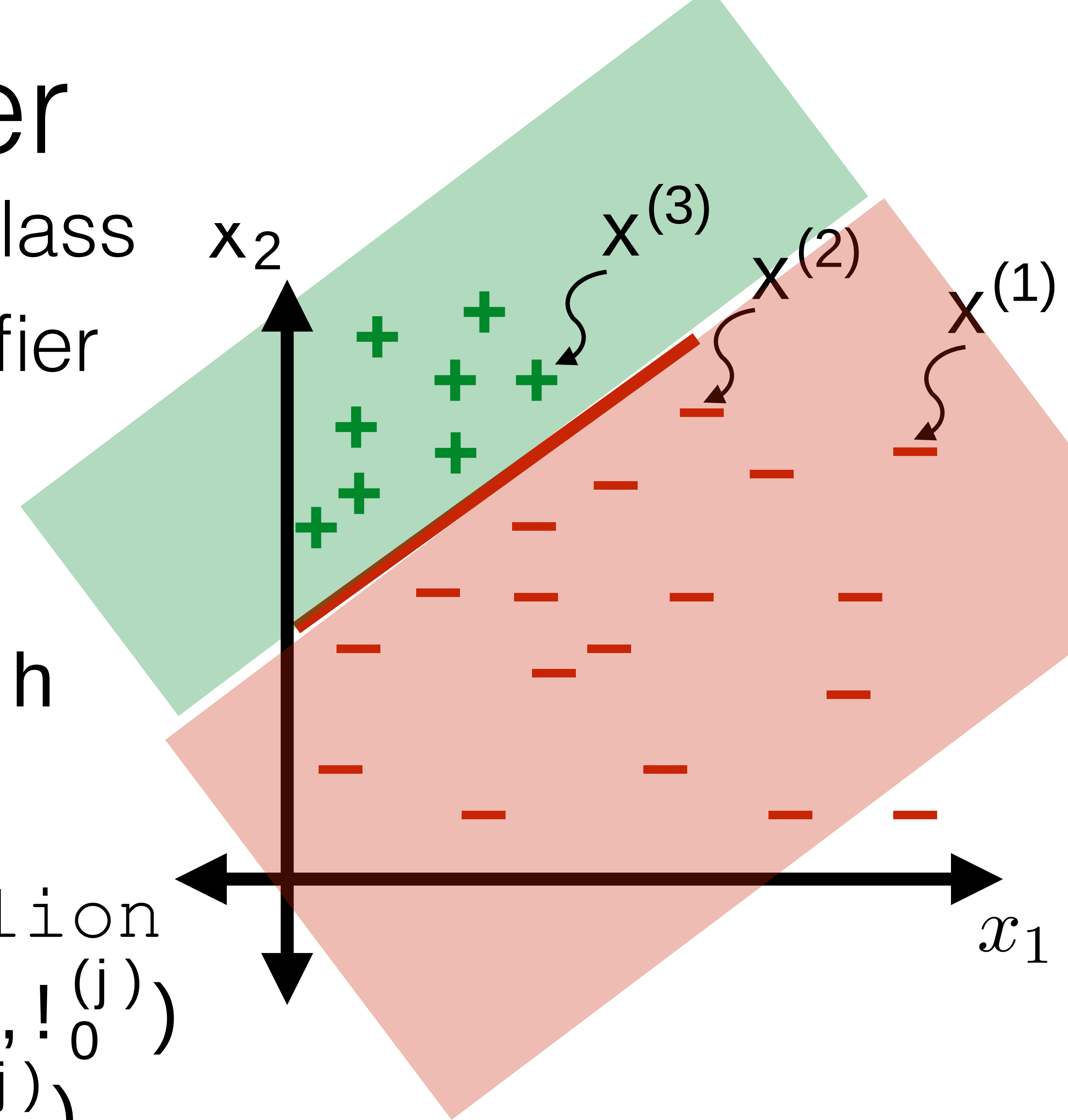


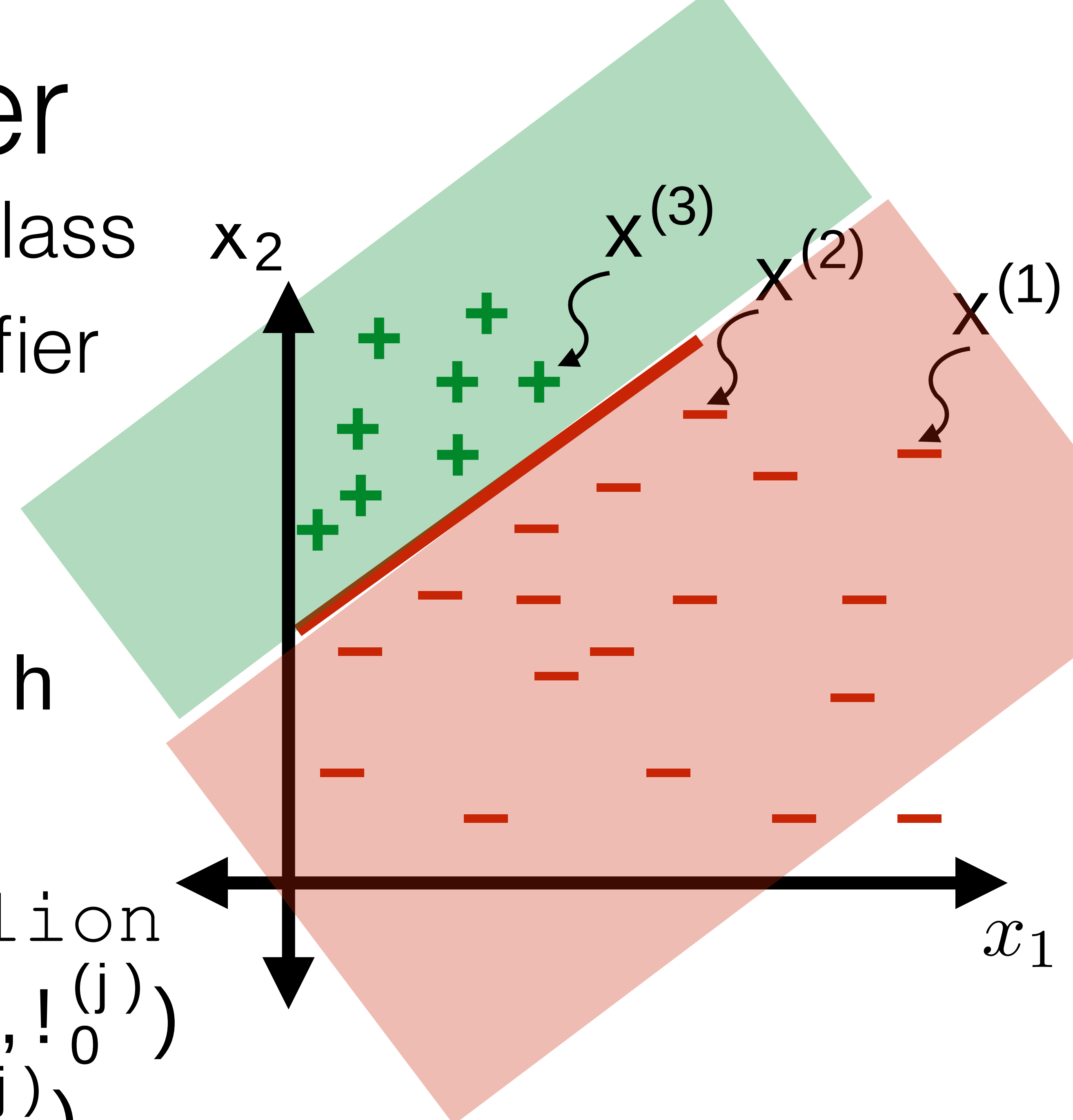
- Example:

```
for j = 1, …, 1 trillion
   Randomly sample (!(j), !0(j))
   Set h(j)(x) = h(x; !(j), !0(j))
Ex_learning_alg( Dn ; k < 1 trillion)
   Set j! = argmin j " {1,...,k} En(h(j))
   Return h(j!)
```

hyperparameter

Learning a classifier

- Have data; have hypothesis class
- Want to choose a good classifier
  - Recall: x → **h** → y
  - New: D_n → **learning algorithm** → h



- Example:

```
for j = 1, …, 1 trillion
   Randomly sample (!(j), !0(j))
   Set h(j)(x) = h(x; !(j), !0(j))
Ex_learning_alg( Dn ; k < 1 trillion)
   Set j! = argmin j " {1,…,k} En(h(j))
   Return h(j!)
```

hyperparameter

- How does training error of `Ex_learning_alg`(D_n;1) compare to the training error of `Ex_learning_alg`(D_n;2)?

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