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 3" category)

Materials: Will all be available at course website

Last Time(s)

I. Linear classifiers
II. Perceptron algorithm
III. Linear separability
IV. Perceptron theorem

Today's Plan

I. A more-complete ML analysis
II. Choosing good features
III. Evaluation

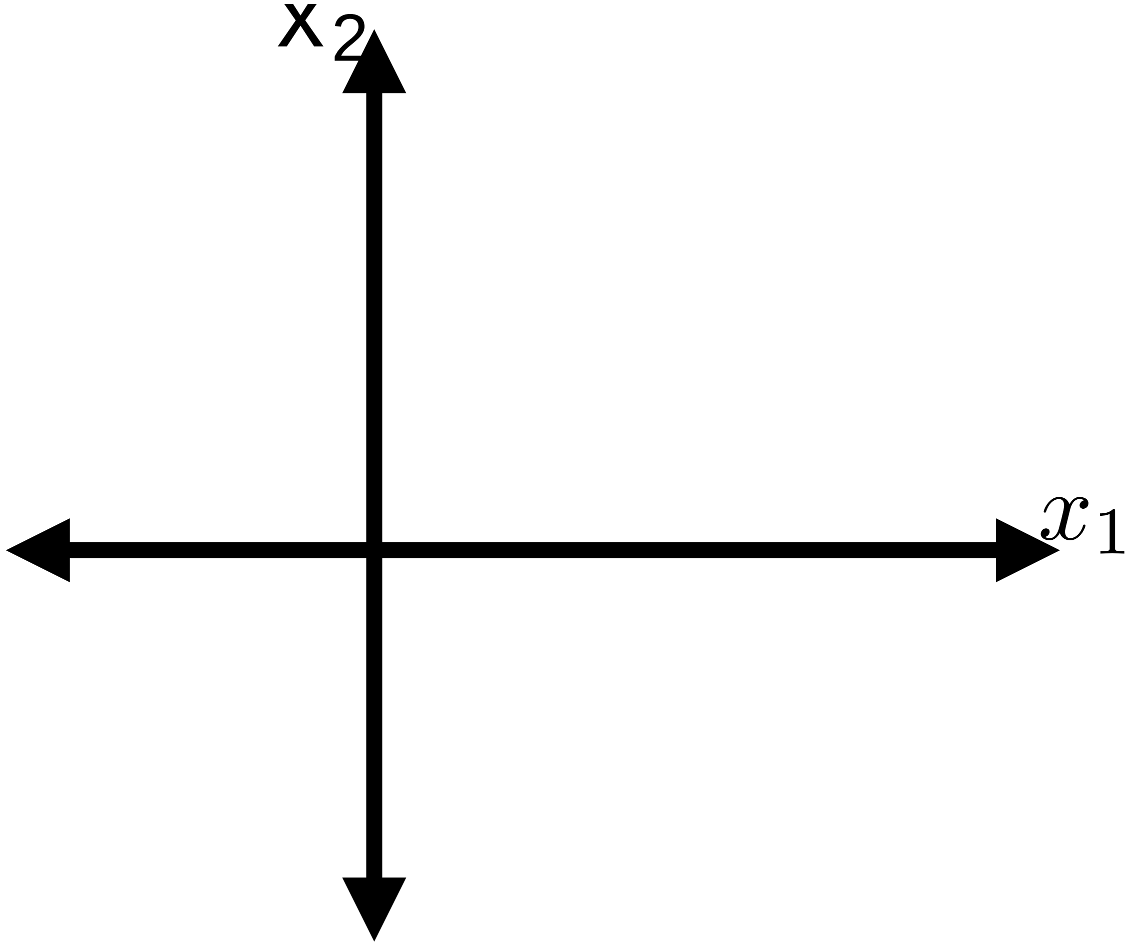
Recall

Recall

- Linear classifier h

Recall

- Linear classifier h



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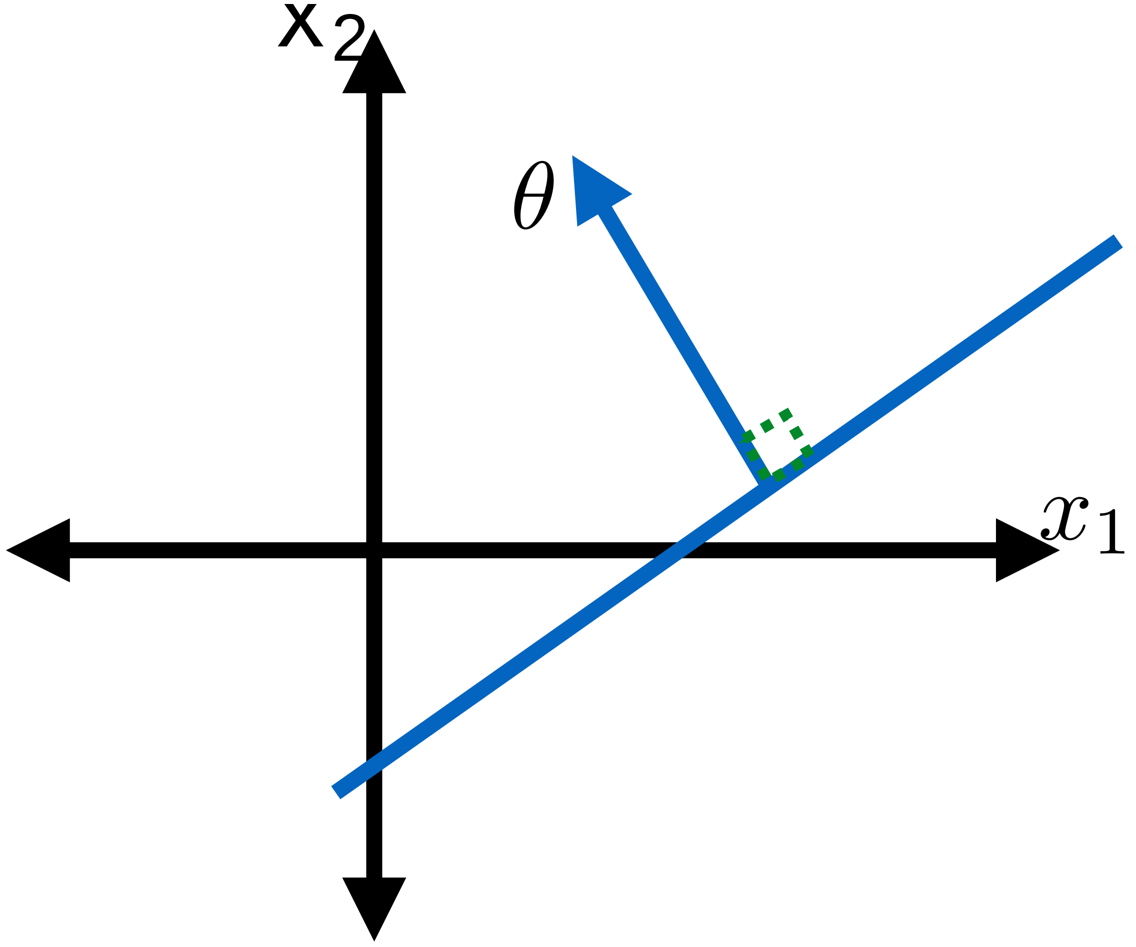

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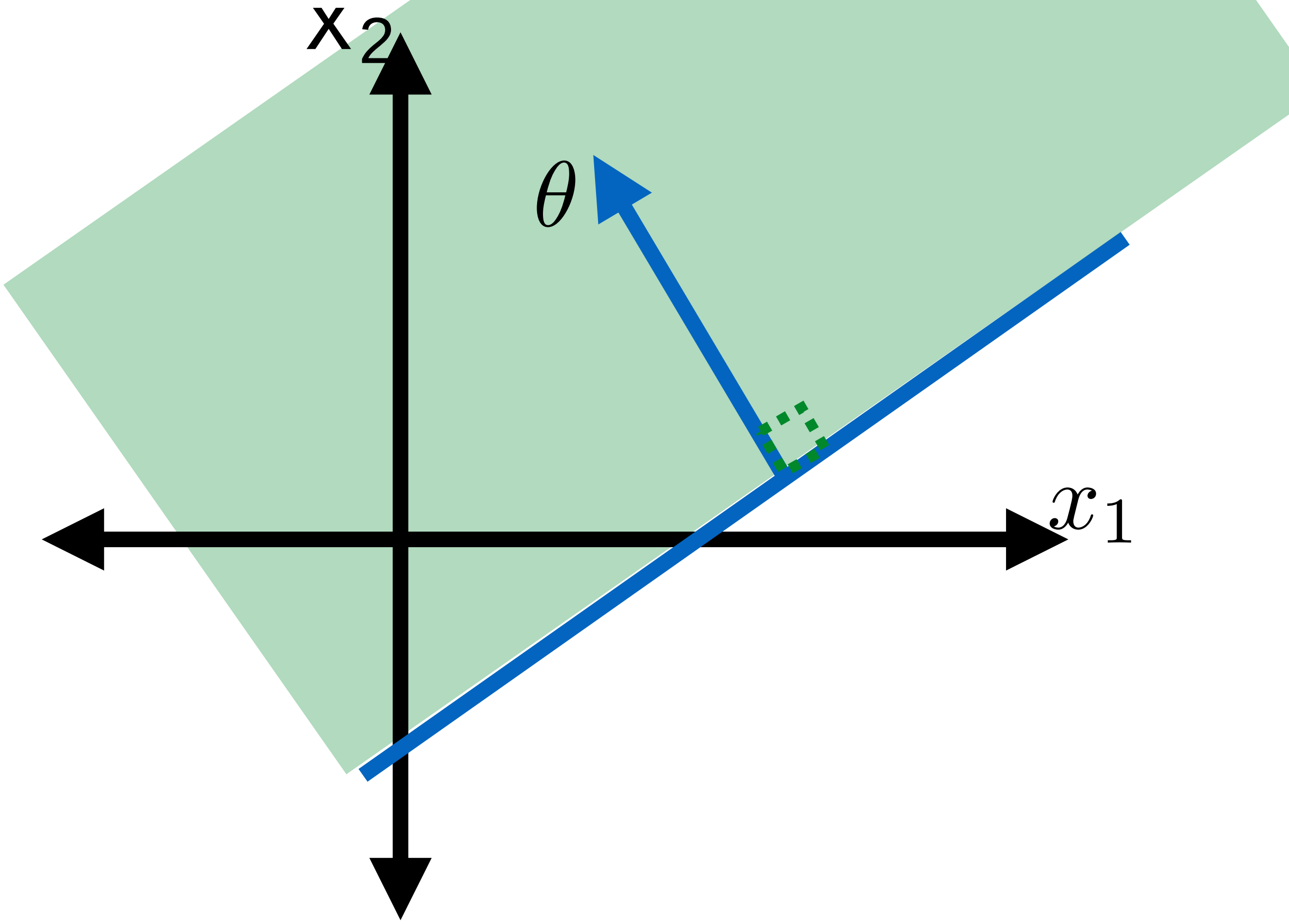

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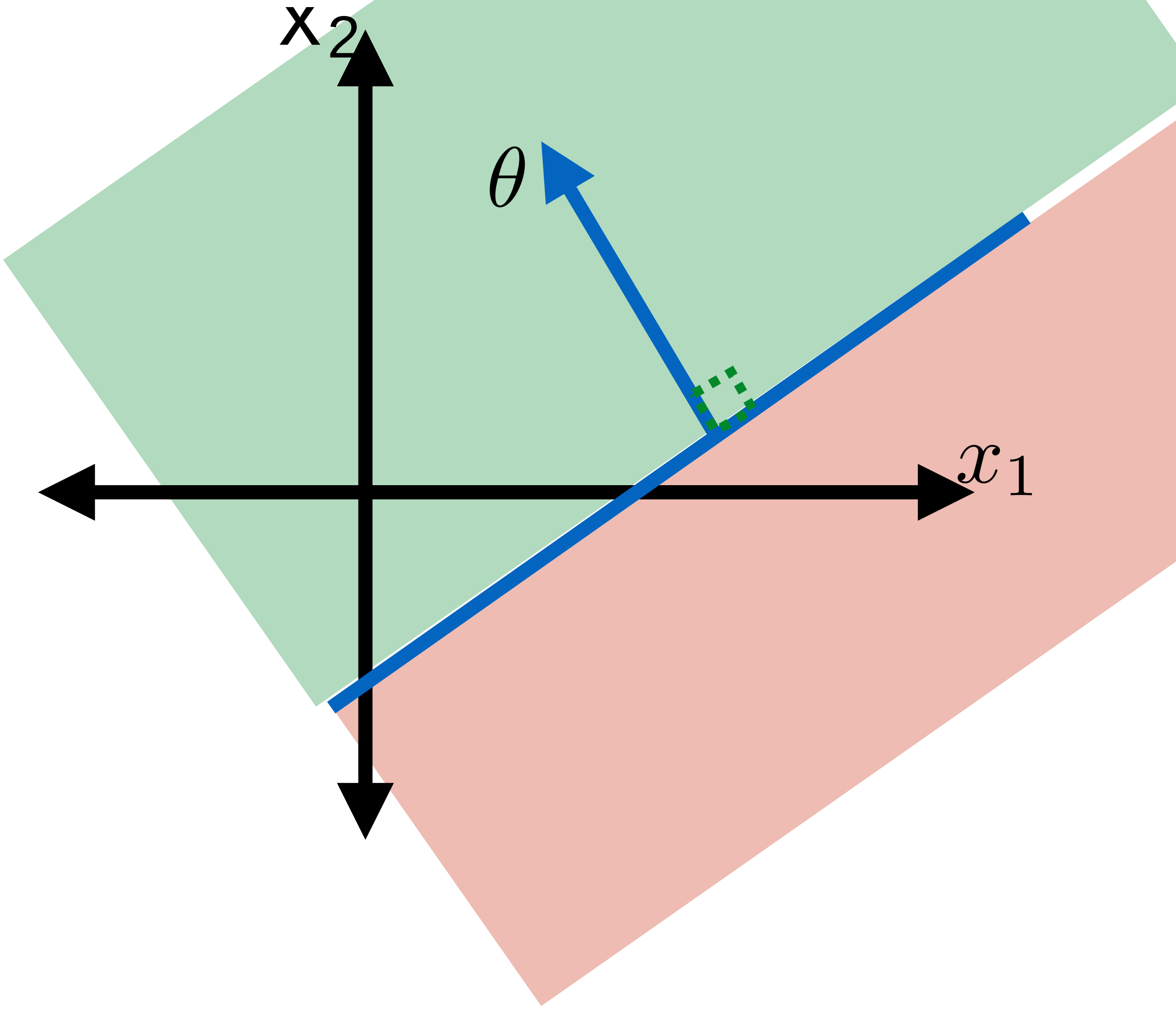

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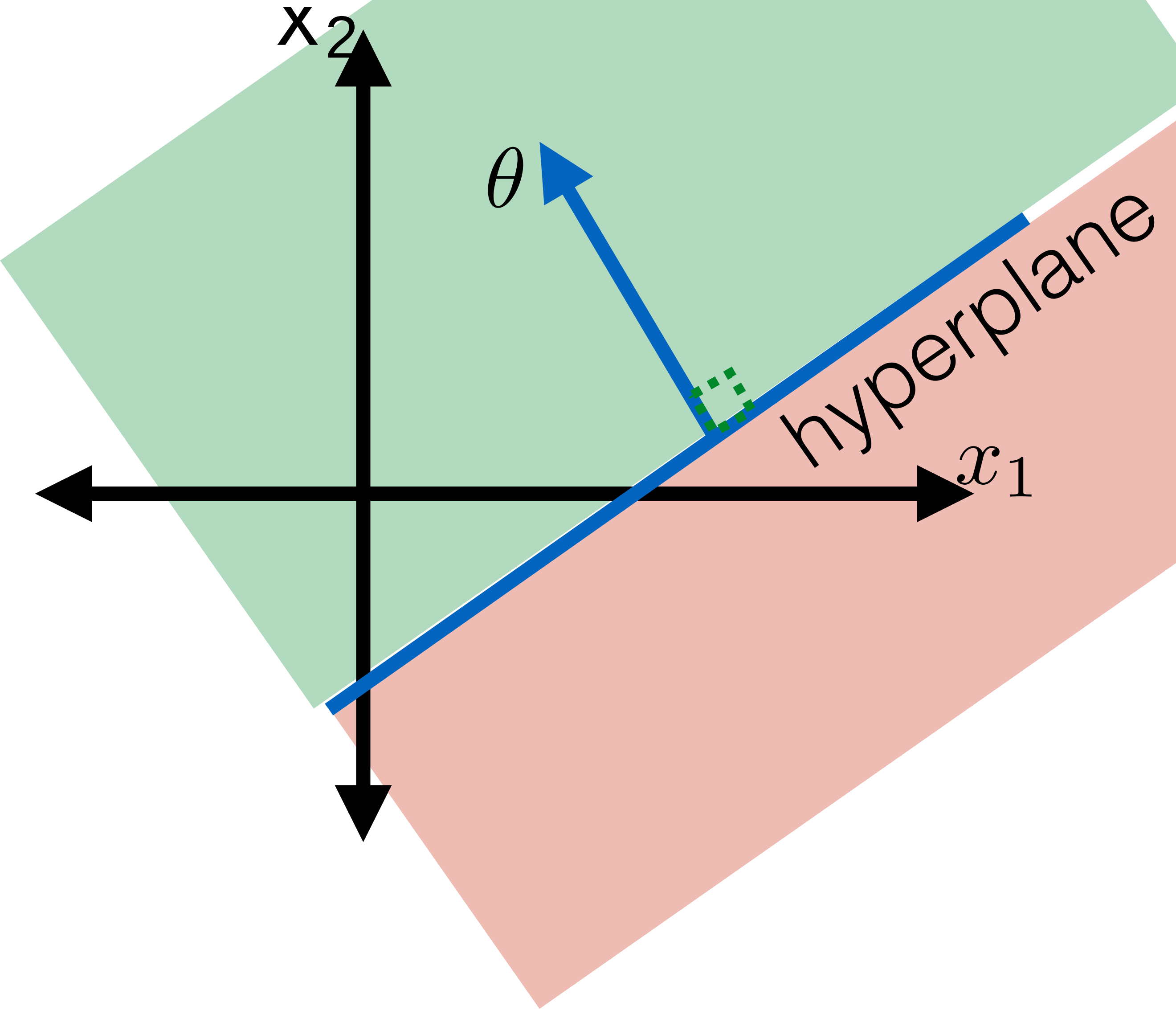
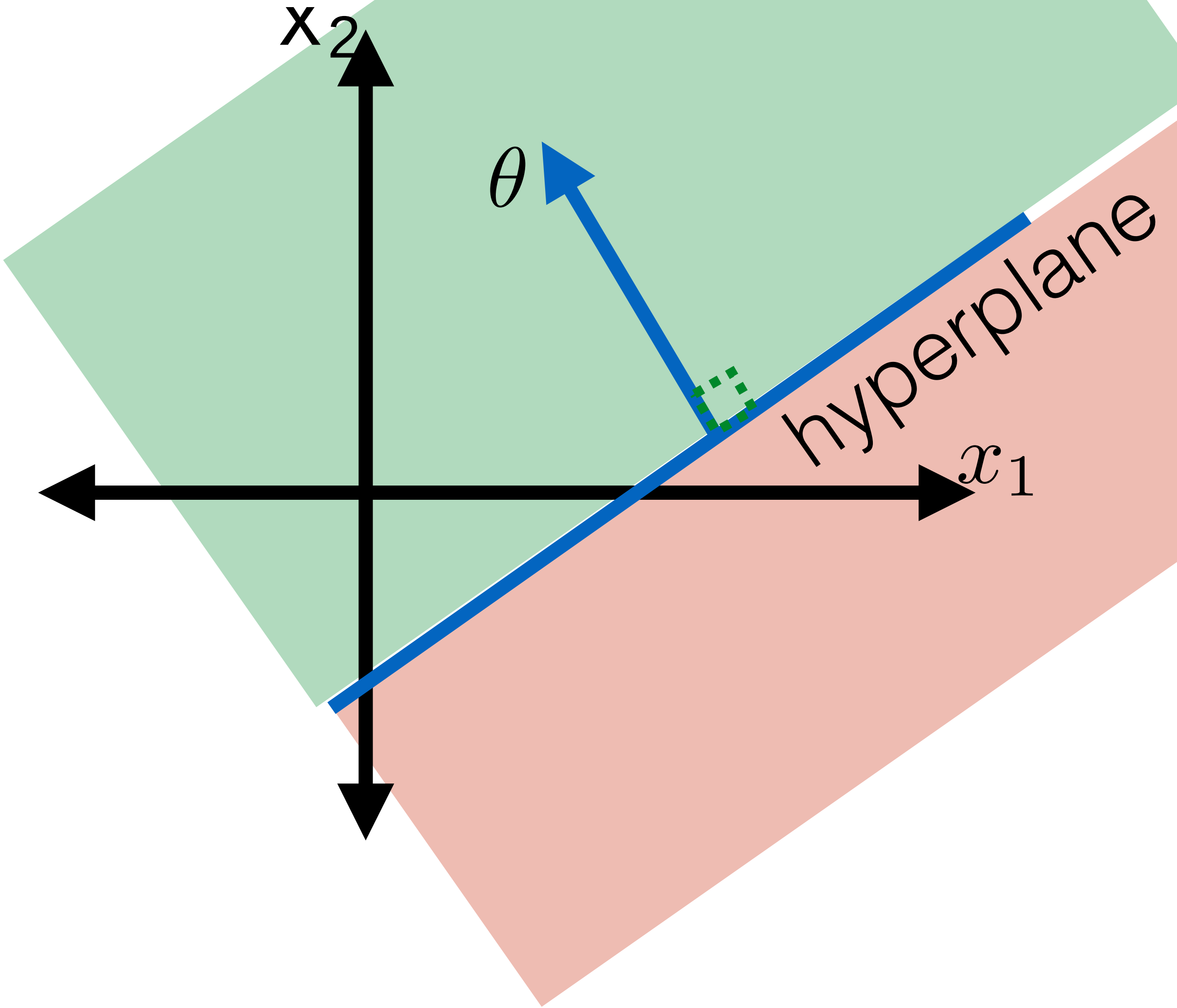


Recall

- Linear classifier h
- 0-1 Loss

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



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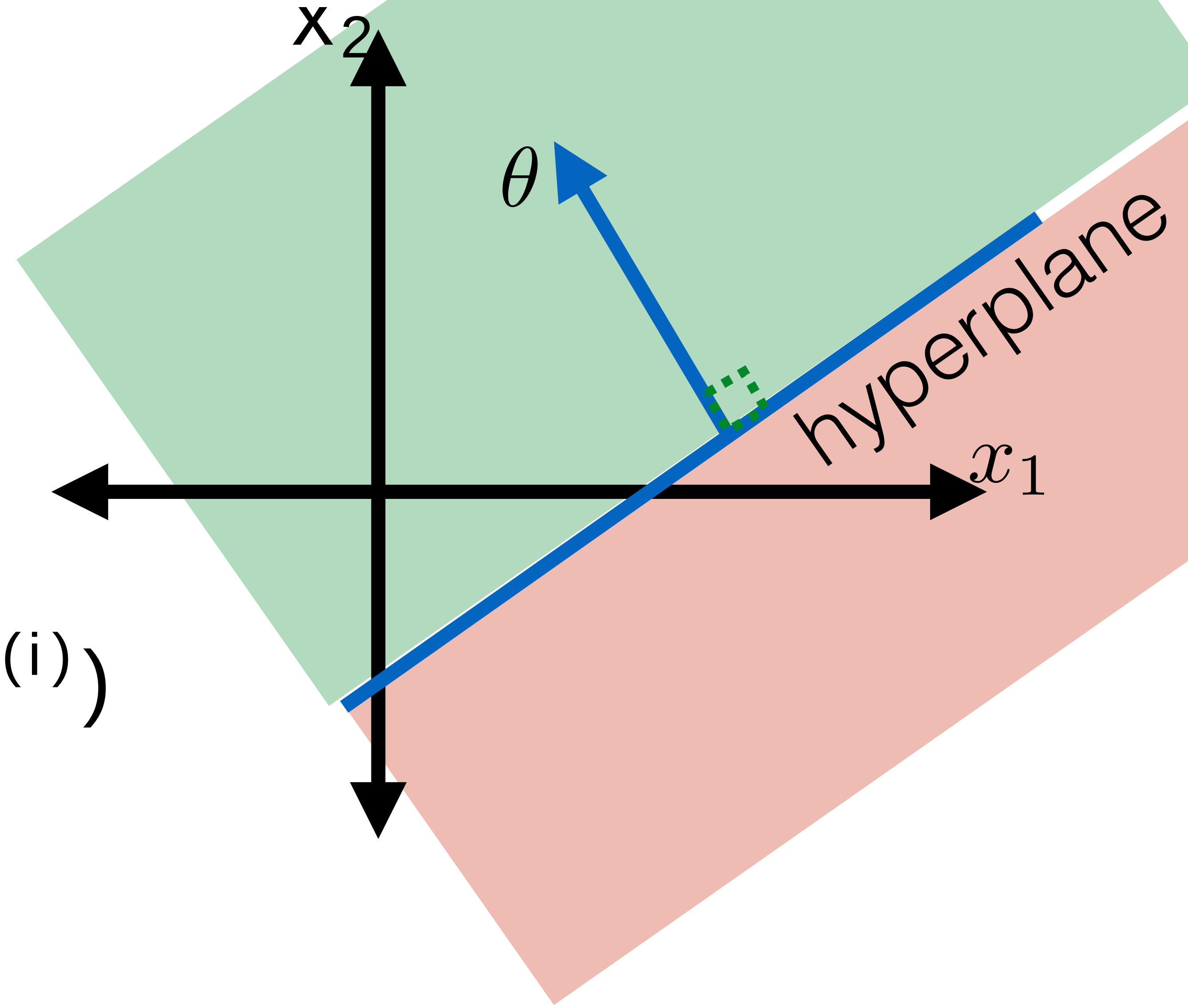
- Training error

$$E_n(h) = \frac{1}{n} \overset{!\,''}{\underset{i=1}{}} L(h(x^{(i)}), y^{(i)})$$



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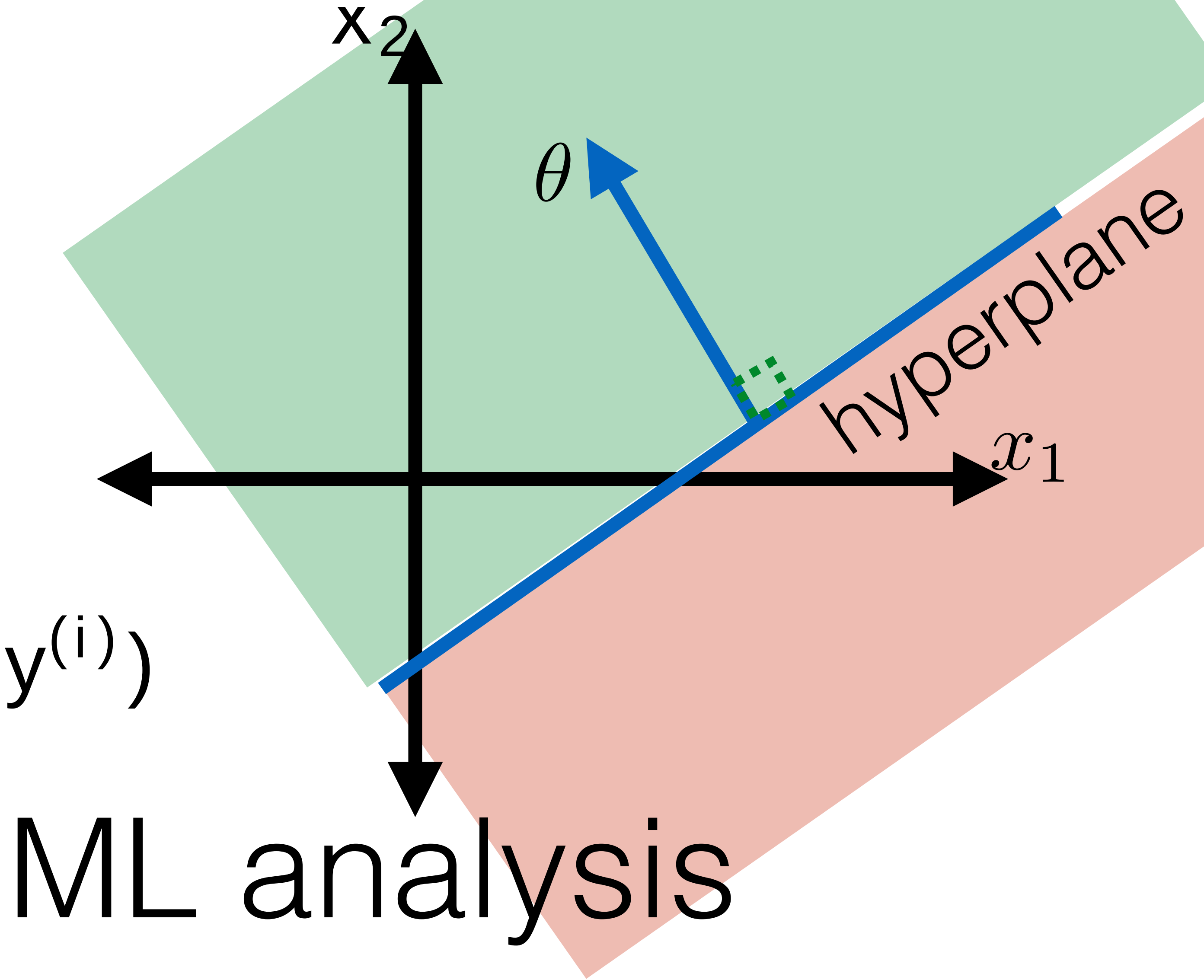

A more-complete ML analysis

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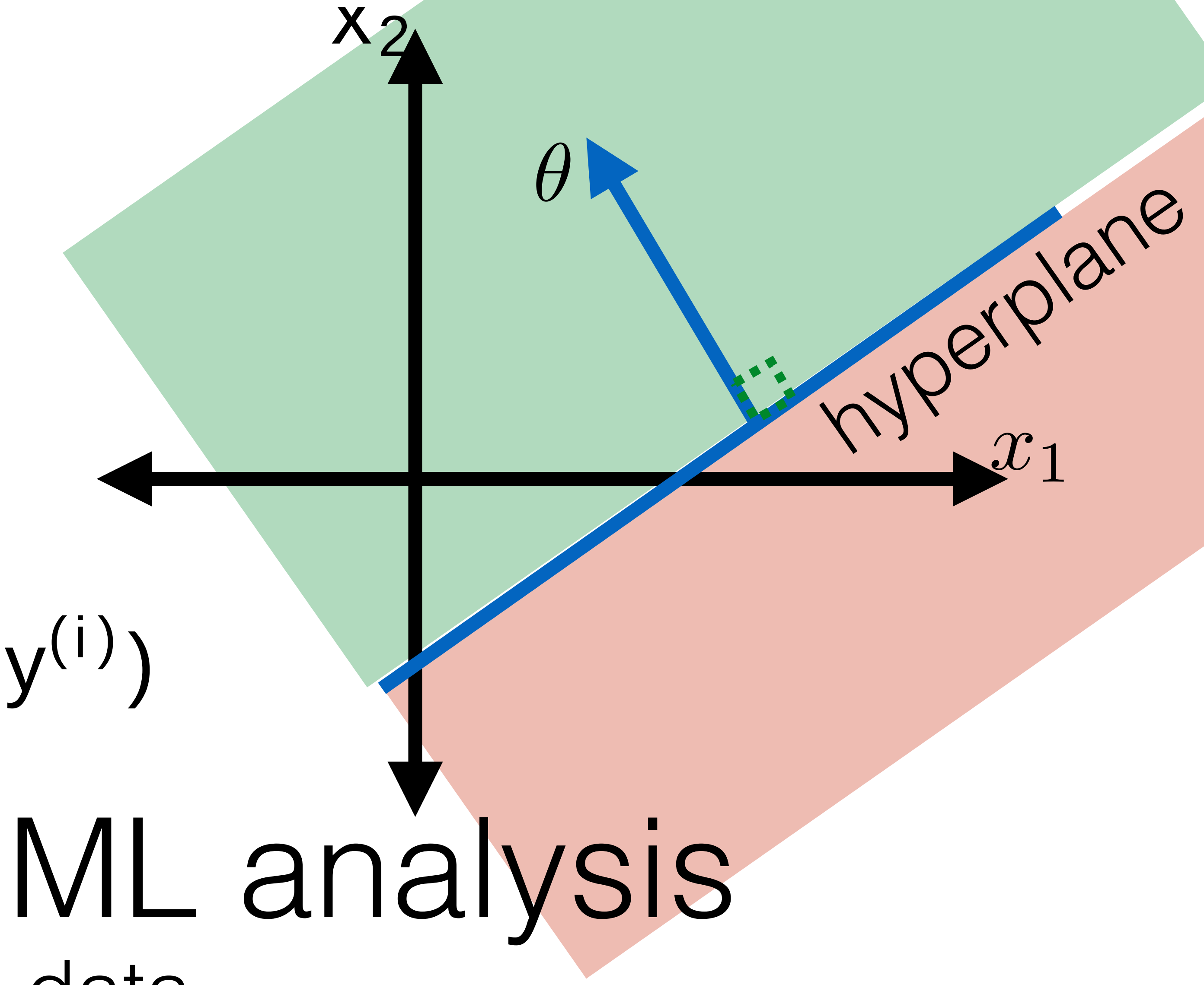

A more-complete ML analysis

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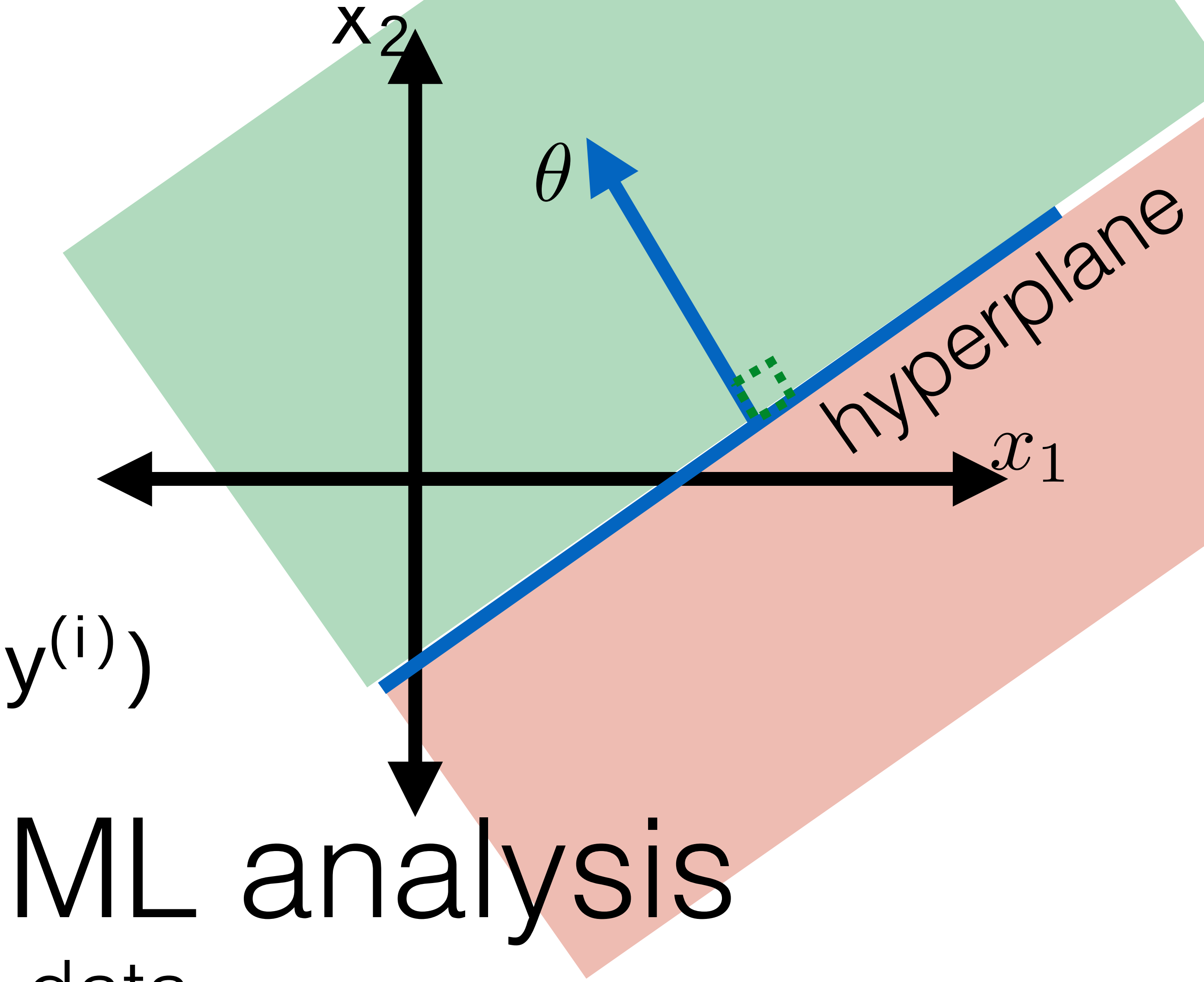

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    - Example goal: diagnose whether people have heart disease based on their available information

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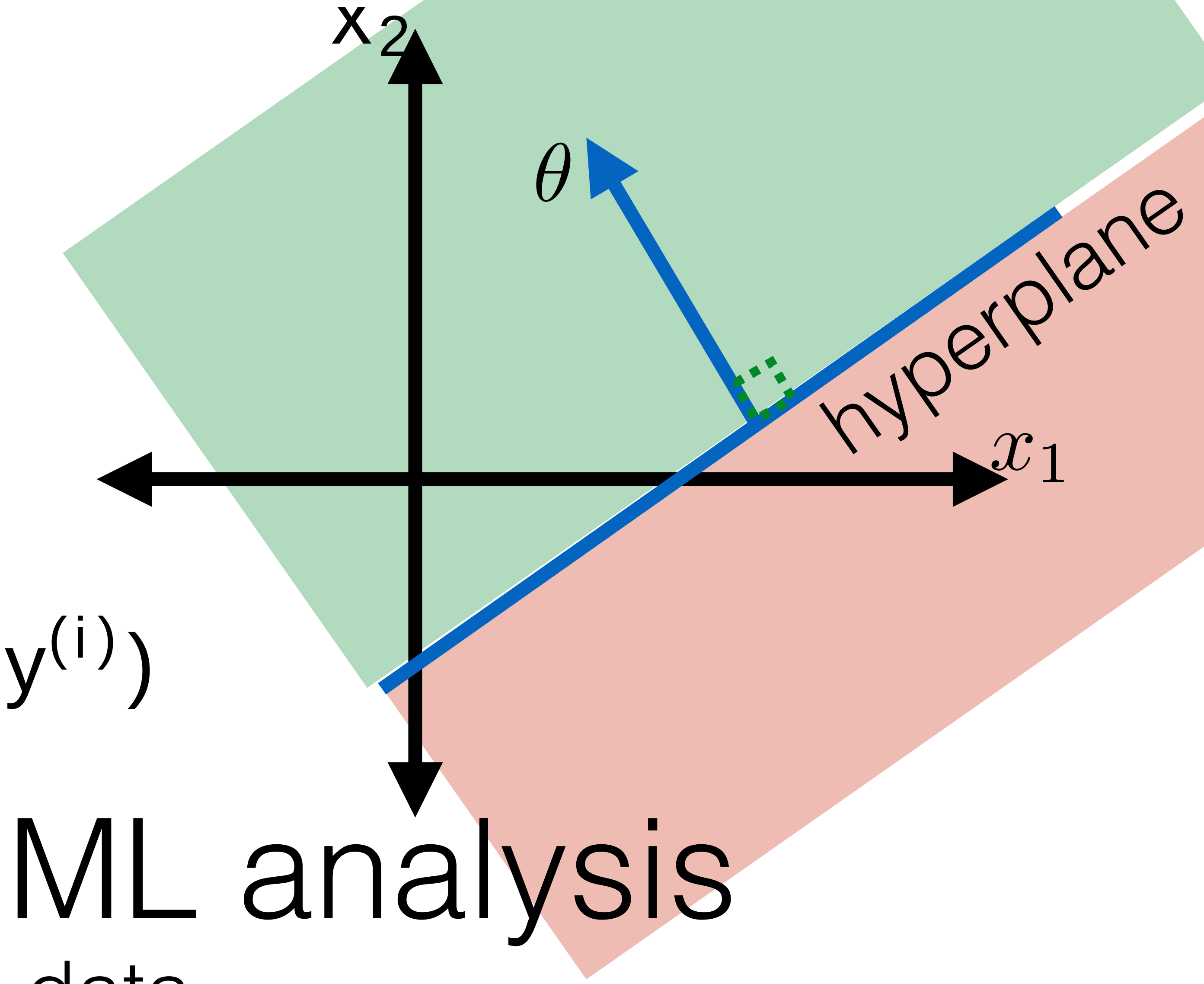

A more-complete ML analysis

1. Establish a goal & find data
   - Example goal: diagnose whether people have heart disease based on their available information
2. Encode data in useful form for the ML algorithm

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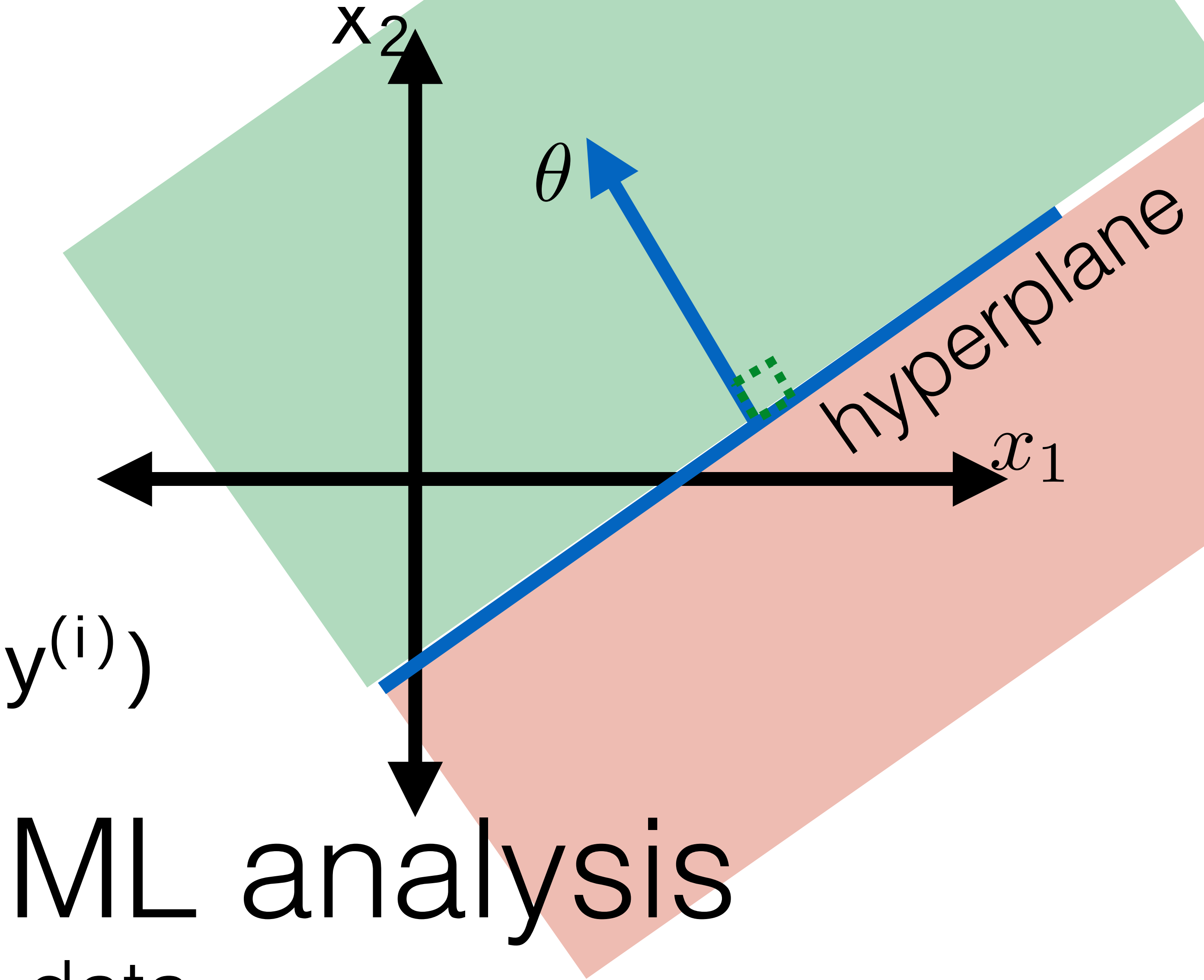

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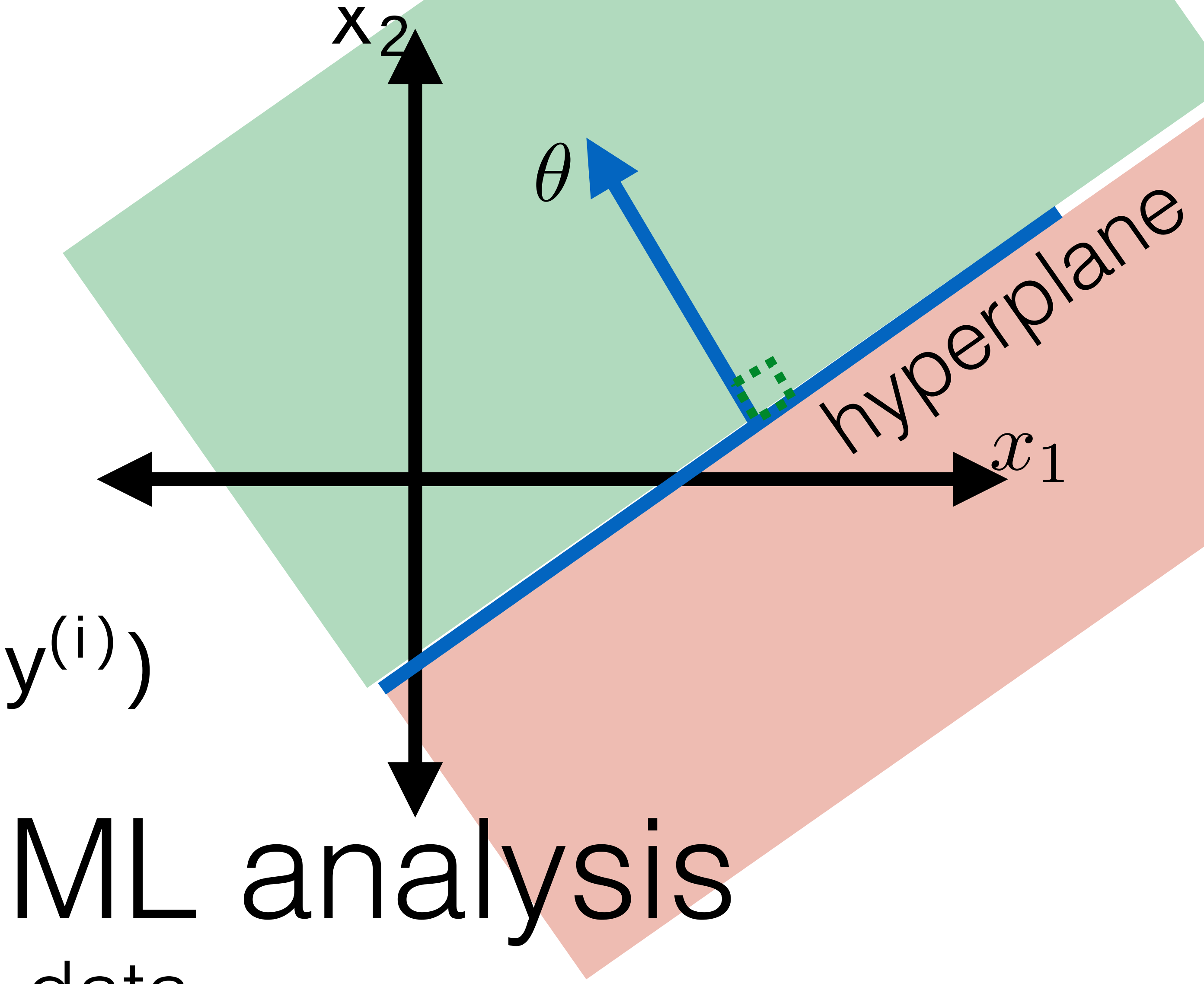

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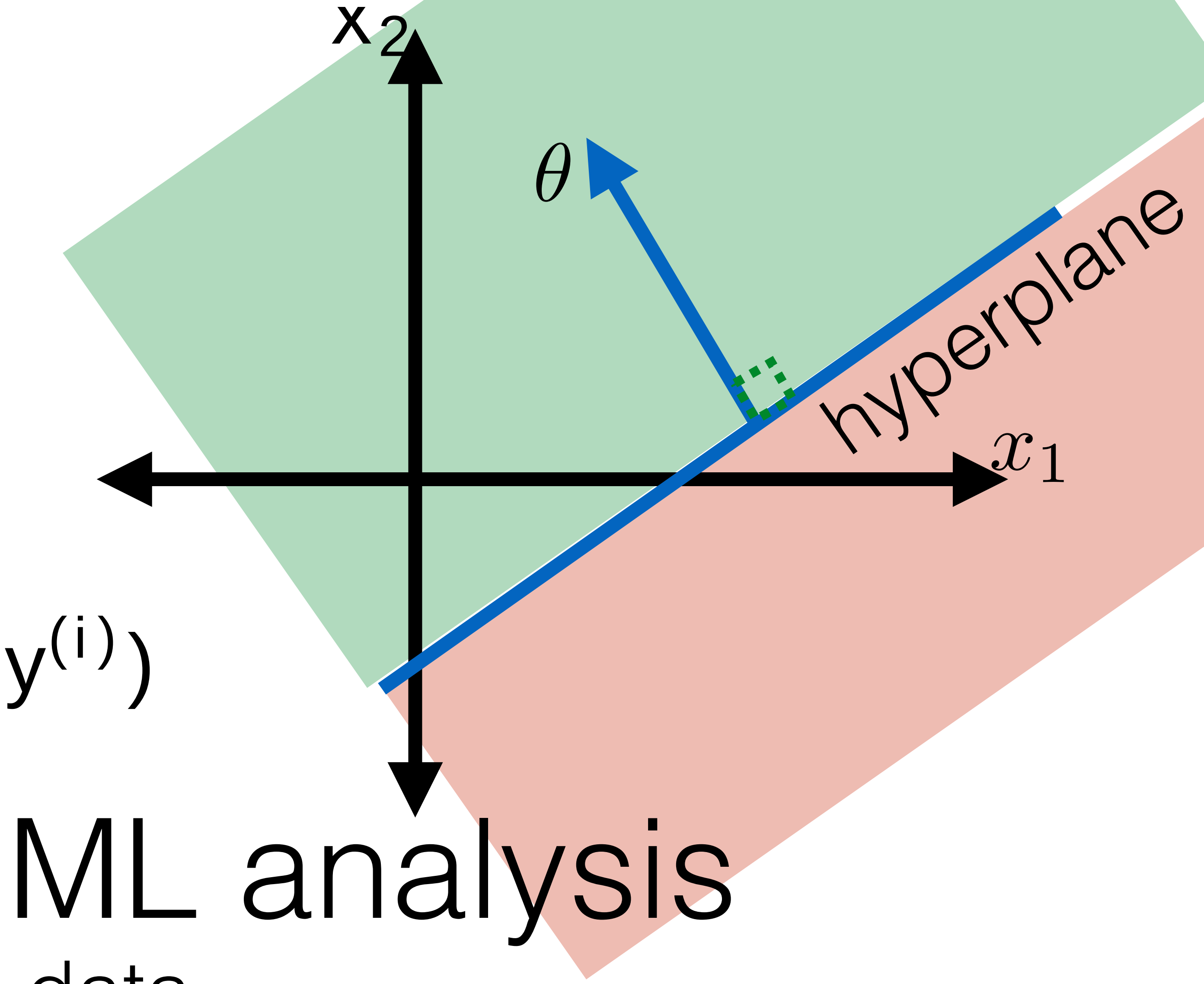

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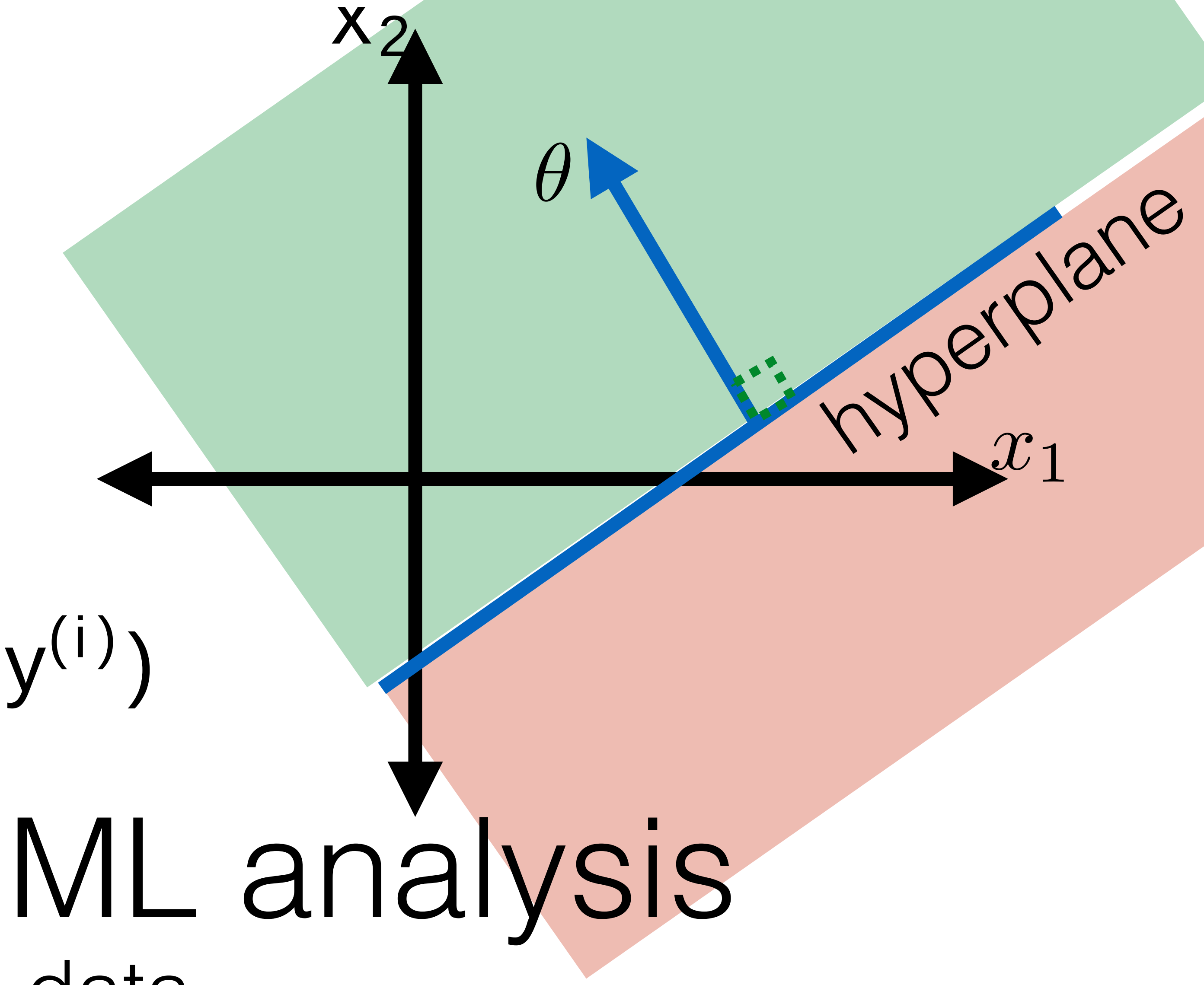

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4. Interpretation & evaluation

A machine learning (ML) analysis

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1	no	55	no	nurse	pain	40s	133000
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4	no	67	no	doctor	none	50s	120000

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Encode data in usable form

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➡

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1	-1 $= y^{(1)}$
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- Depending on your algorithm, might instead use $\{0, 1\}$

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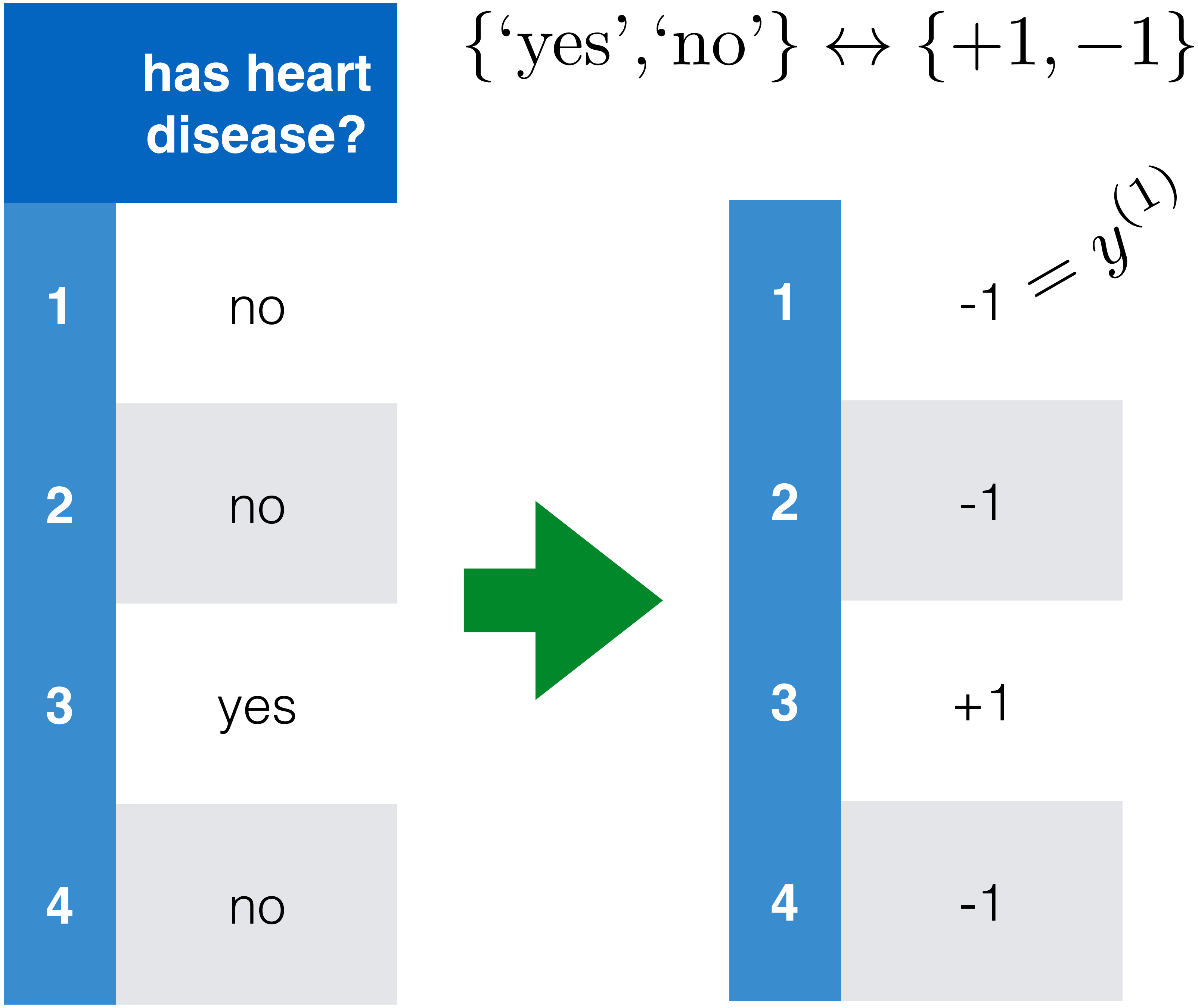

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- Save mapping to recover predictions of new points

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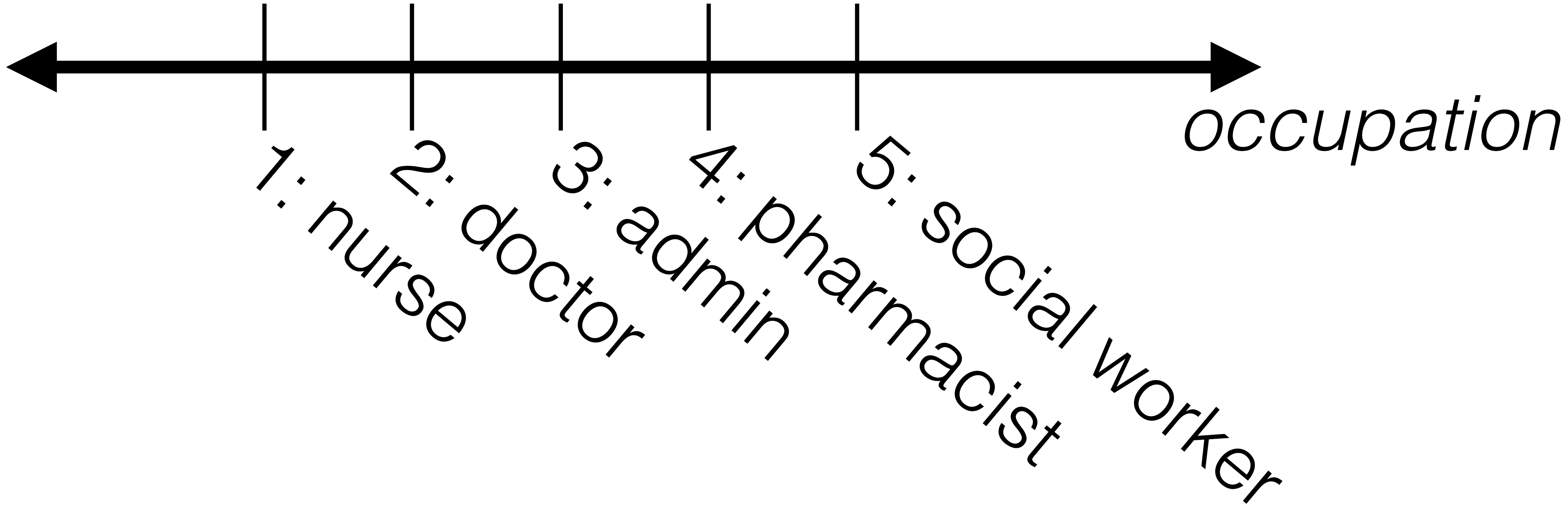

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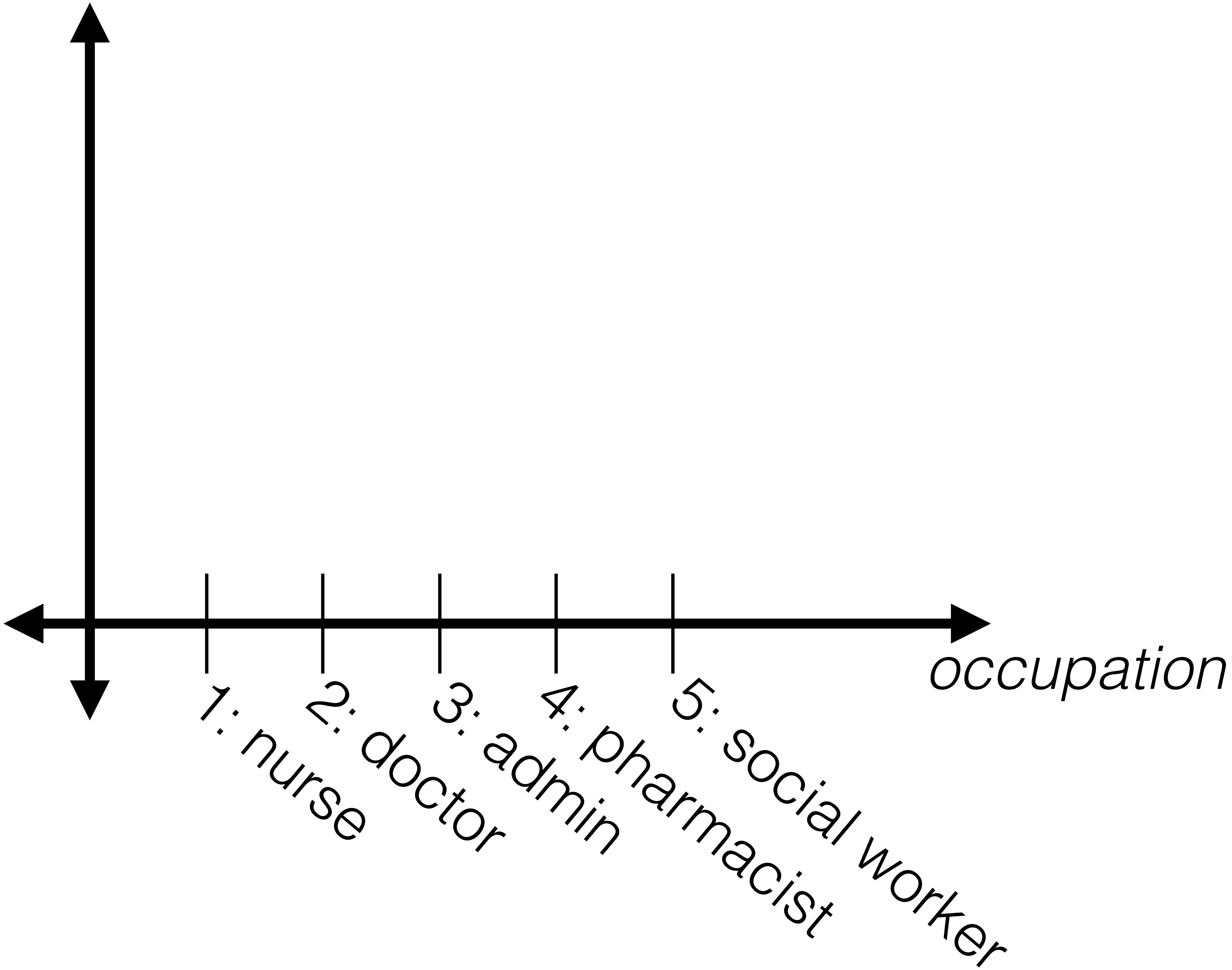

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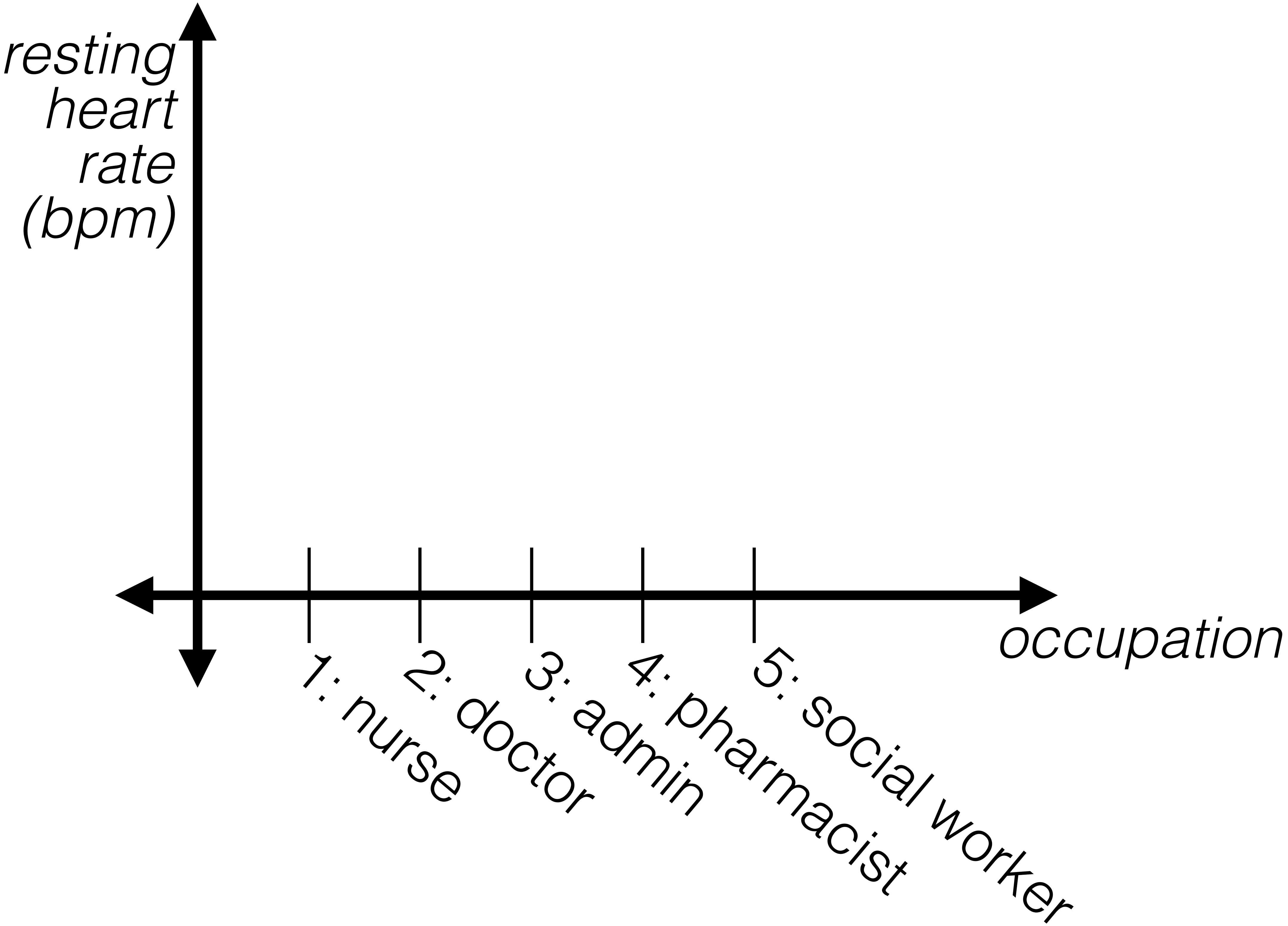

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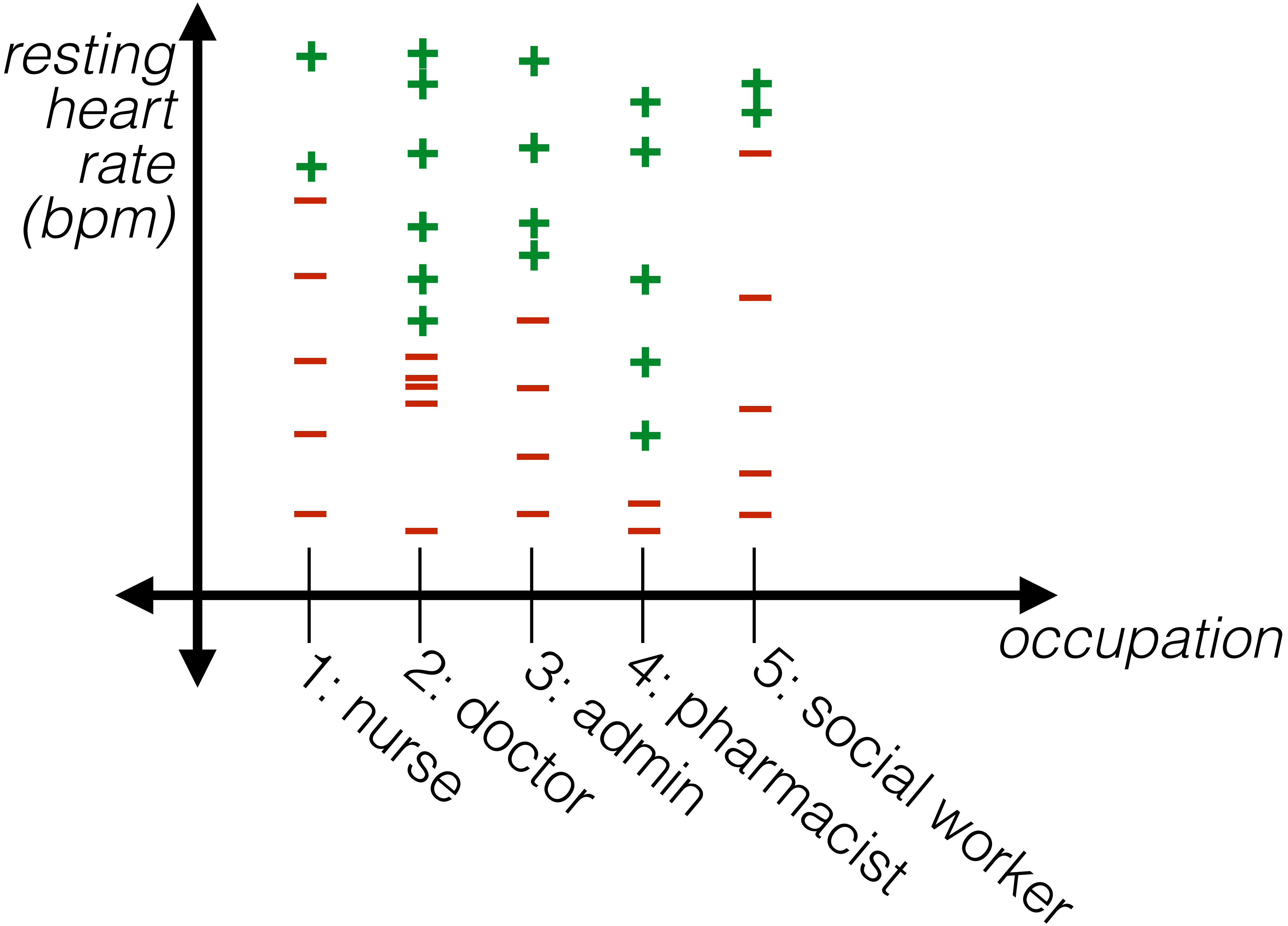

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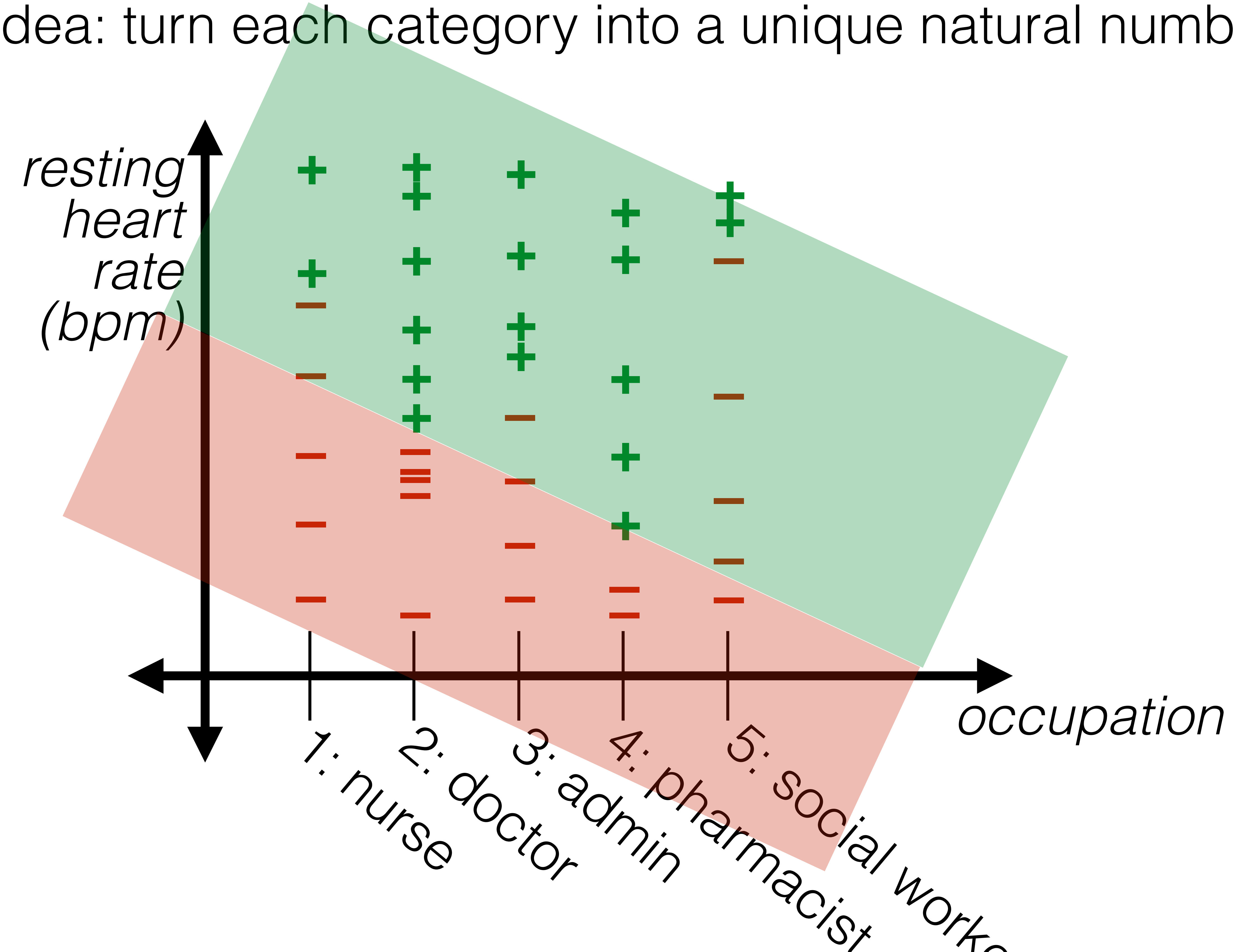

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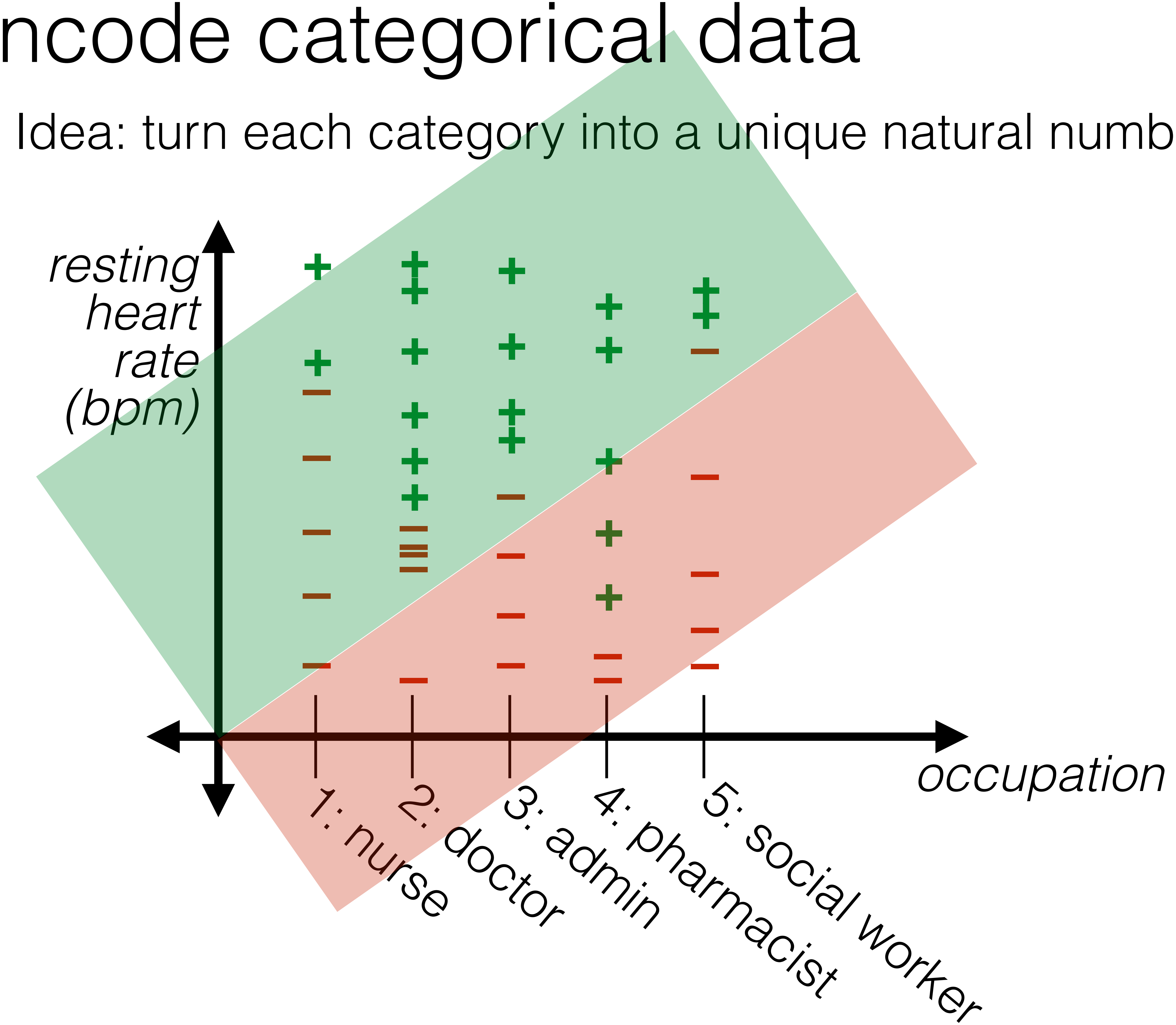

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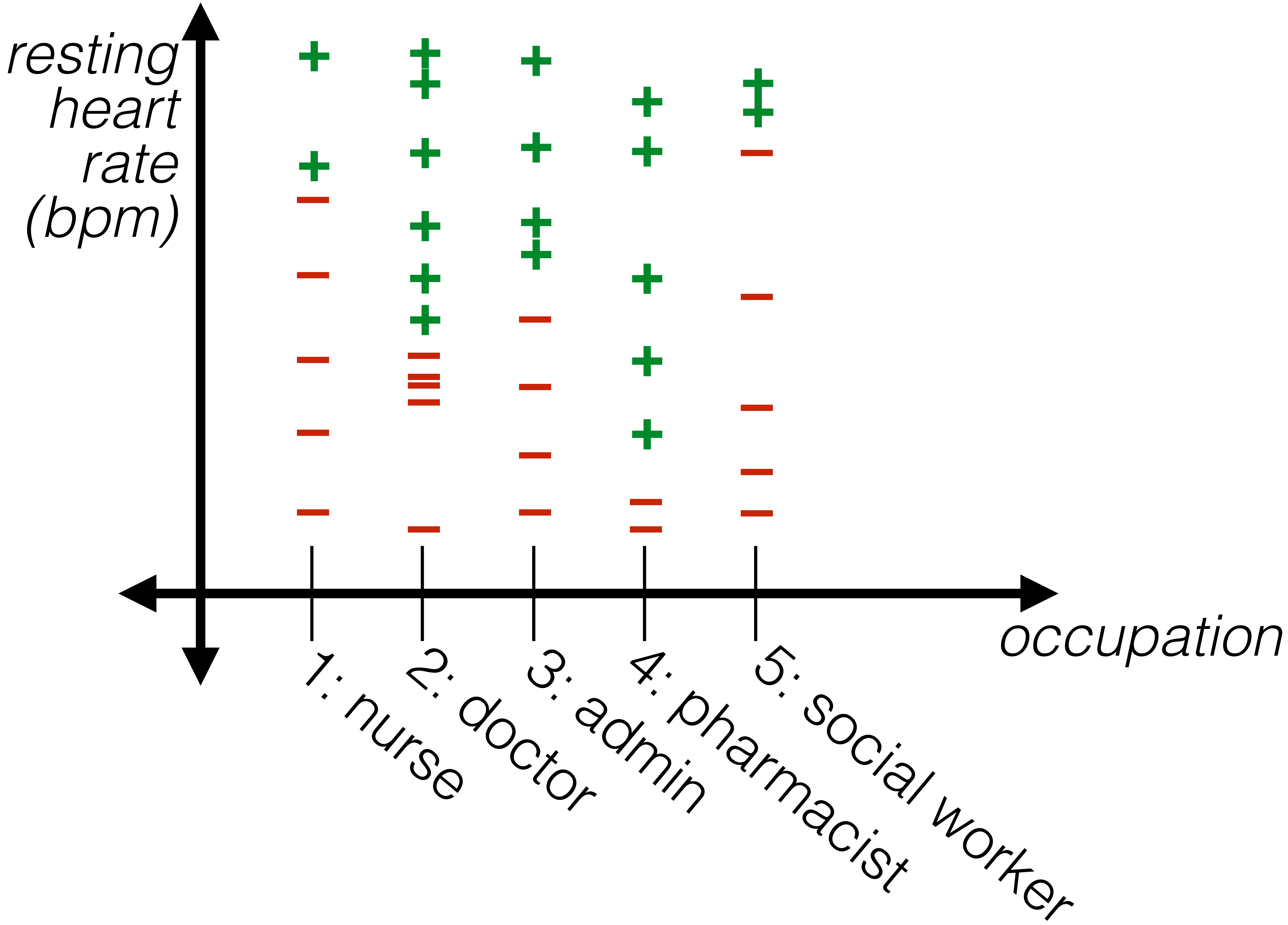

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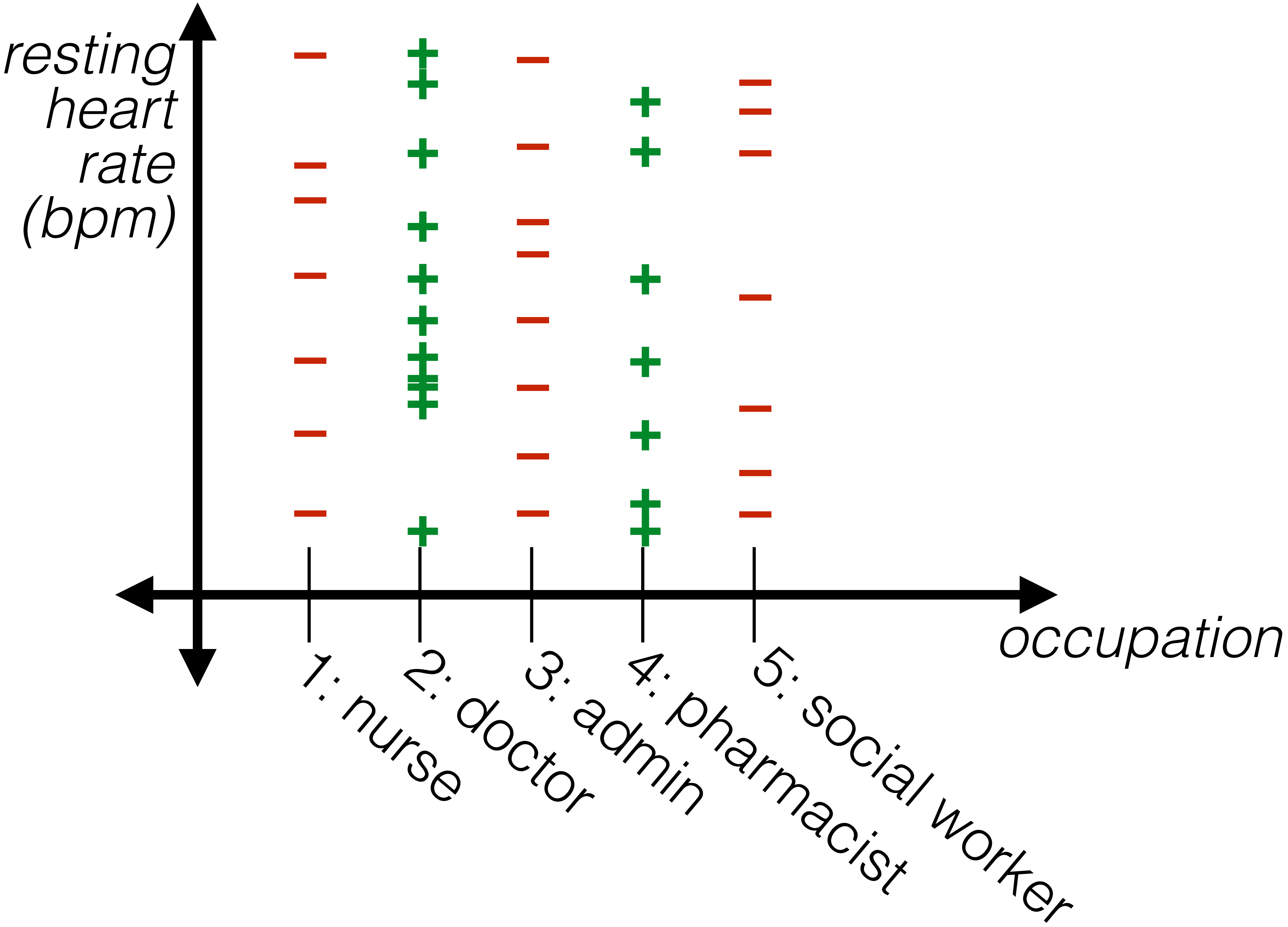

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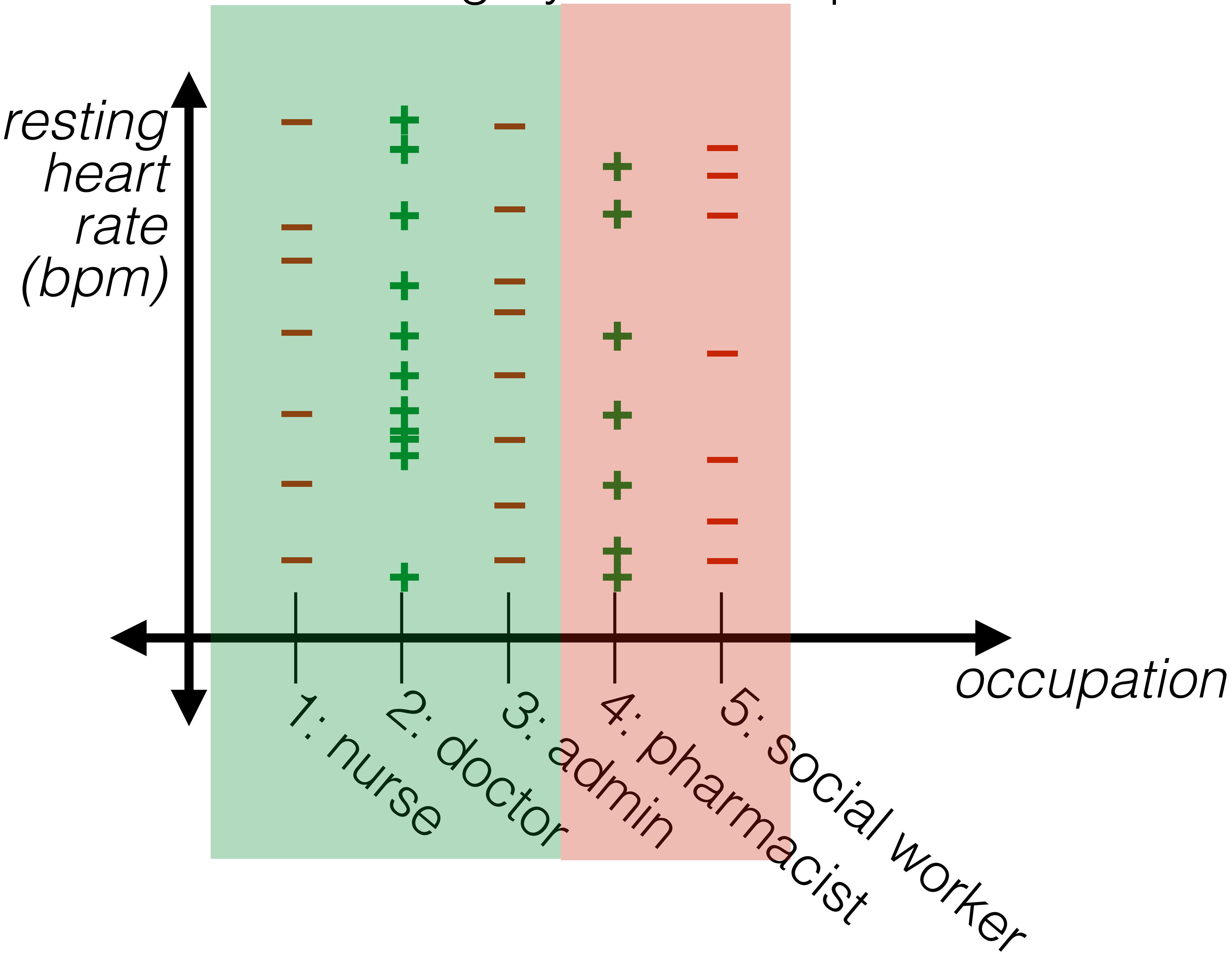

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	! d	ϕ_{d+1}	! d+2
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admin	0	0	1
pharmacist	0	1	0
doctor	0	1	1
social worker	1	0	0

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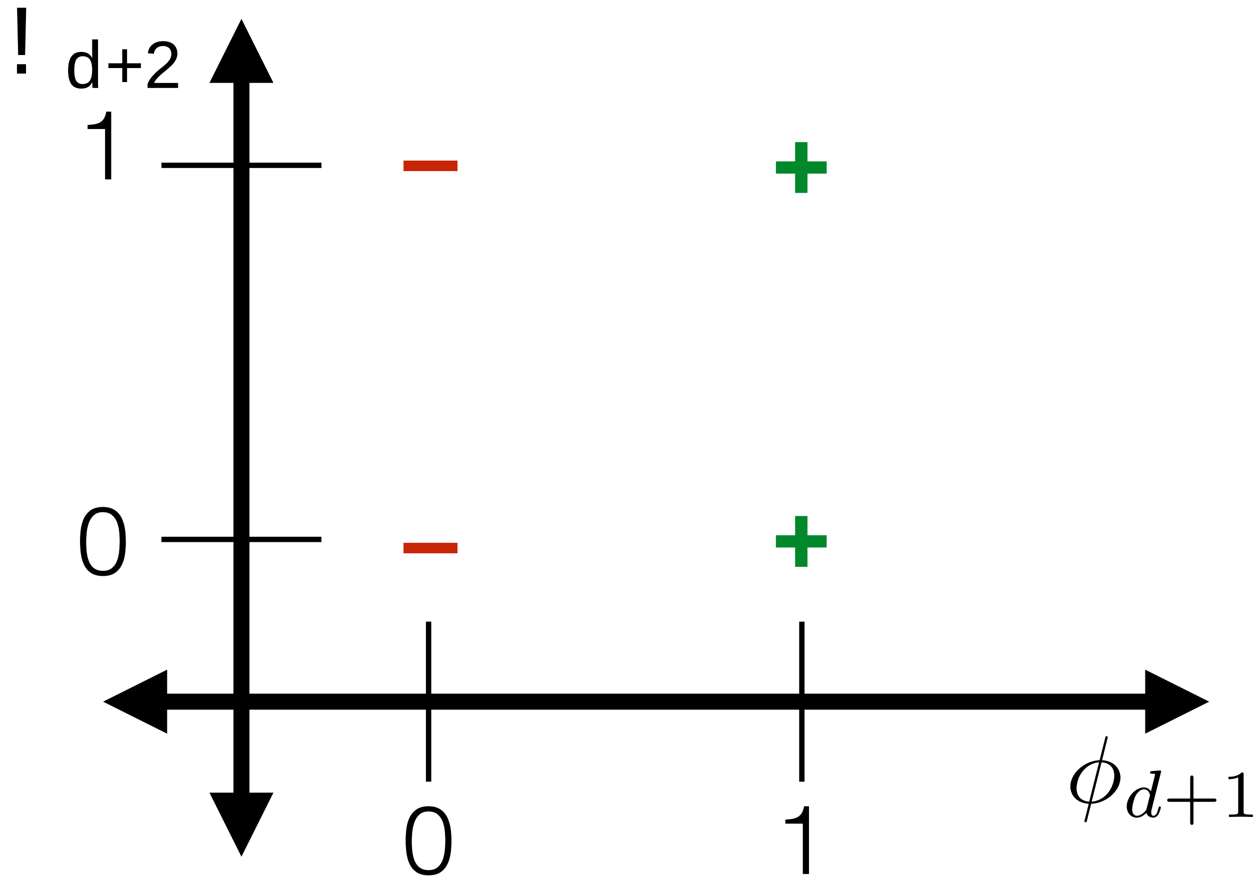
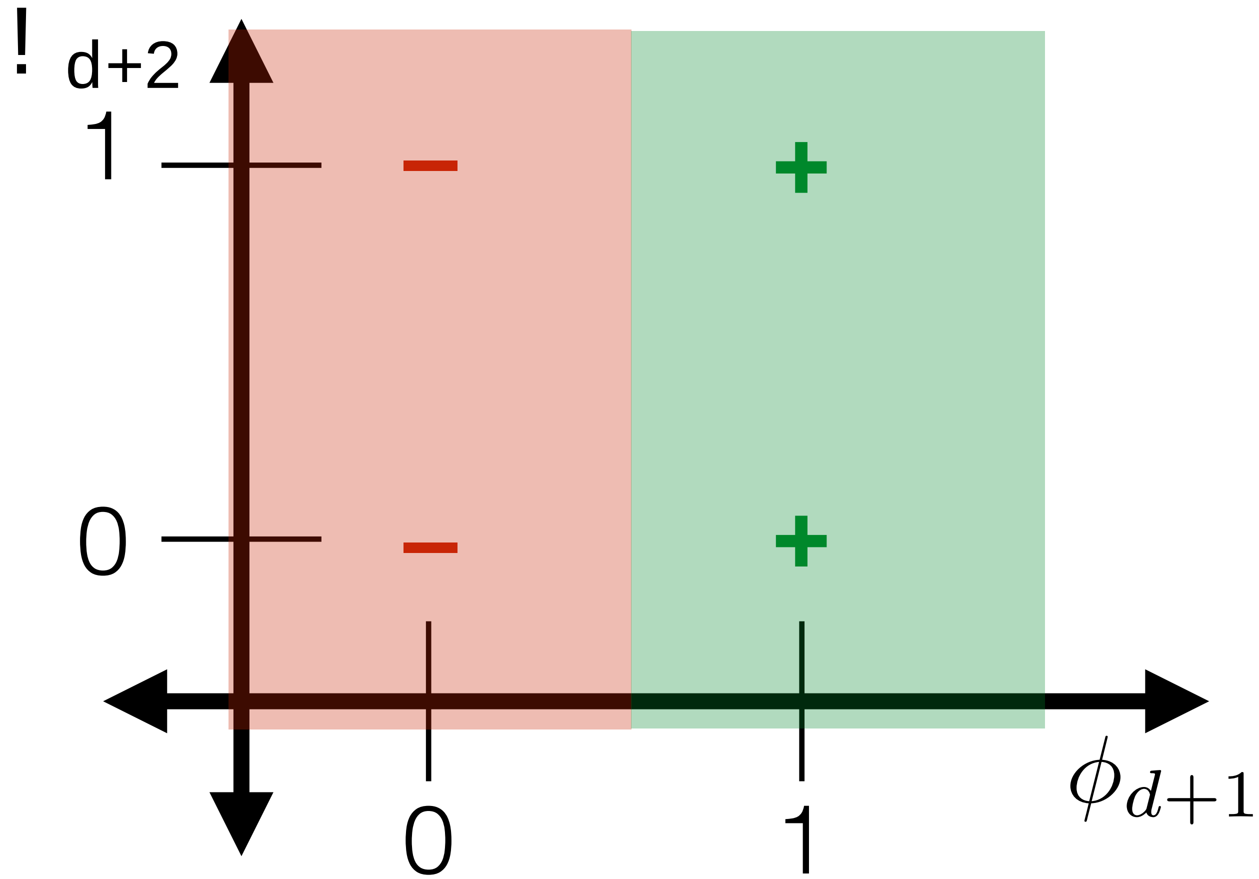
doctor	0	1	1
social worker	1	0	0



Encode categorical data

- Idea: turn each category into a unique binary number

	! d	ϕ_{d+1}	! d+2
nurse	0	0	0
admin	0	0	1
pharmacist	0	1	0
doctor	0	1	1
social worker	1	0	0



Encode categorical data

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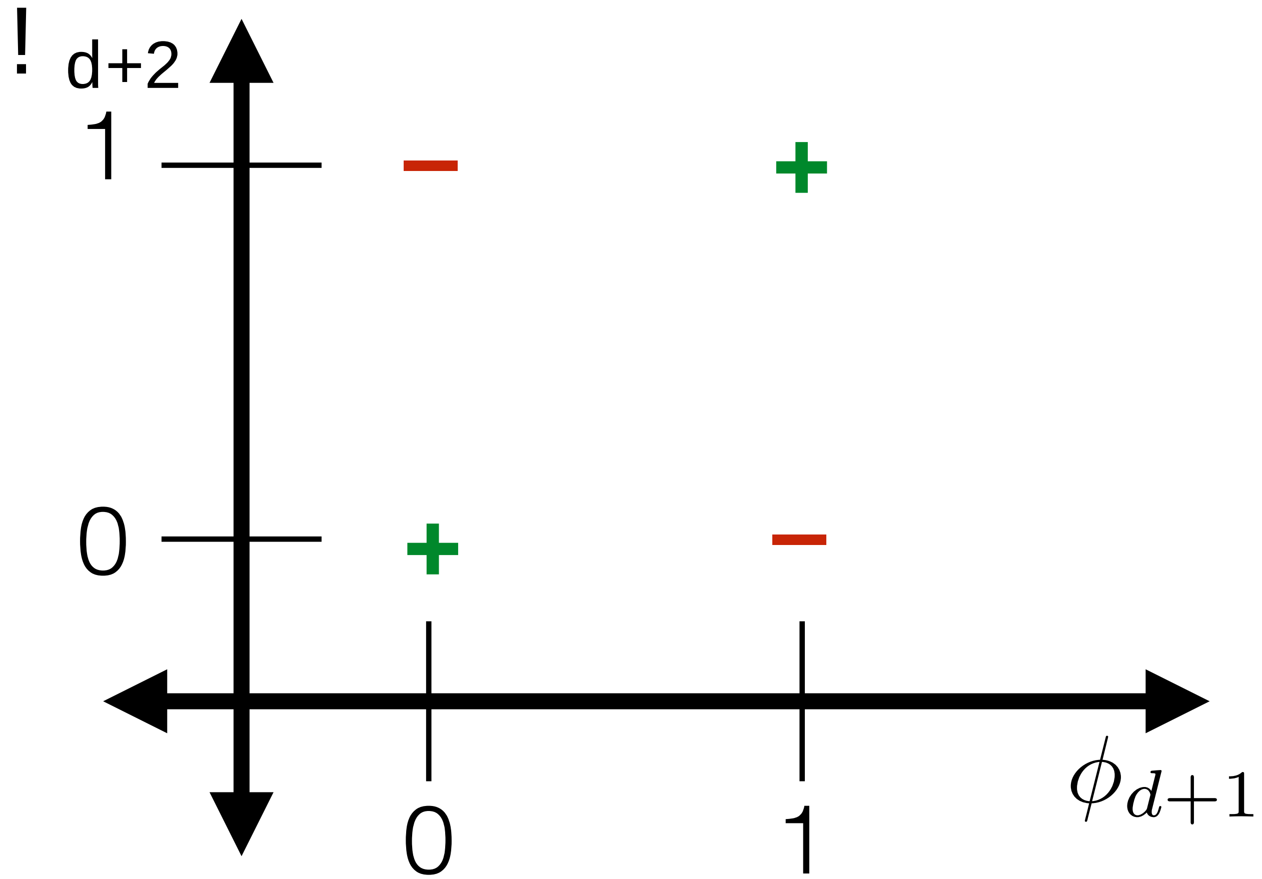
	! d	ϕ_{d+1}	! d+2
nurse	0	0	0
admin	0	0	1
pharmacist	0	1	0
doctor	0	1	1
social worker	1	0	0



Encode categorical data

Encode categorical data

- Idea: turn each category into own unique 0-1 feature

Encode categorical data

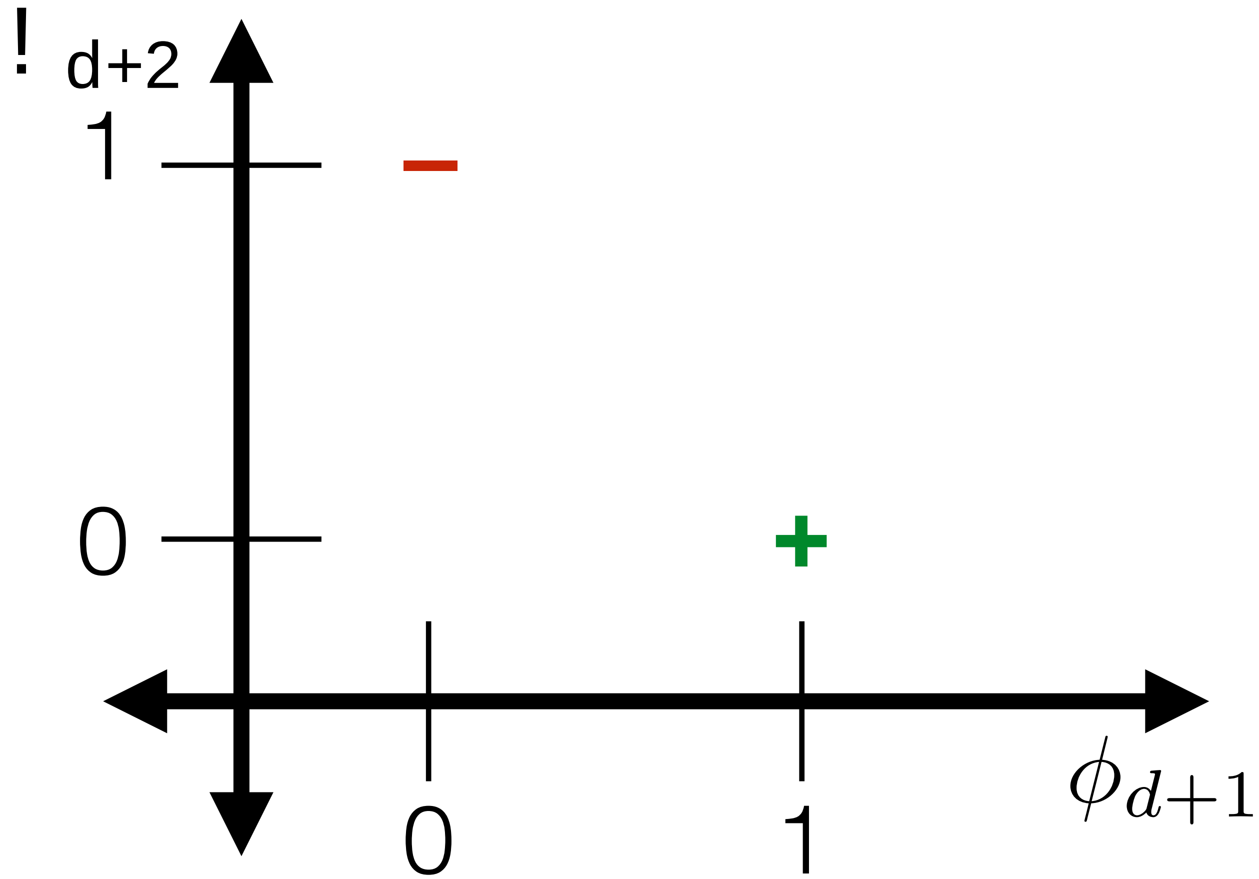
- Idea: turn each category into own unique 0-1 feature

	! d	ϕ_{d+1}	! d+2	! d+3	! d+4
nurse	1	0	0	0	0
admin	0	1	0	0	0
pharmacist	0	0	1	0	0
doctor	0	0	0	1	0
social worker	0	0	0	0	1

Encode categorical data

- Idea: turn each category into own unique 0-1 feature

	! d	ϕ_{d+1}	! d+2	! d+3	! d+4
nurse	1	0	0	0	0
admin	0	1	0	0	0
pharmacist	0	0	1	0	0
doctor	0	0	0	1	0
social worker	0	0	0	0	1

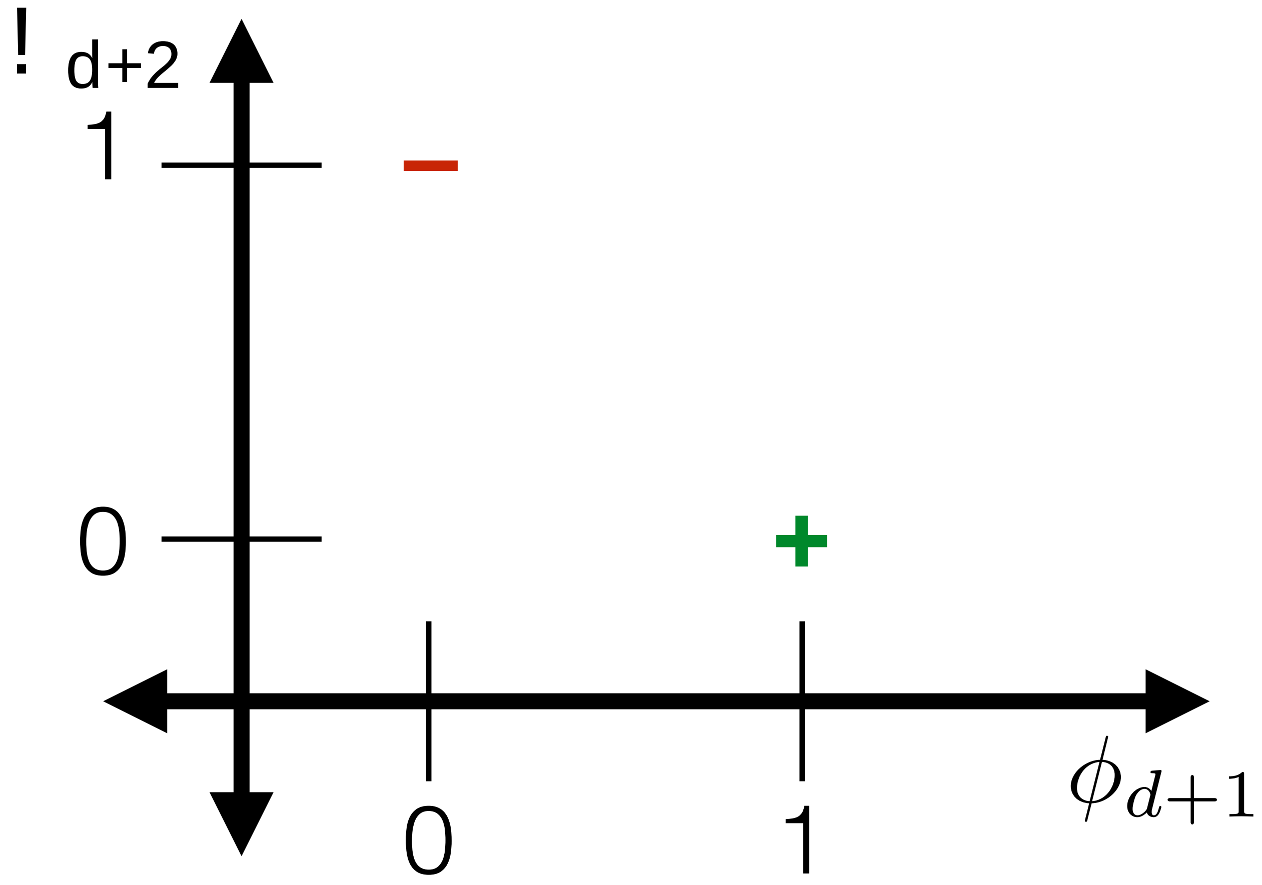


Encode categorical data

- Idea: turn each category into own unique 0-1 feature

	! d	ϕ_{d+1}	! d+2	! d+3	! d+4
nurse	1	0	0	0	0
admin	0	1	0	0	0
pharmacist	0	0	1	0	0
doctor	0	0	0	1	0
social worker	0	0	0	0	1

- “one-hot encoding”



Encode data in usable form

- Identify the features and encode as real numbers

	resting heart rate (bpm)	pain?	job	medicines	age	family income (USD)
1	55	0	nurse	pain	40s	133000
2	71	0	admin	beta blockers, pain	20s	34000
3	89	1	nurse	beta blockers	50s	40000
4	67	0	doctor	none	50s	120000

Encode data in usable form

- Identify the features and encode as real numbers

	resting heart rate (bpm)	pain?	j1,j2,j3,j4,j5	medicines	age	family income (USD)
1	55	0	1,0,0,0,0	pain	40s	133000
2	71	0	0,1,0,0,0	beta blockers, pain	20s	34000
3	89	1	1,0,0,0,0	beta blockers	50s	40000
4	67	0	0,0,0,1,0	none	50s	120000

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	resting heart rate (bpm)	pain?	j1,j2,j3,j4,j5	medicines	age	family income (USD)
1	55	0	1,0,0,0,0	pain	40s	133000
2	71	0	0,1,0,0,0	beta blockers, pain	20s	34000
3	89	1	1,0,0,0,0	beta blockers	50s	40000
4	67	0	0,0,0,1,0	none	50s	120000

Encode categorical data

pain
pain & beta blockers
beta blockers
no medications

Encode categorical data

- Should we use one-hot encoding?

pain
pain & beta blockers
beta blockers
no medications

Encode categorical data

- Should we use one-hot encoding?

	! d	ϕ_{d+1}	! d+2	! d+3
pain	1	0	0	0
pain & beta blockers	0	1	0	0
beta blockers	0	0	1	0
no medications	0	0	0	1

Encode categorical data

- Should we use one-hot encoding?

	! d	ϕ_{d+1}	! d+2	! d+3
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- Idea: factored encoding

Encode categorical data

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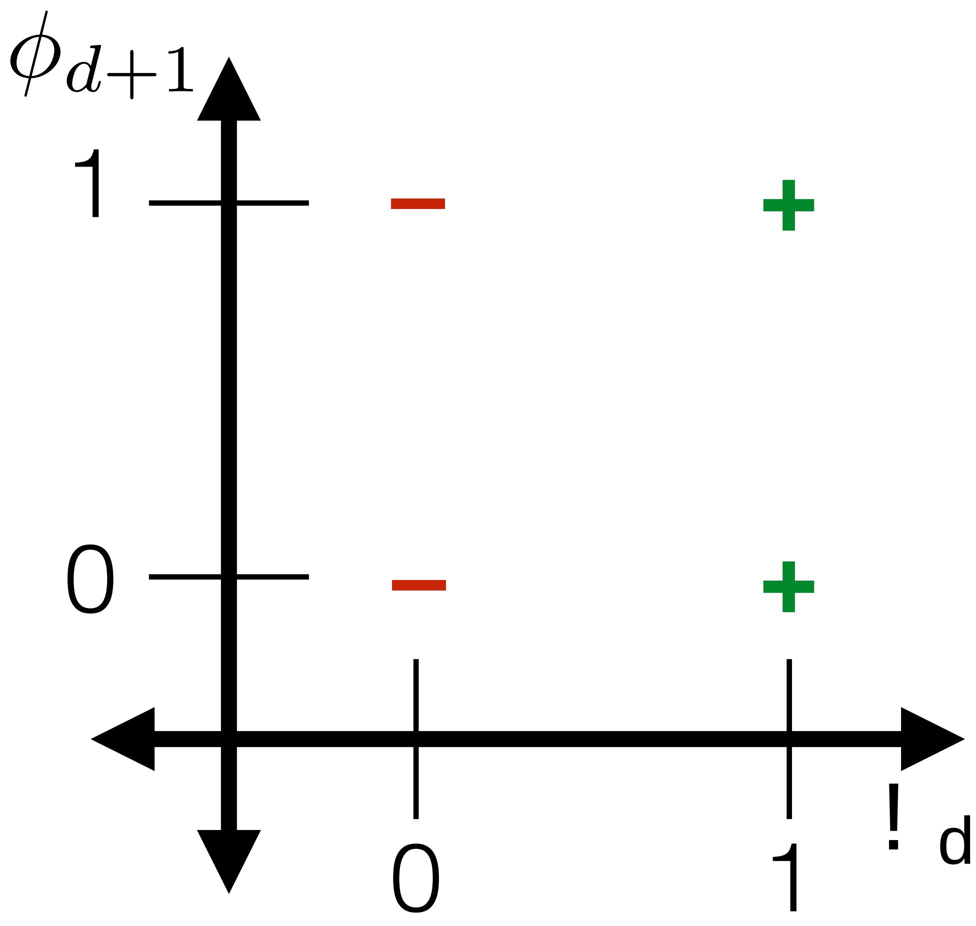

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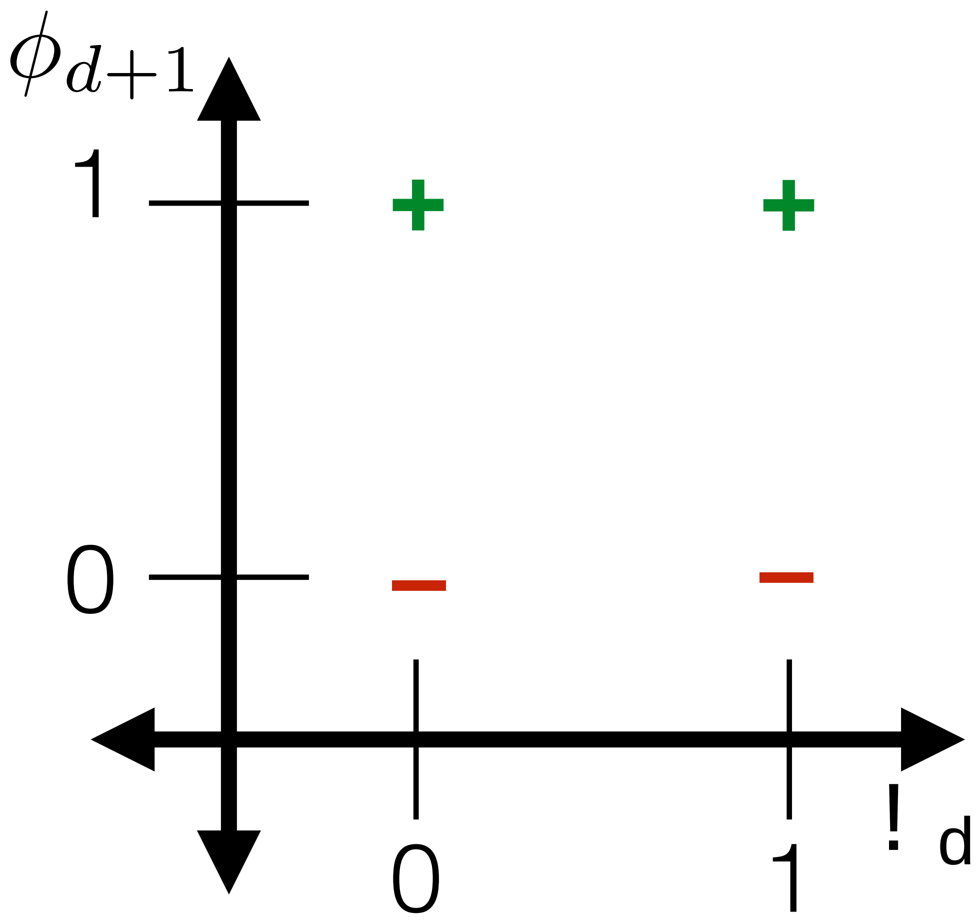

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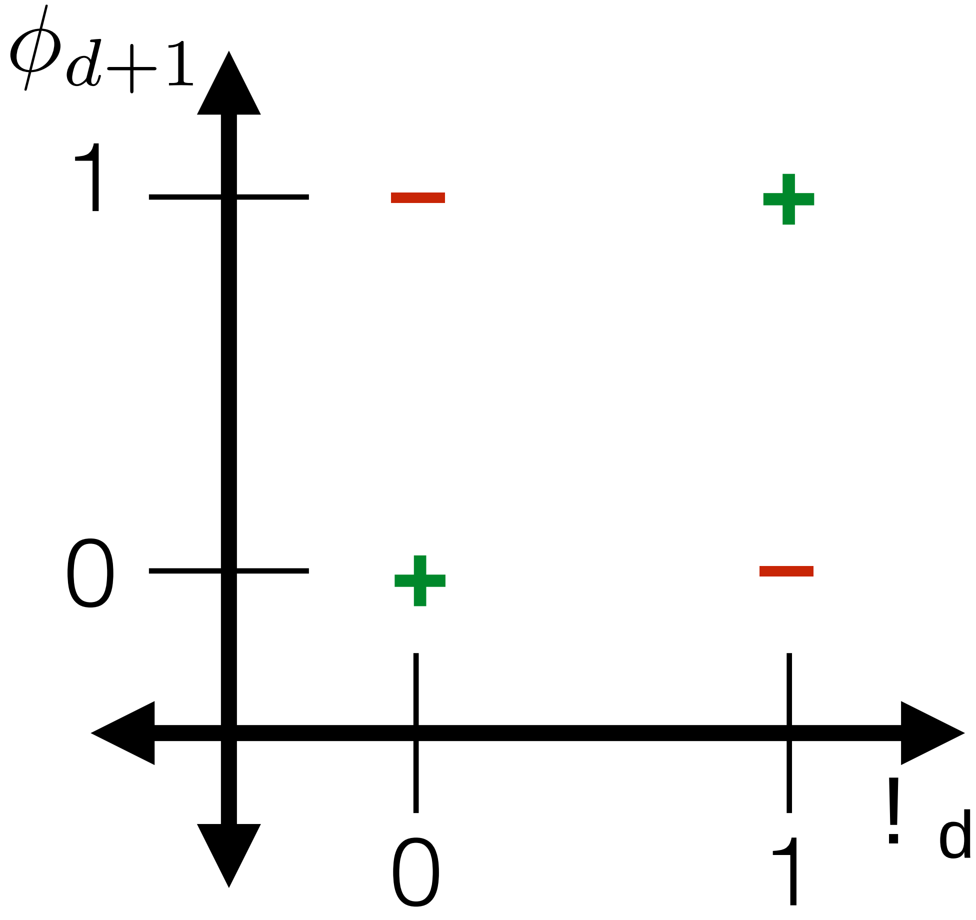

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3	89	1	1,0,0,0,0	beta blockers	50s	40000
4	67	0	0,0,0,1,0	none	50s	120000

Encode data in usable form

- Identify the features and encode as real numbers

	resting heart rate (bpm)	pain?	j1,j2,j3,j4,j5	m1, m2	age	family income (USD)
1	55	0	1,0,0,0,0	1,0	40s	133000
2	71	0	0,1,0,0,0	1,1	20s	34000
3	89	1	1,0,0,0,0	0,1	50s	40000
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	resting heart rate (bpm)	pain?	j1,j2,j3,j4,j5	m1, m2	age	family income (USD)
1	55	0	1,0,0,0,0	1,0	40s	133000
2	71	0	0,1,0,0,0	1,1	20s	34000
3	89	1	1,0,0,0,0	0,1	50s	40000
4	67	0	0,0,0,1,0	0,0	50s	120000

Encode data in usable form

- Identify the features and encode as real numbers

	resting heart rate (bpm)	pain?	j1,j2,j3,j4,j5	m1, m2	age	family income (USD)
1	55	0	1,0,0,0,0	1,0	45	133000
2	71	0	0,1,0,0,0	1,1	25	34000
3	89	1	1,0,0,0,0	0,1	55	40000
4	67	0	0,0,0,1,0	0,0	55	120000

Using a representative # for a range

age
45
25
55
55

Using a representative # for a range

- Potential pitfall: level of detail might be treated as meaningful (by you or others using the data)

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55

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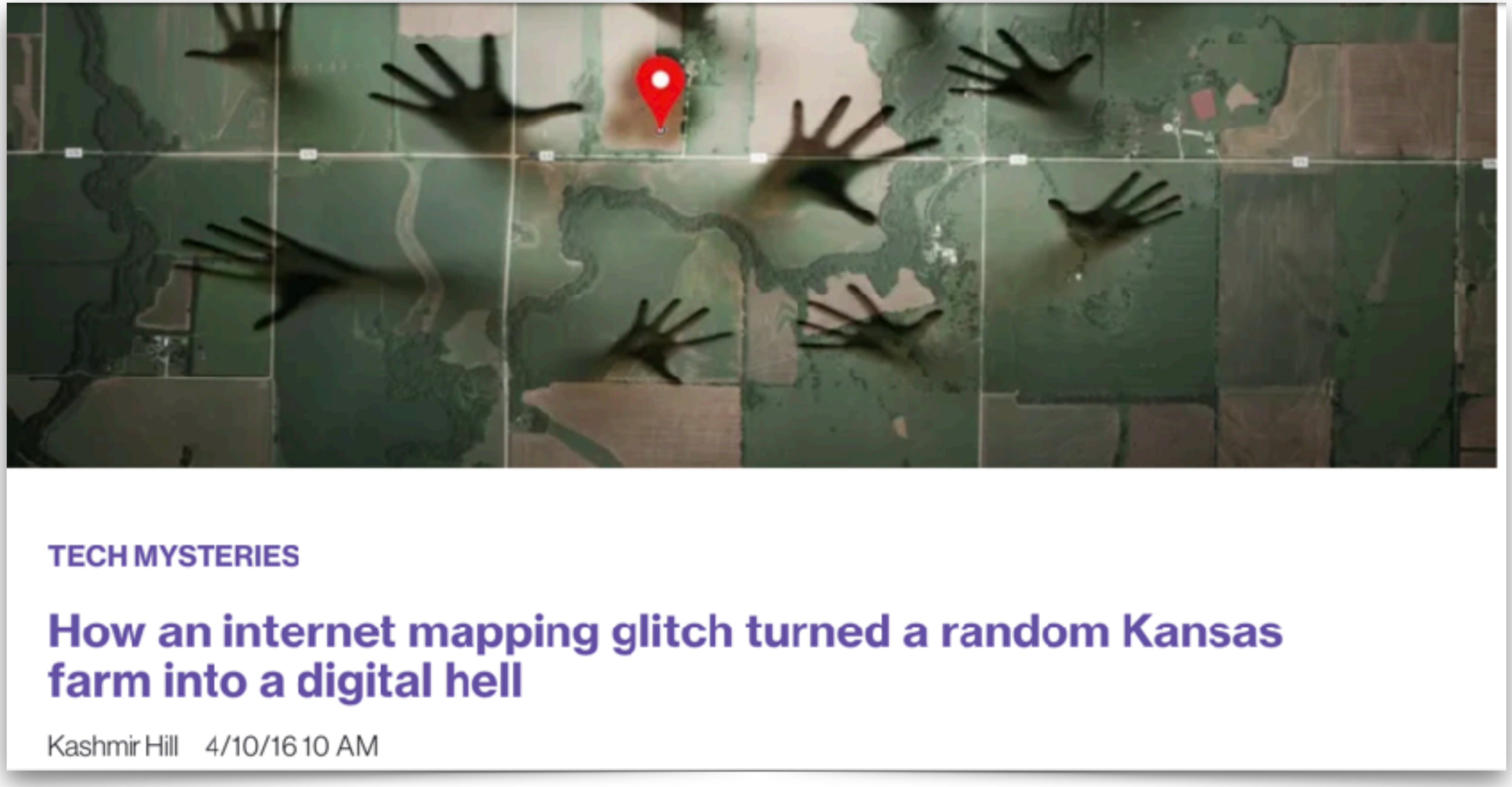


TECH MYSTERIES

How an internet mapping glitch turned a random Kansas farm into a digital hell

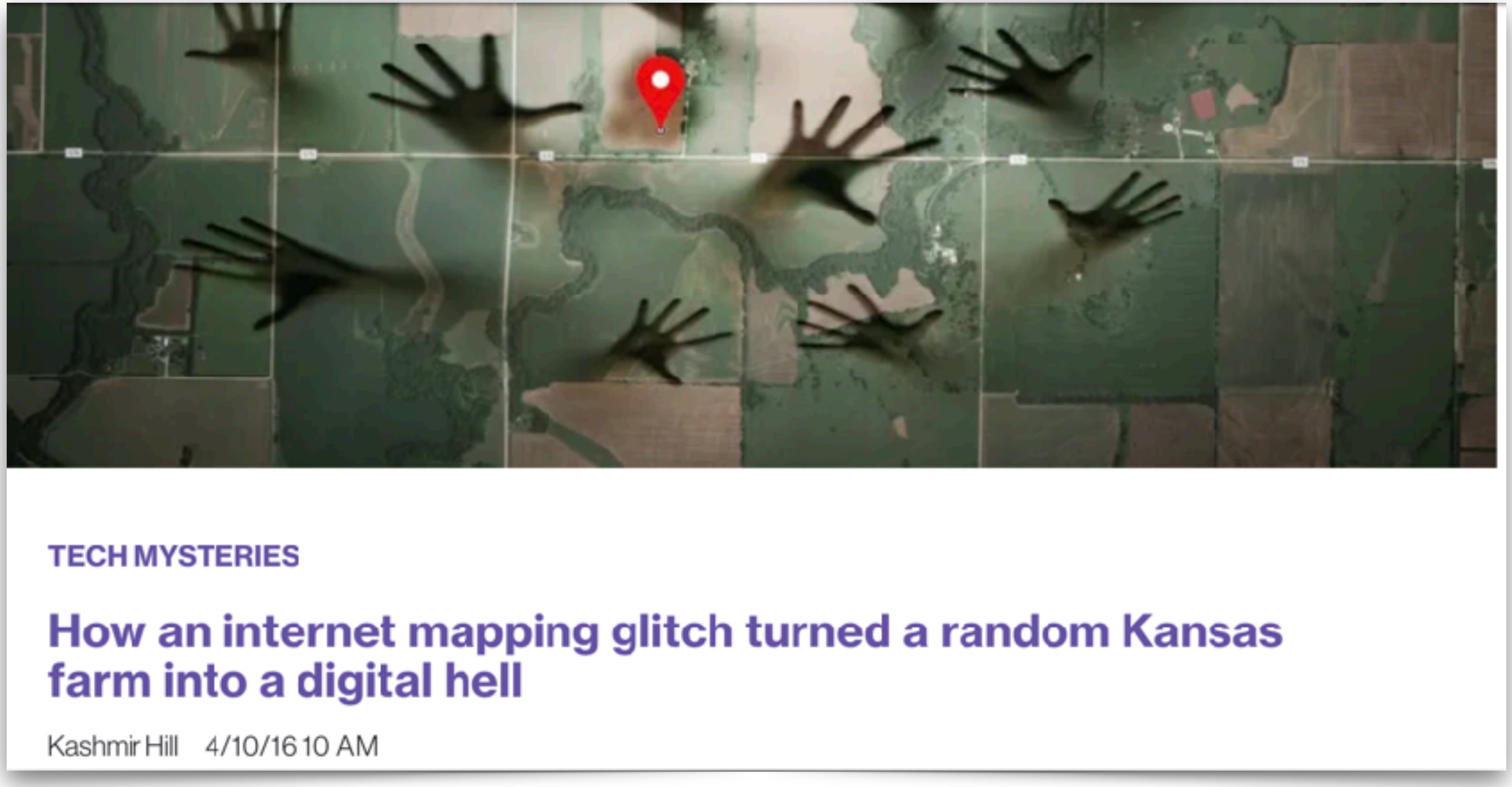
Kashmir Hill 4/10/16 10 AM

[https://fusion.tv/story/287592/internet-mapping-glitch-kansas-farm/?utm_medium=social]

Using a representative # for a range

- Potential pitfall: level of detail might be treated as meaningful (by you or others using the data)
- A way to diagnose many problems: plot your data!

age
45
25
55
55



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1	55	0	1,0,0,0,0	1,0	45	133000
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3	89	1	1,0,0,0,0	0,1	55	40000
4	67	0	0,0,0,1,0	0,0	55	120000

Encode data in usable form

- Identify the features and encode as real numbers

	resting heart rate (bpm)	pain?	j1,j2,j3,j4,j5	m1, m2	decade	family income (USD)
1	55	0	1,0,0,0,0	1,0	4	133000
2	71	0	0,1,0,0,0	1,1	2	34000
3	89	1	1,0,0,0,0	0,1	5	40000
4	67	0	0,0,0,1,0	0,0	5	120000

Encode ordinal data

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Strongly disagree	Disagree	Neutral	Agree	Strongly agree
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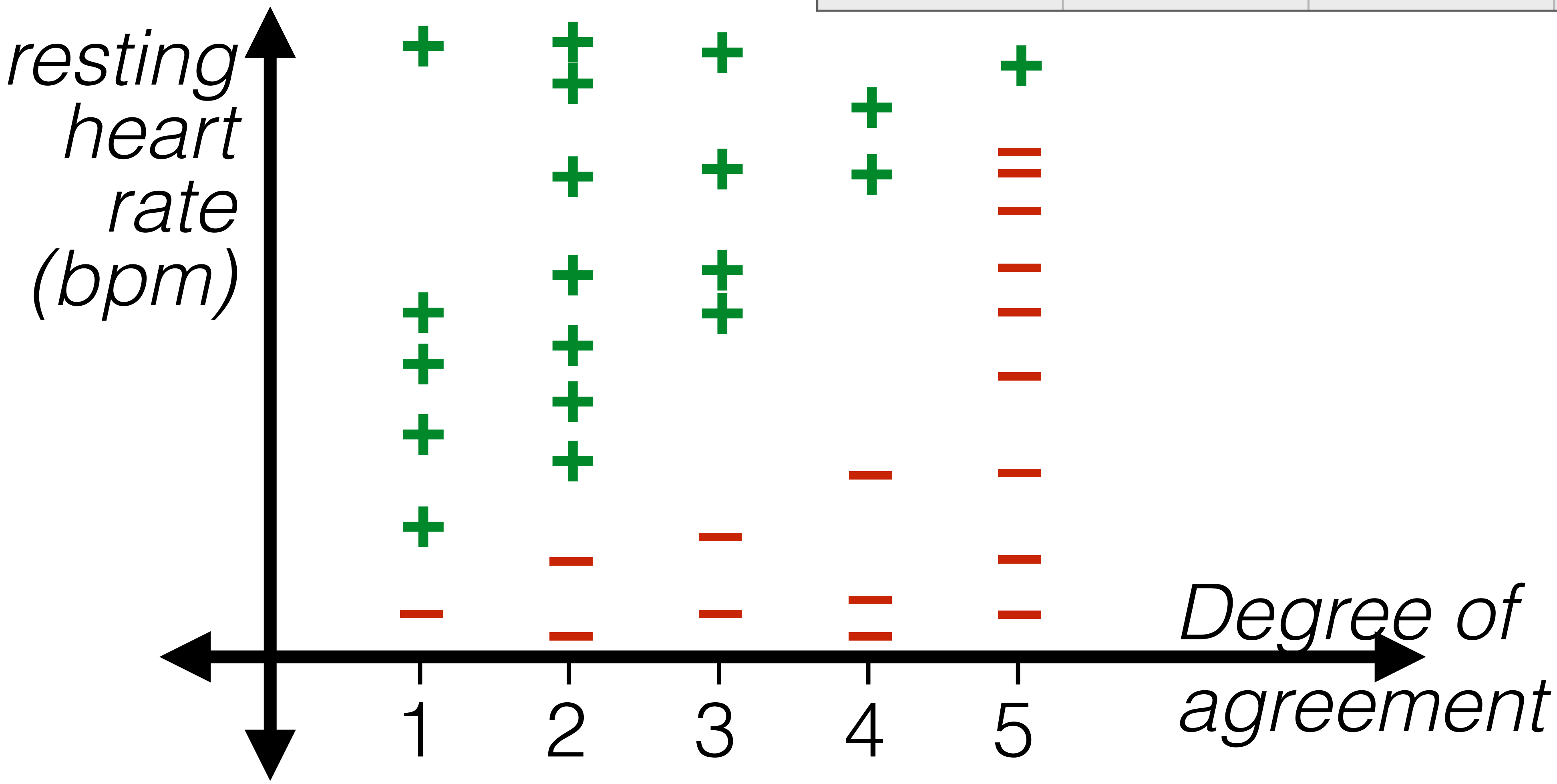

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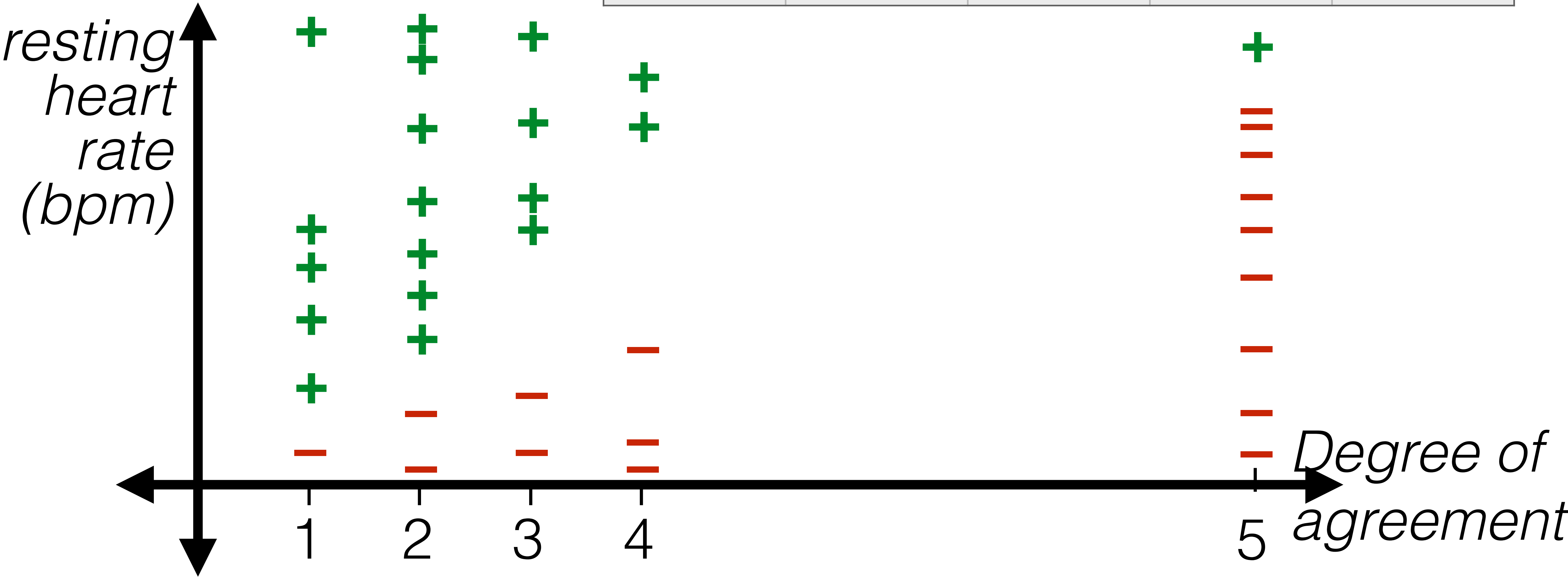

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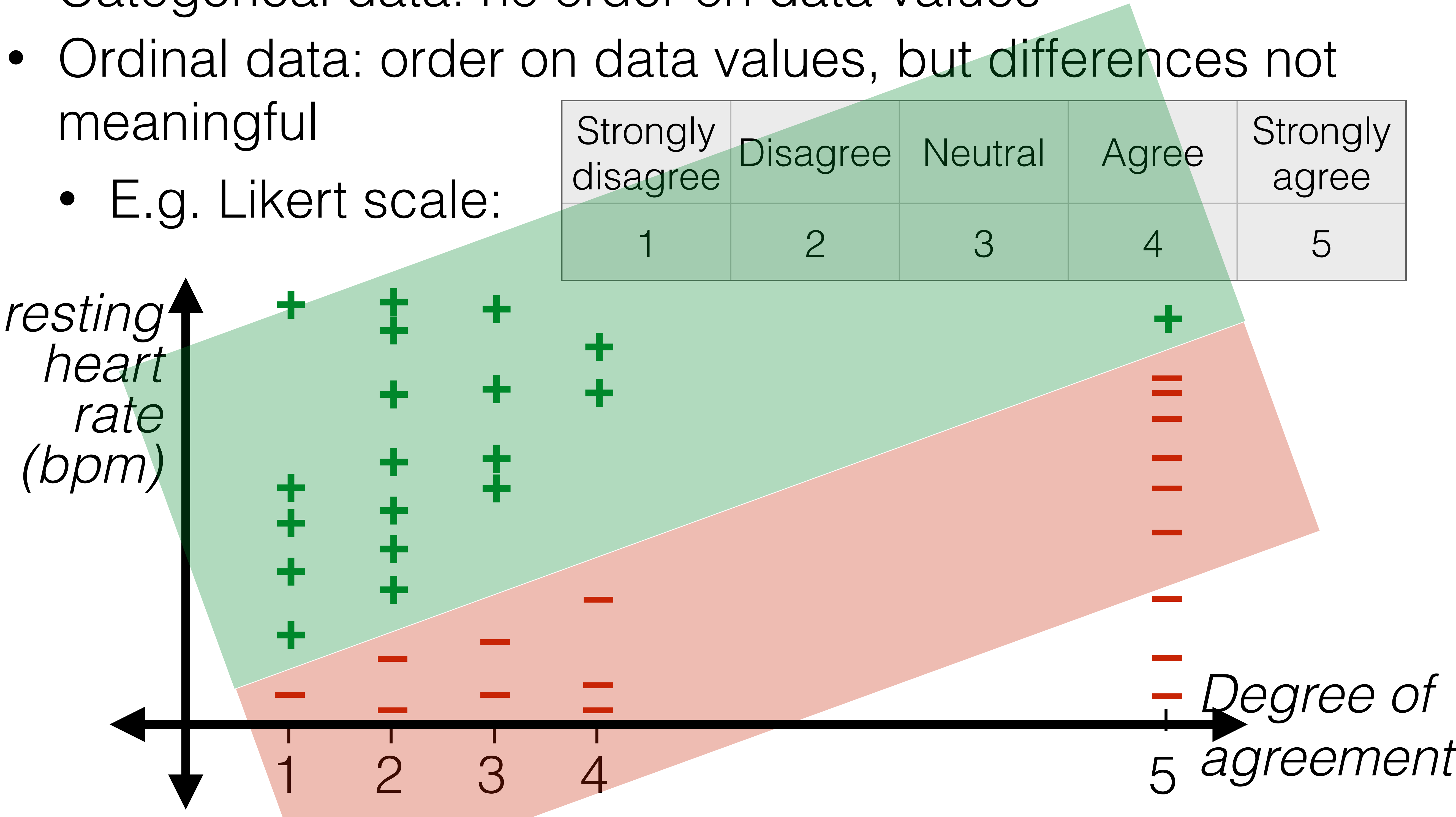

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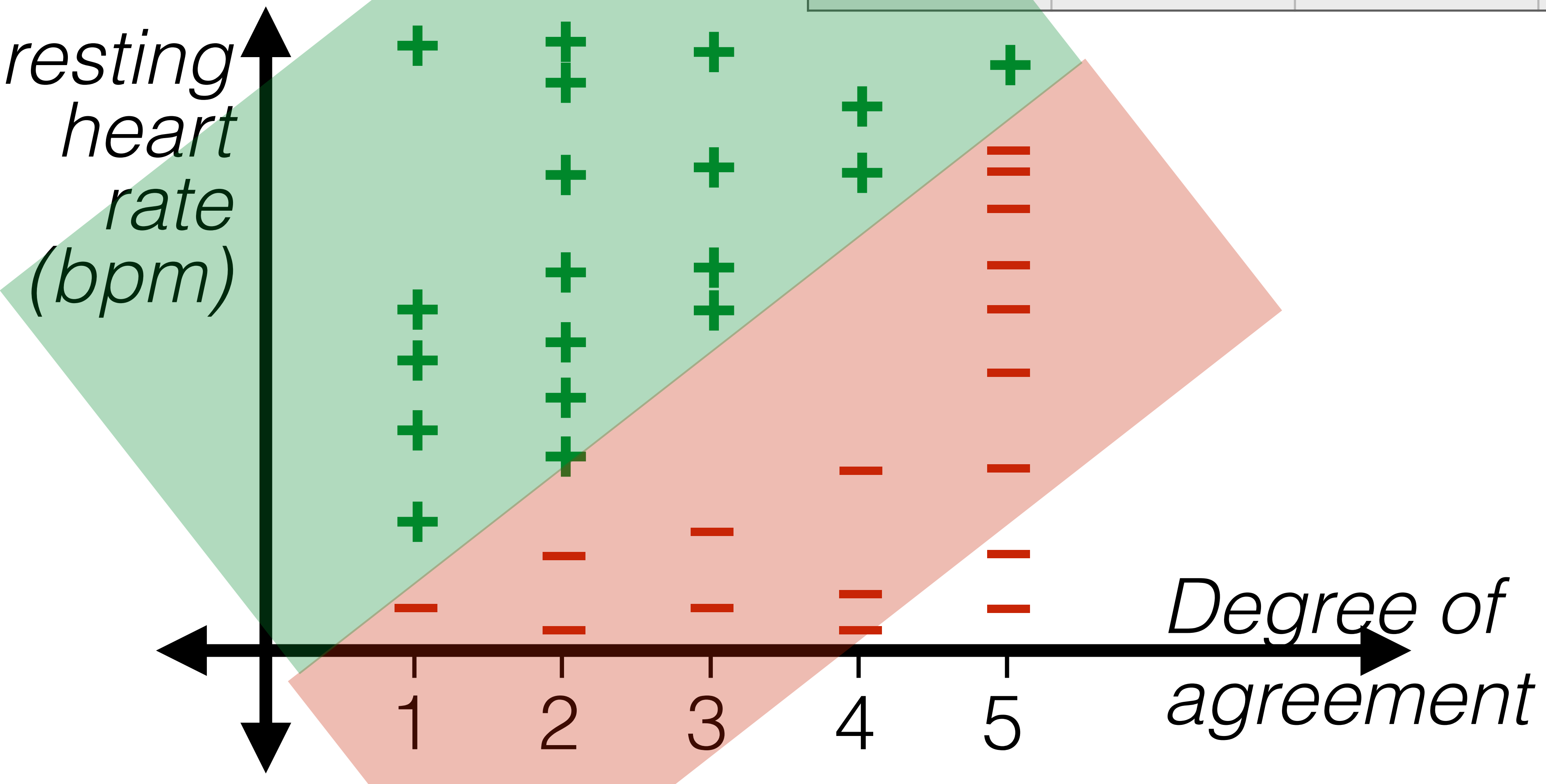

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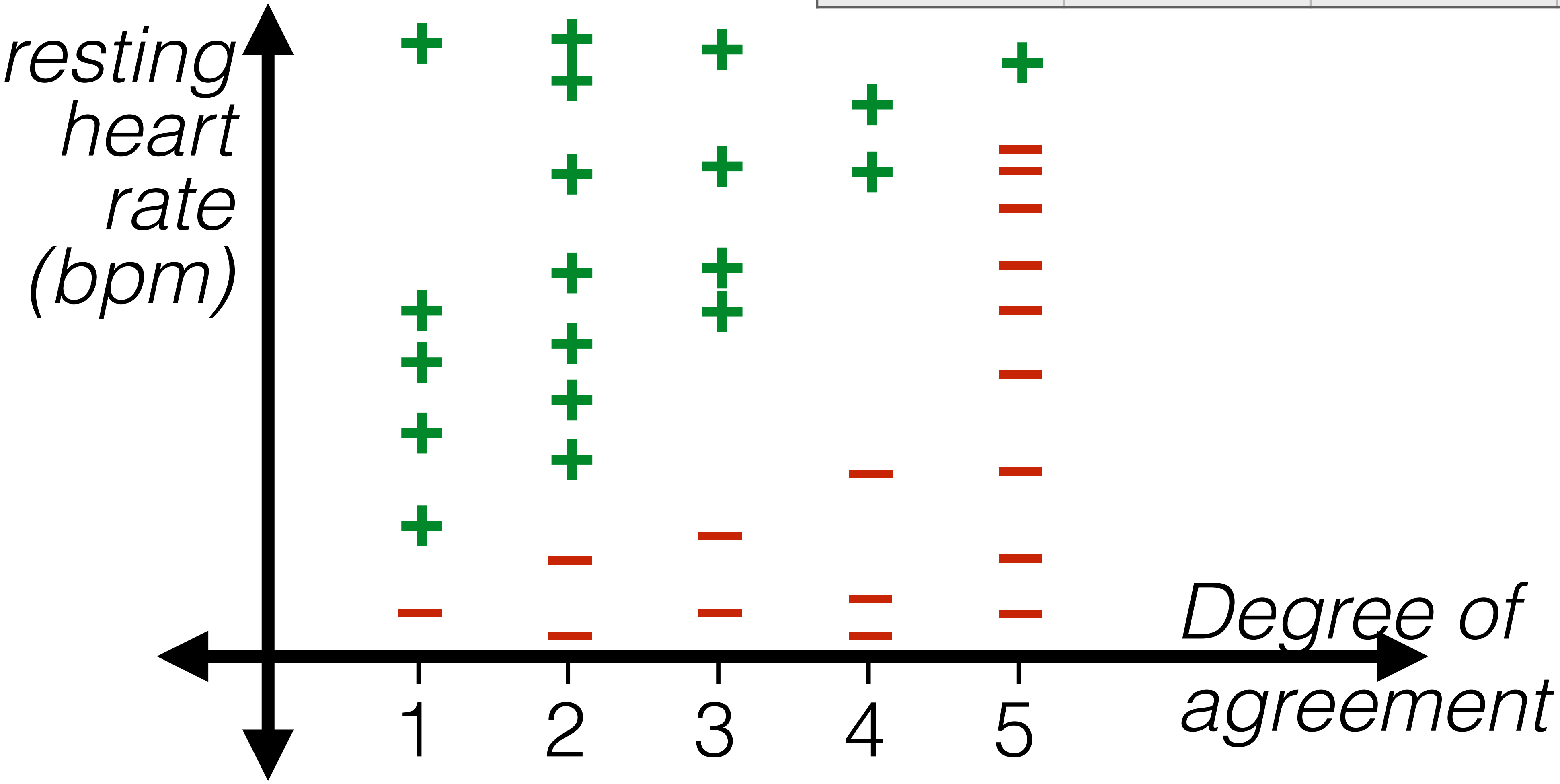

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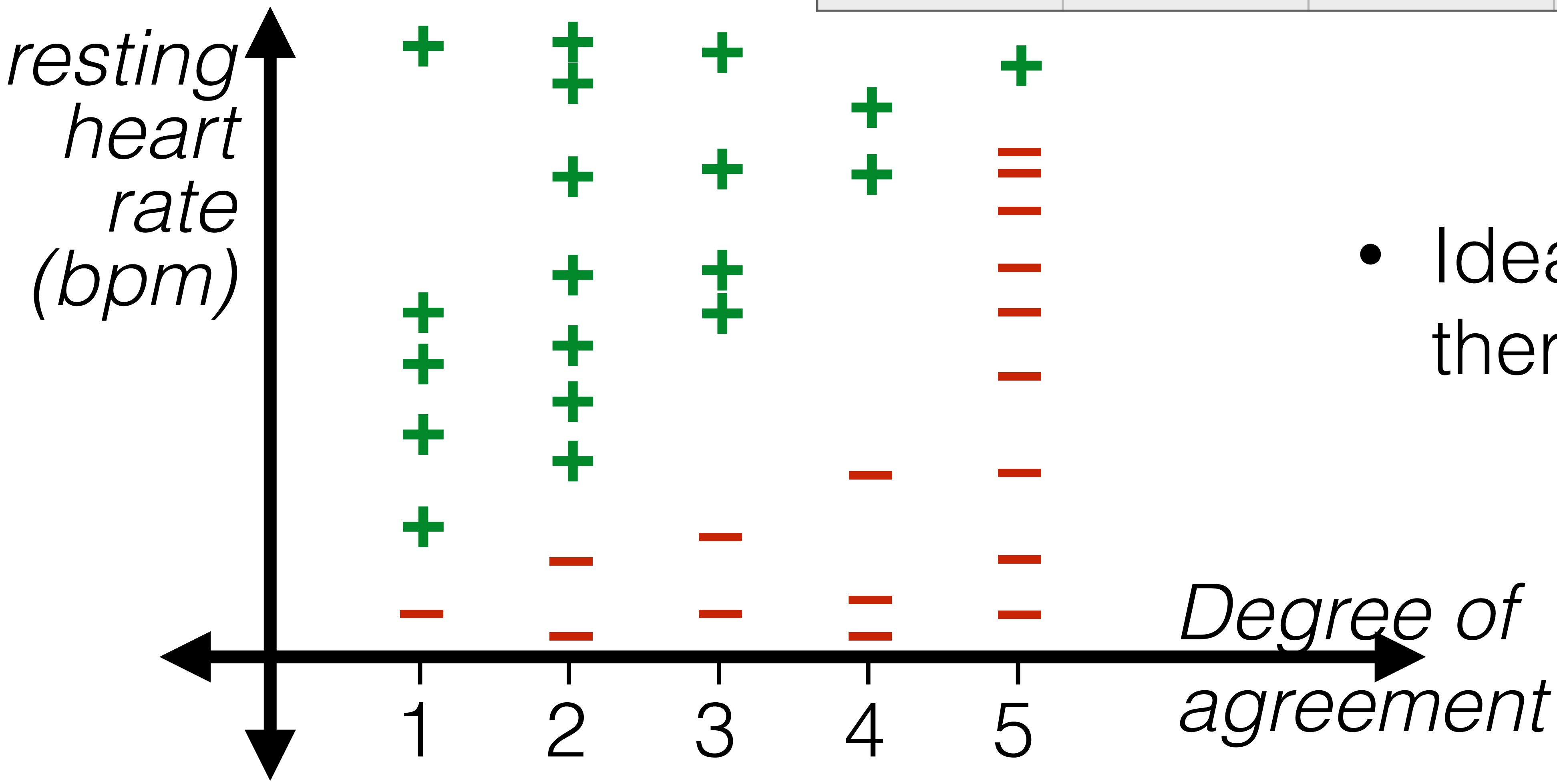

- Idea: Unary/ thermometer code

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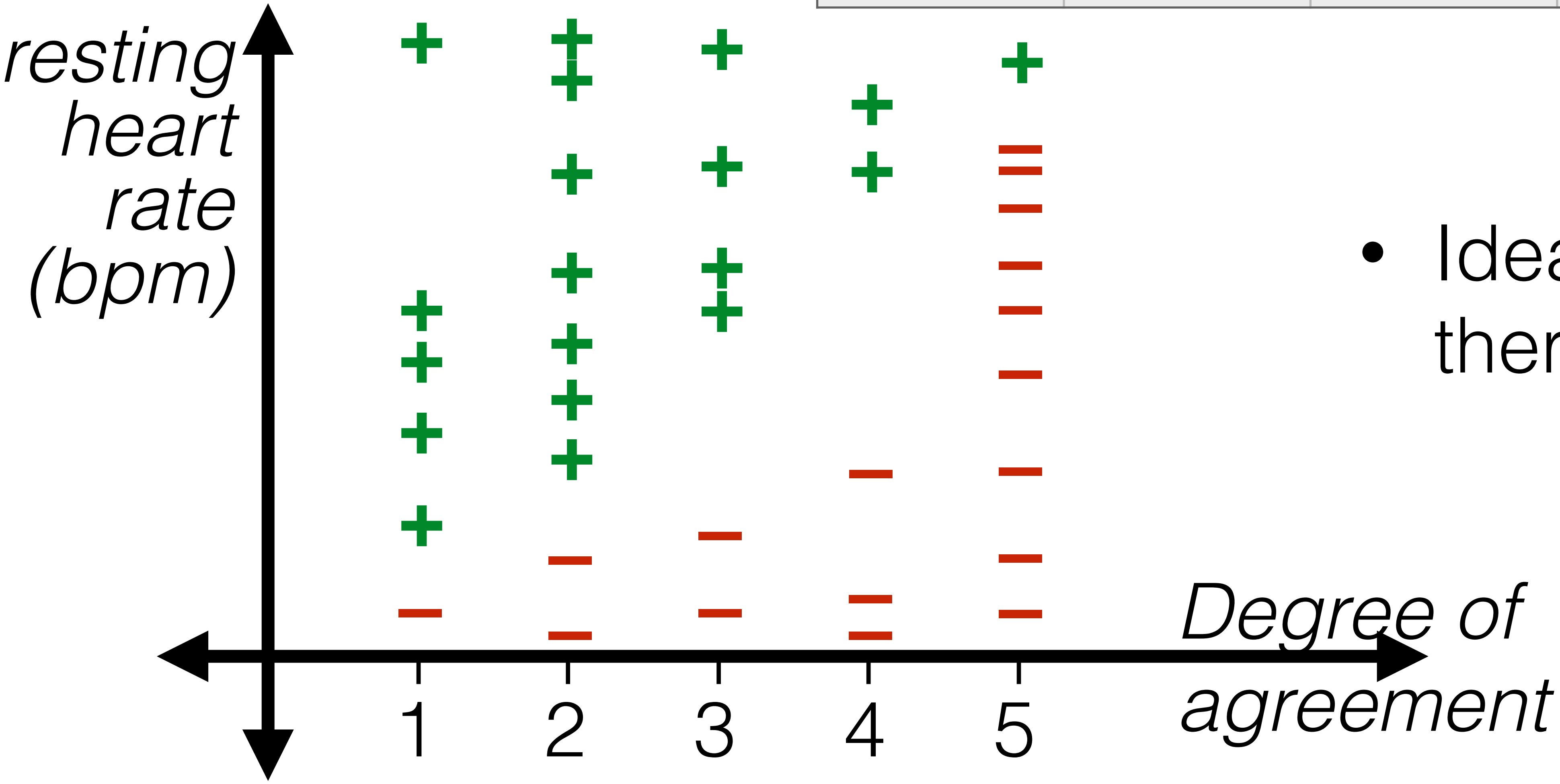
Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1,0,0,0,0	1,1,0,0,0	1,1,1,0,0	1,1,1,1,0	1,1,1,1,1



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3	89	1	1,0,0,0,0	0,1	5	40000
4	67	0	0,0,0,1,0	0,0	5	120000

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Encode numerical data

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- A closer look at the output of a linear classifier

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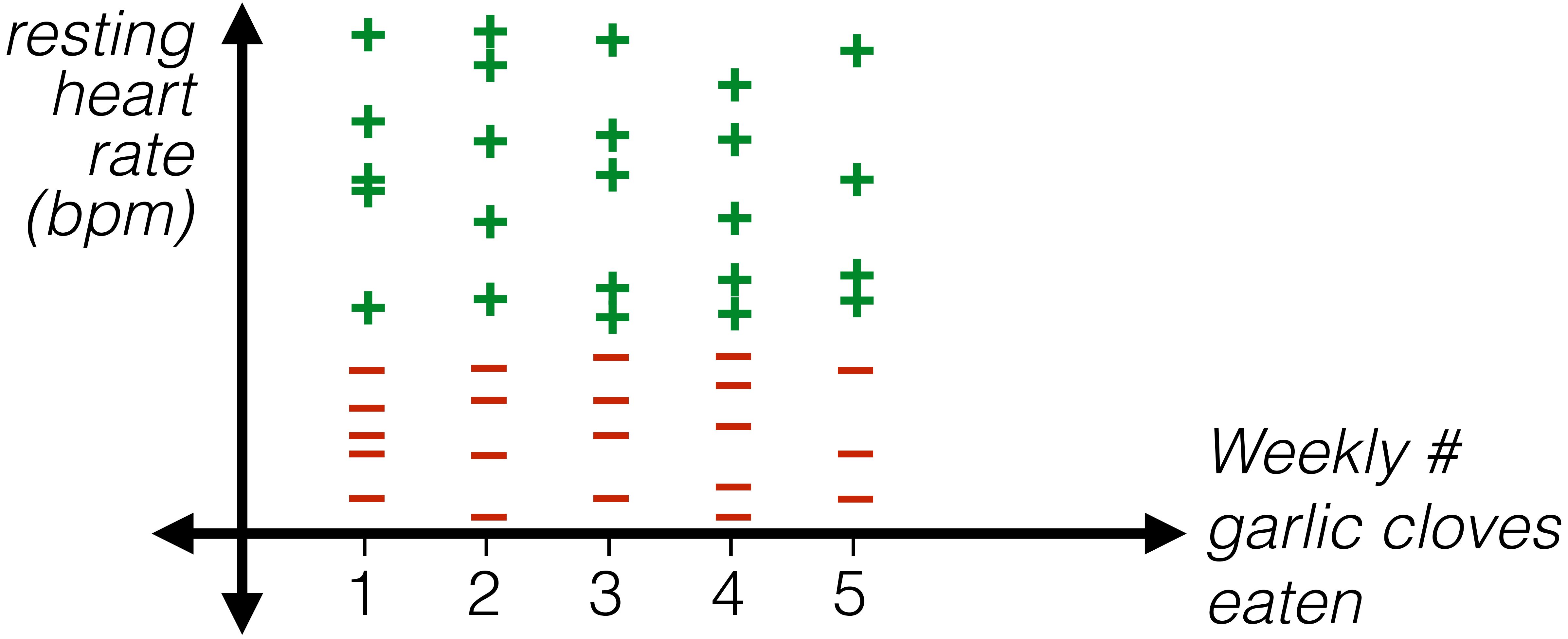

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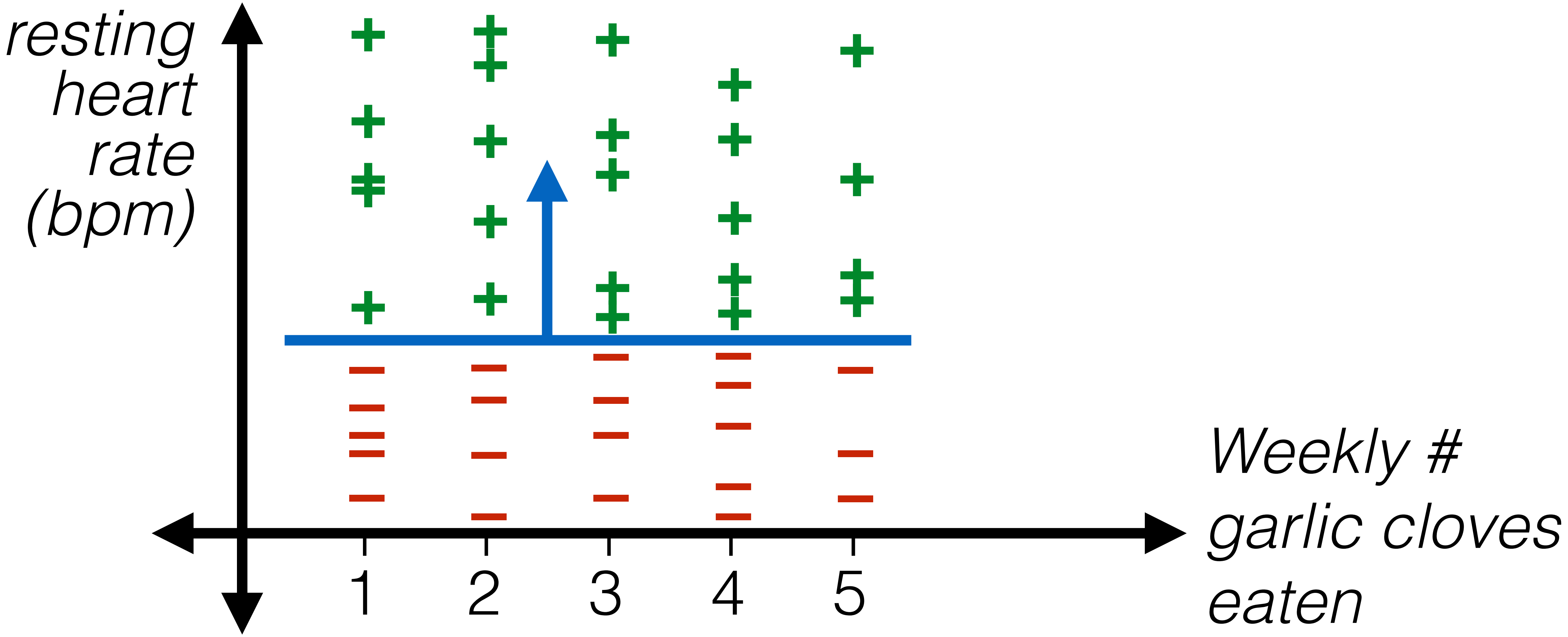

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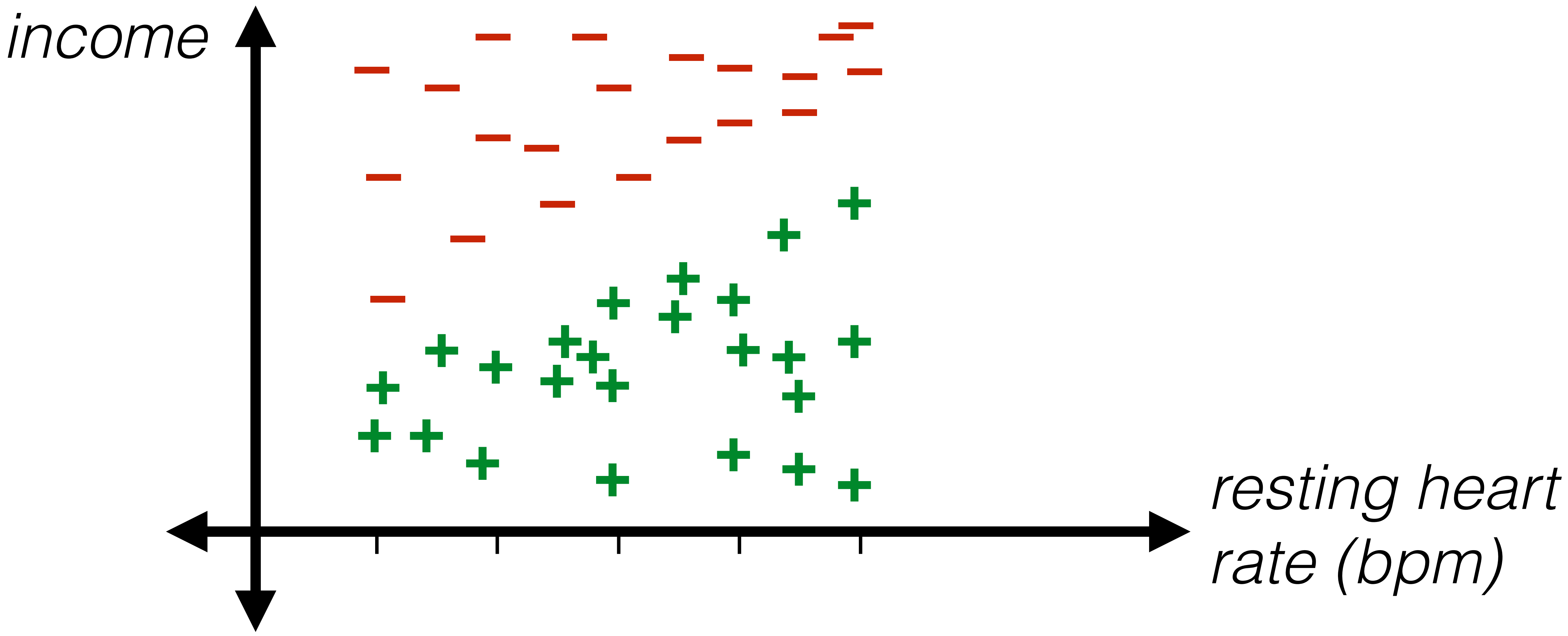

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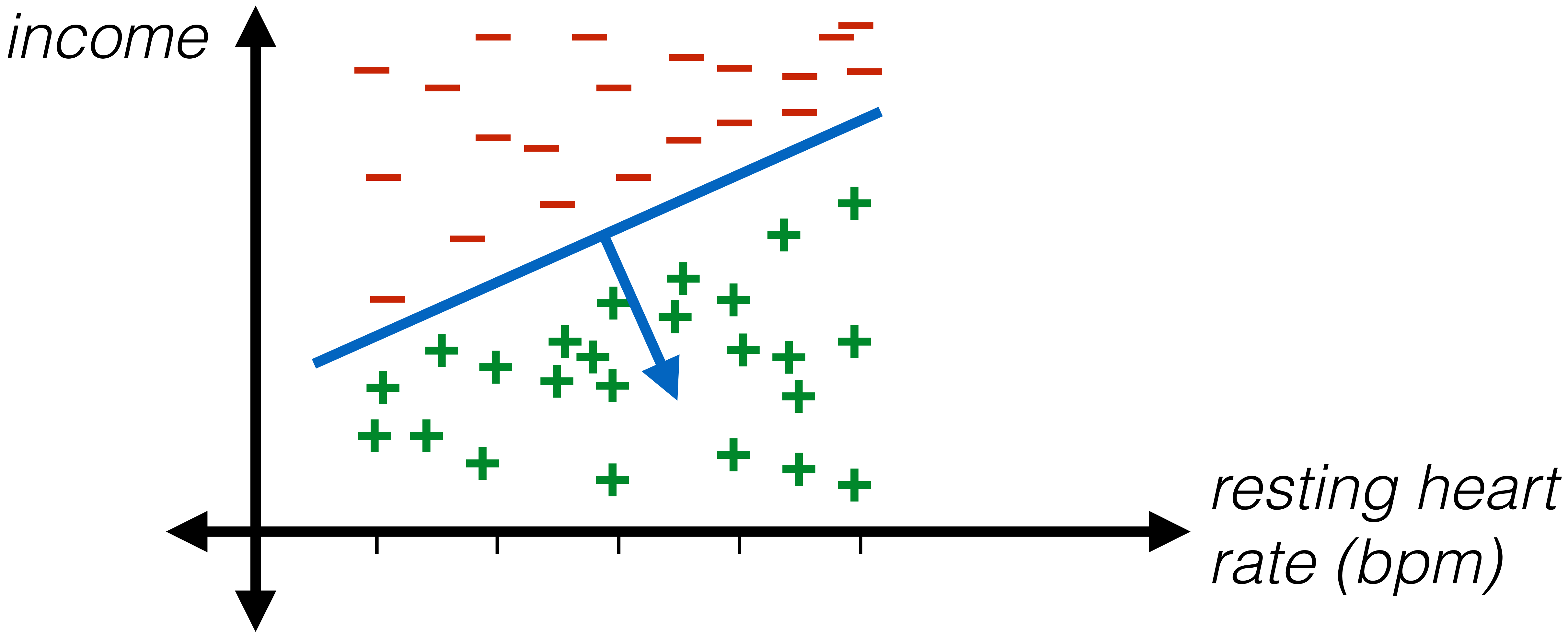

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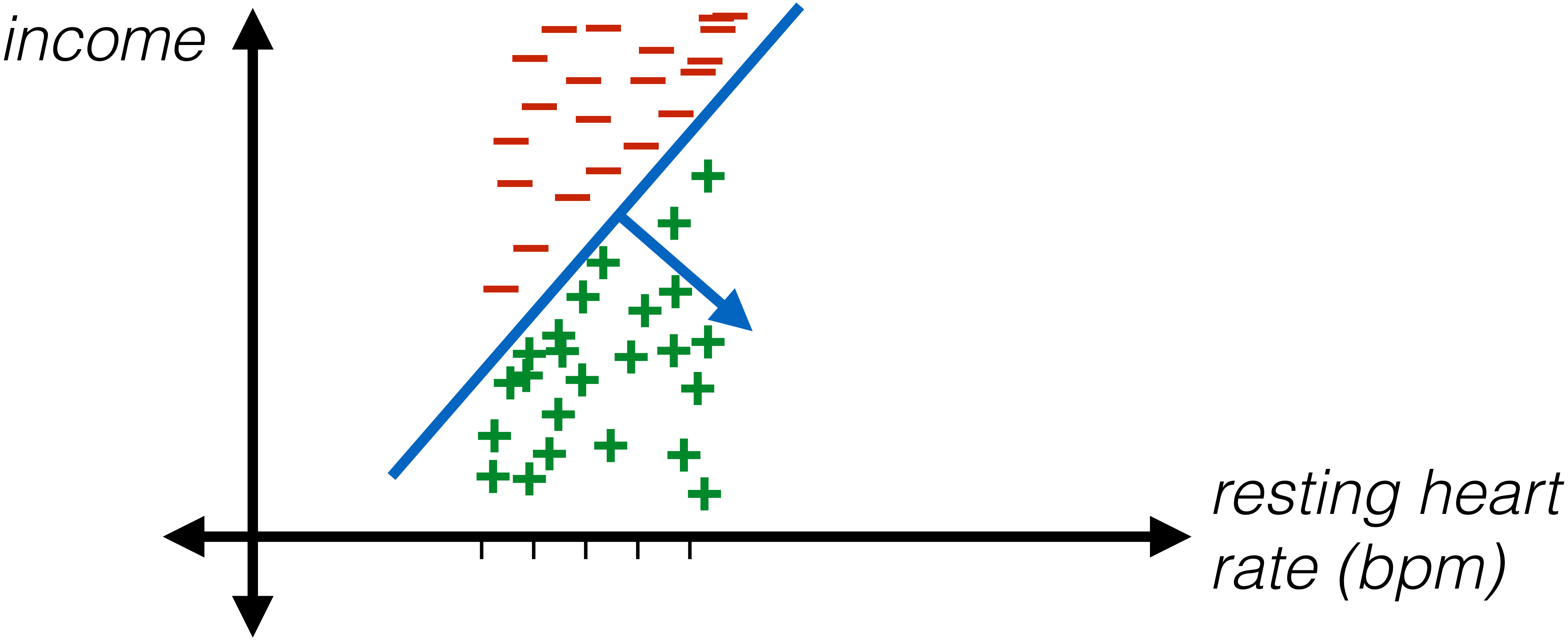

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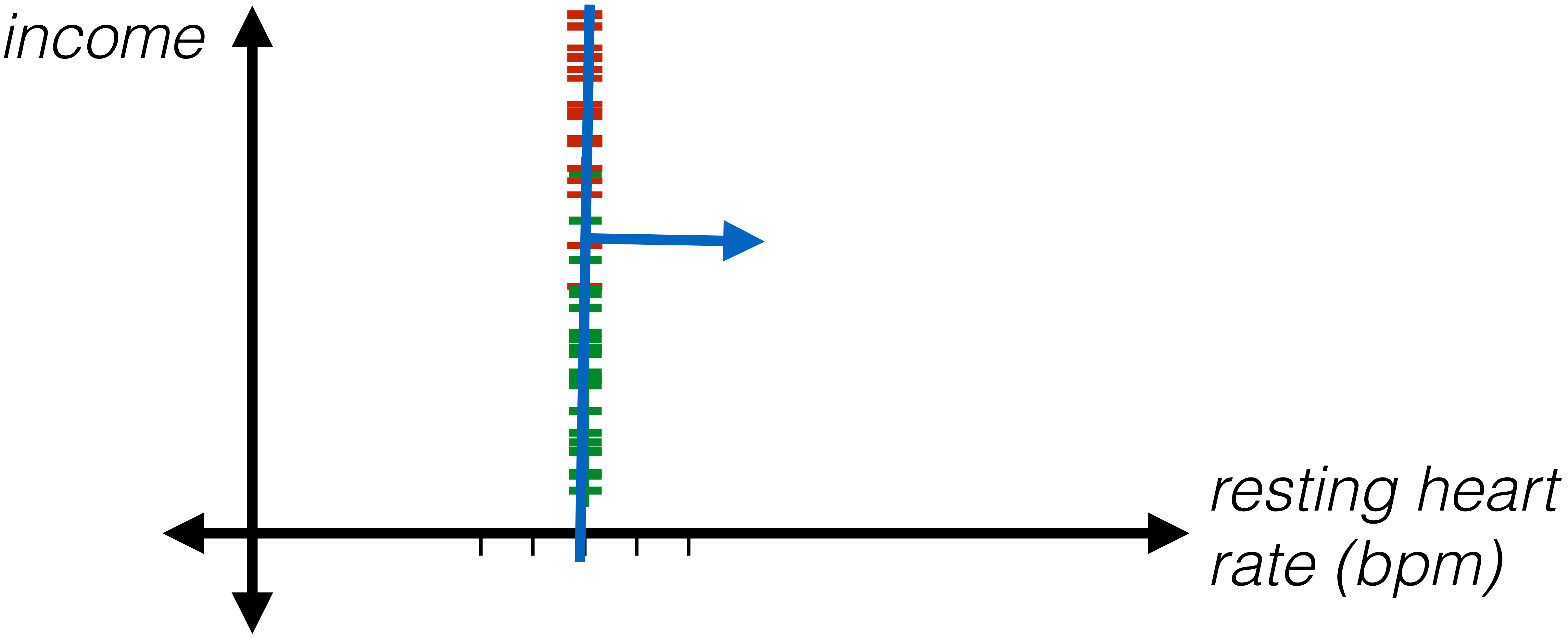
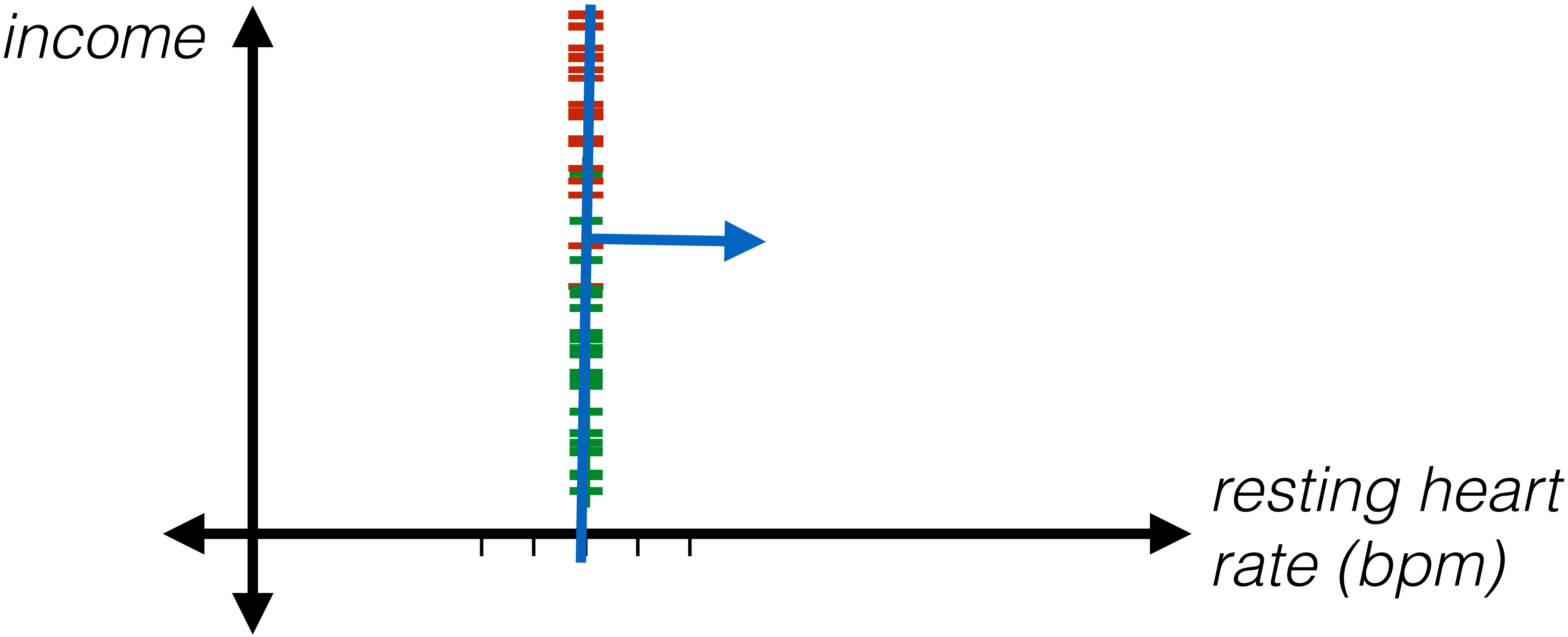


Encode numerical data

- A closer look at the output of a linear classifier
- Idea: standardize numerical data



Encode numerical data

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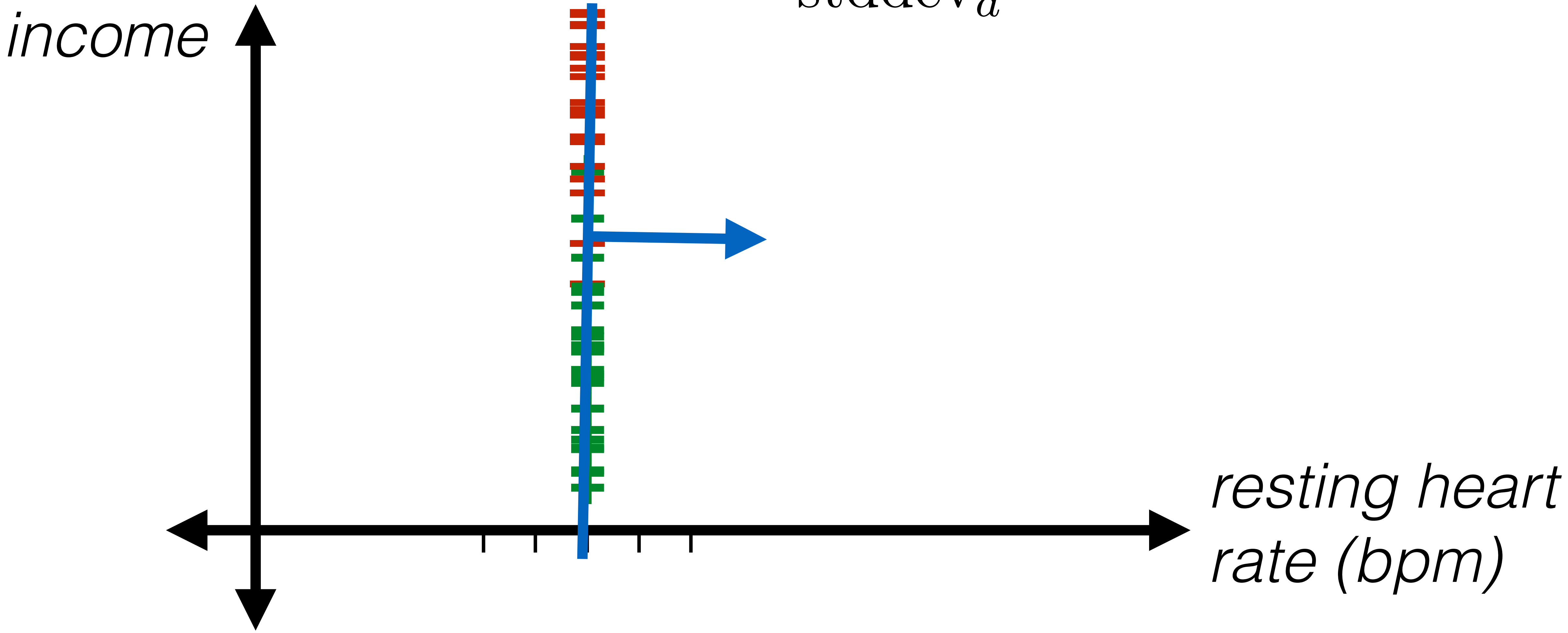
- Idea: standardize numerical data
  - For *d*th feature: $\phi_d^{(k)} = \frac{x_d^{(k)} - \text{mean}_d}{\text{stddev}_d}$



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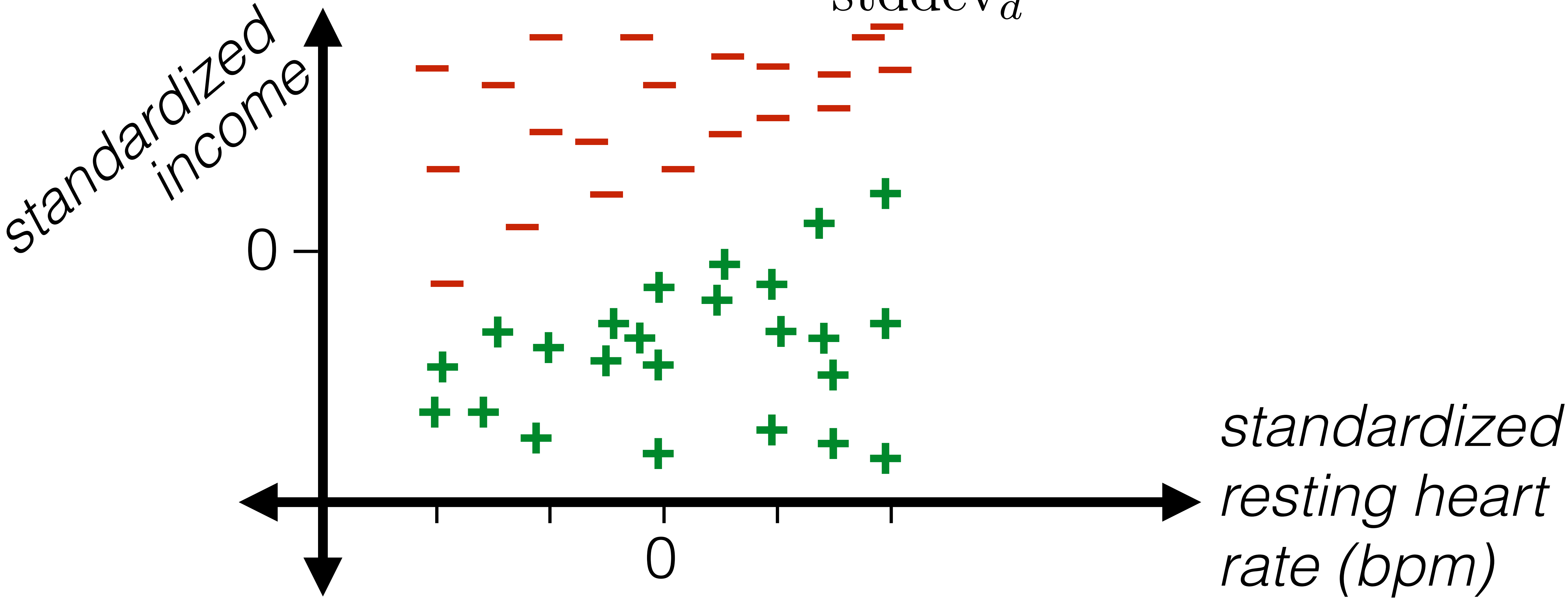

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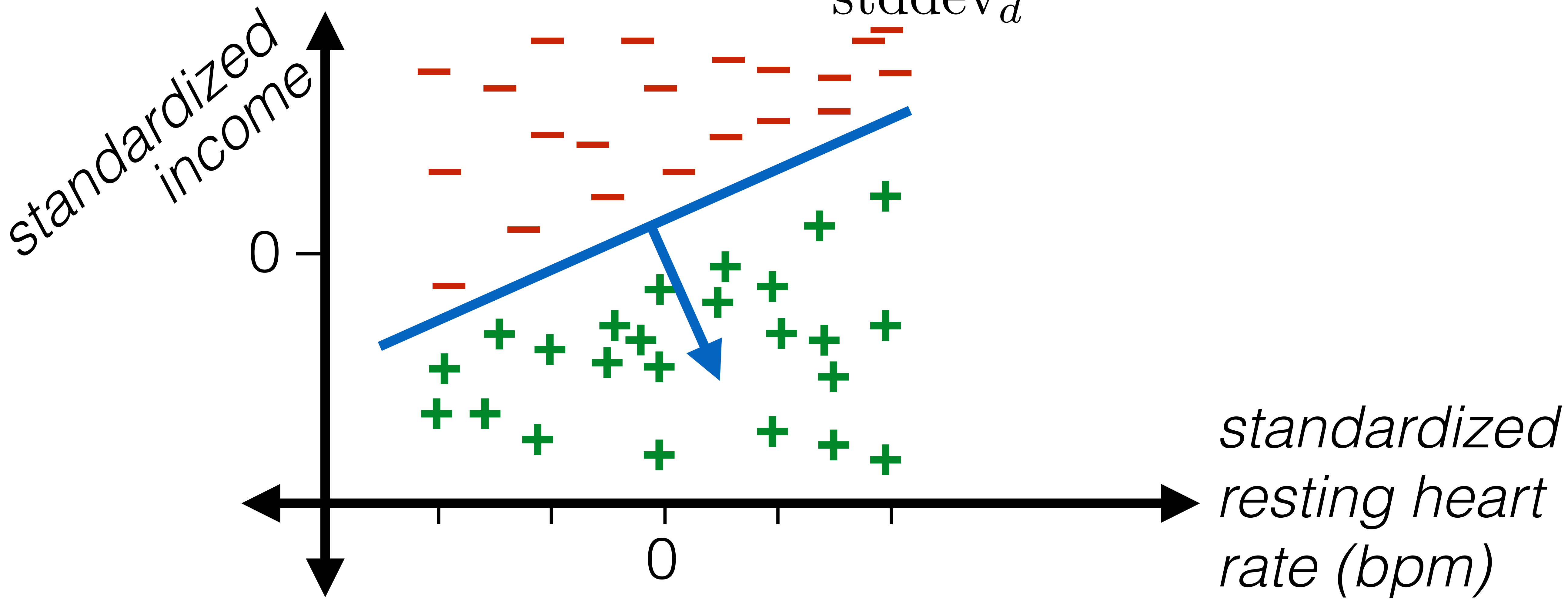

More benefits of plotting your data

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- And talking to experts

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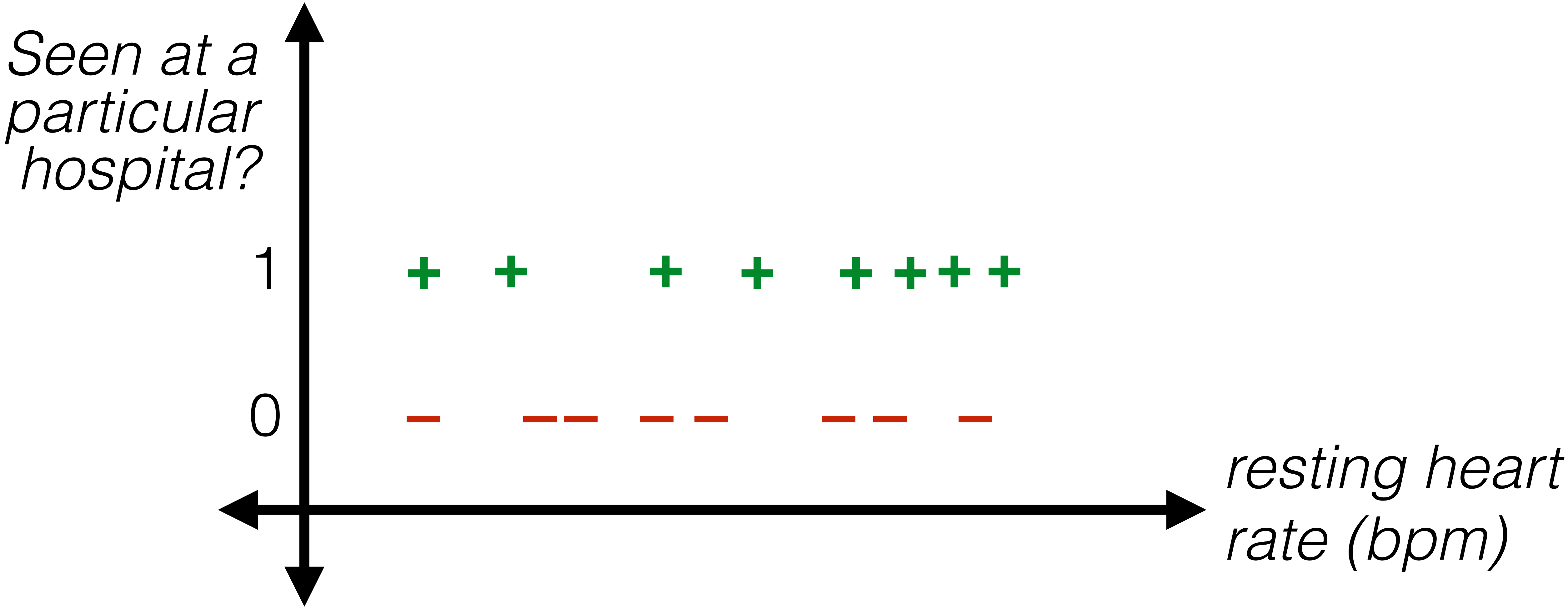

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3	89	1	1,0,0,0,0	0,1	5	40000
4	67	0	0,0,0,1,0	0,0	5	120000

Encode data in usable form

- Identify the features and encode as real numbers
- Standardize numerical features

	resting heart rate (bpm)	pain?	j1,j2,j3,j4,j5	m1, m2	decade	family income (USD)
1	55	0	1,0,0,0,0	1,0	4	133000
2	71	0	0,1,0,0,0	1,1	2	34000
3	89	1	1,0,0,0,0	0,1	5	40000
4	67	0	0,0,0,1,0	0,0	5	120000

Encode data in usable form

- Identify the features and encode as real numbers
- Standardize numerical features

	resting heart rate (bpm)	pain?	j1,j2,j3,j4,j5	m1, m2	decade	family income (USD)
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- Identify the features and encode as real numbers
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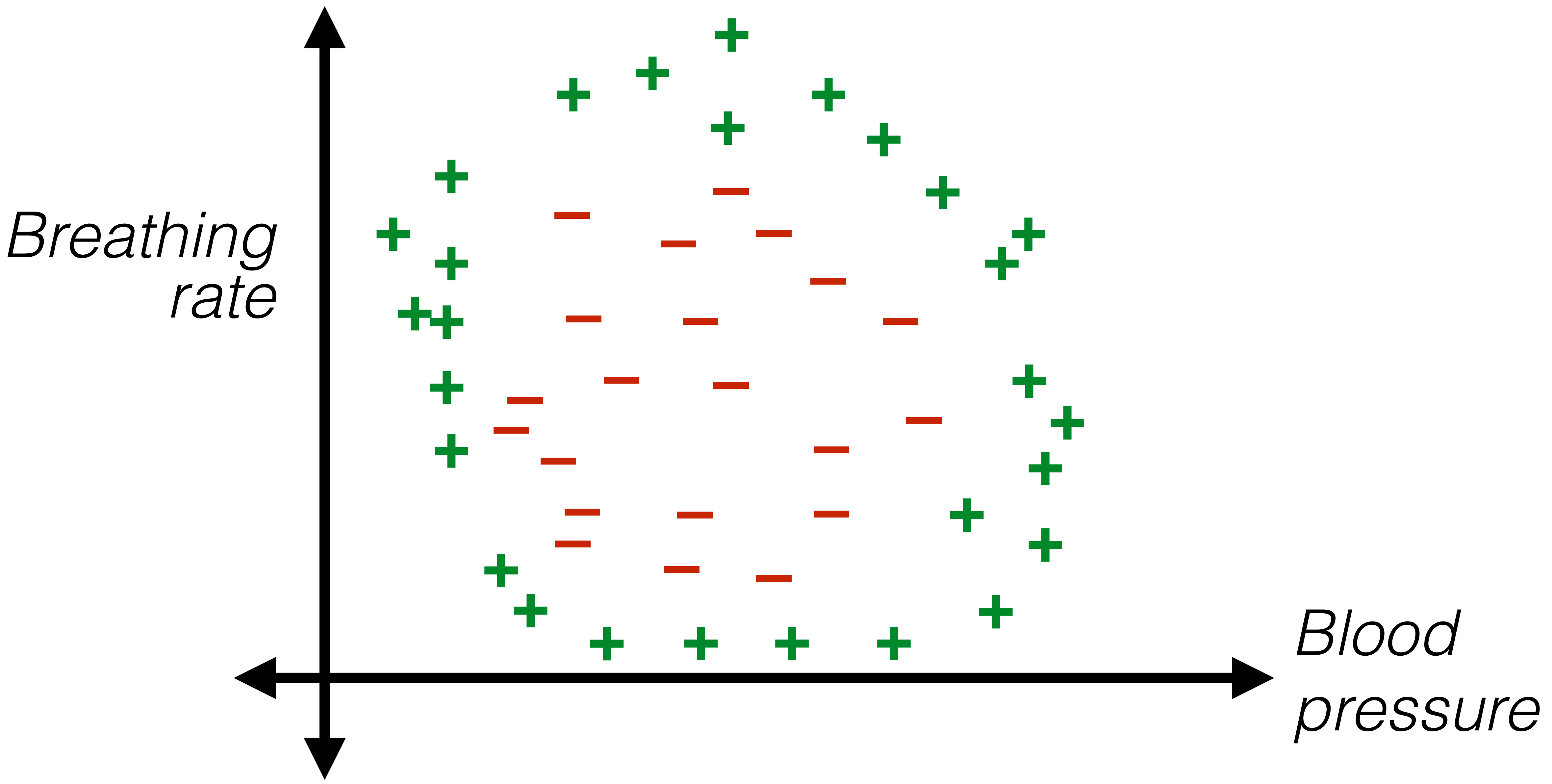
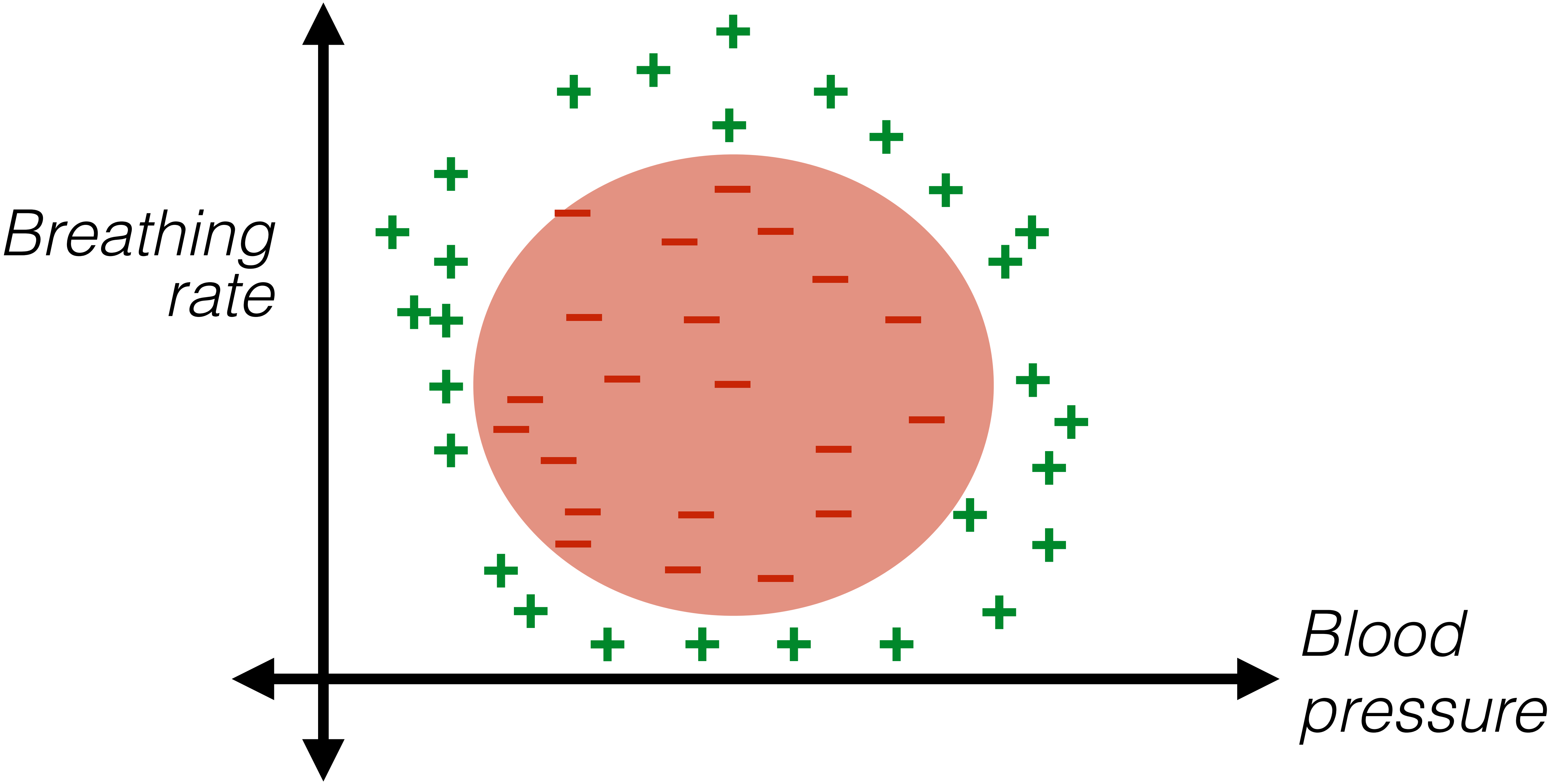
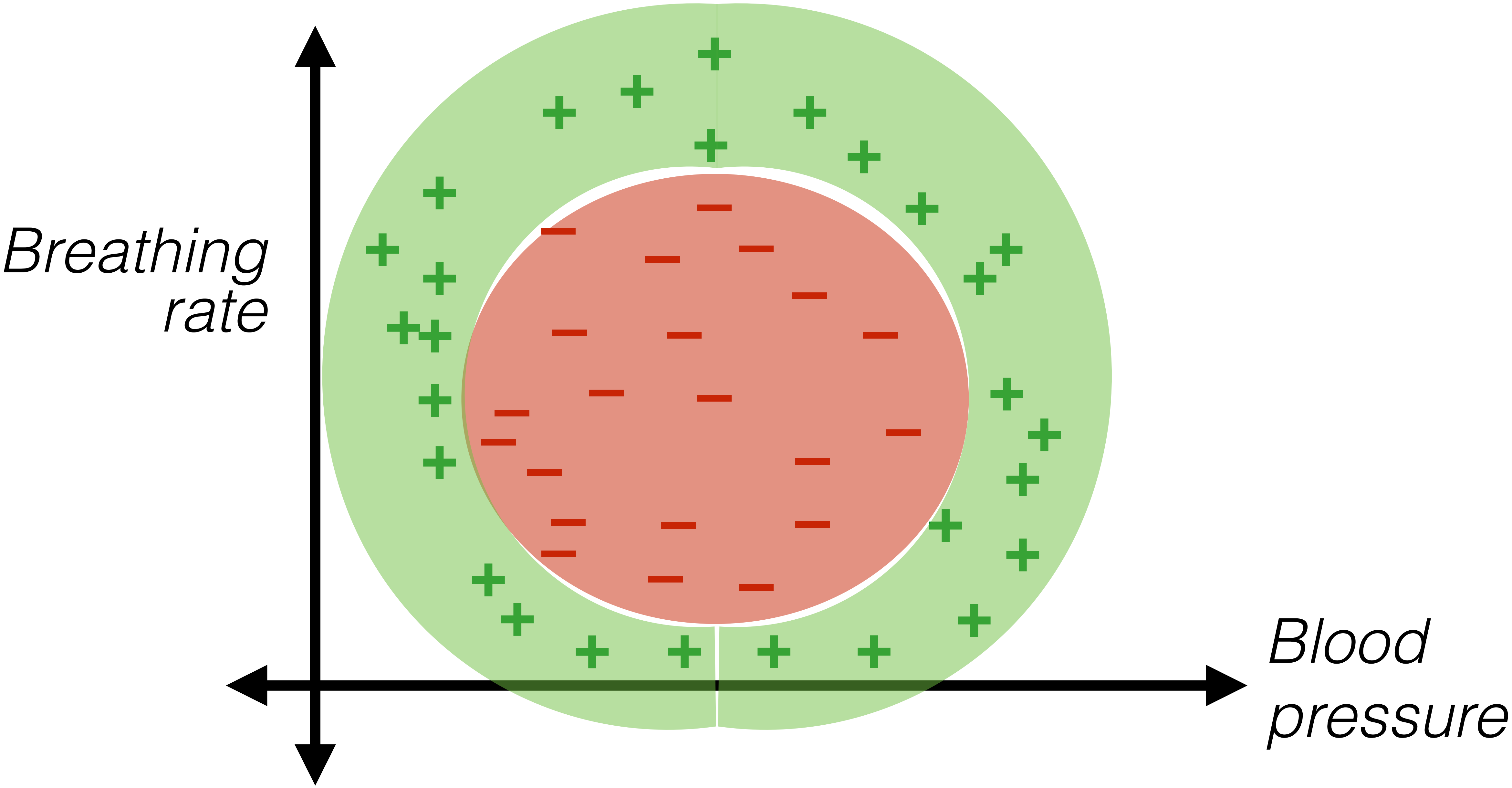
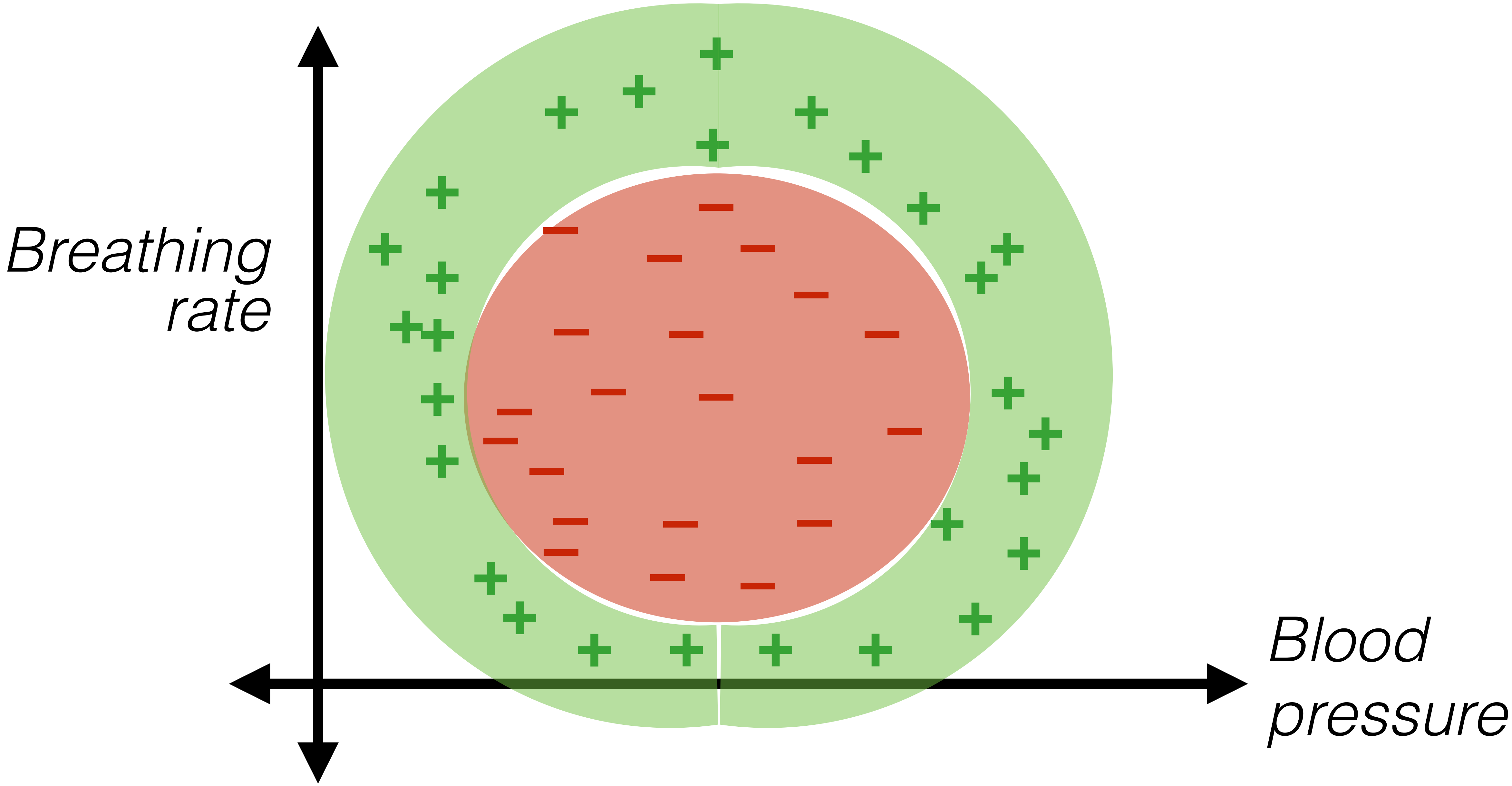
	resting heart rate (bpm)	pain?	j1,j2,j3,j4,j5	m1, m2	decade	family income (USD)
1	-1.5	0	1,0,0,0,0	1,0	1	2.075
2	0.1	0	0,1,0,0,0	1,1	-1	-0.4
3	1.9	1	1,0,0,0,0	0,1	2	-0.25
4	-0.3	0	0,0,0,1,0	0,0	2	1.75


Breathing rate
Blood pressure


Breathing rate
Blood pressure


Breathing rate
Blood pressure

Nonlinear boundaries



Classification boundaries

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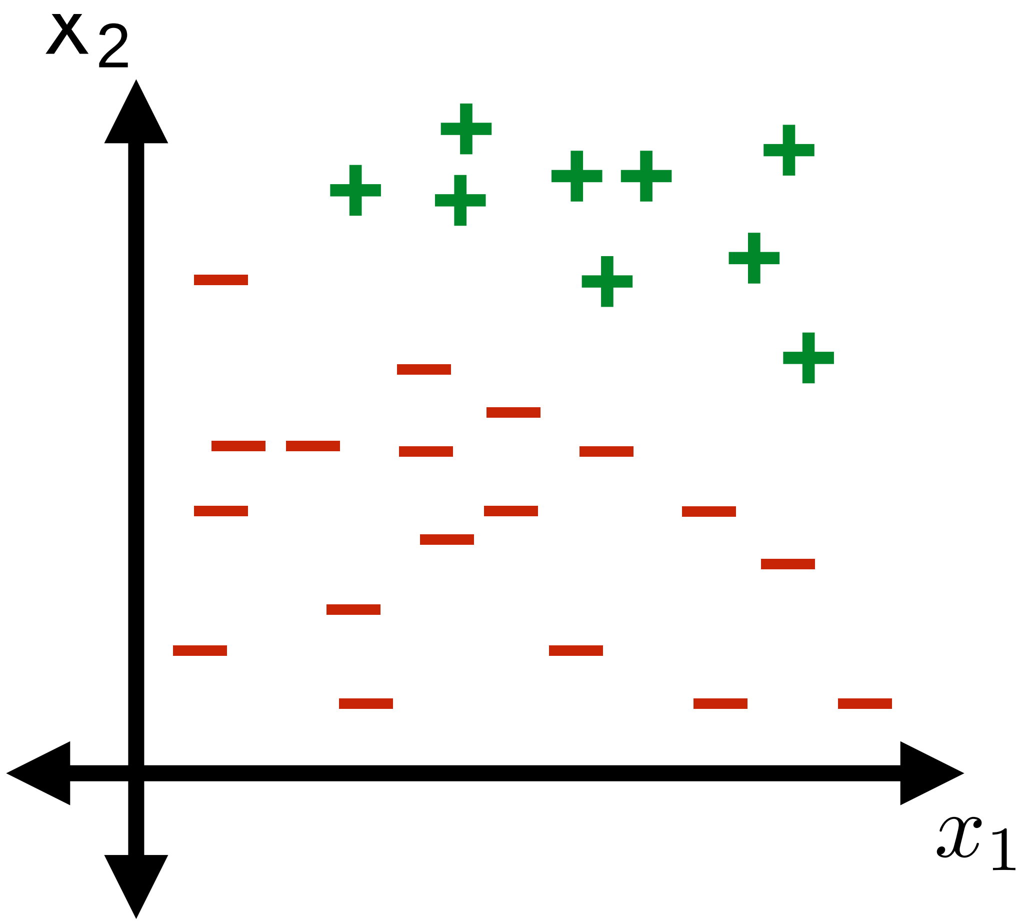

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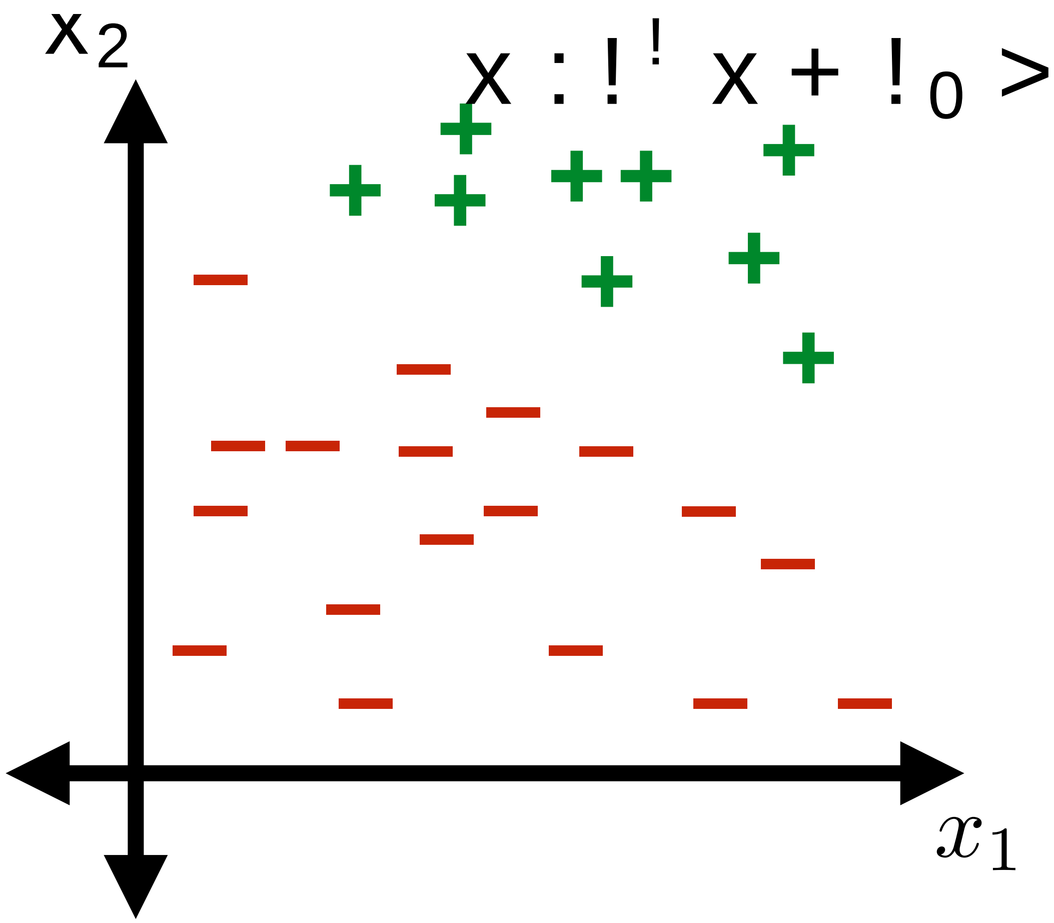
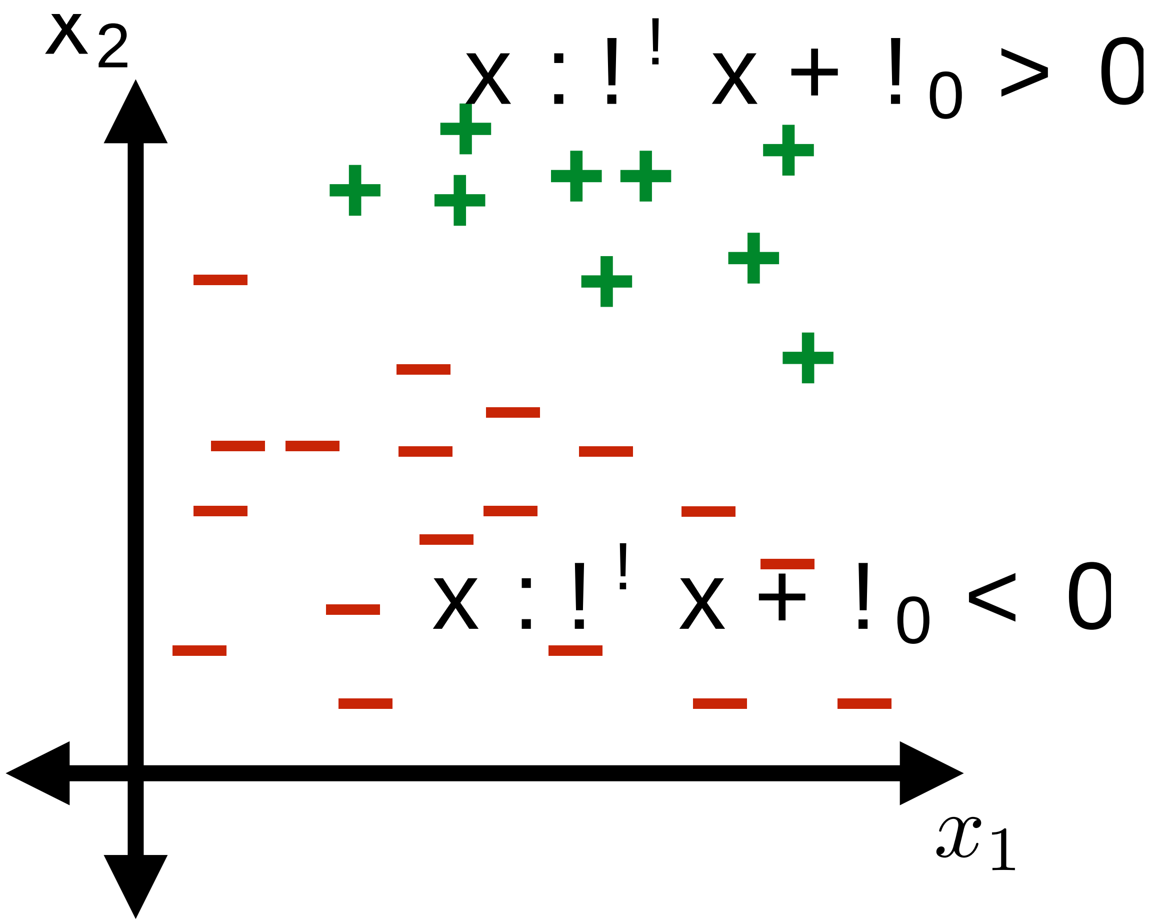


$x : !^{!} x + !_{0} > 0$

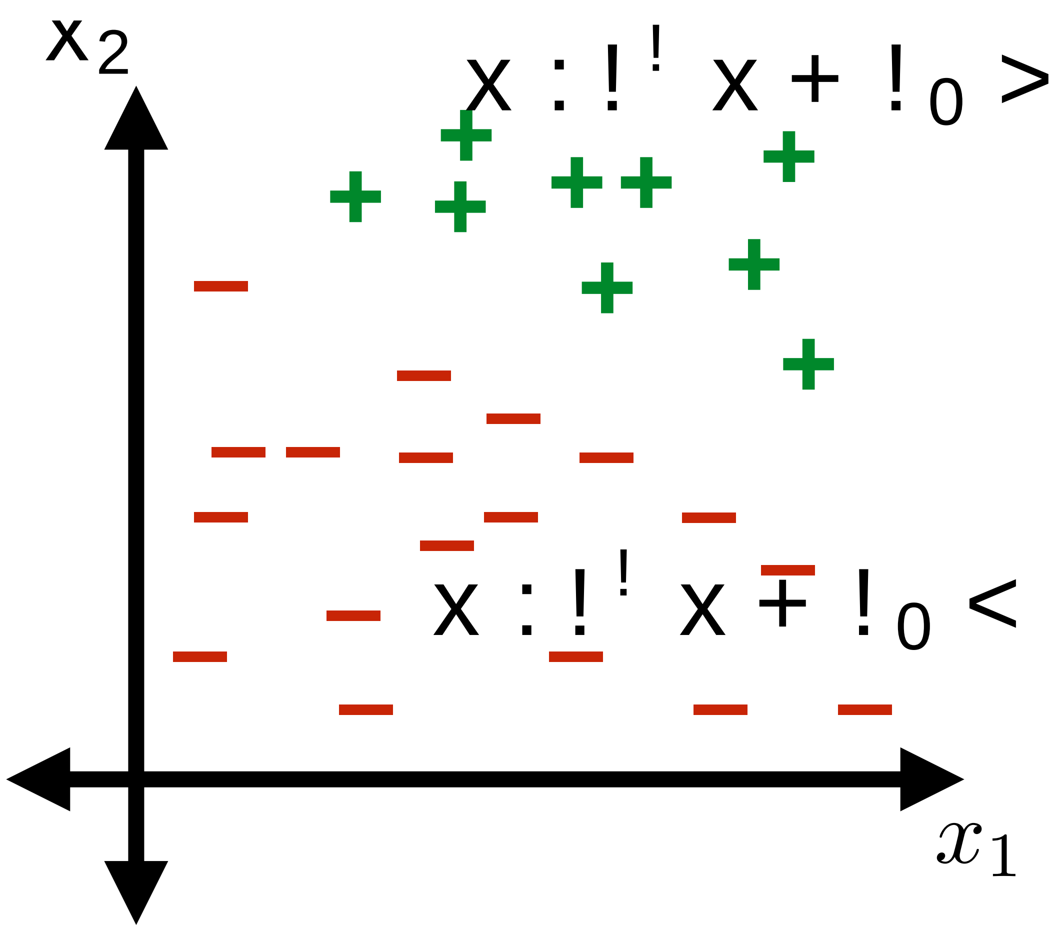
Classification boundaries



$x : !^{!}\ x + !_0 > 0$

$x : !^{!}\ x + !_0 < 0$

Classification boundaries



$x : !^! x + !_0 > 0$

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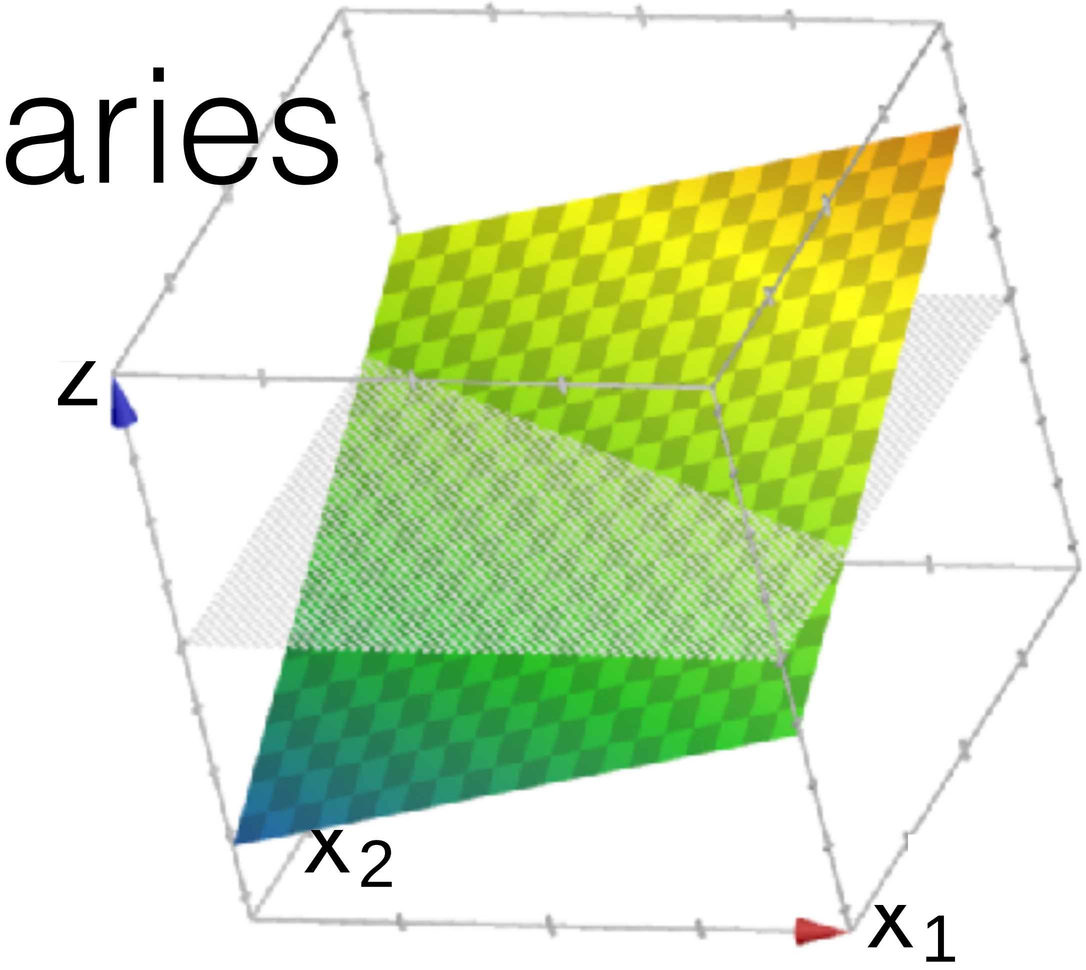

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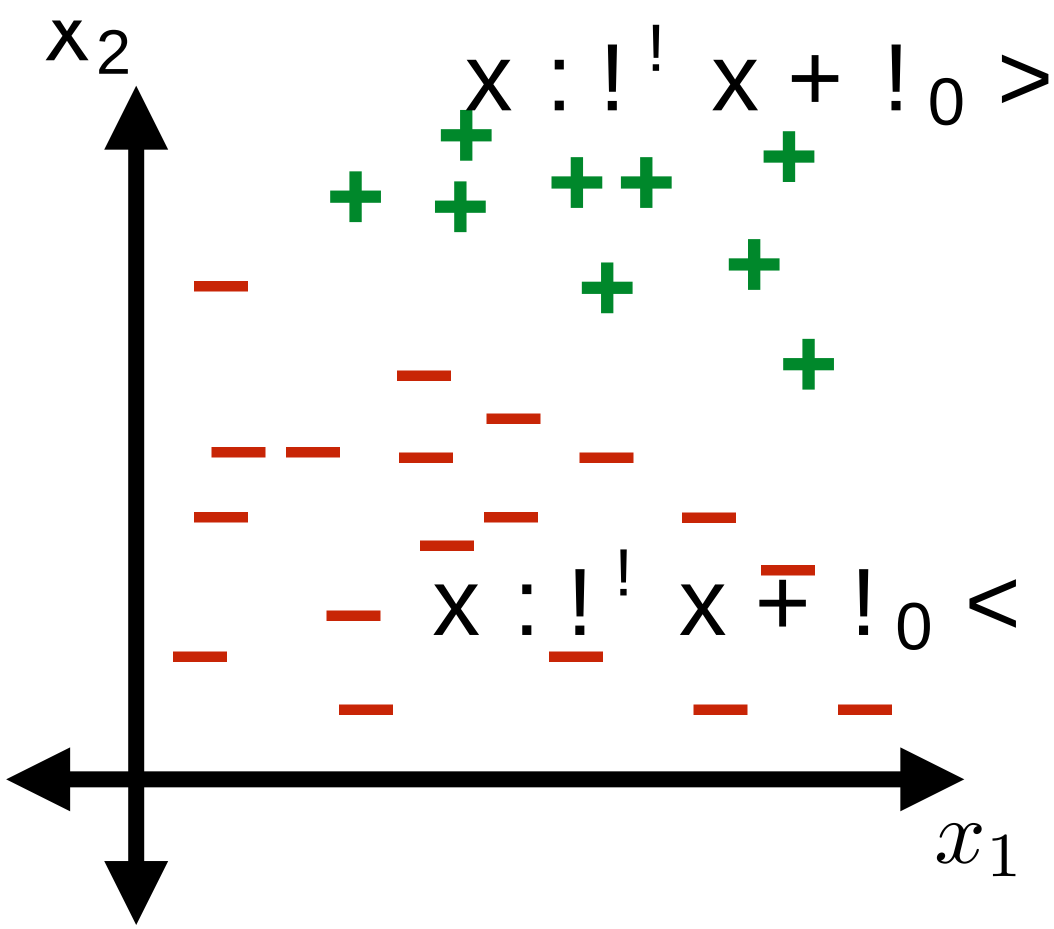

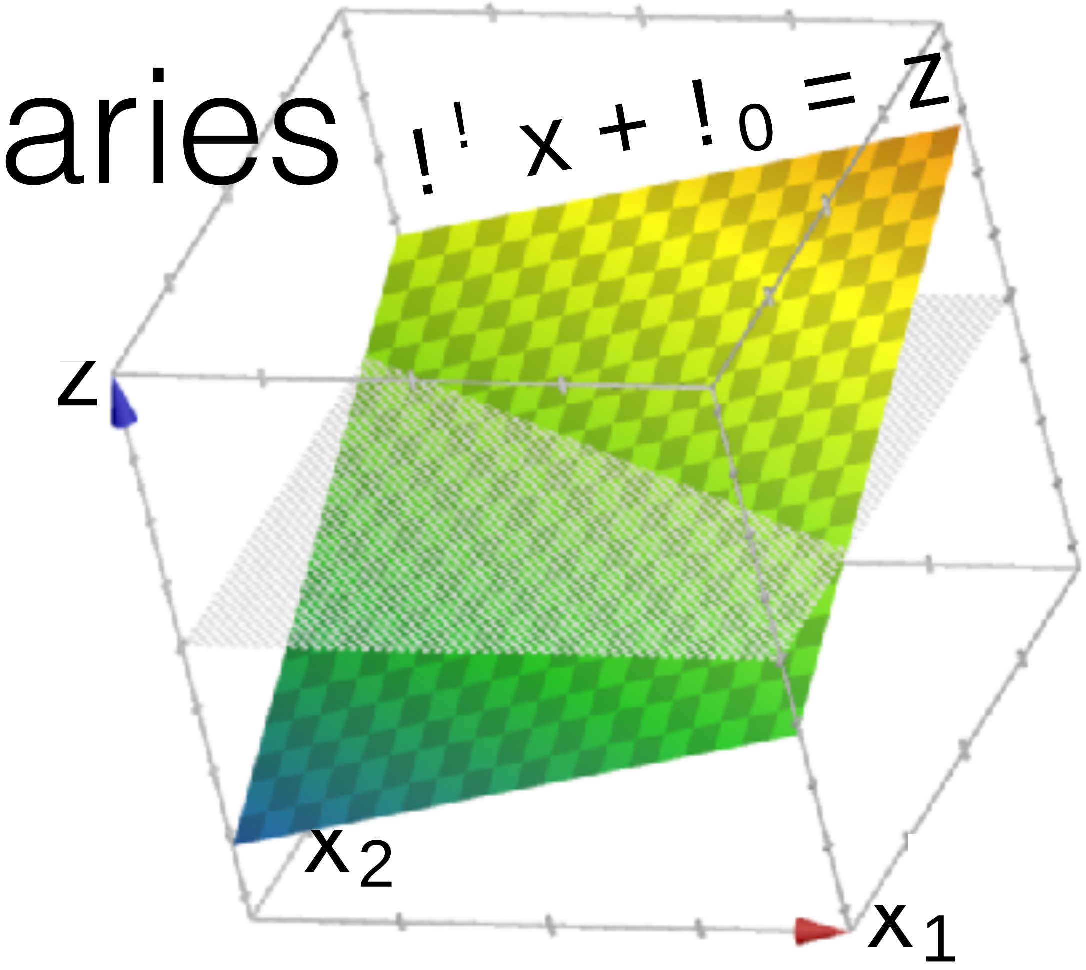

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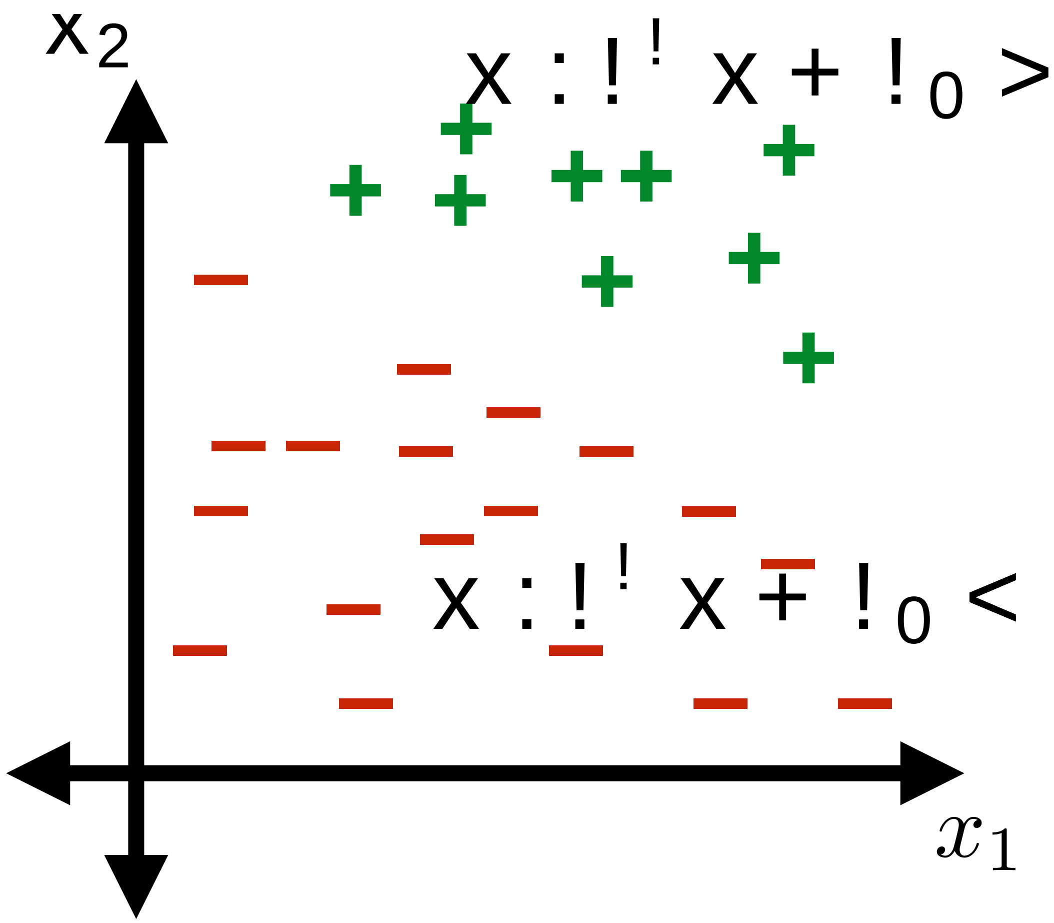

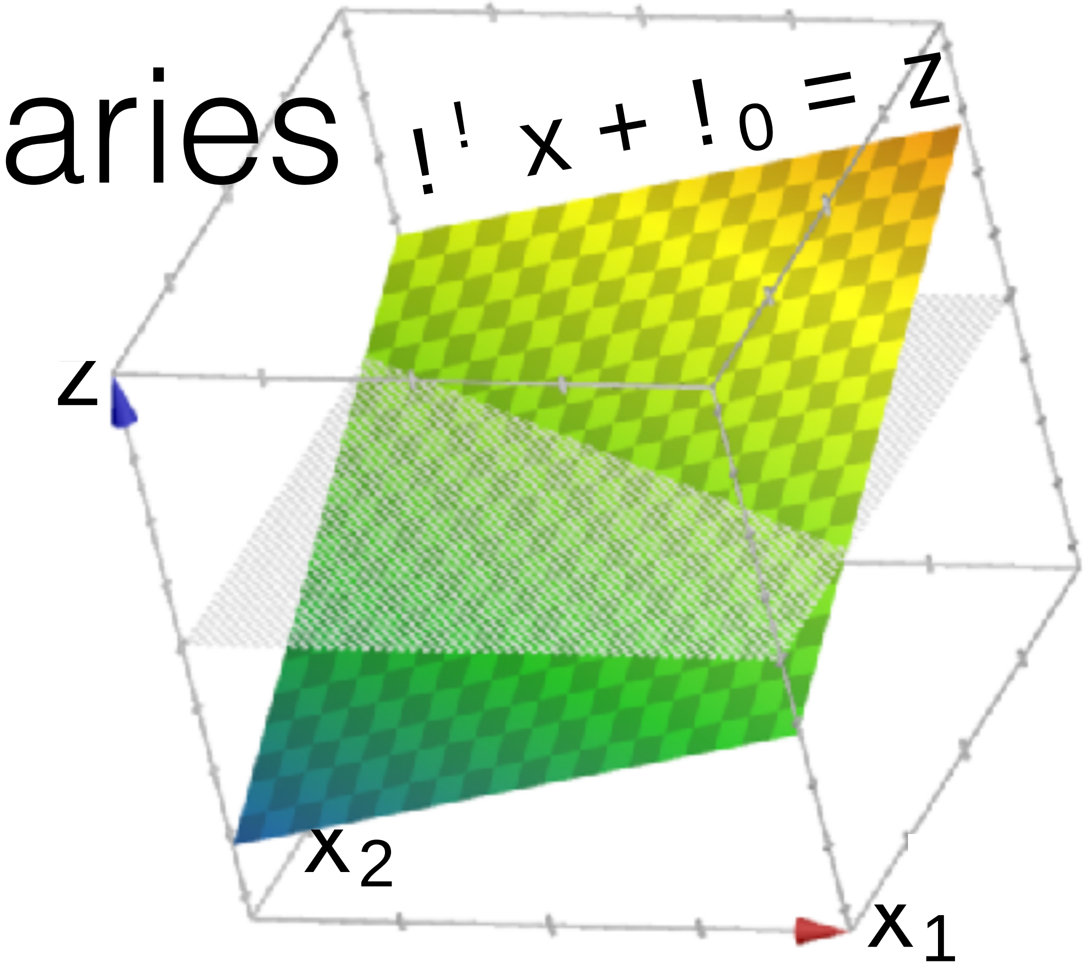

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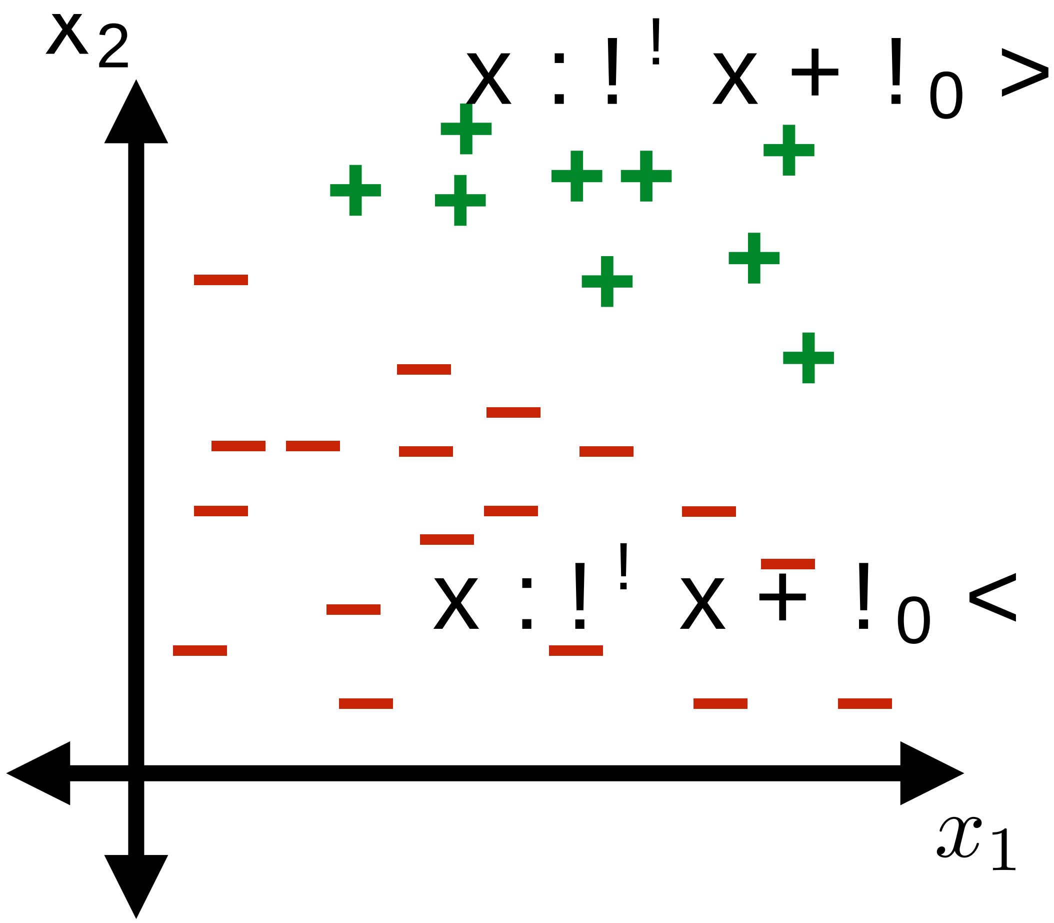

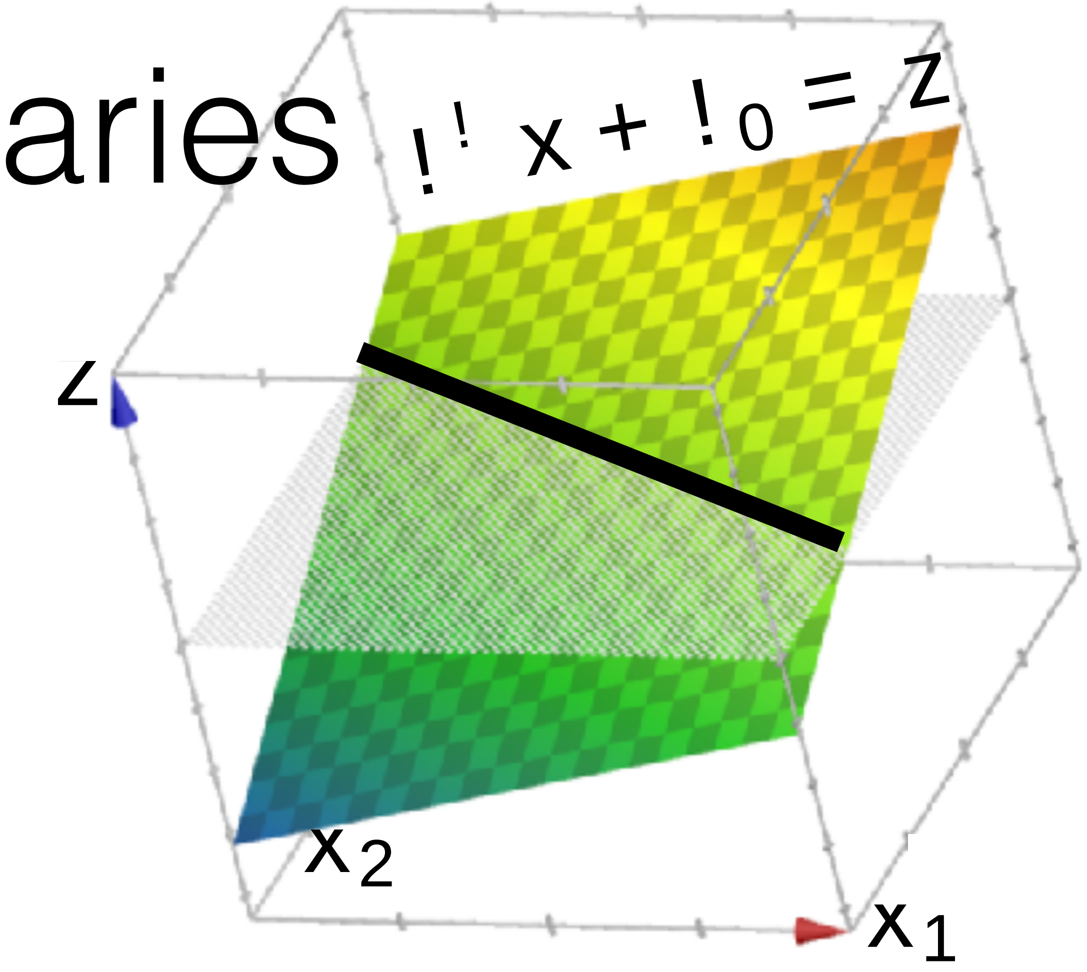

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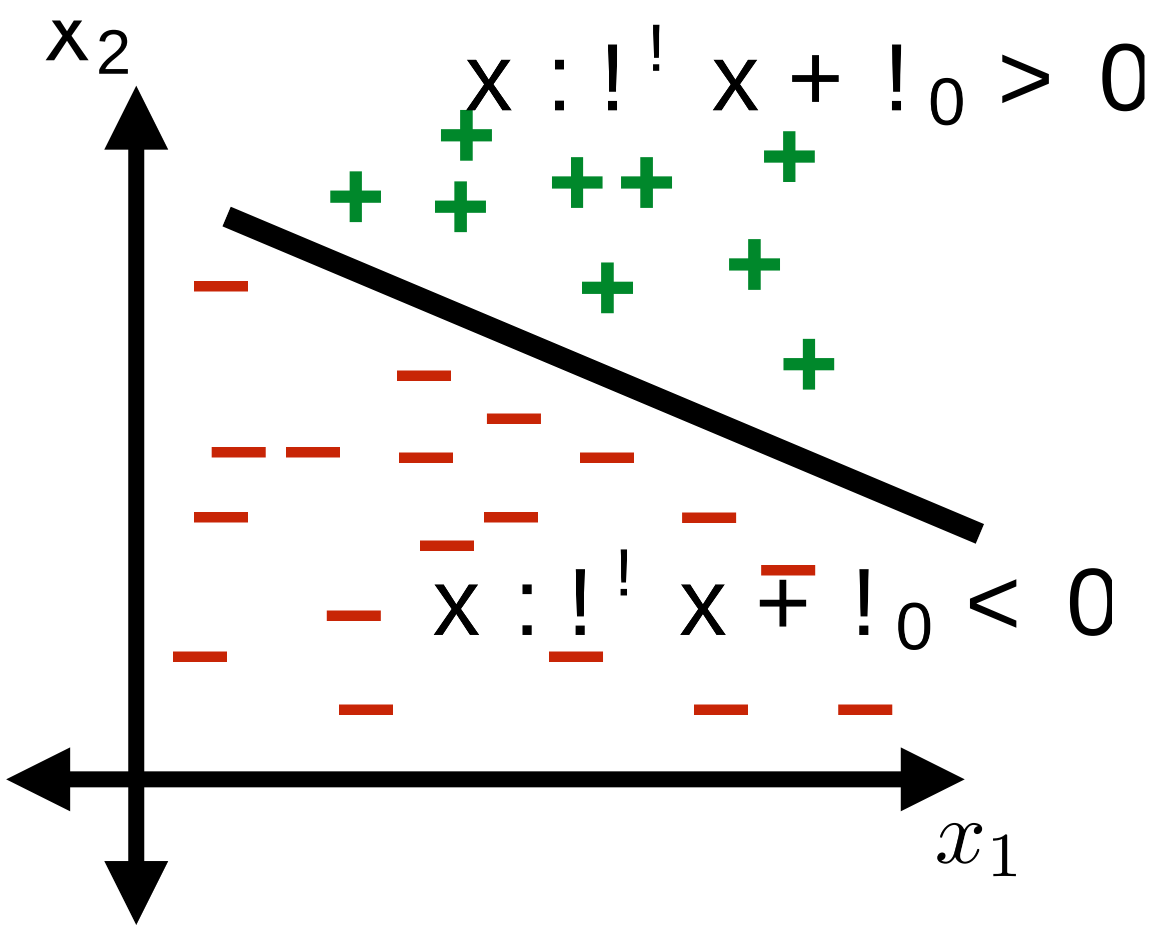

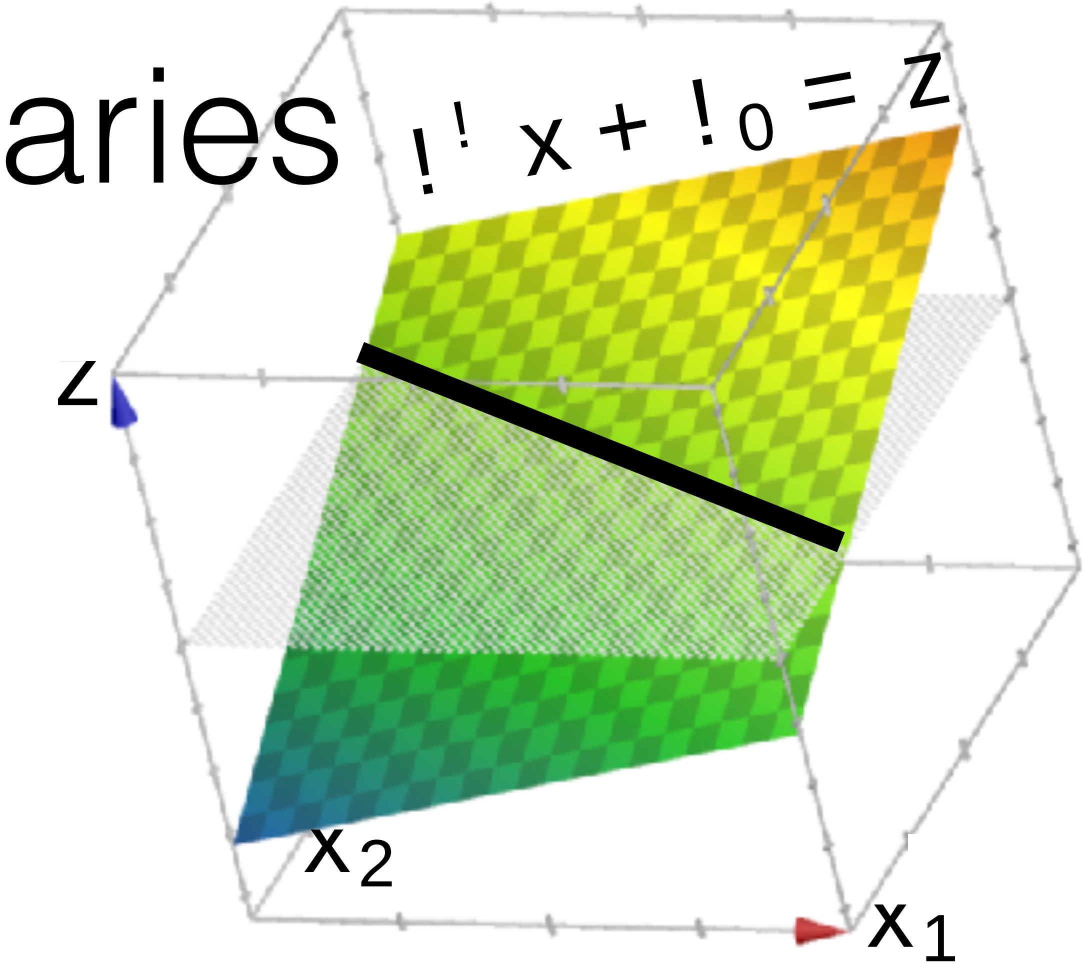

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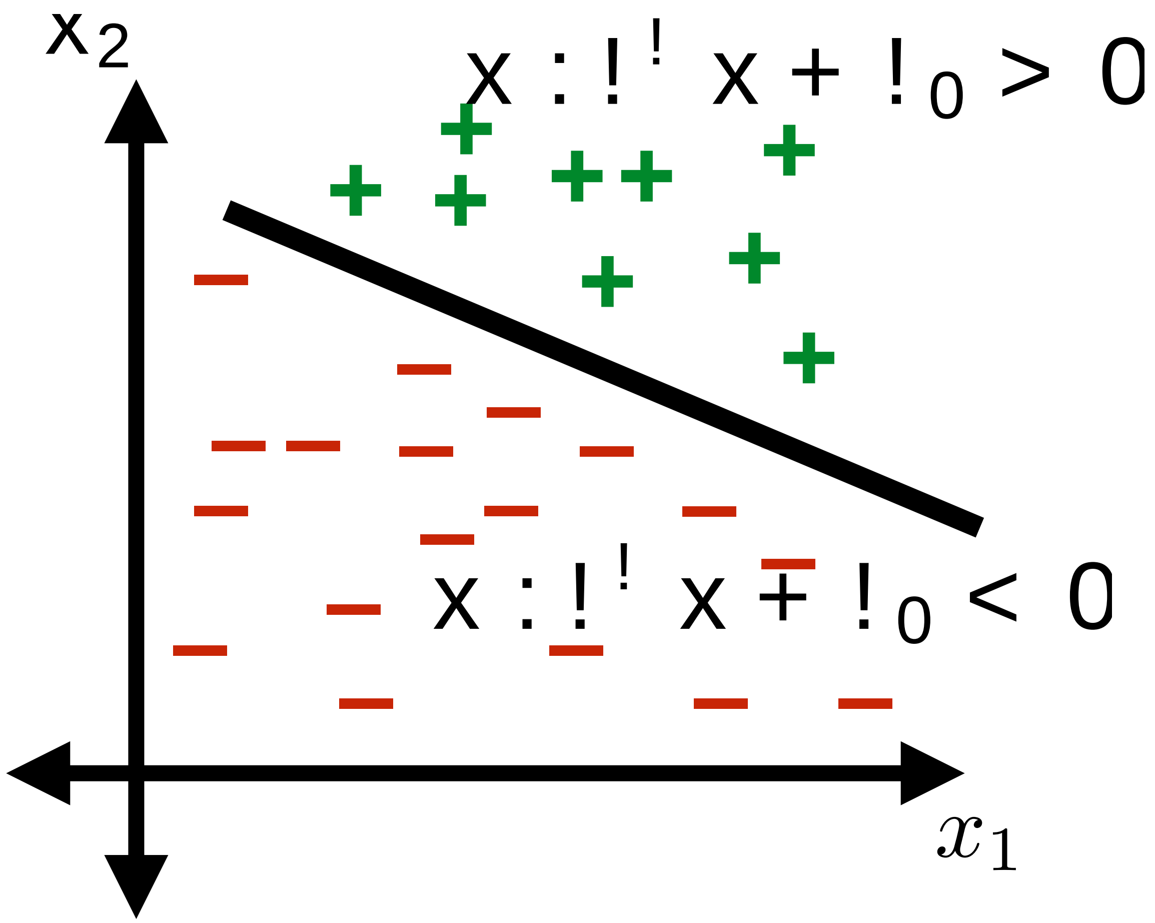

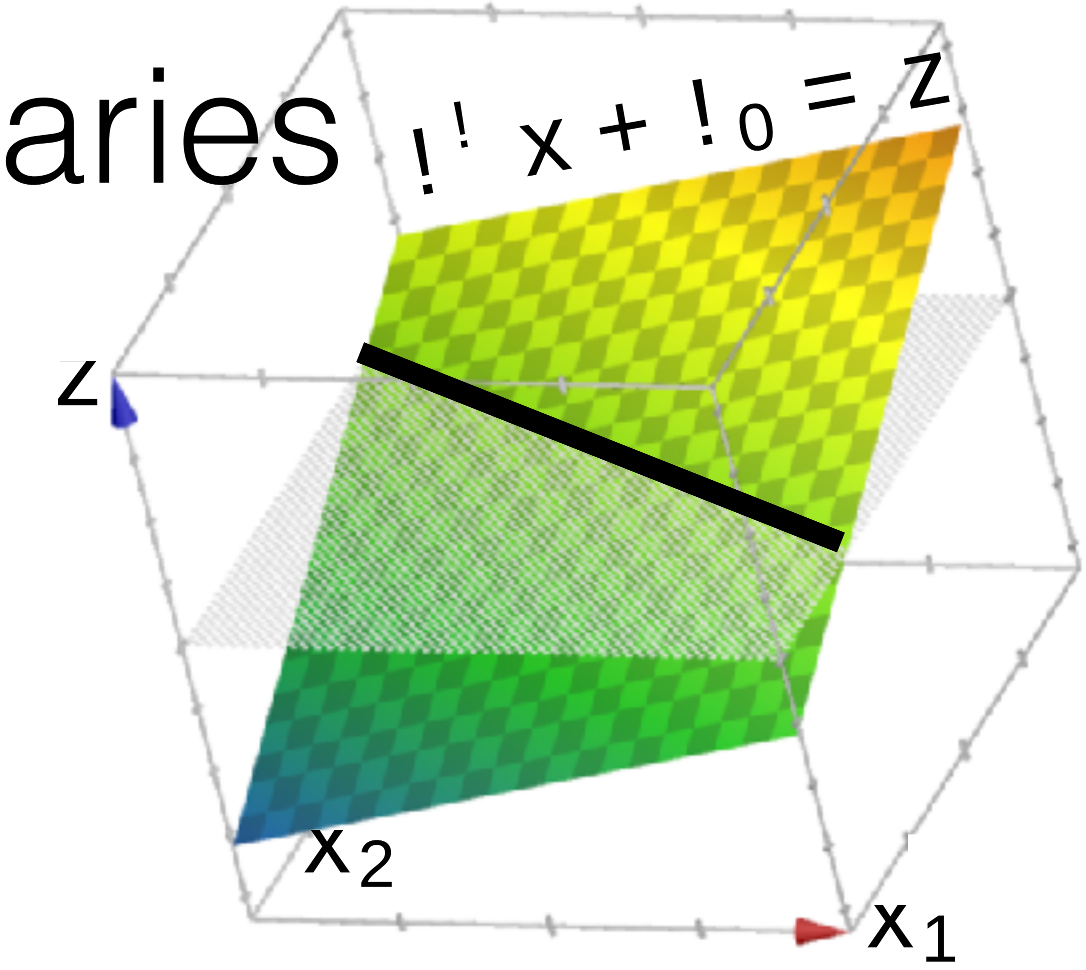

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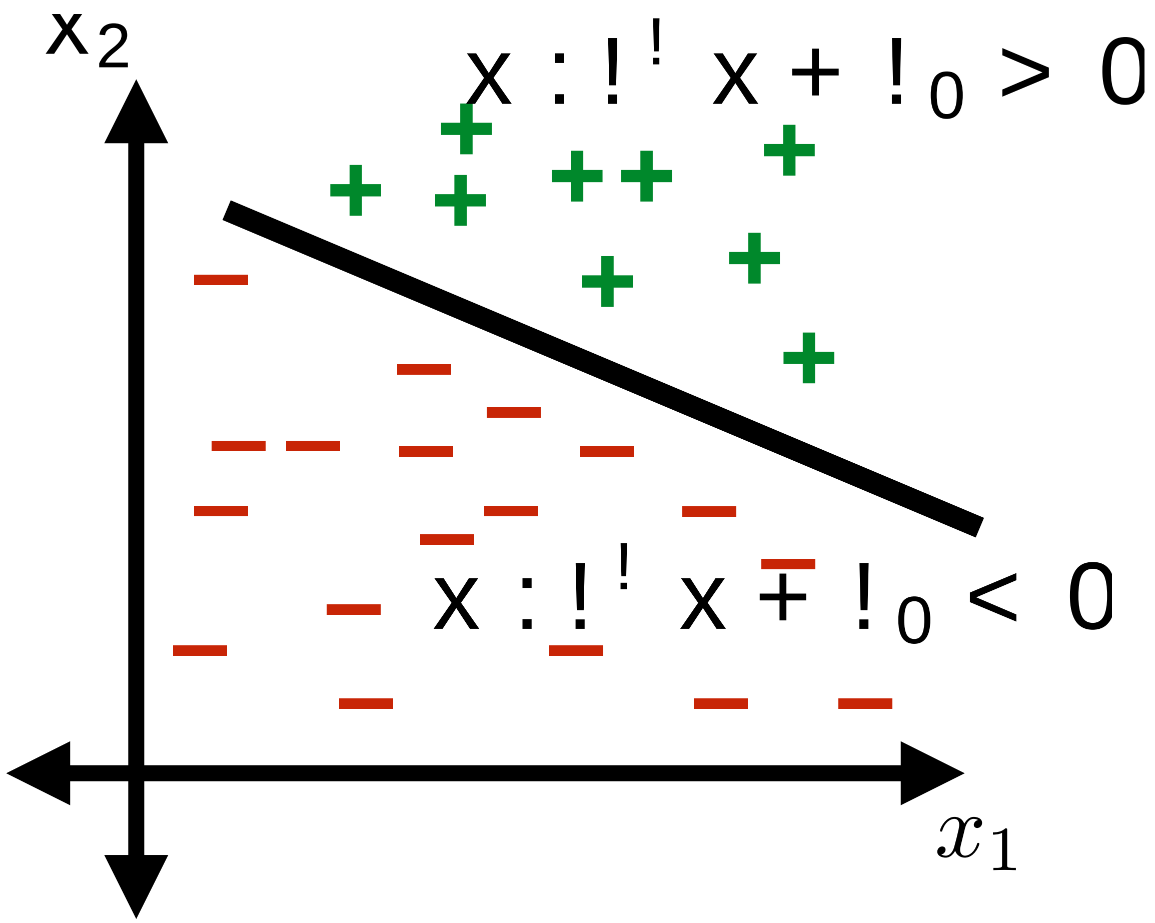

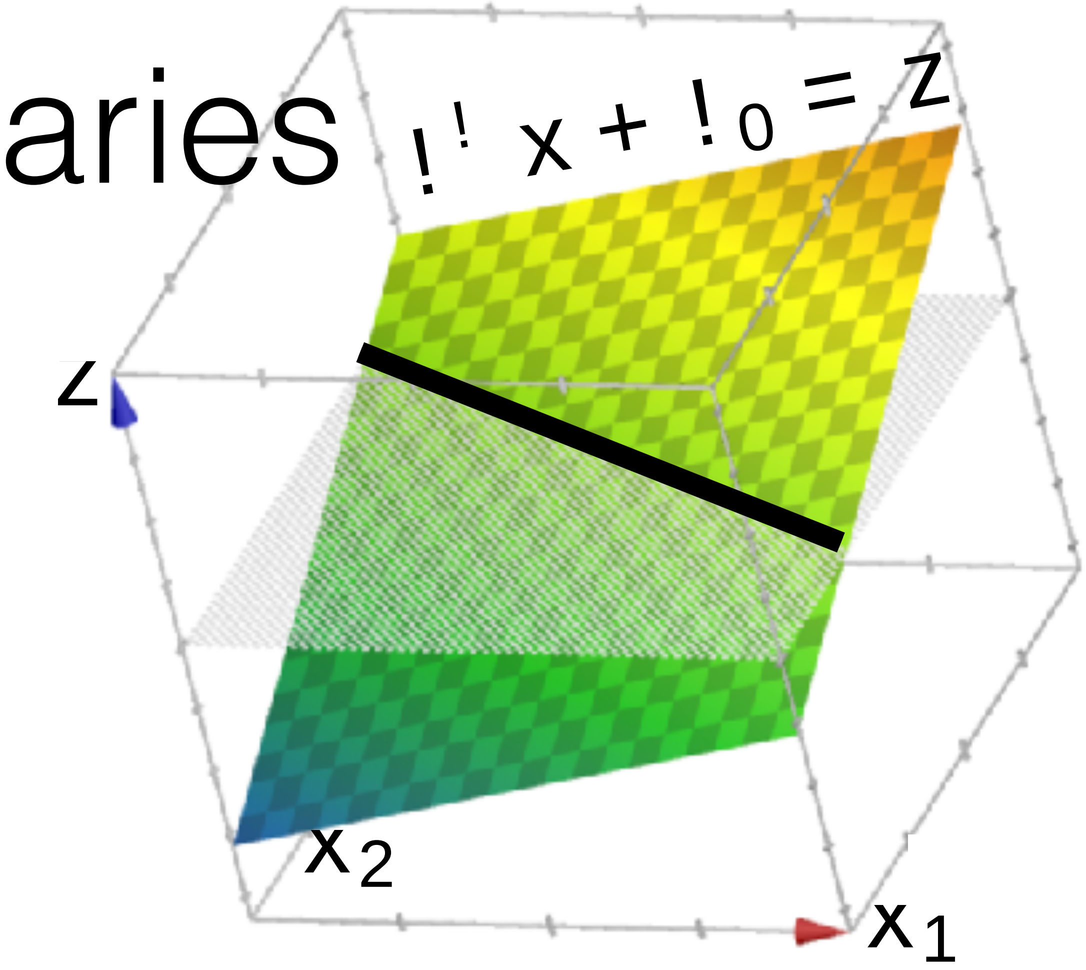

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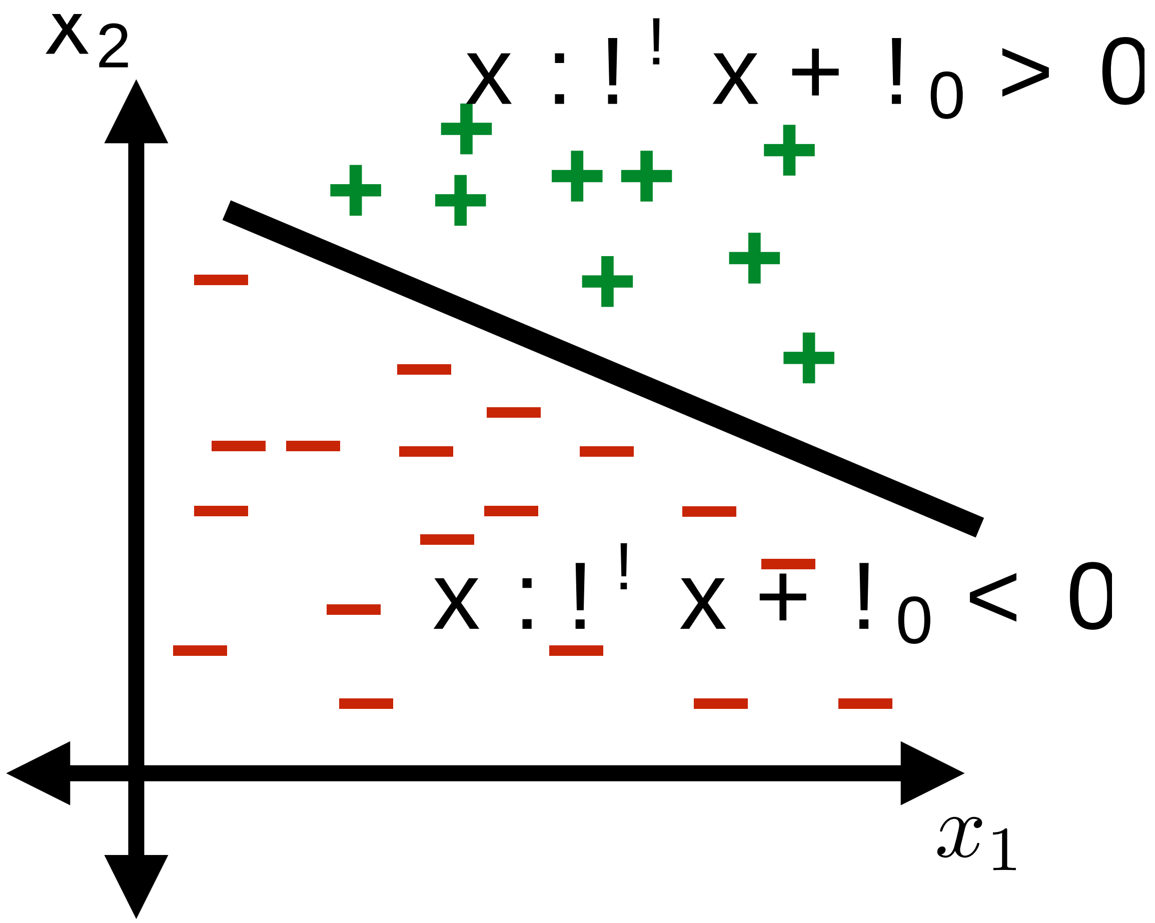

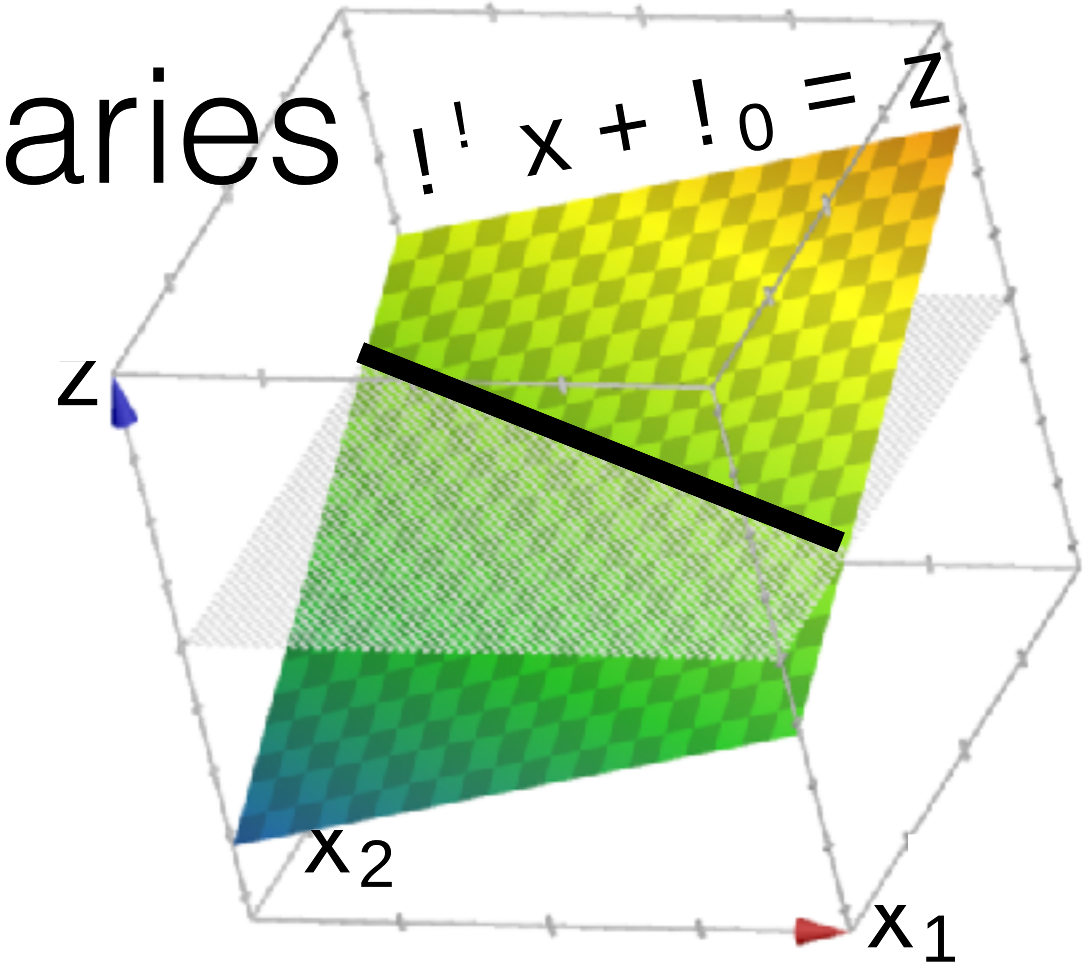

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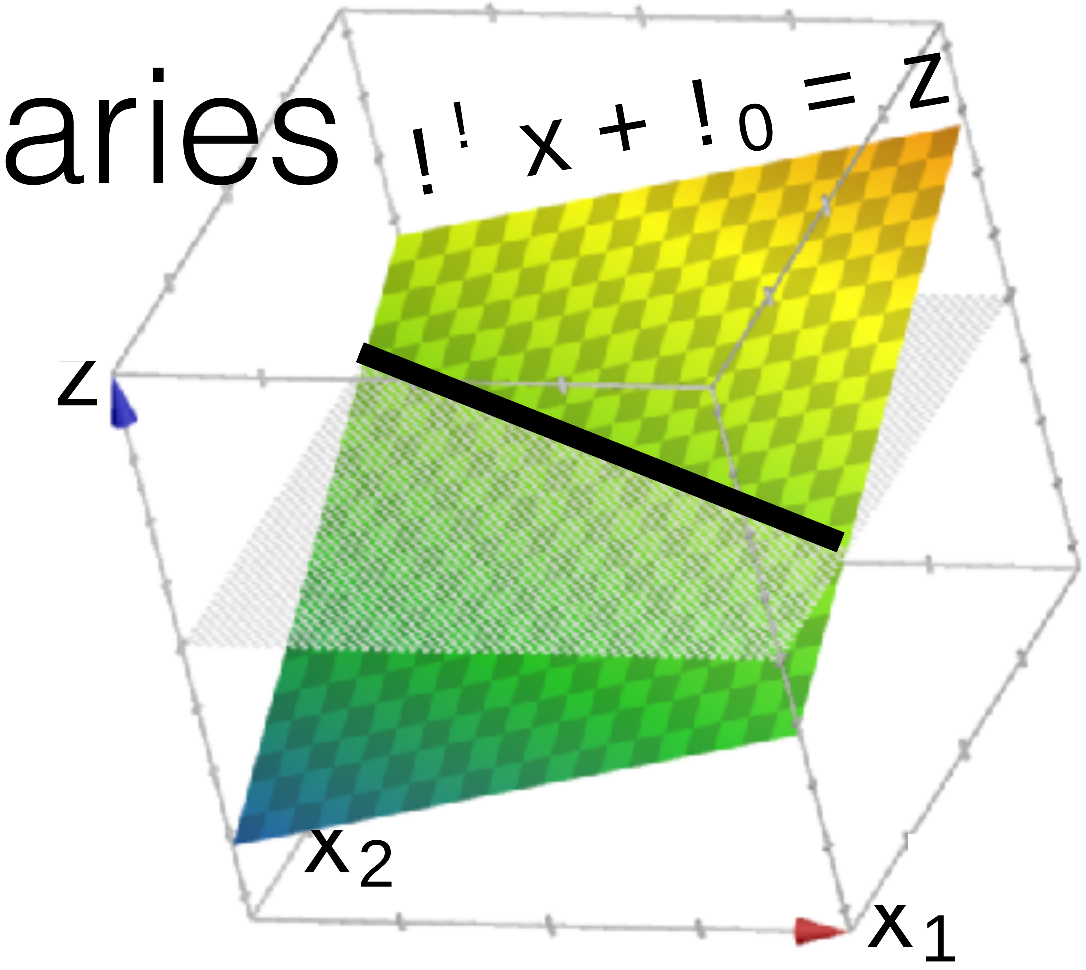

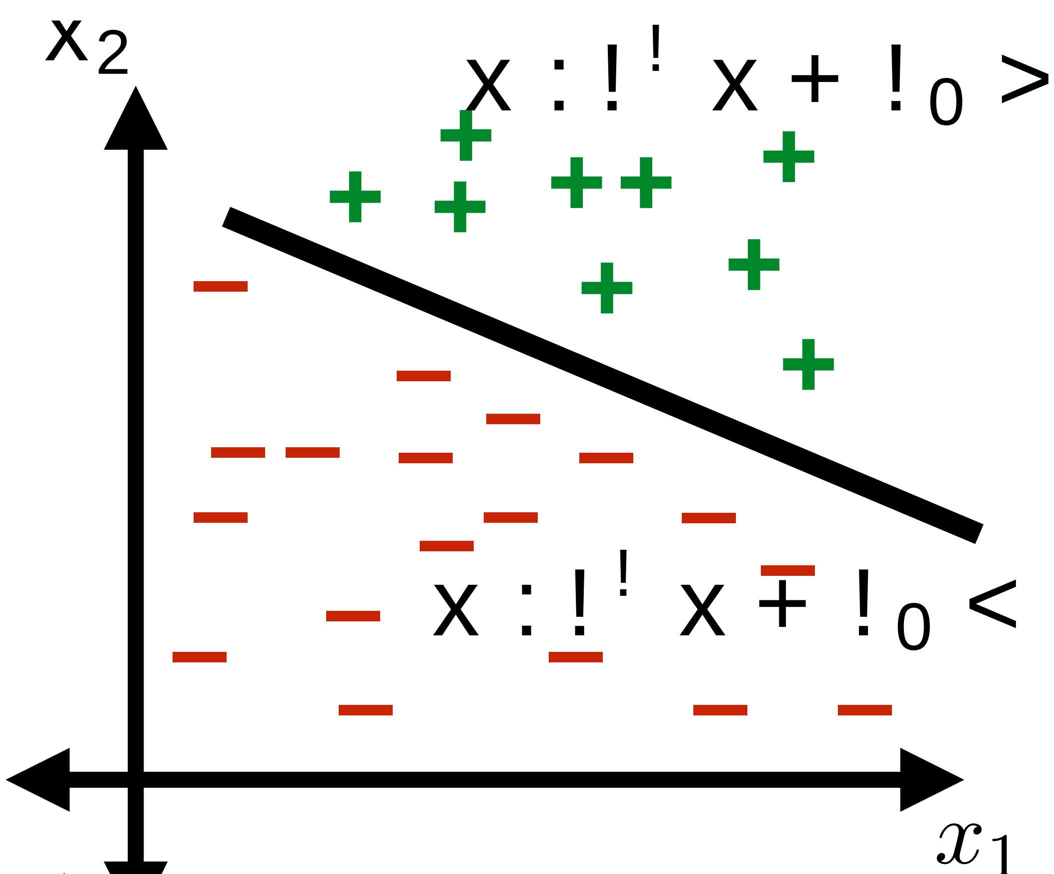

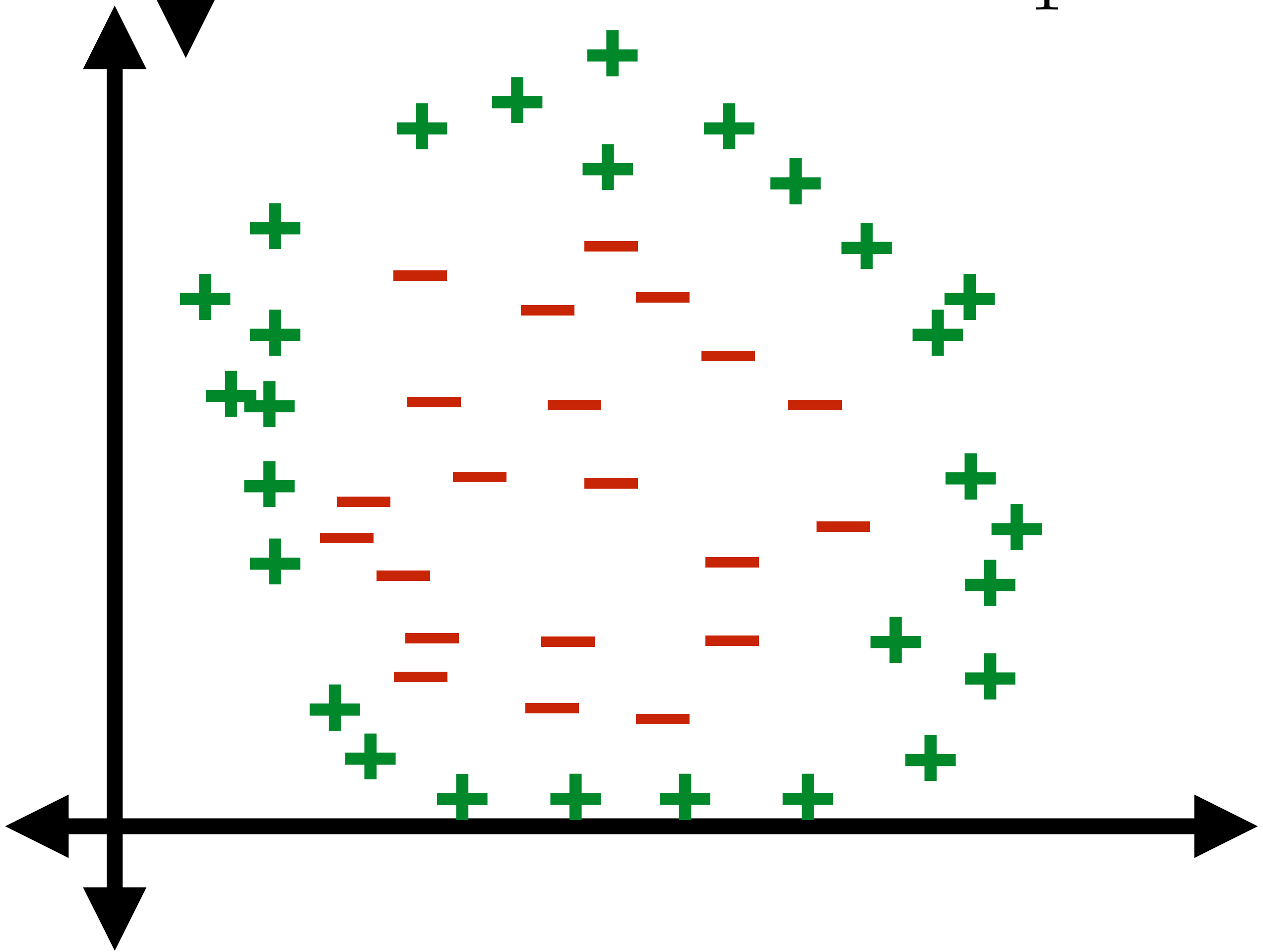

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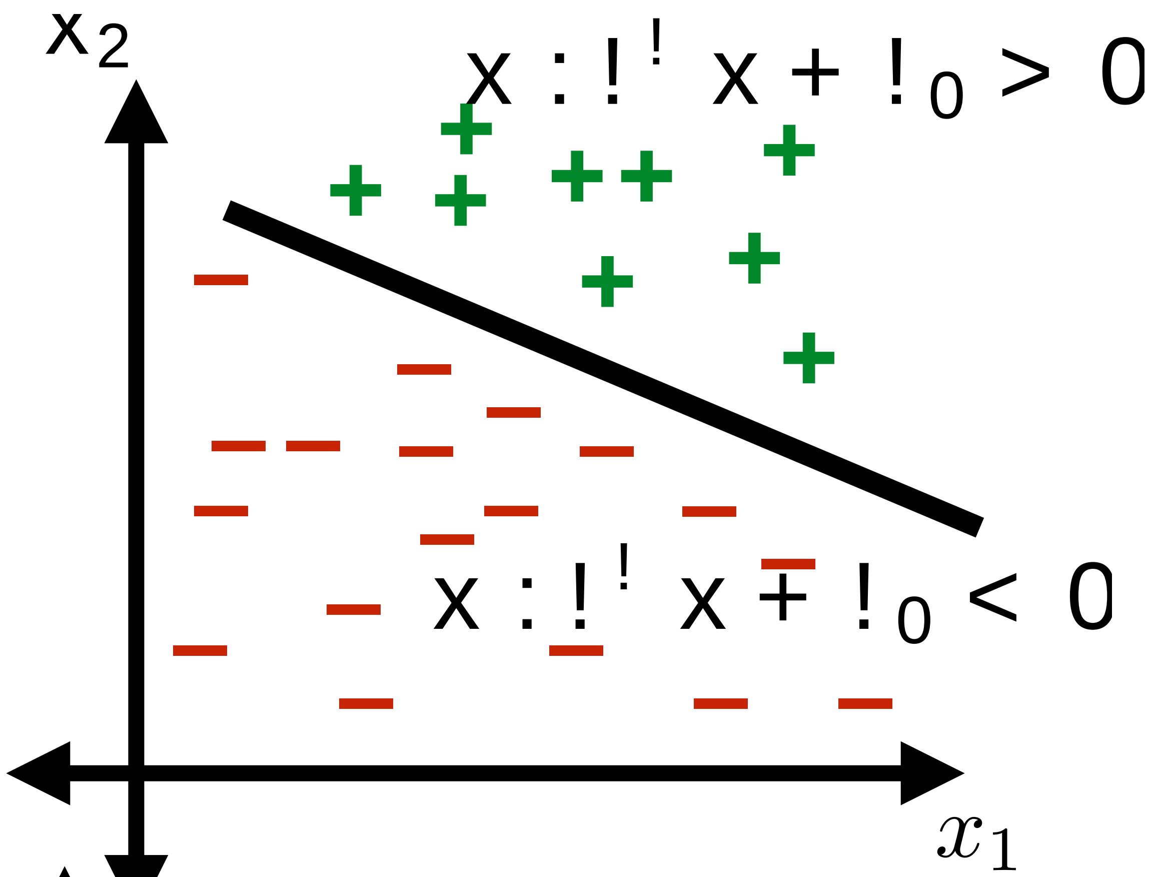

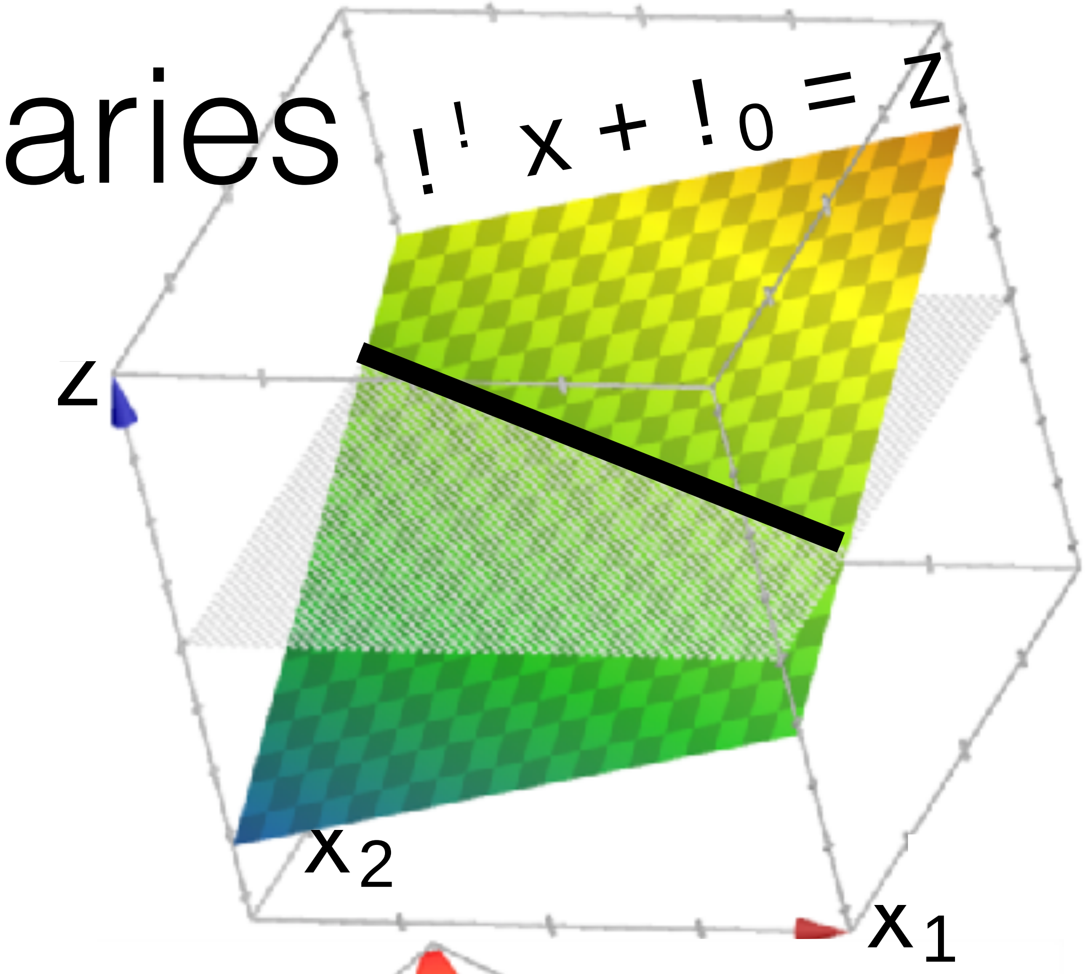

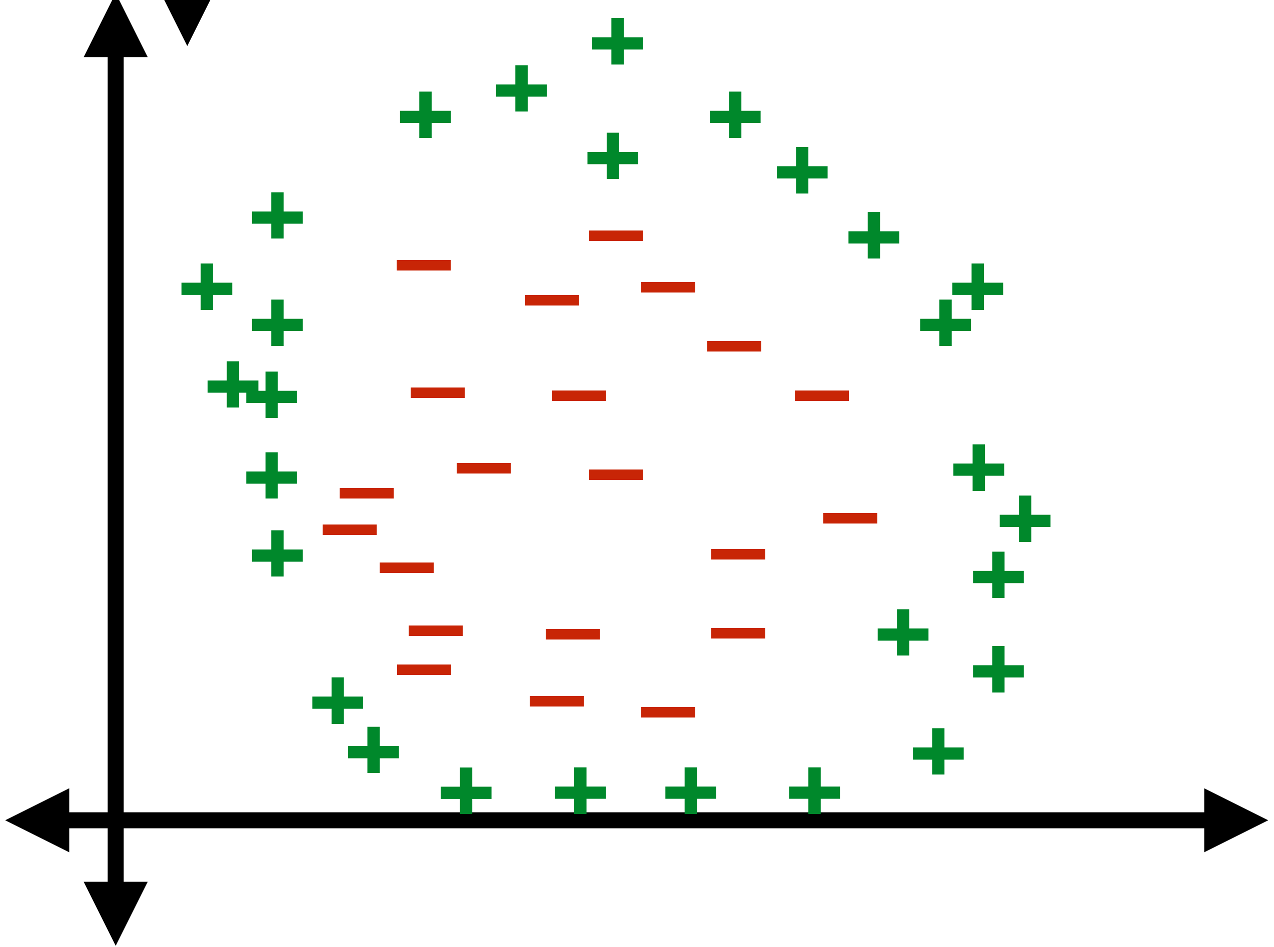

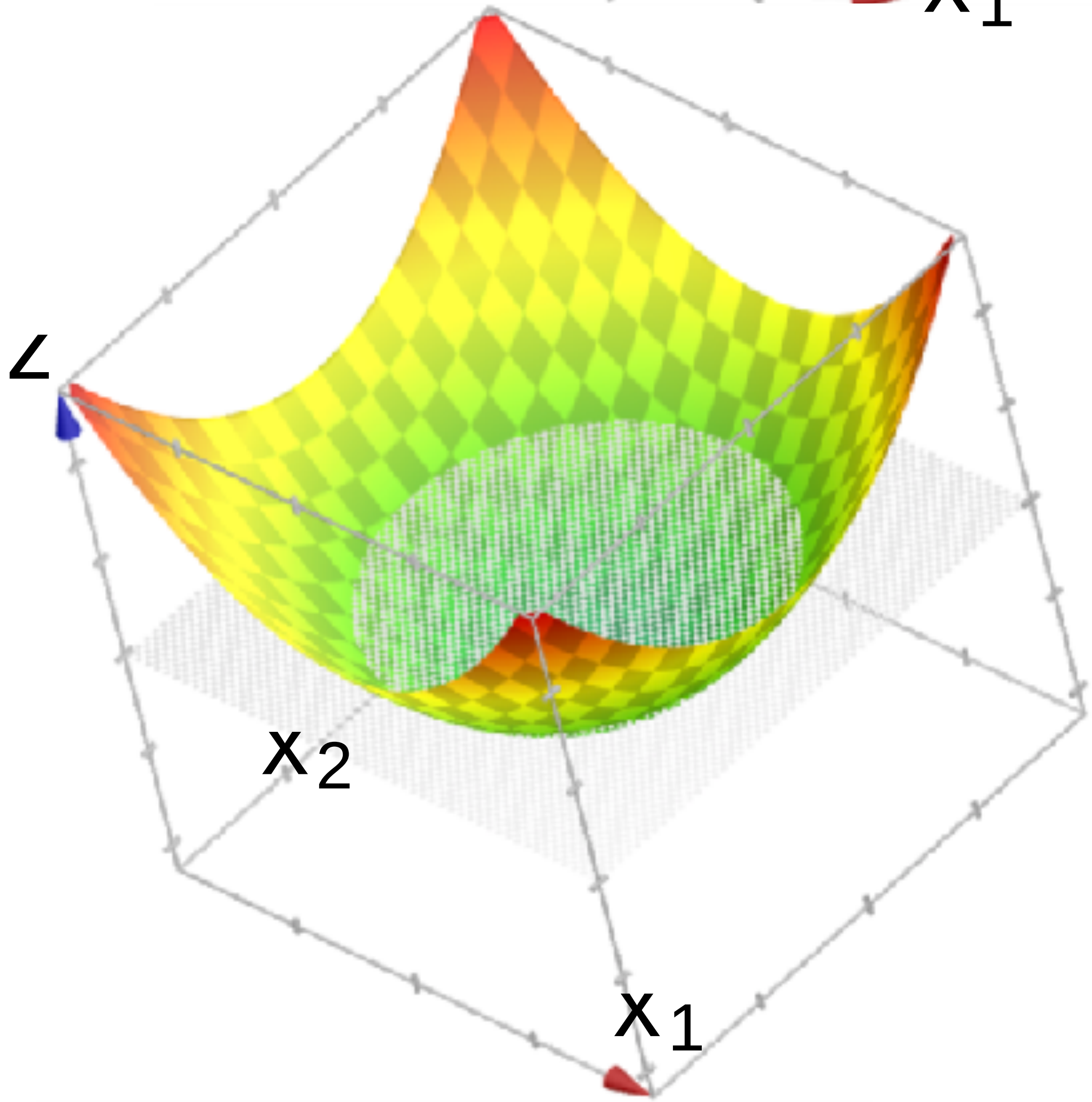

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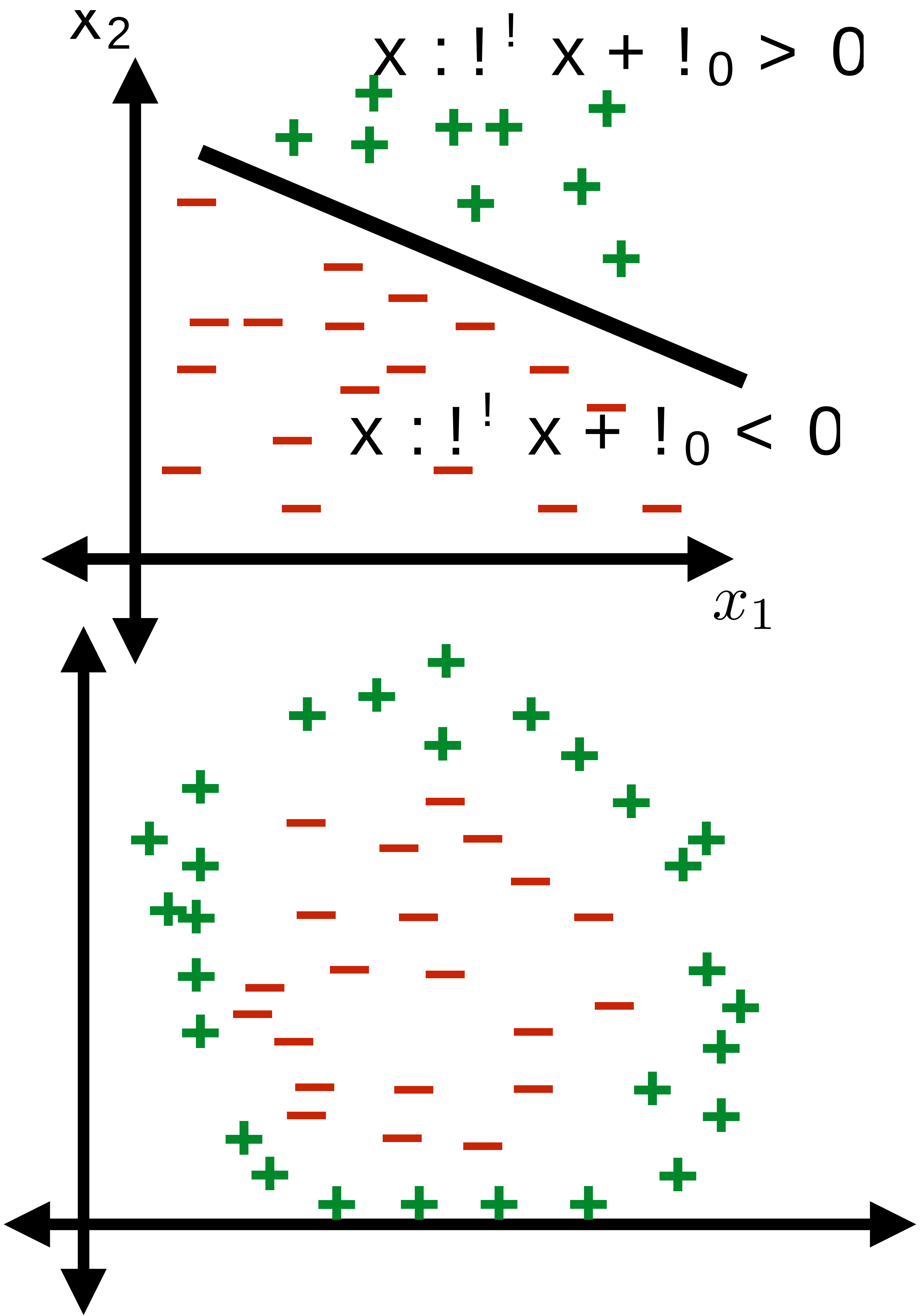

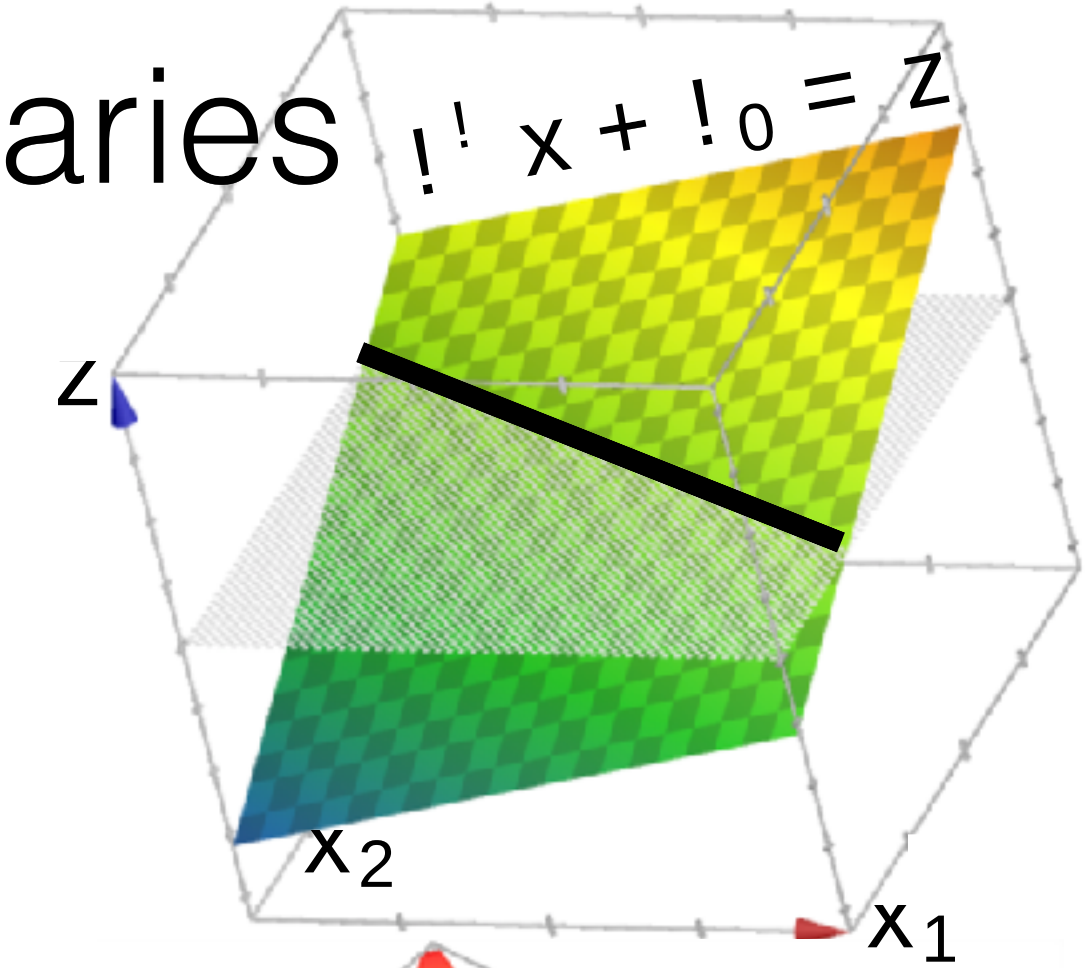

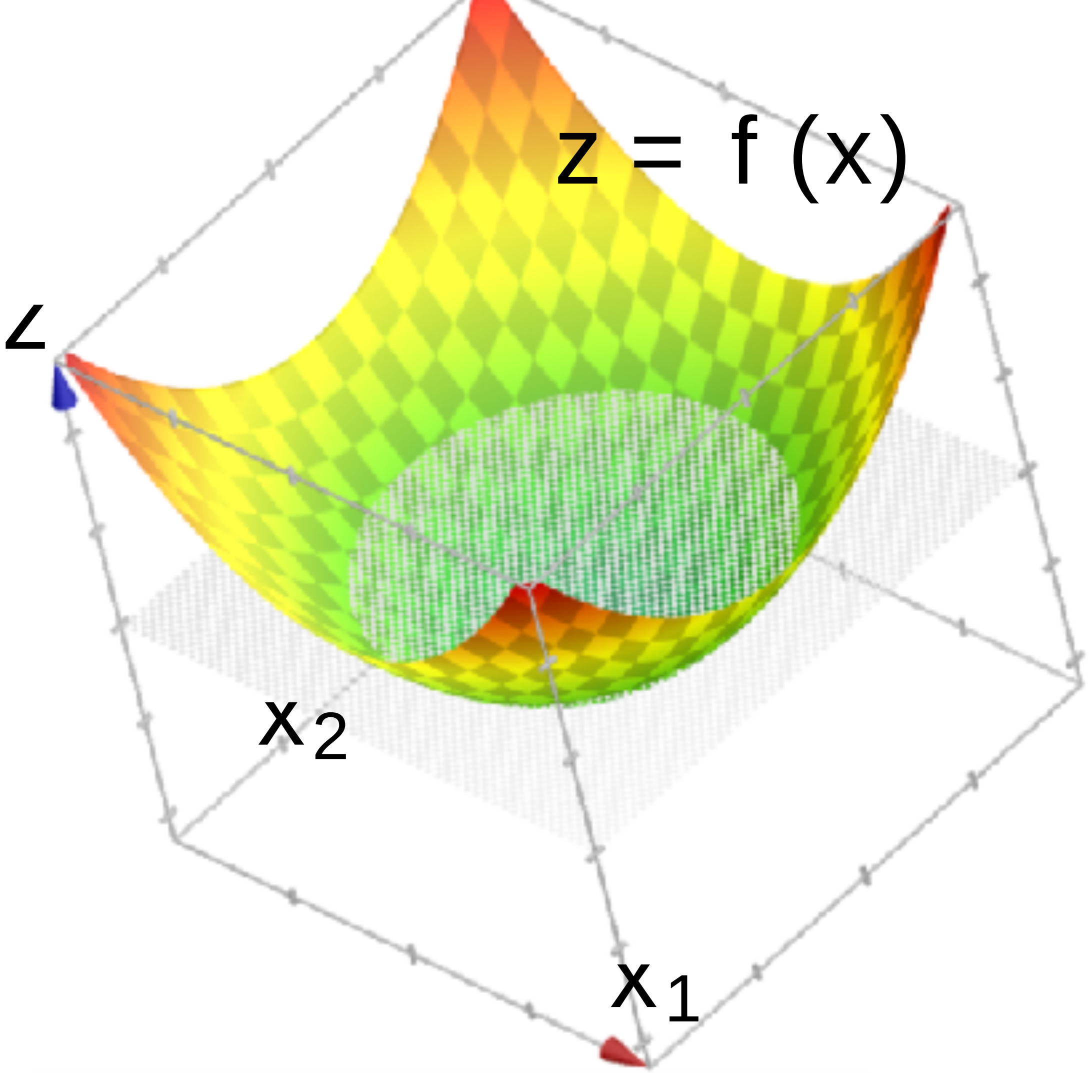

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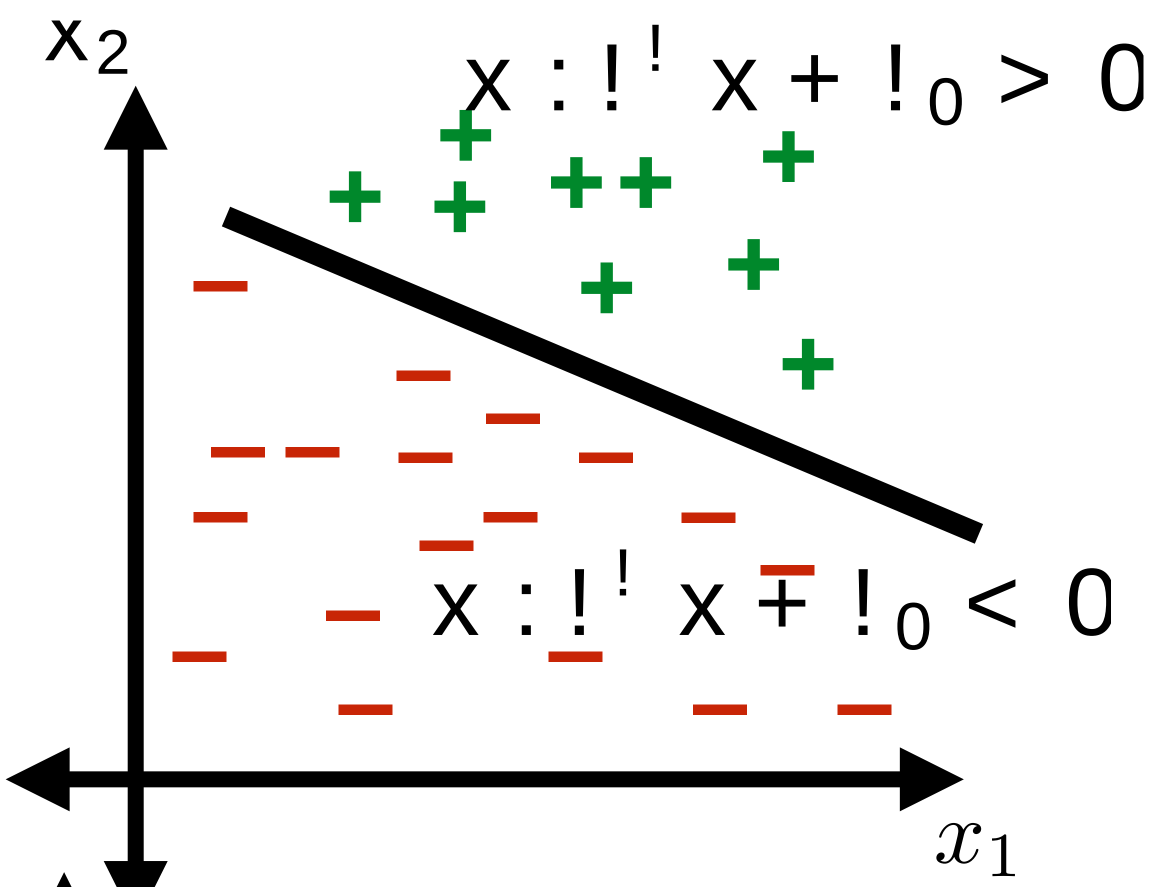

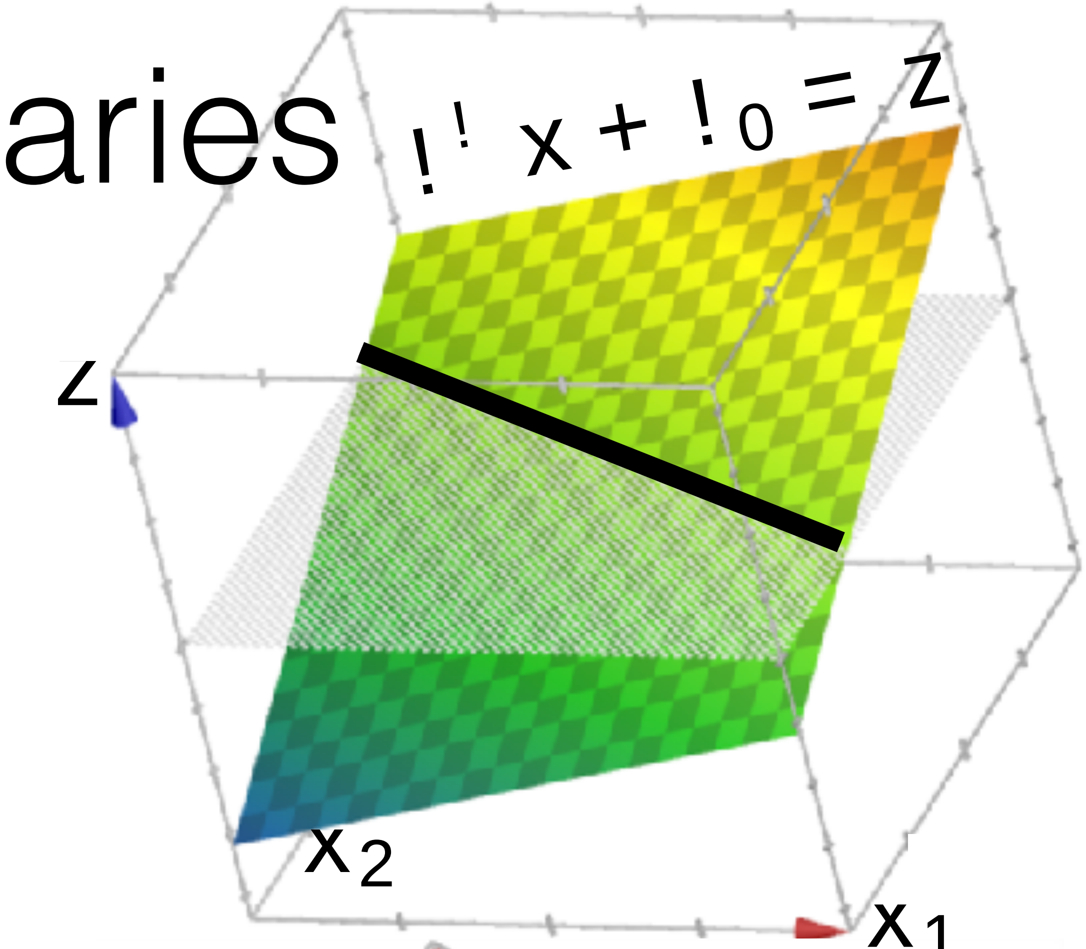

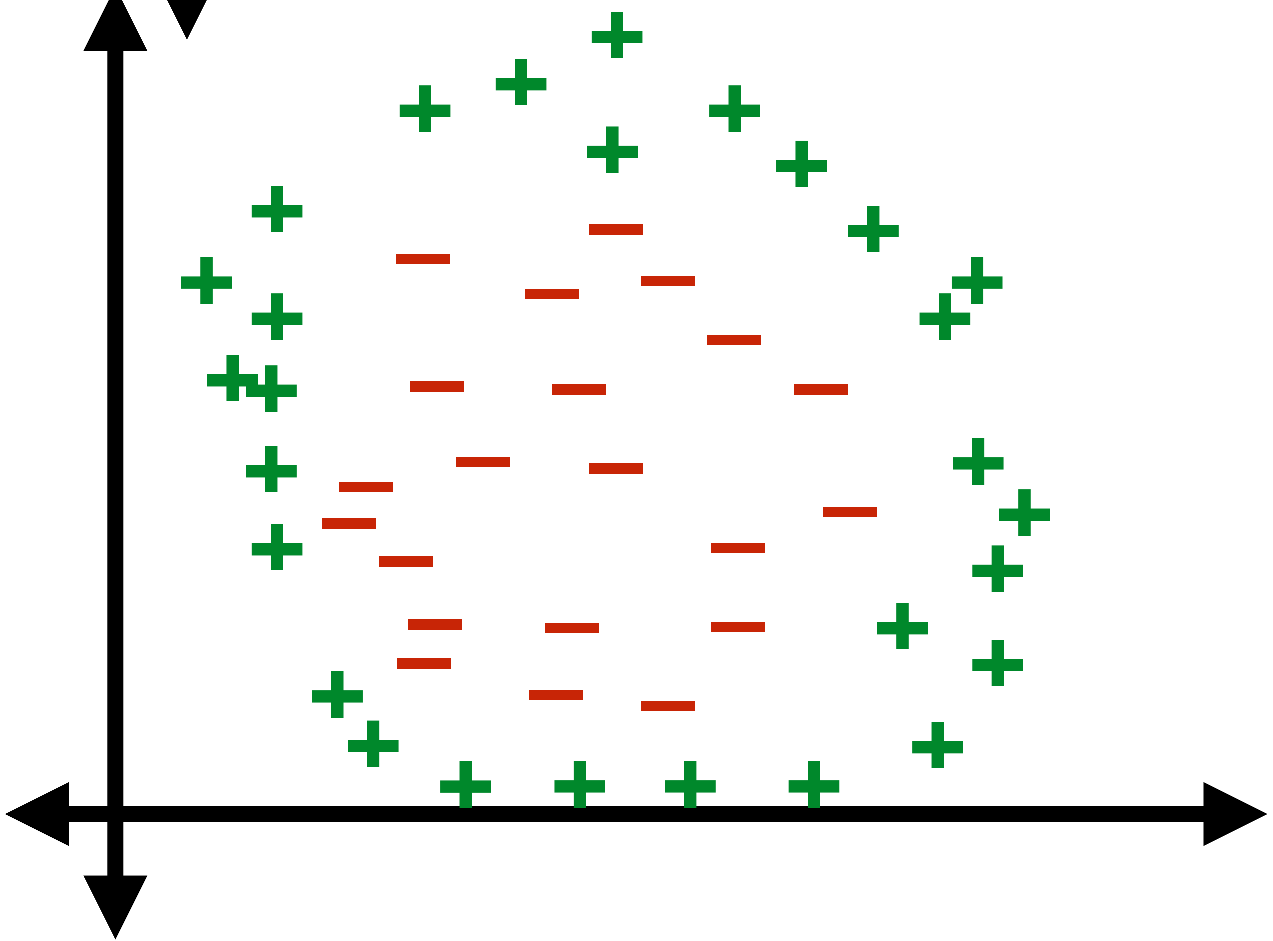

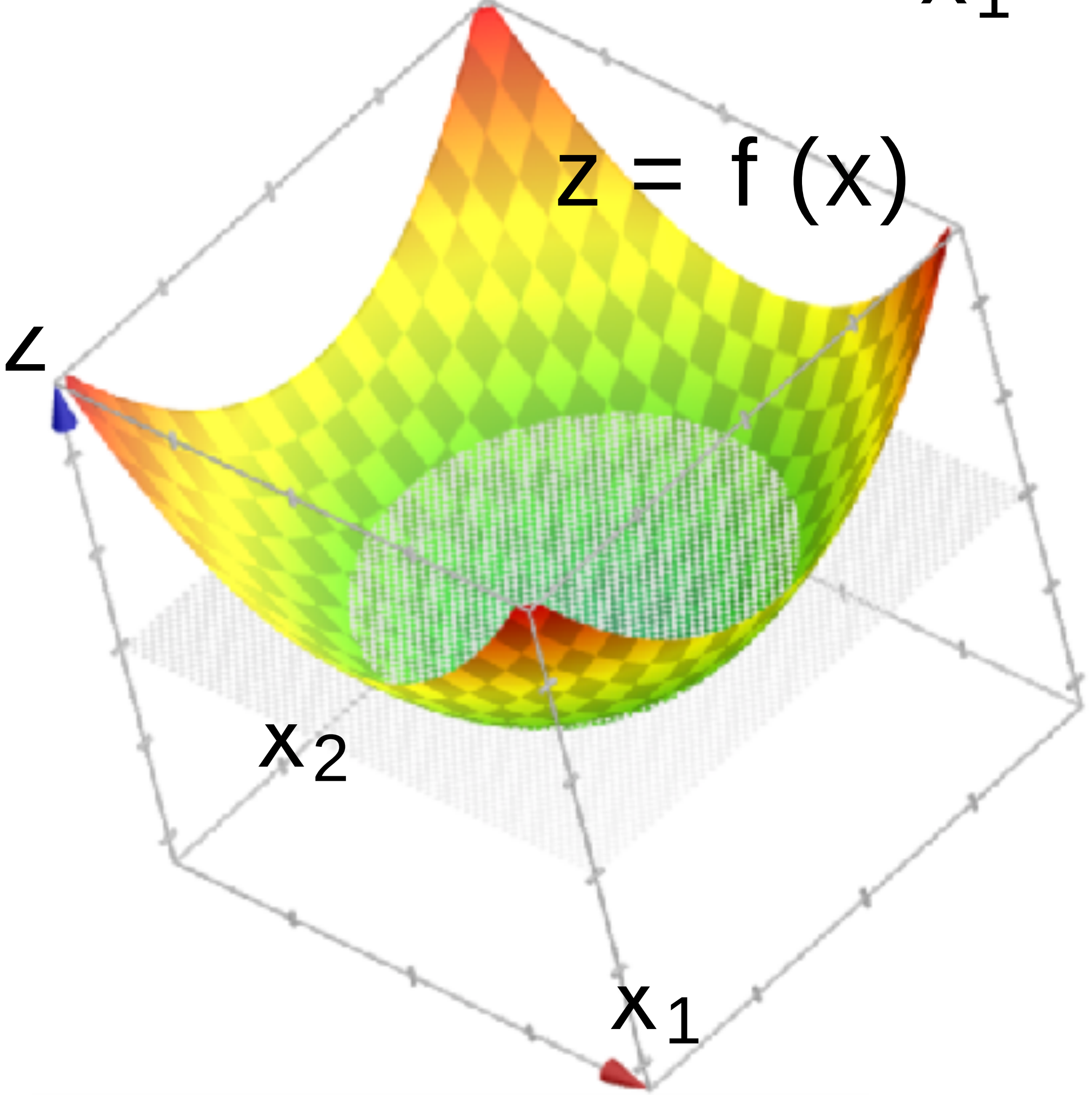

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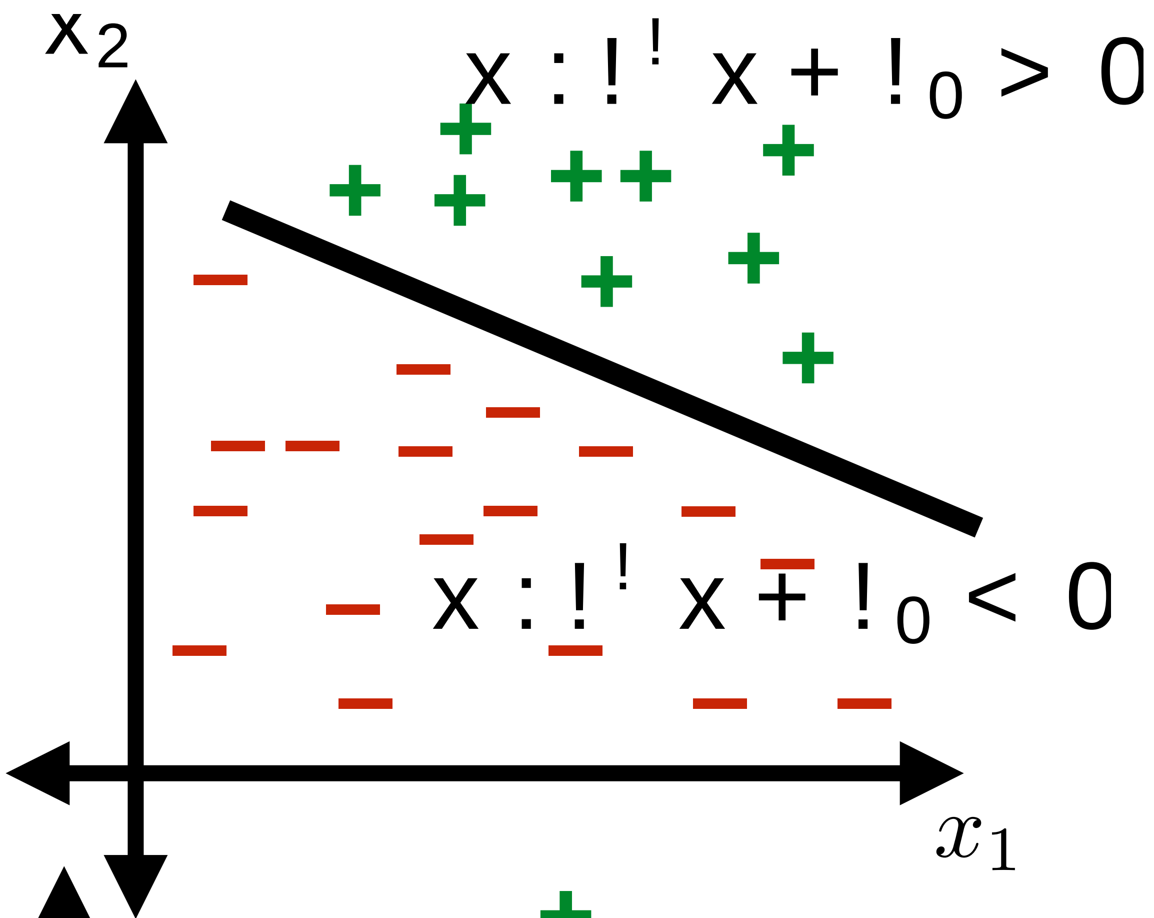

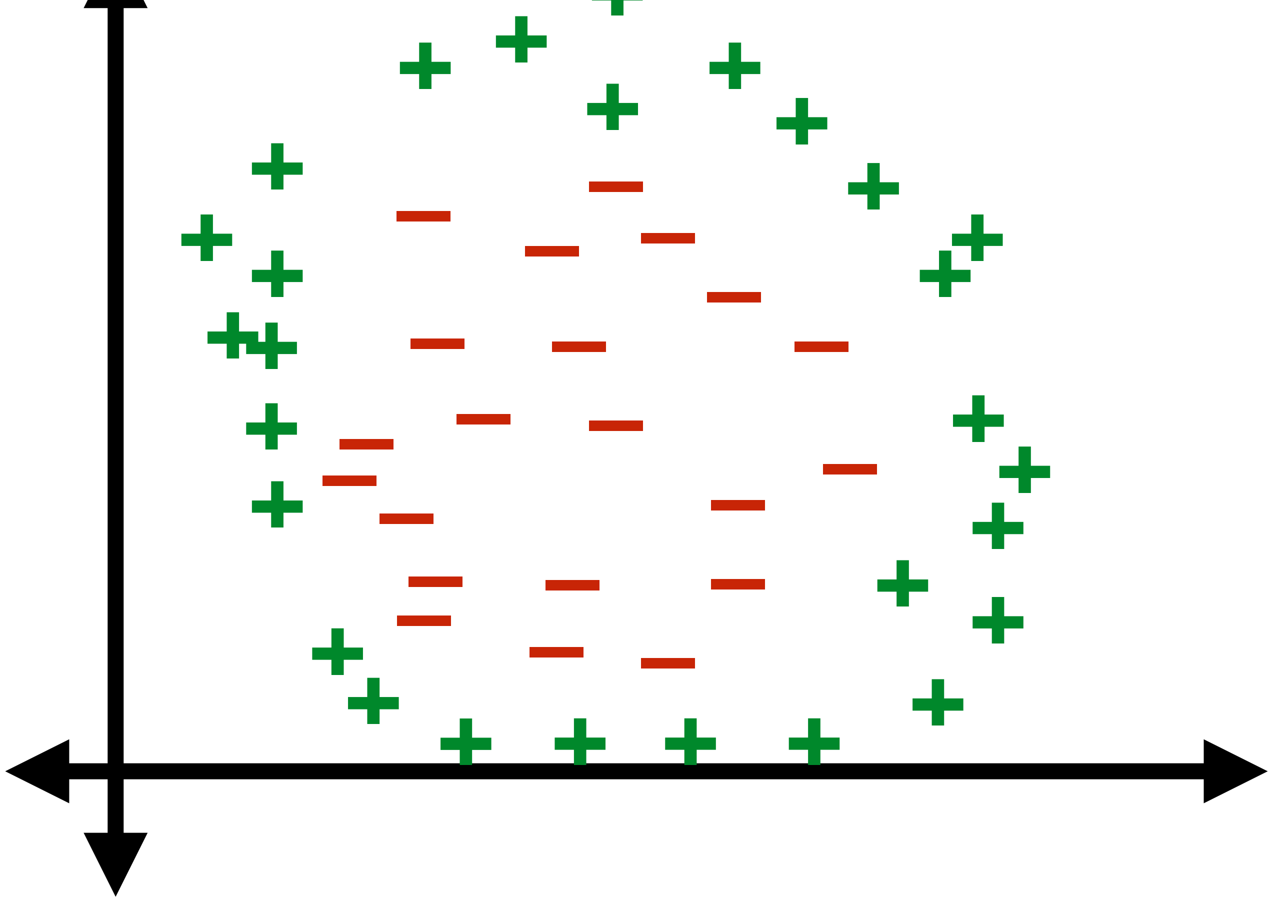

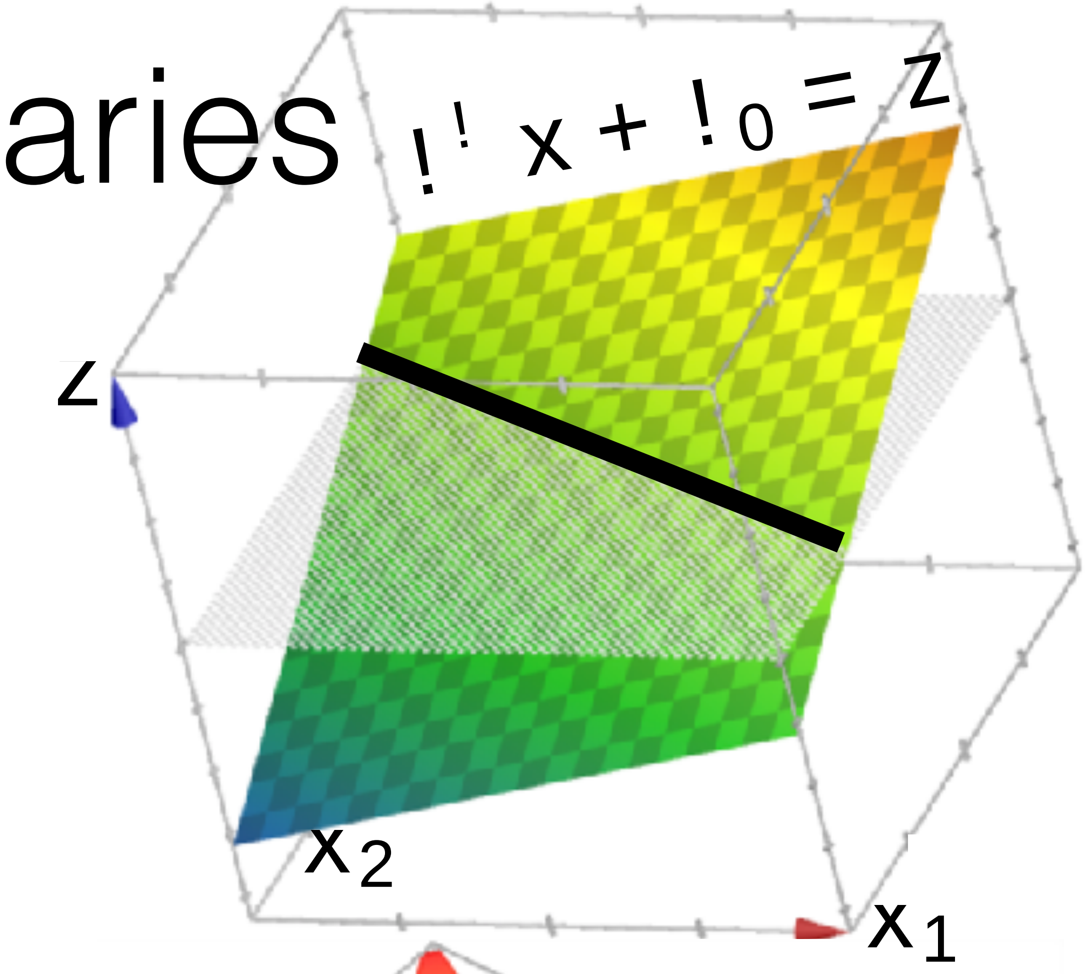

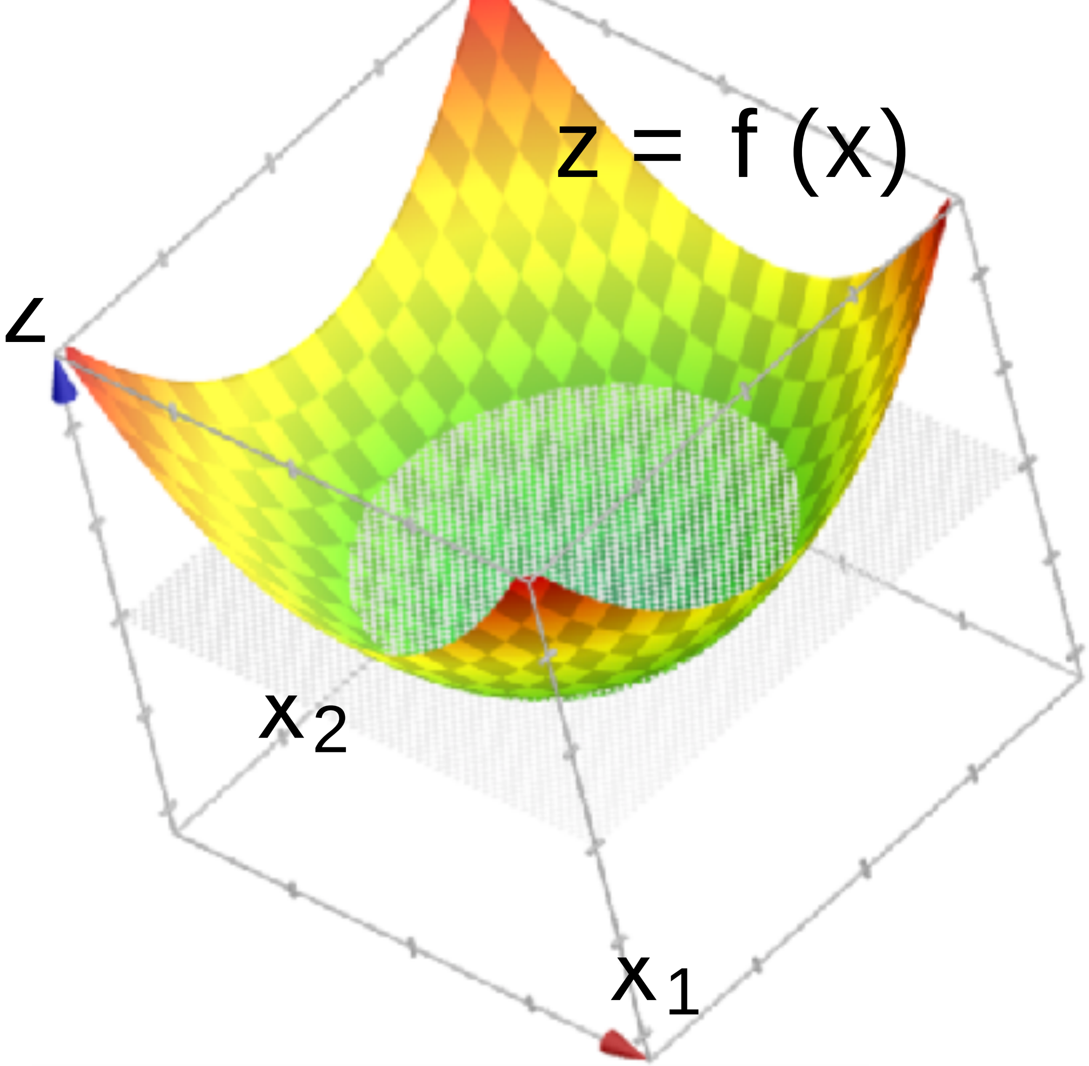

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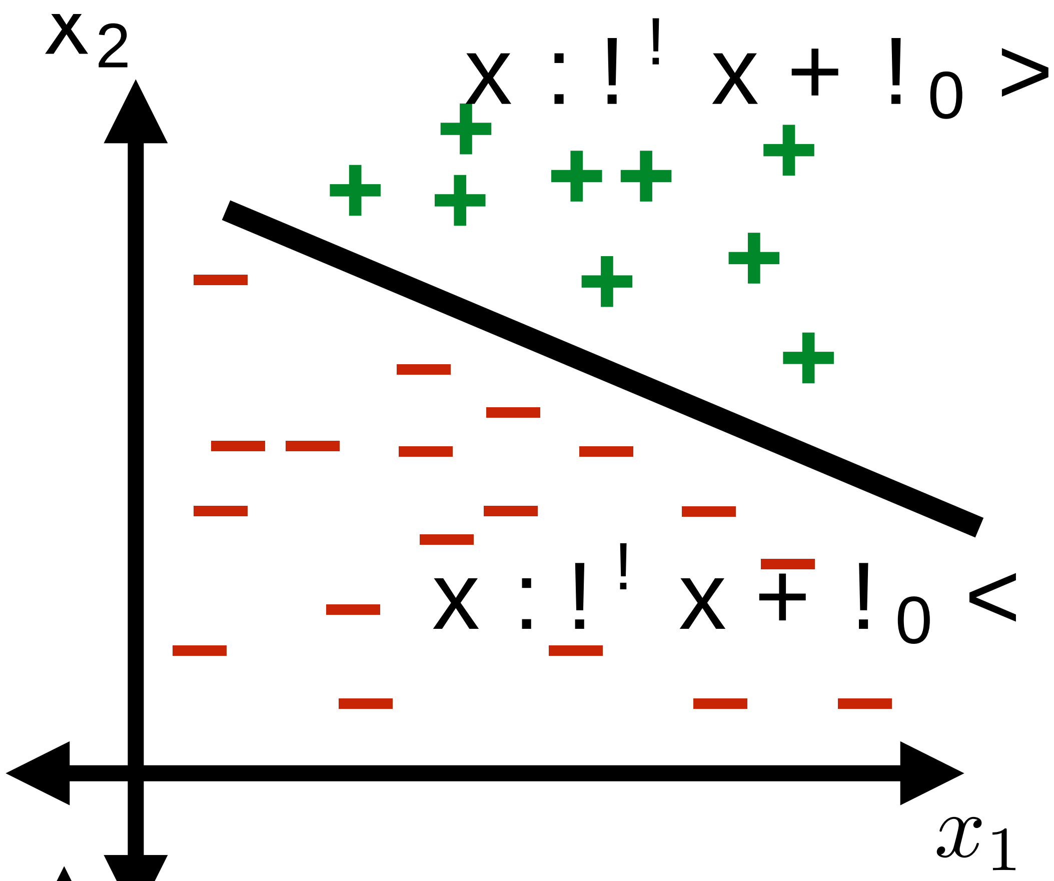

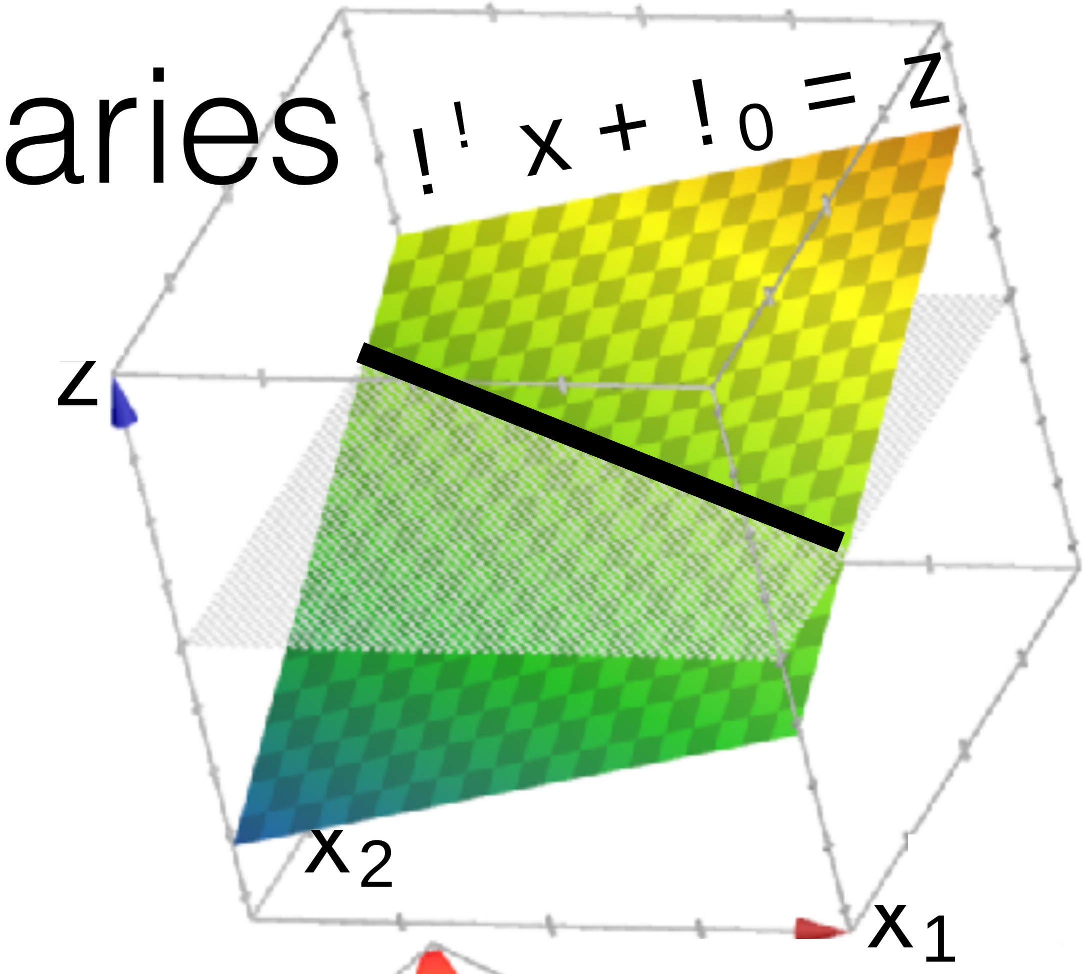

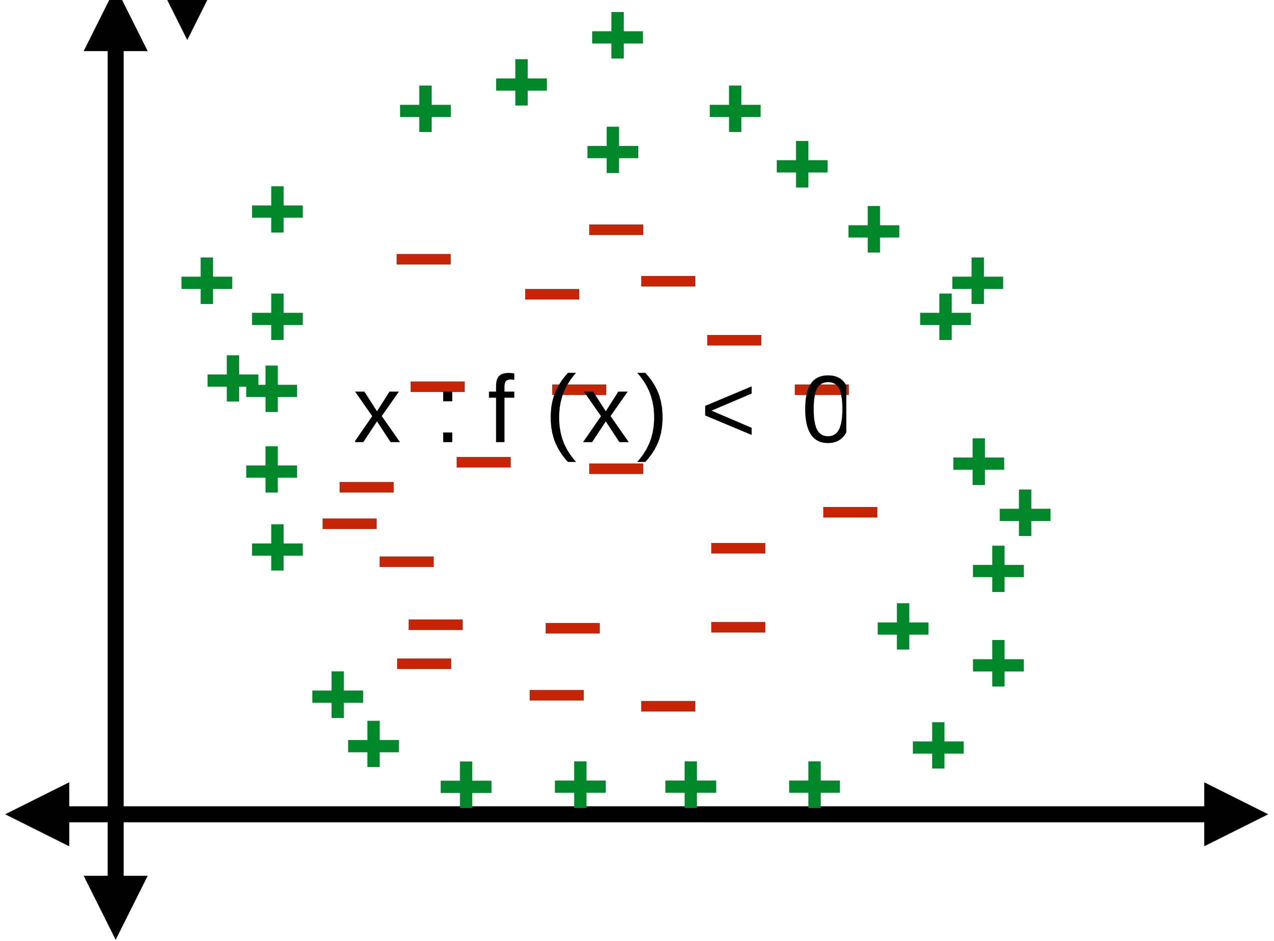

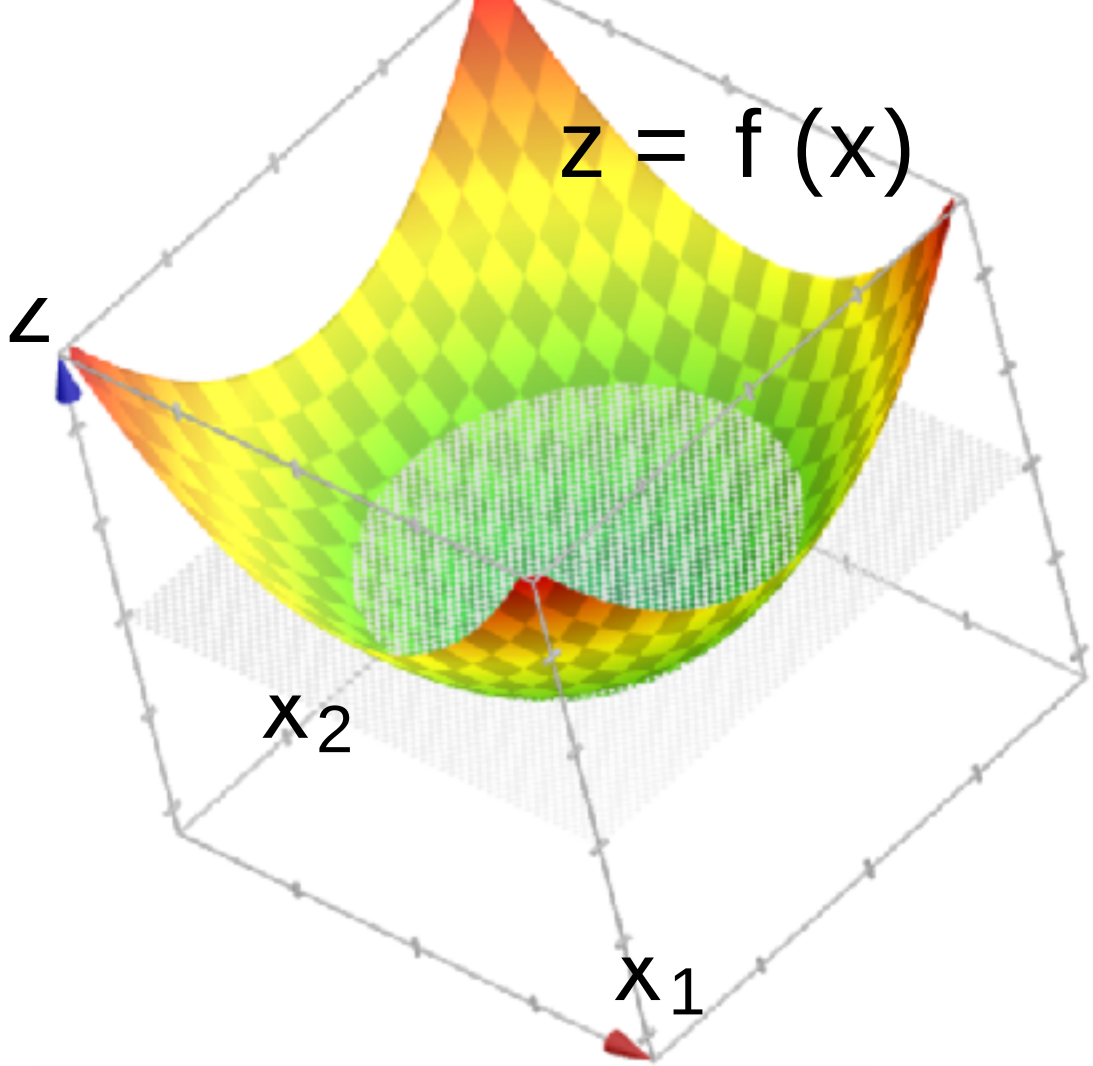

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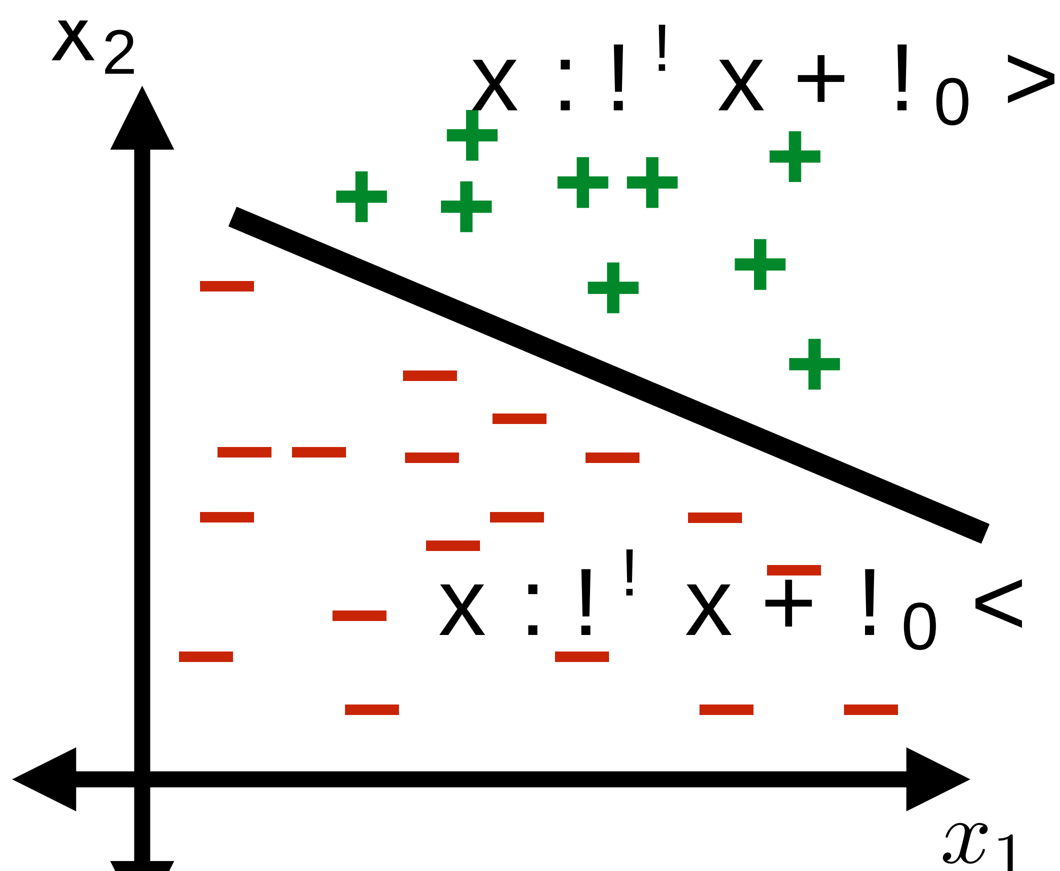

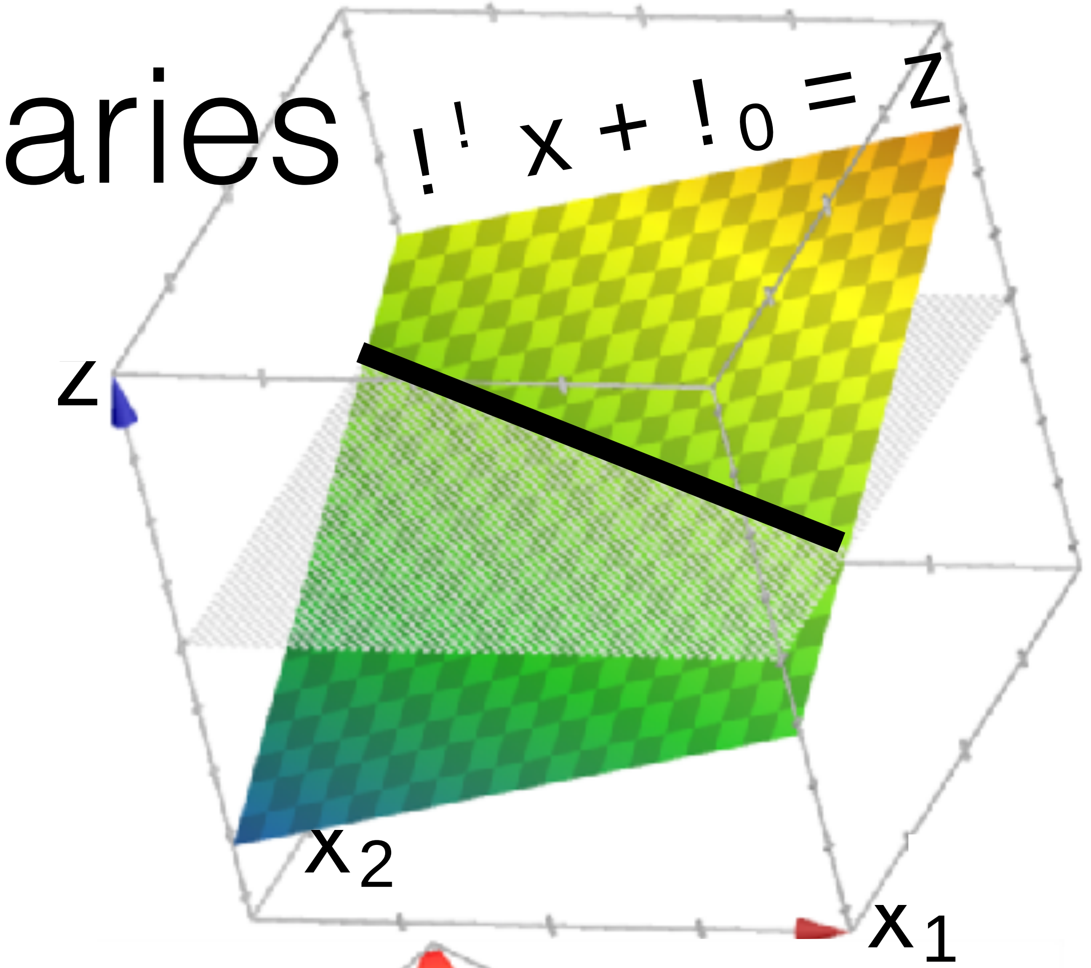

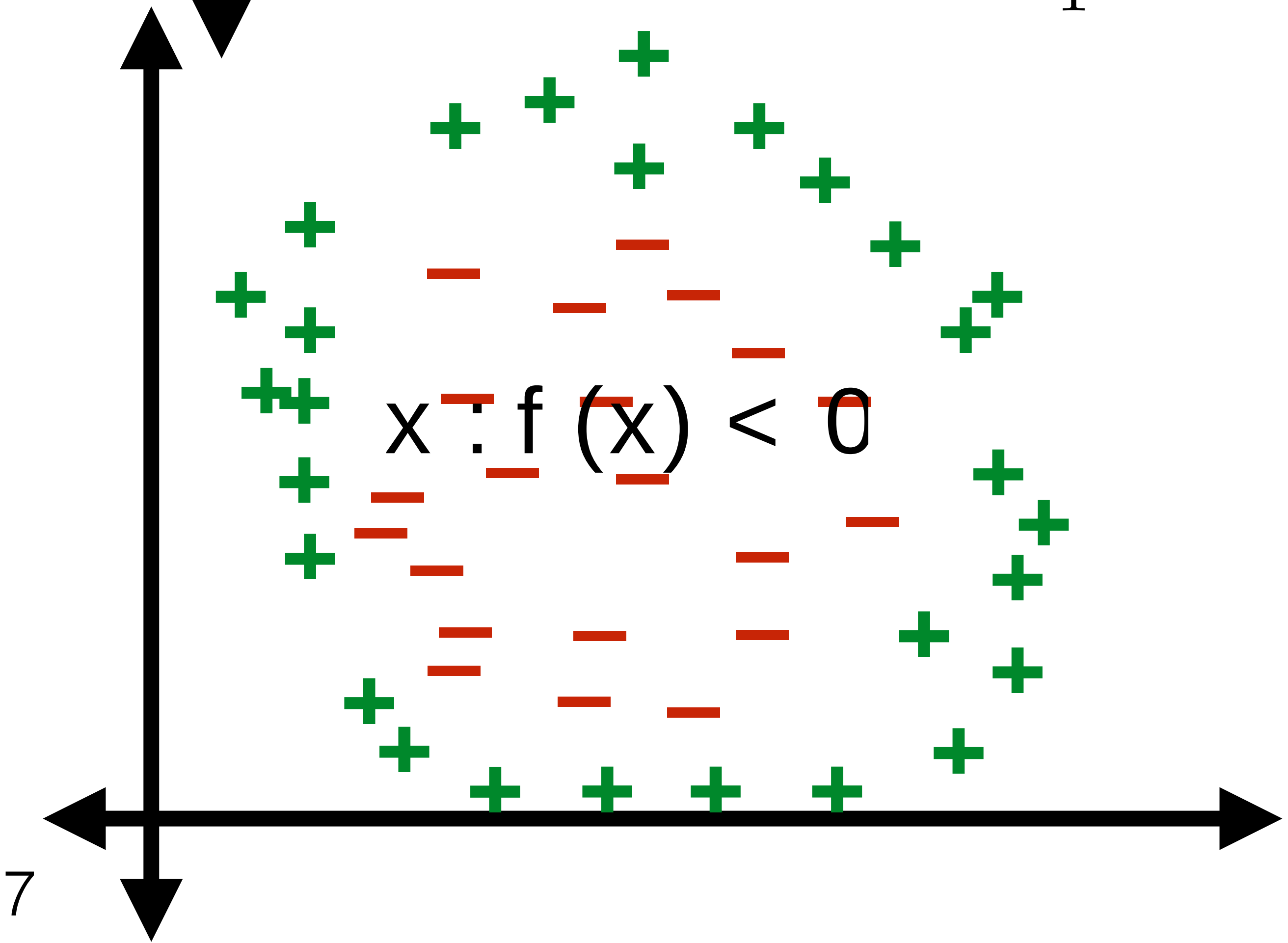

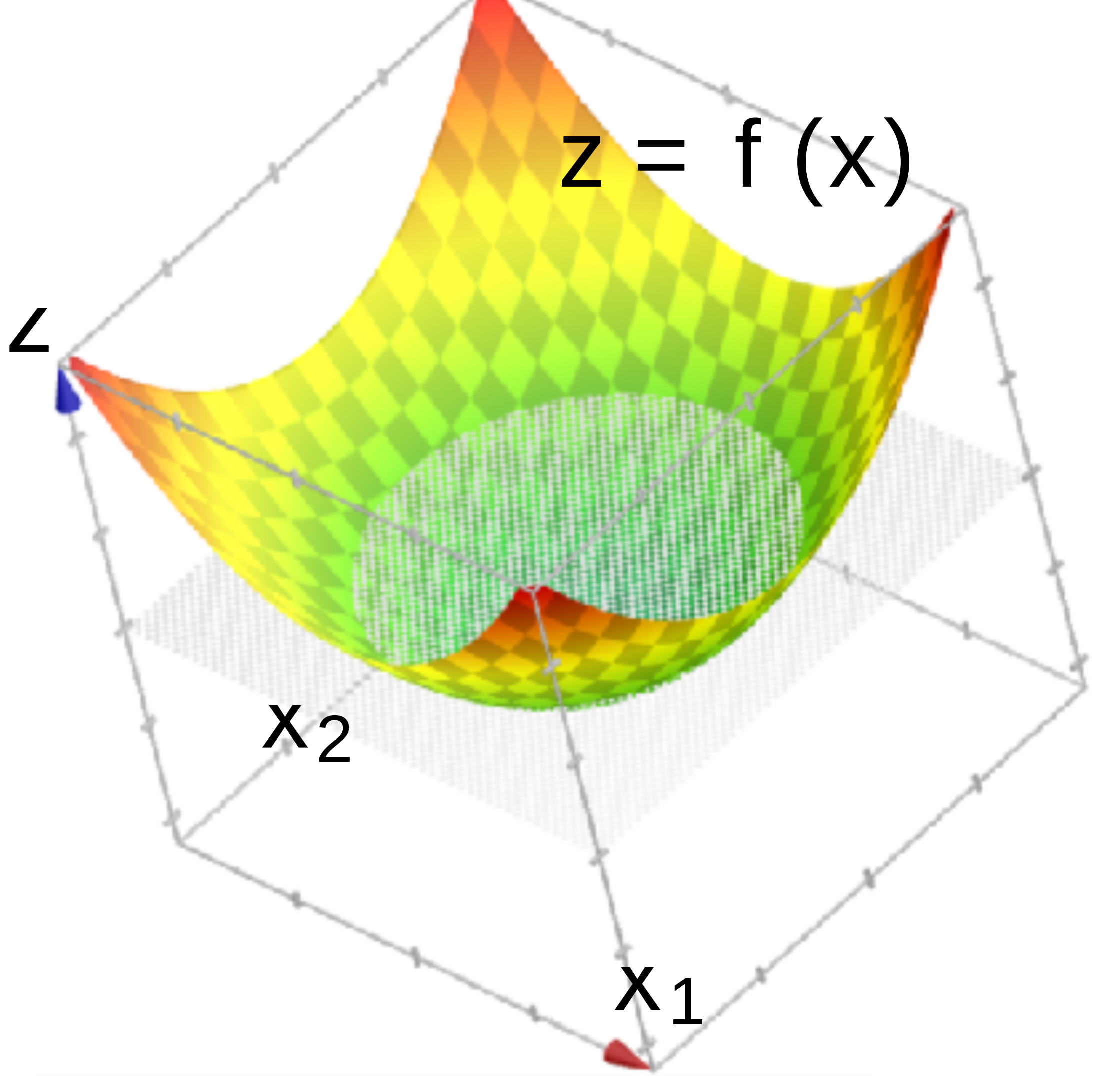

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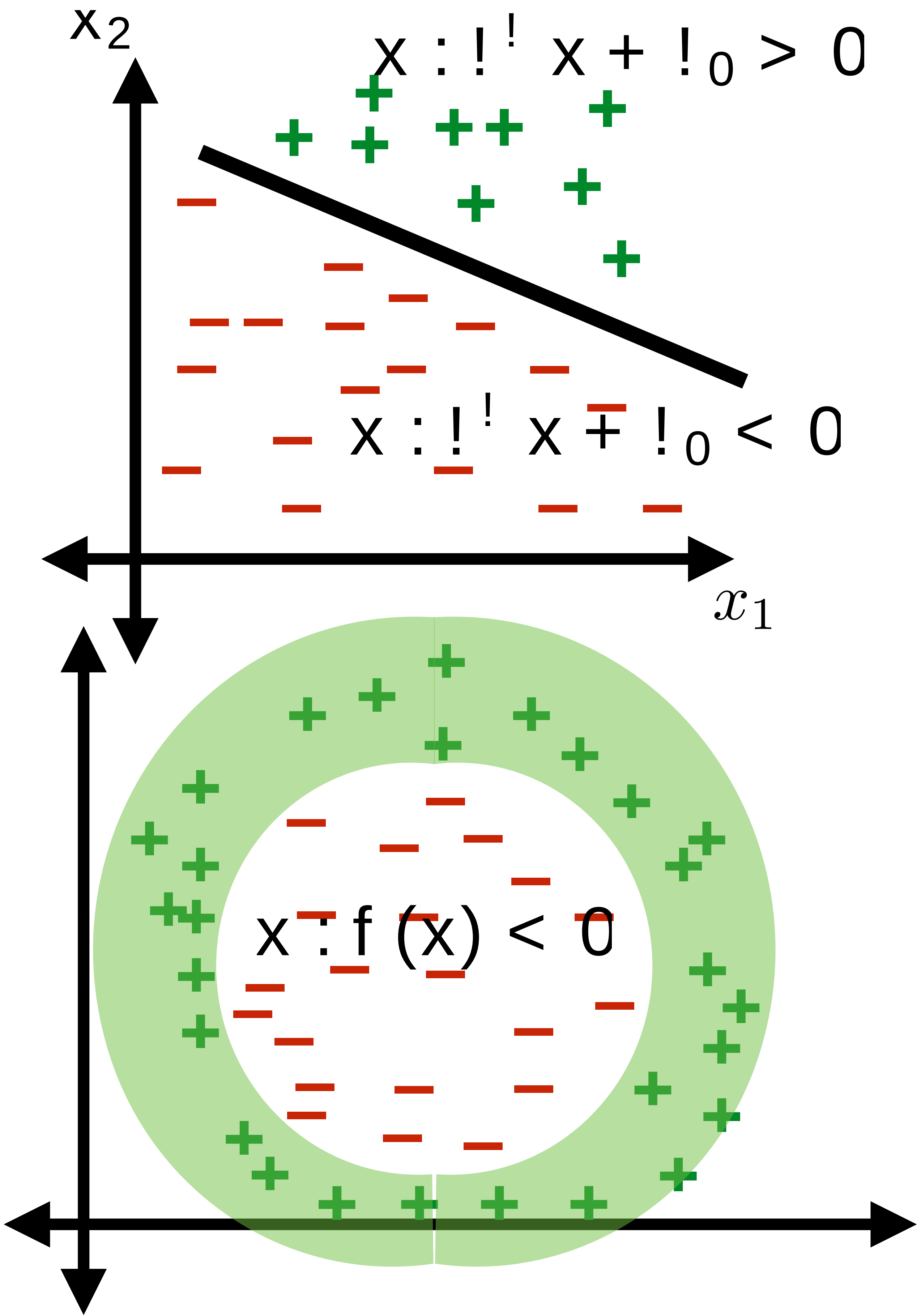

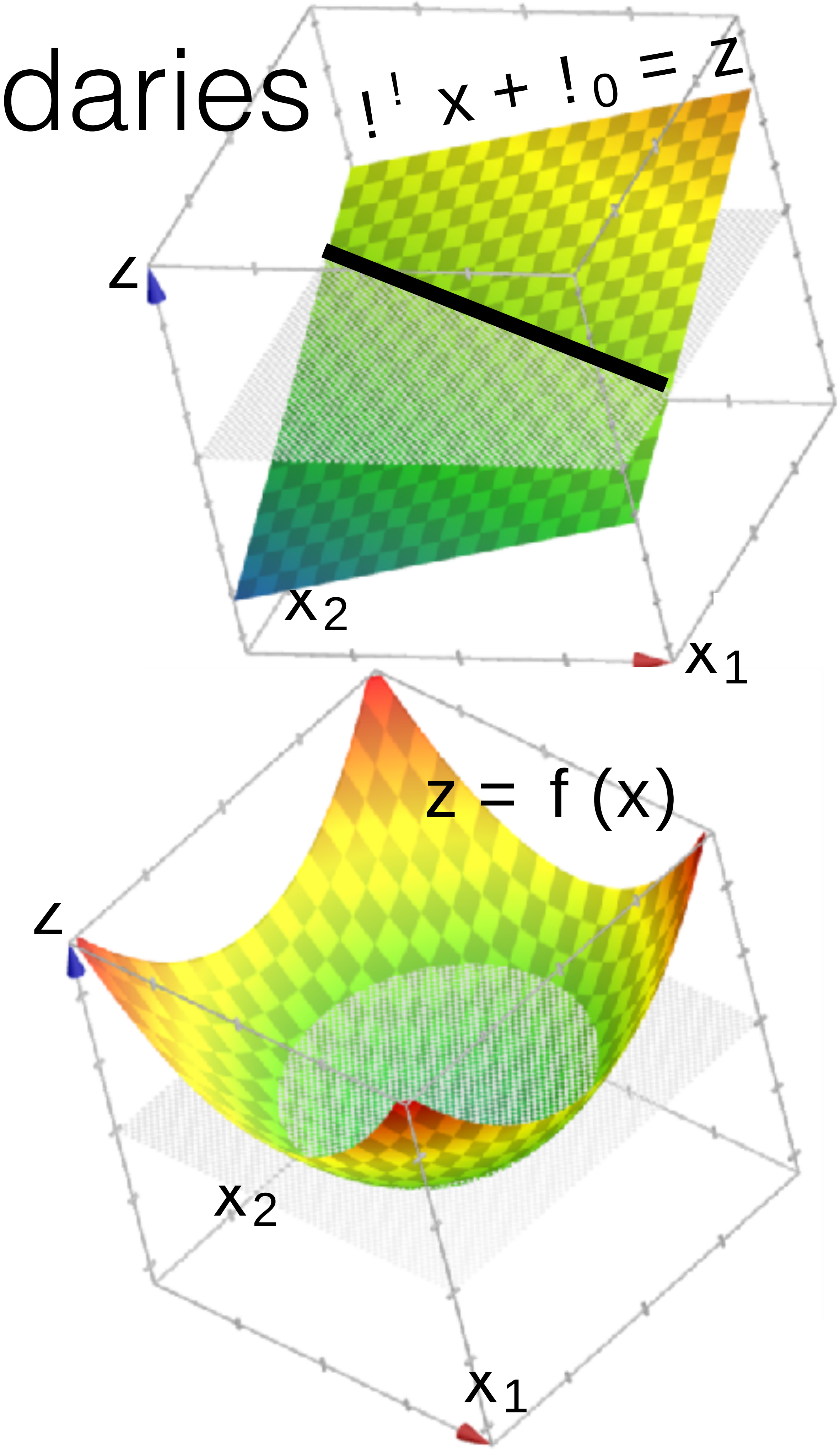

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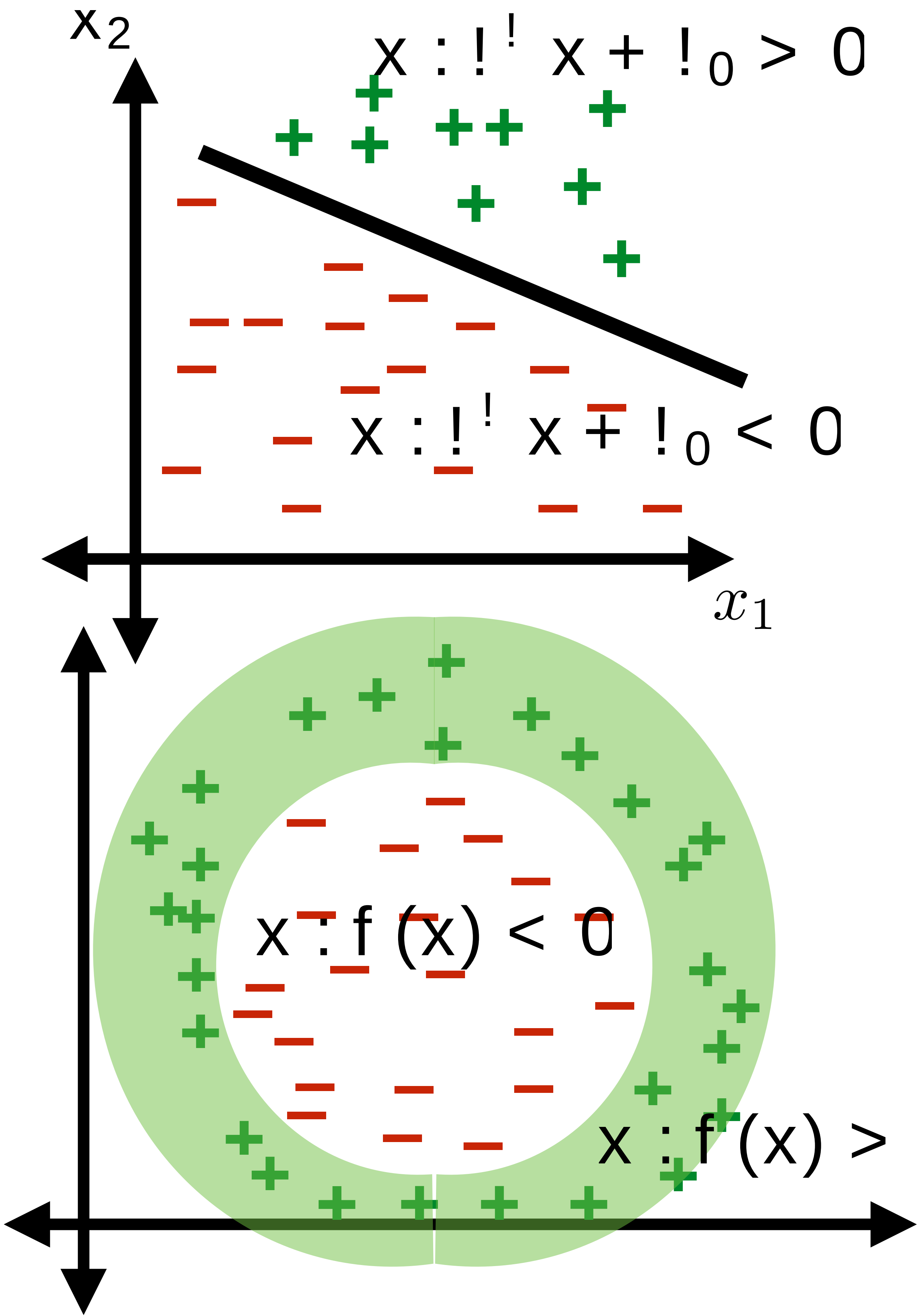

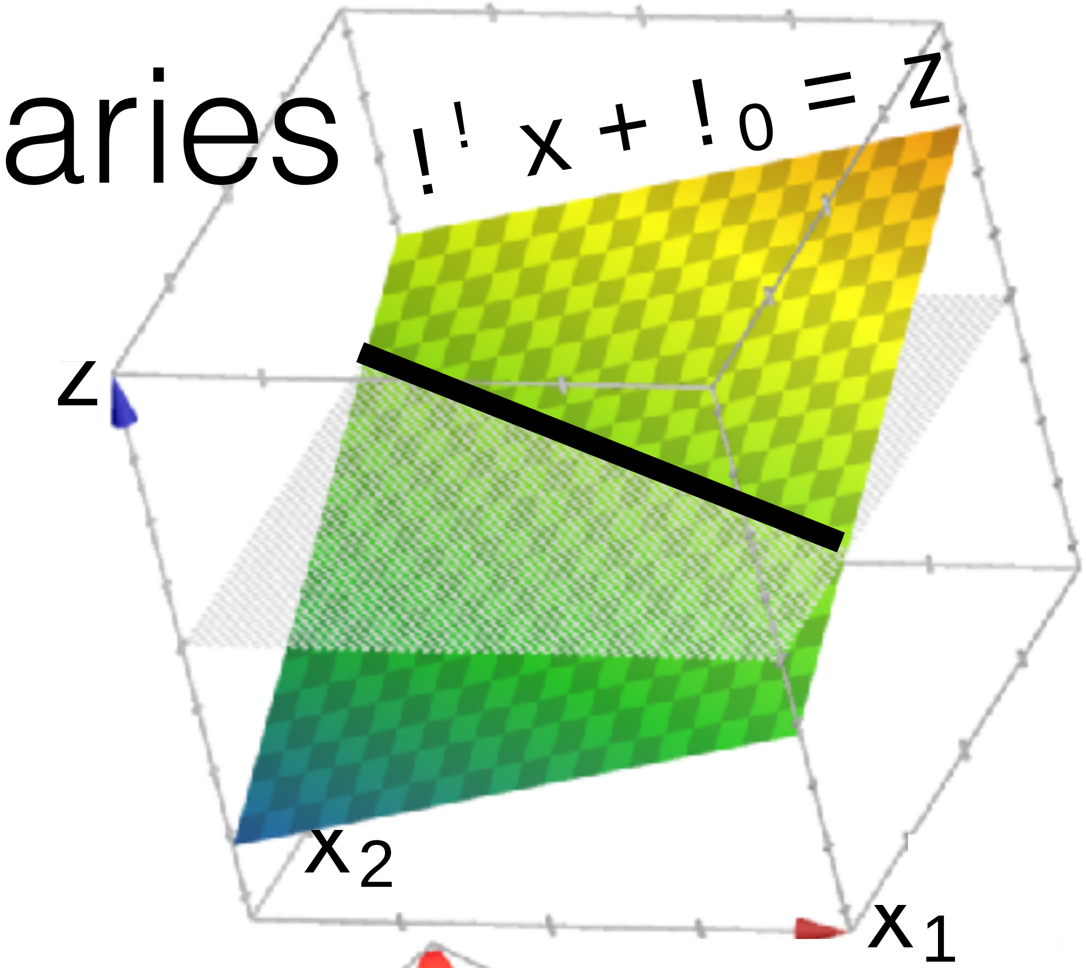

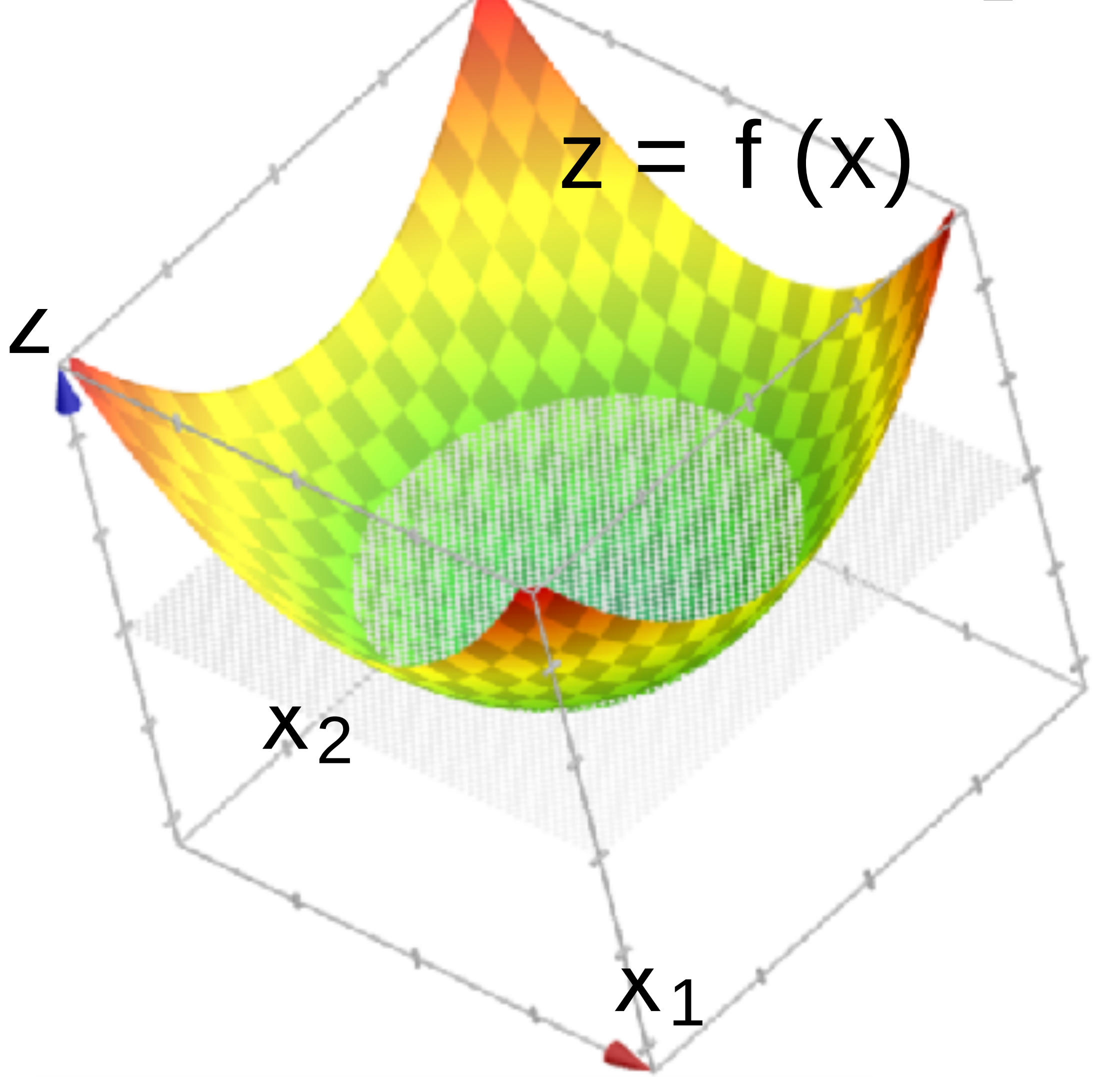

Nonlinear boundaries

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1		
2		
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3	$[1, x_1, x_1^2, x_1^3]$	$[1, x_1, \ldots, x_d,$ $x_1^2, x_1x_2, \ldots, x_{d!\ 1}x_d, x_d^2,$ $x_1^3, x_1^2x_2, x_1x_2x_3, \ldots, x_d^3]$

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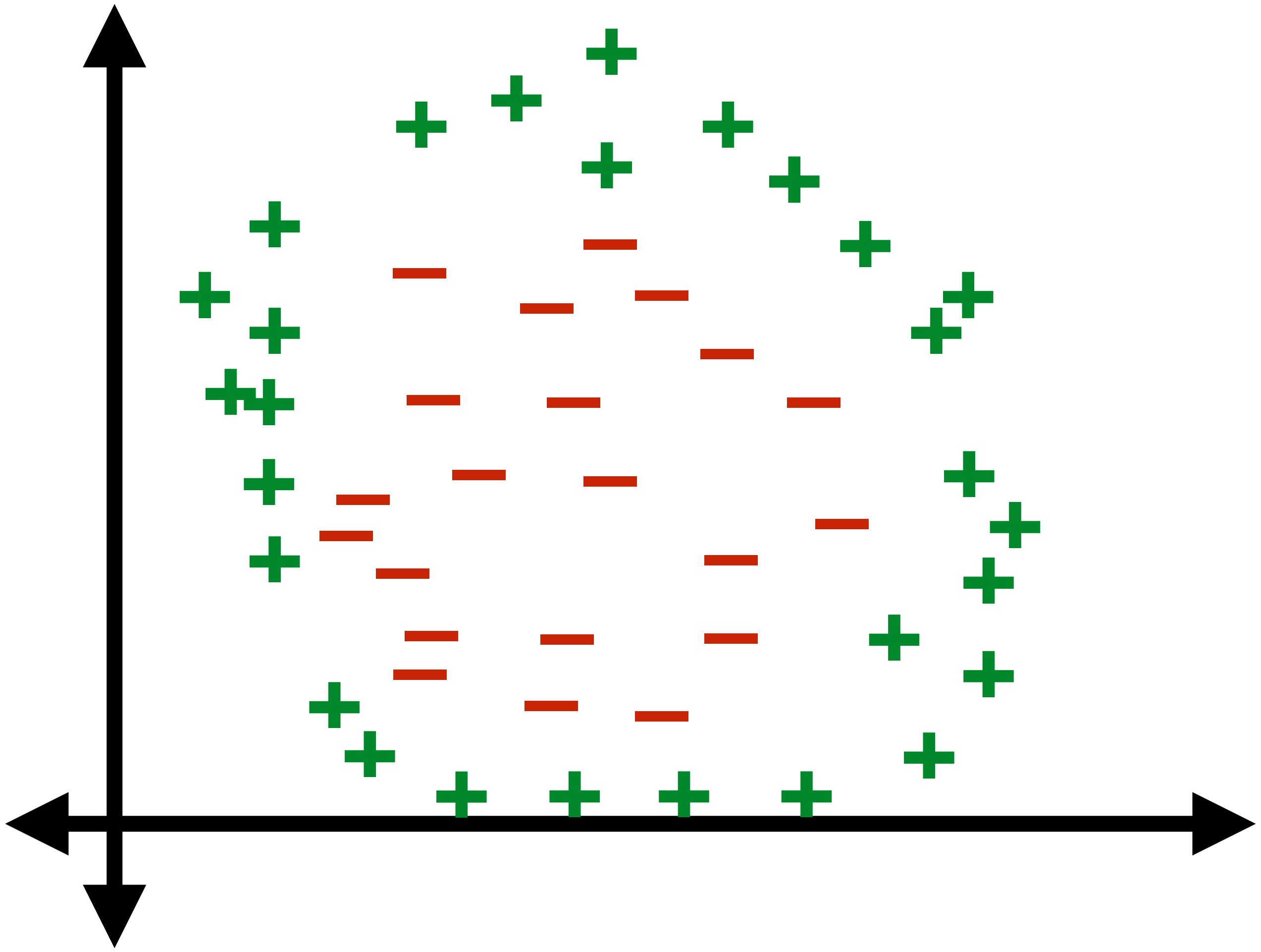

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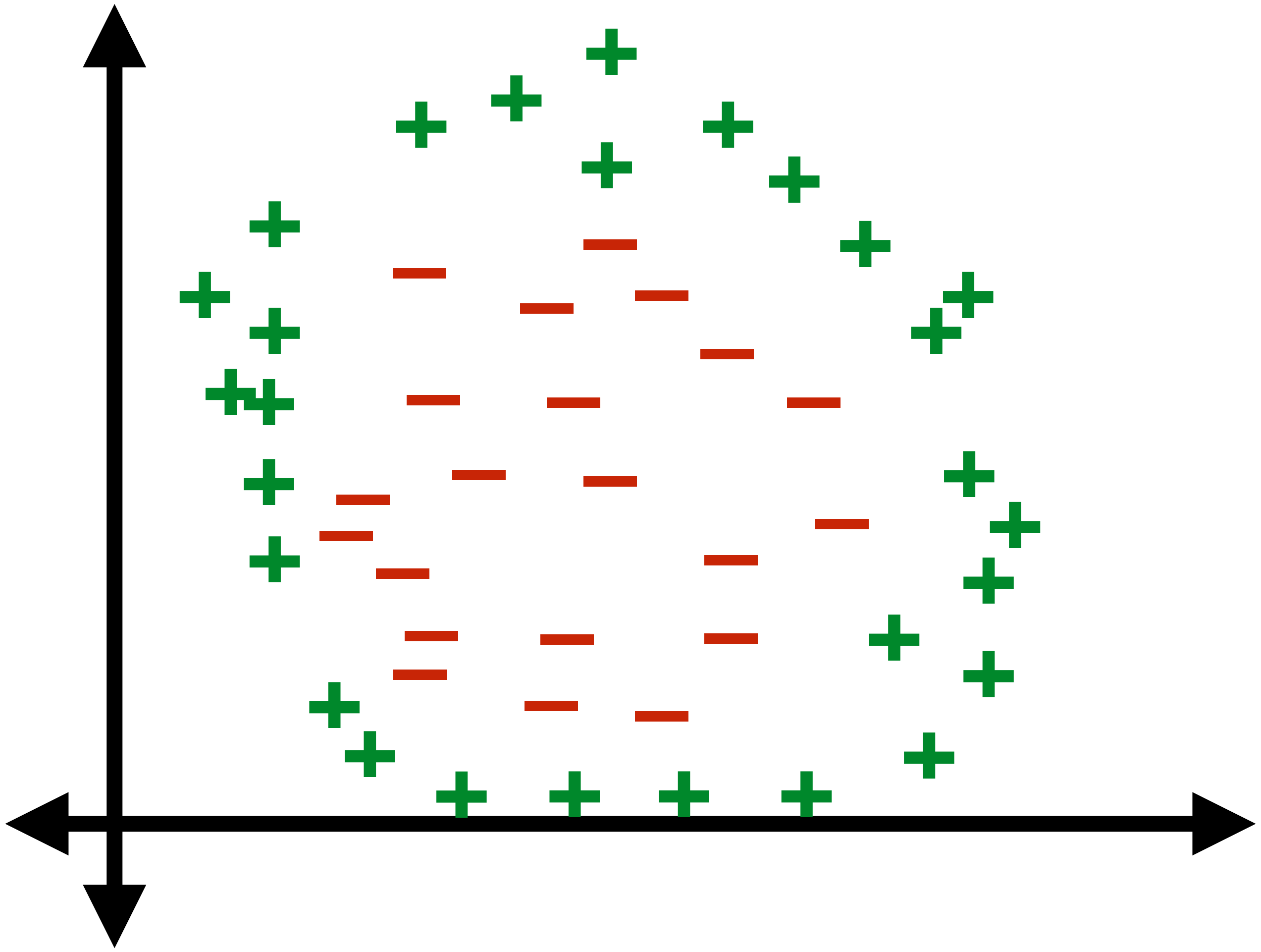

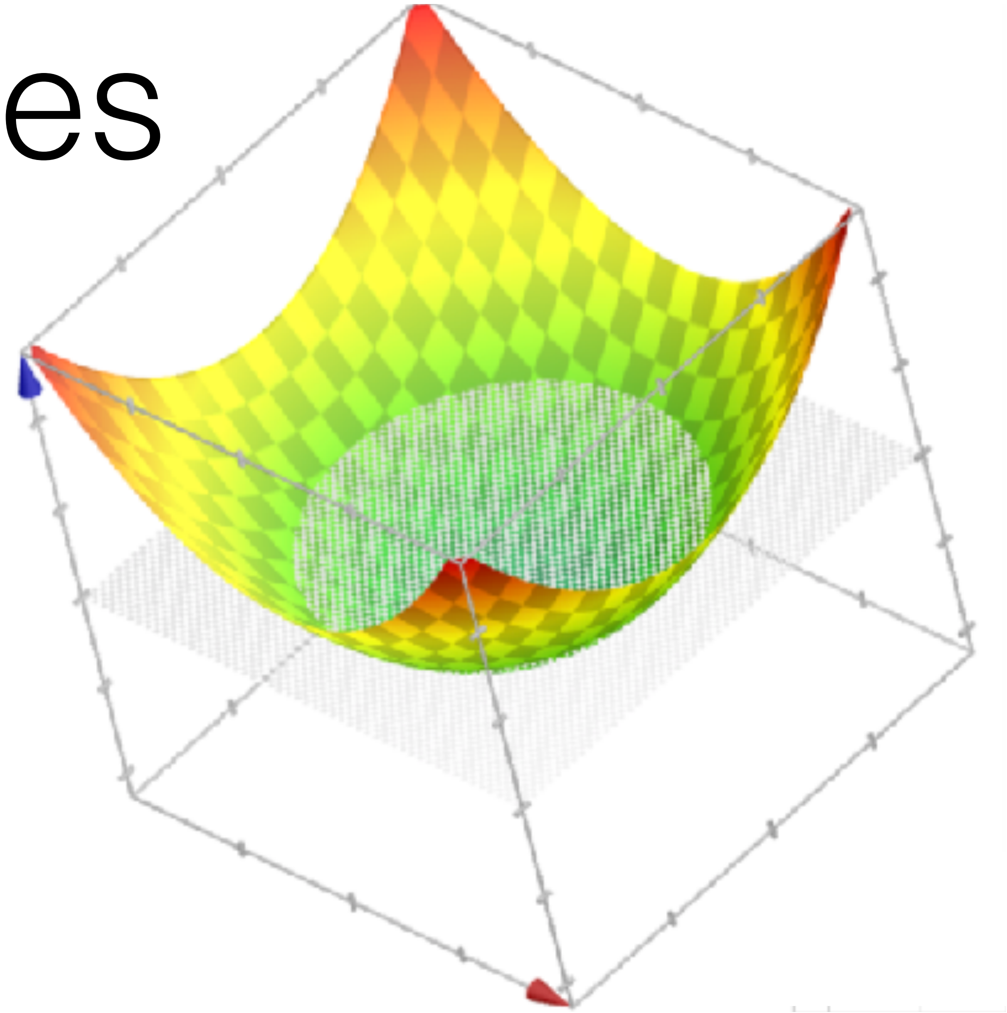

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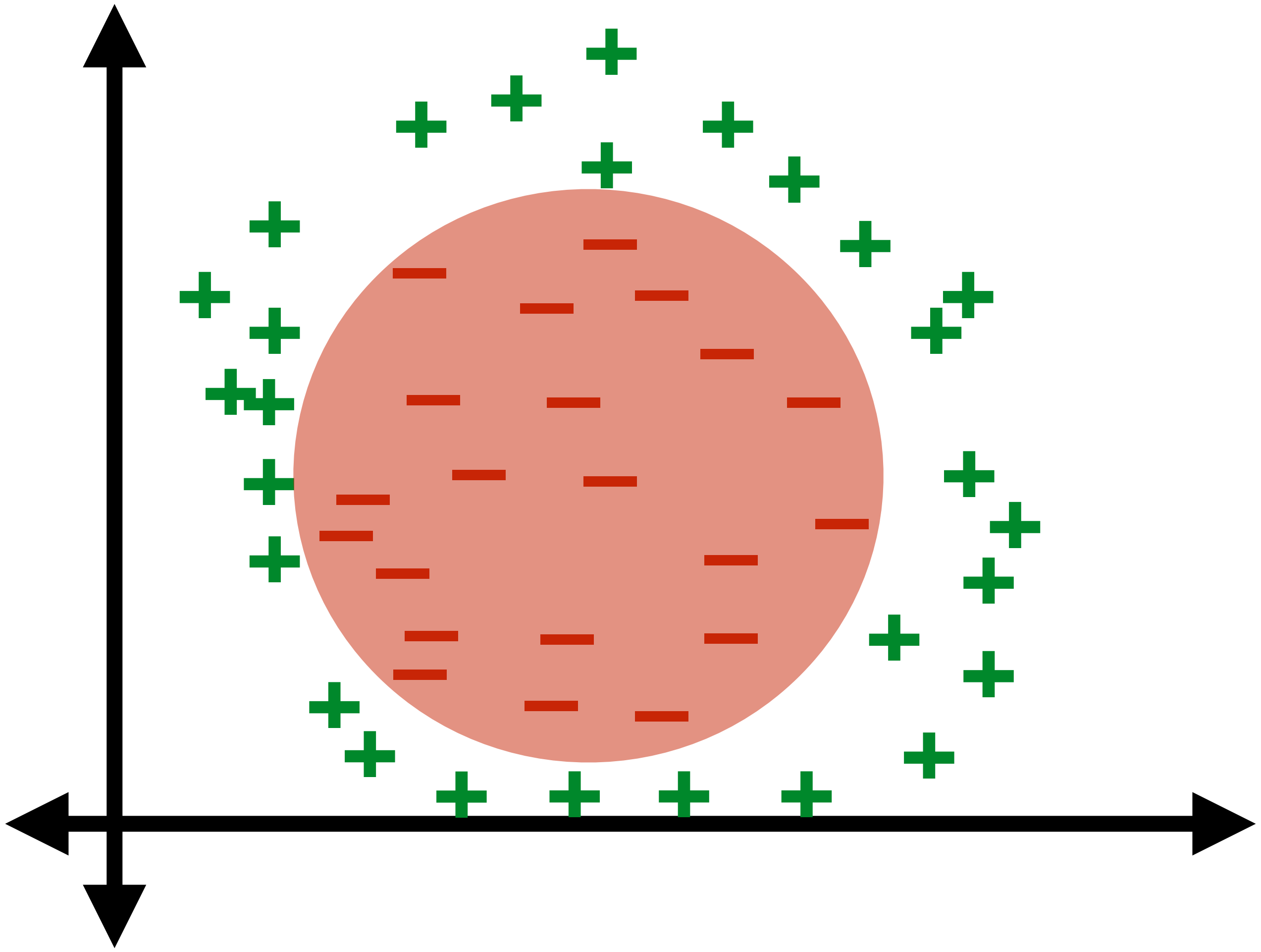
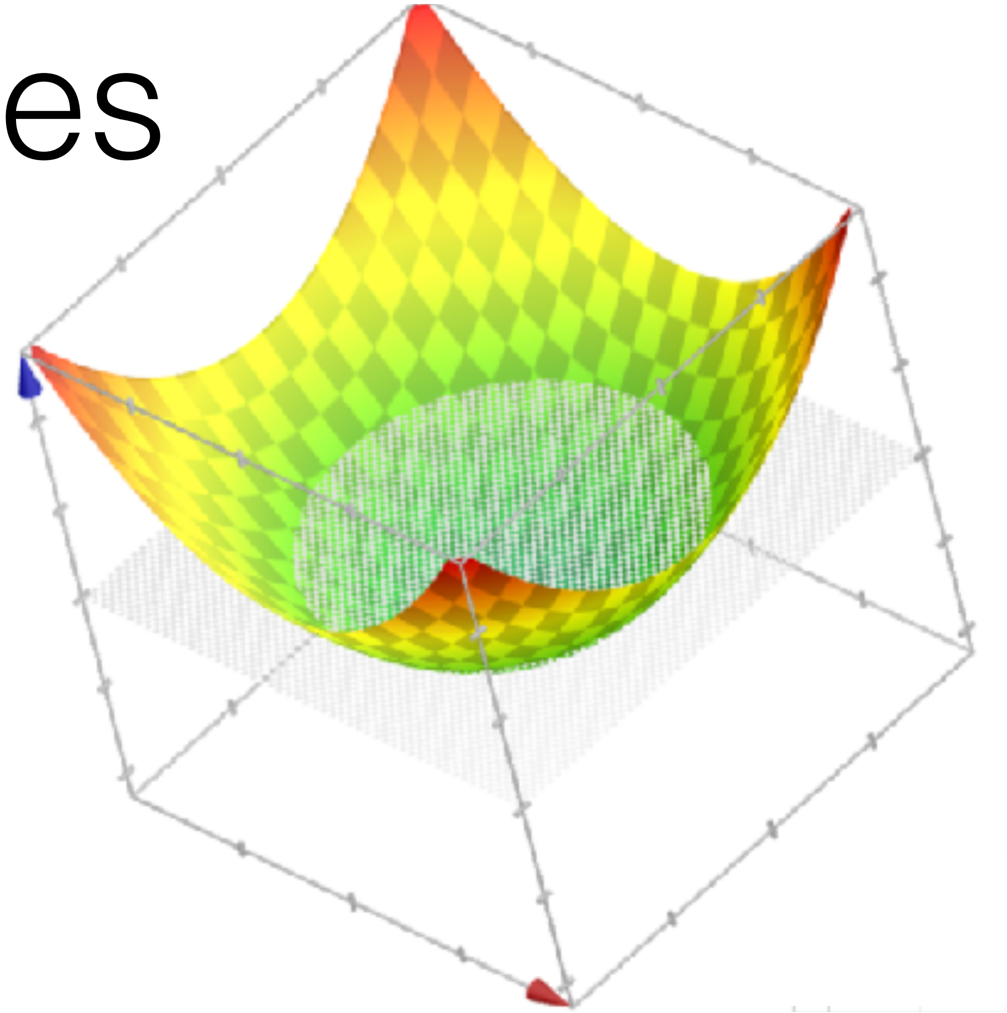
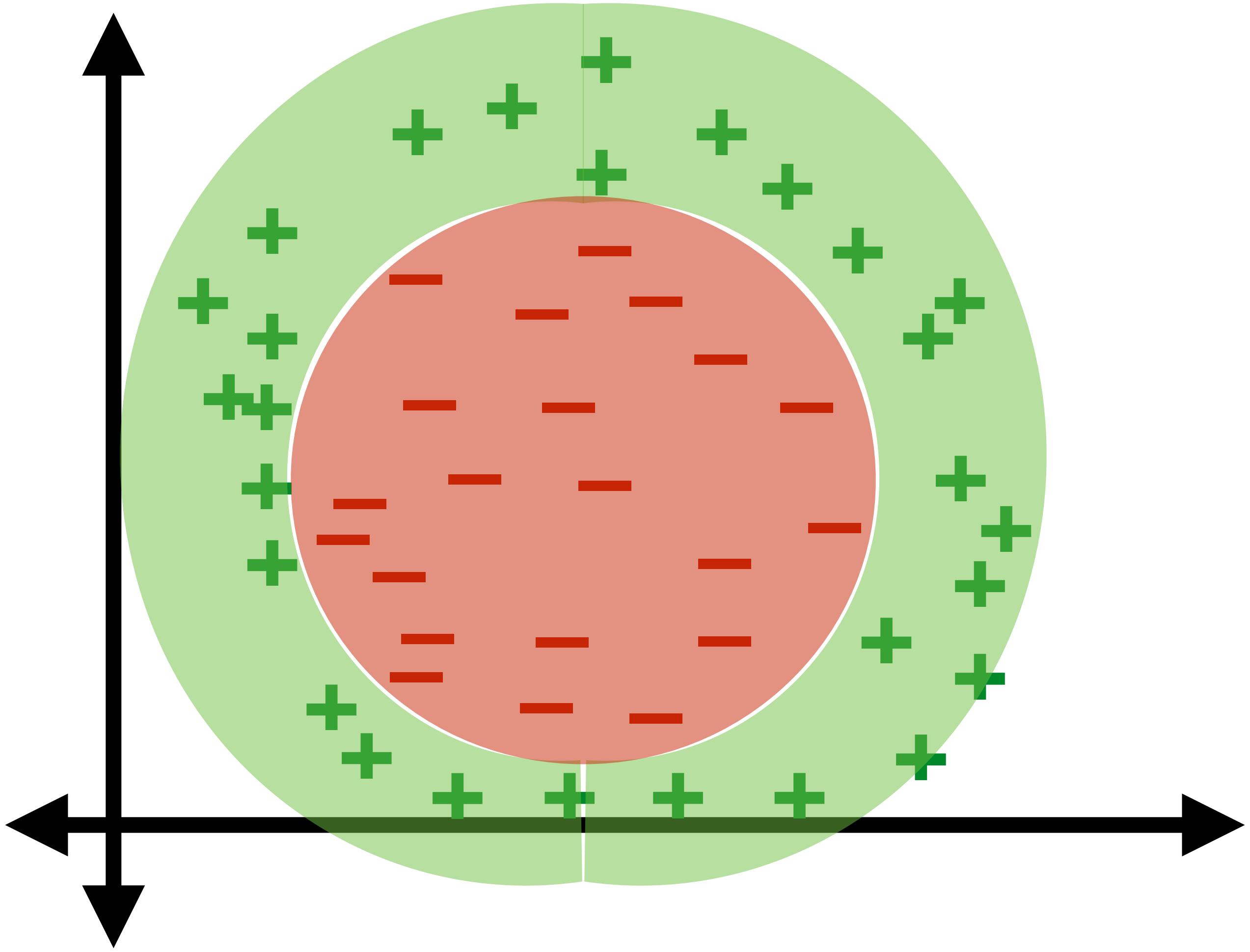
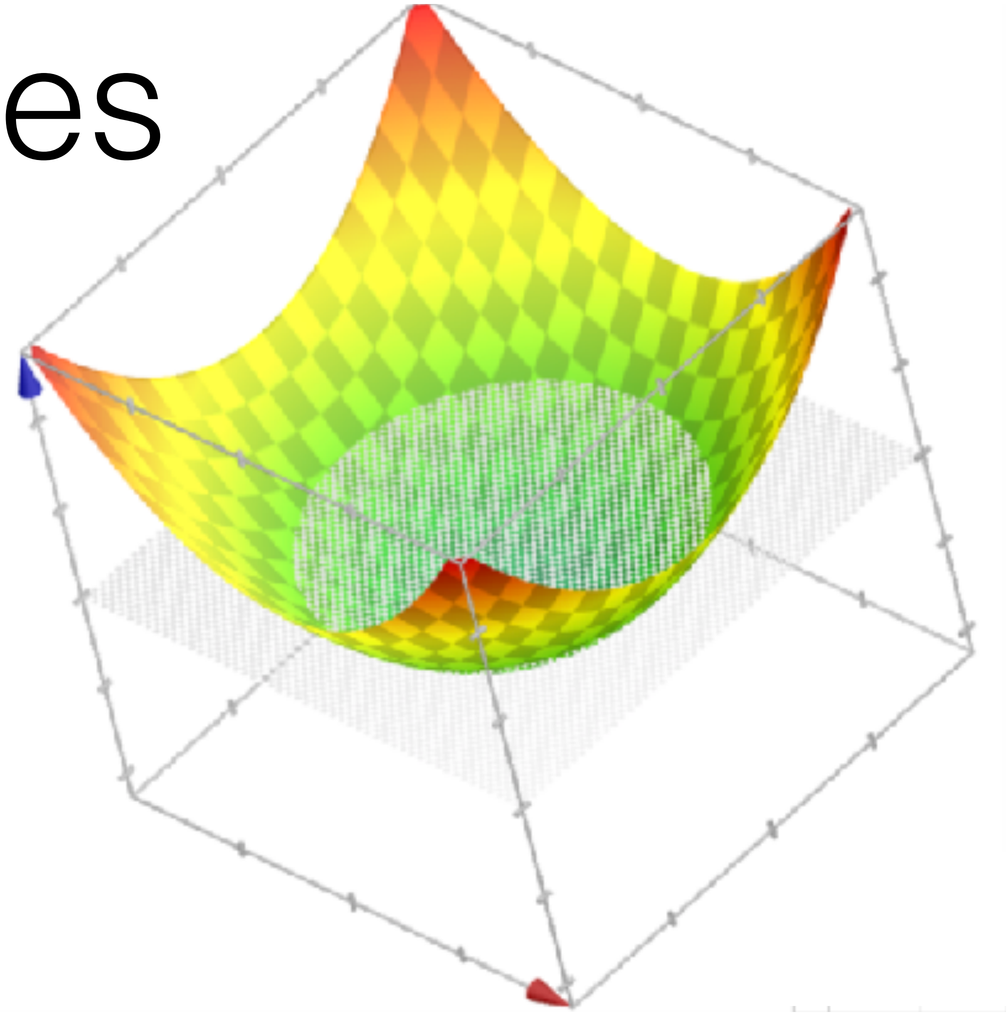




Nonlinear boundaries





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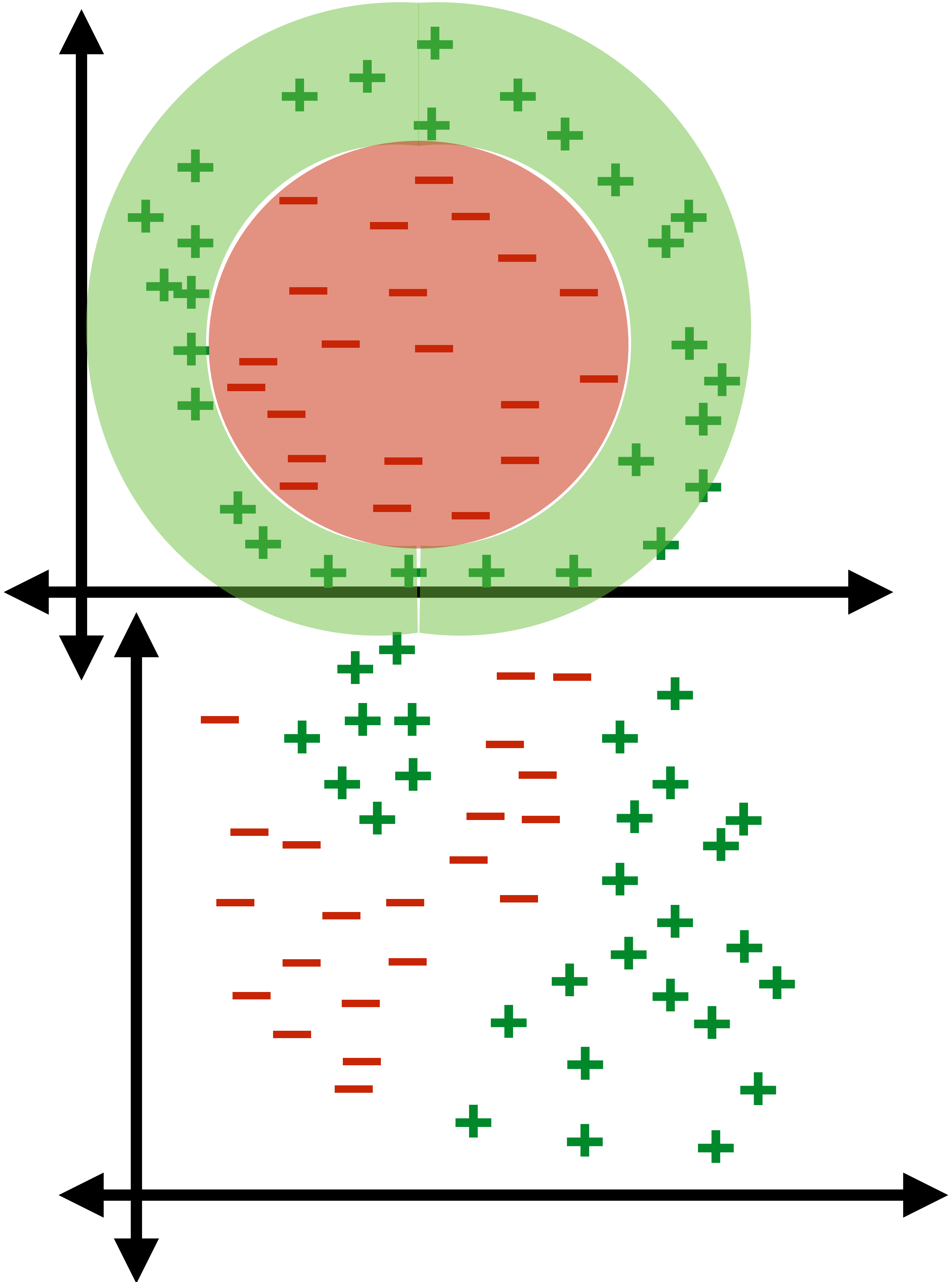

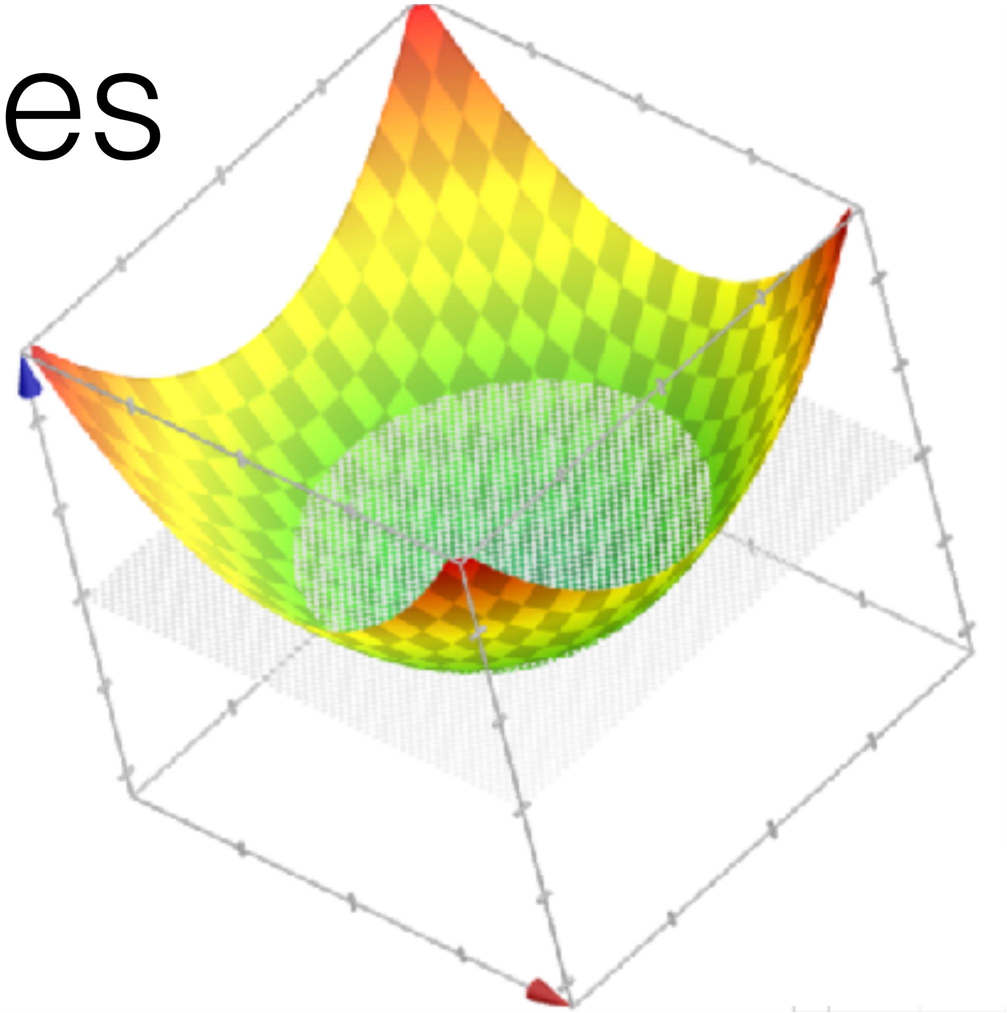

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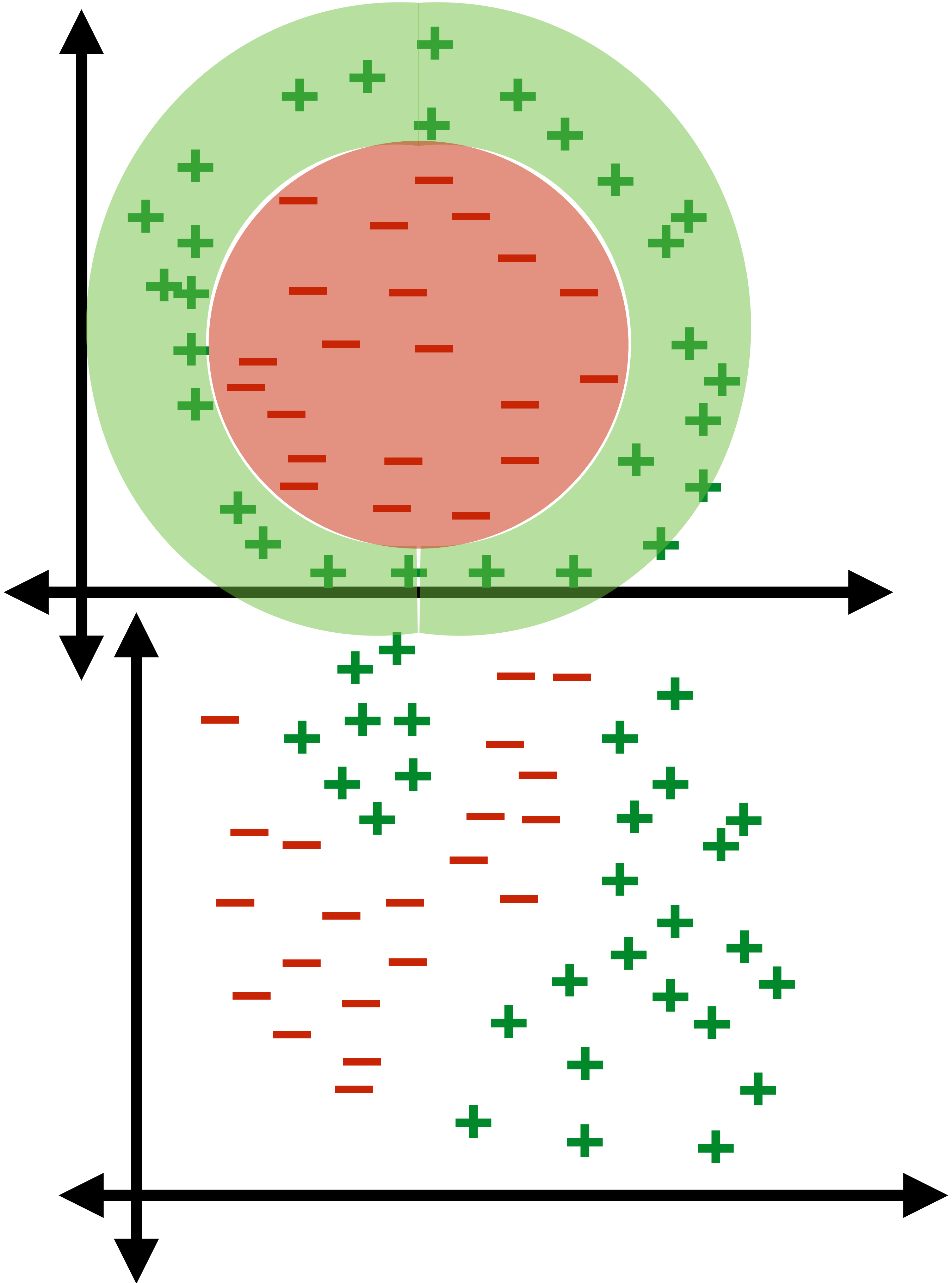

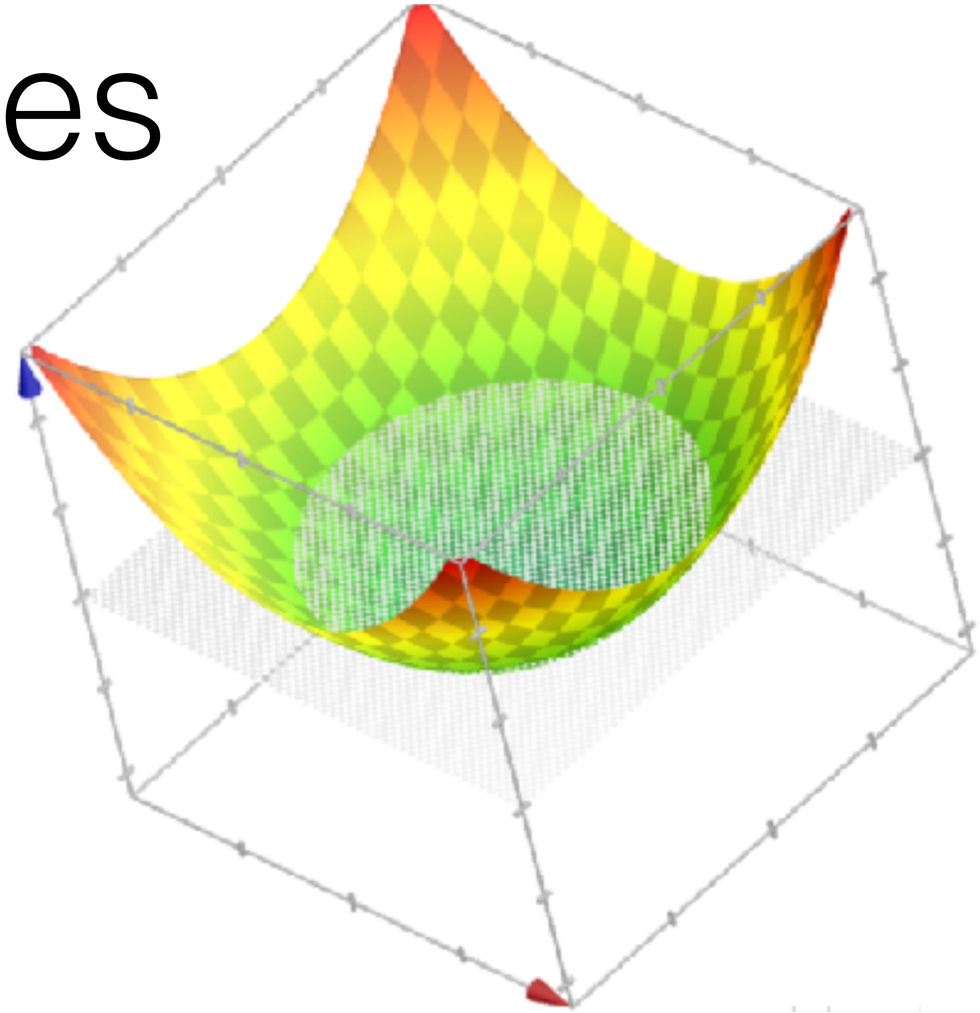

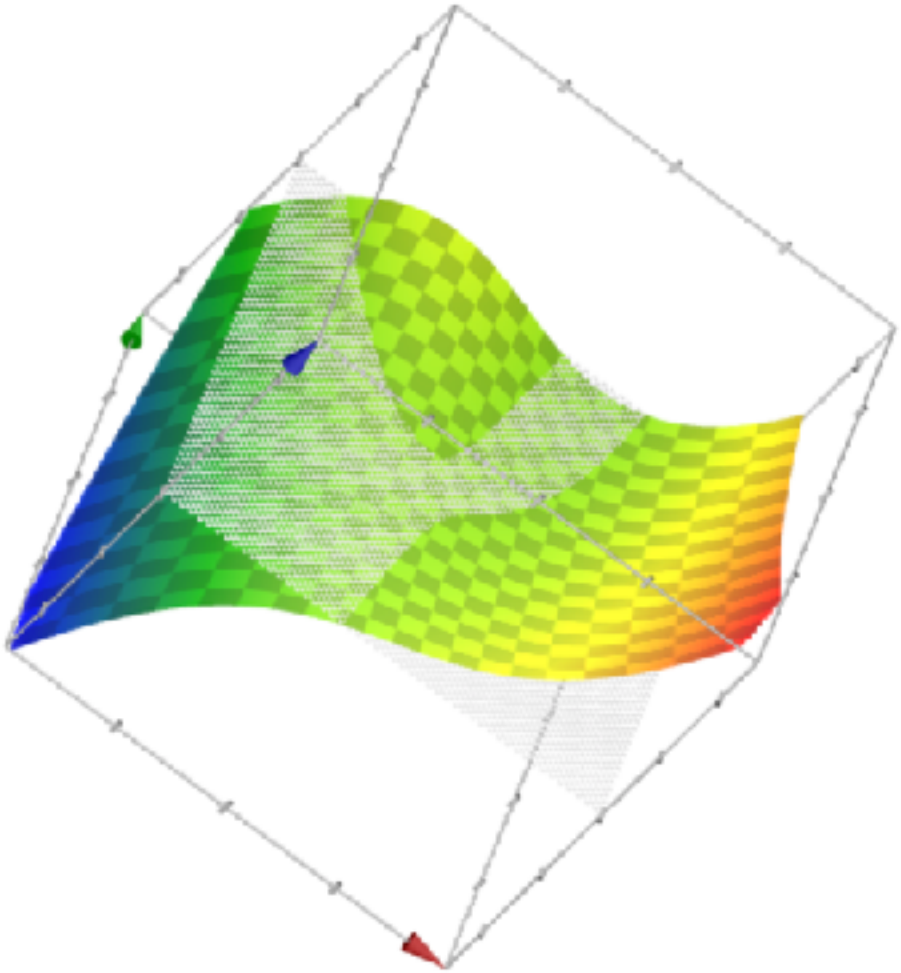

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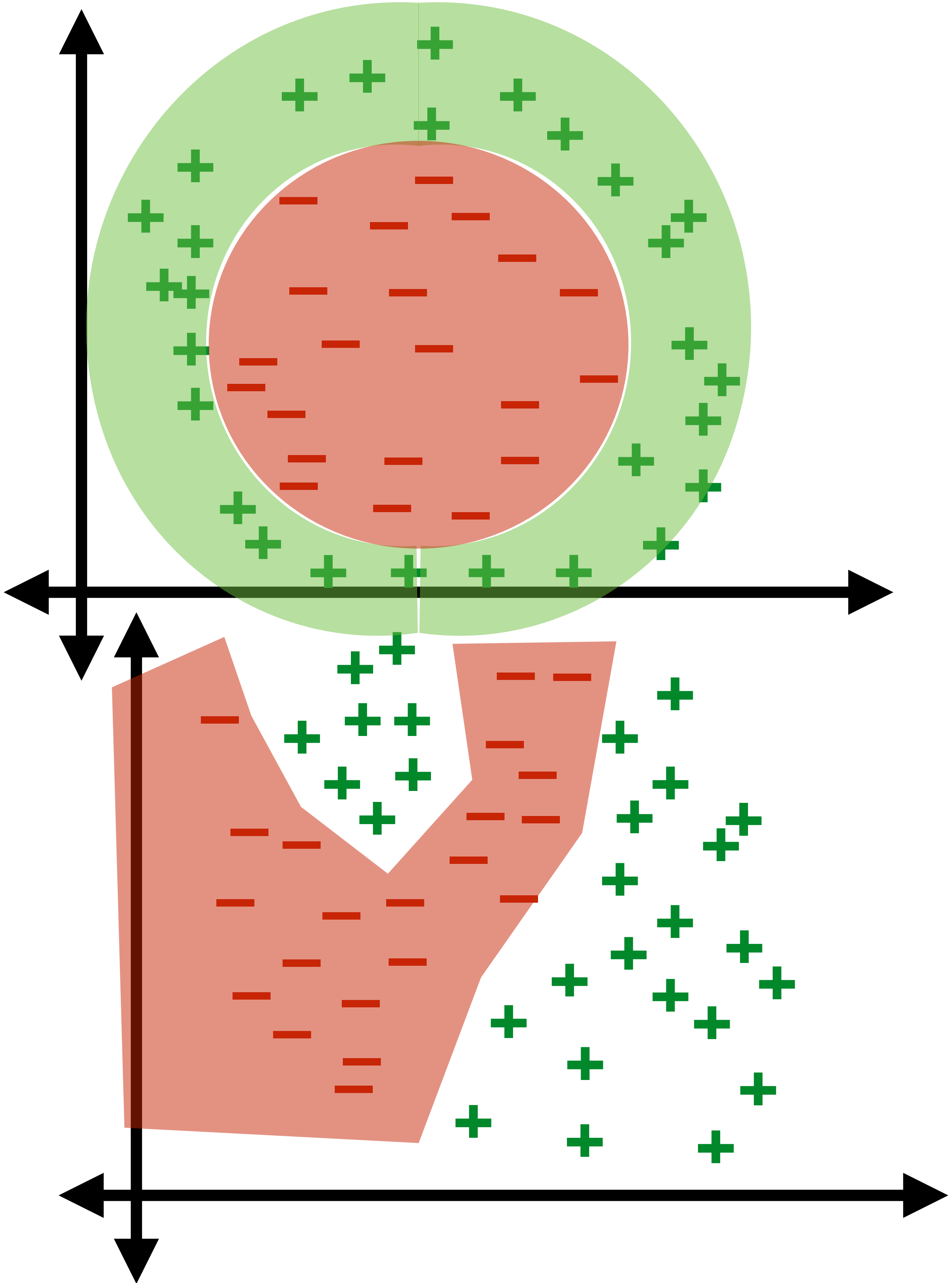

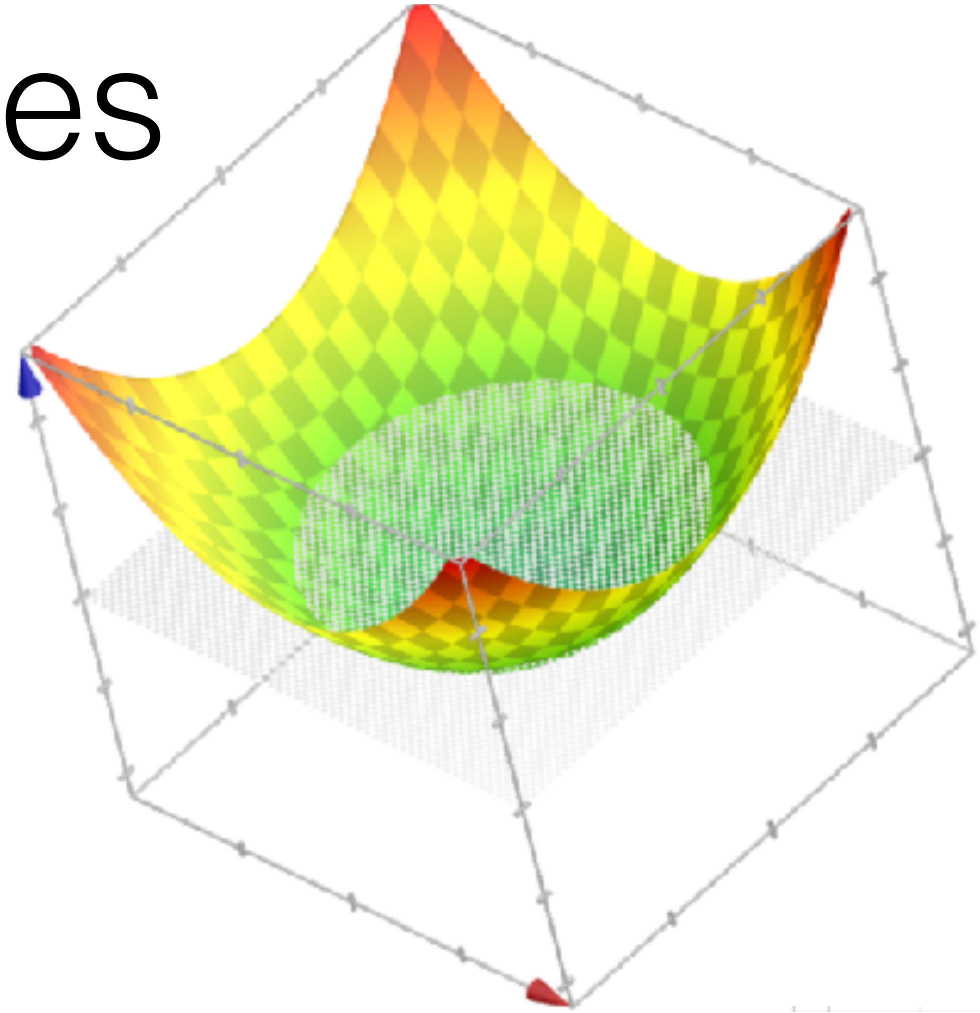

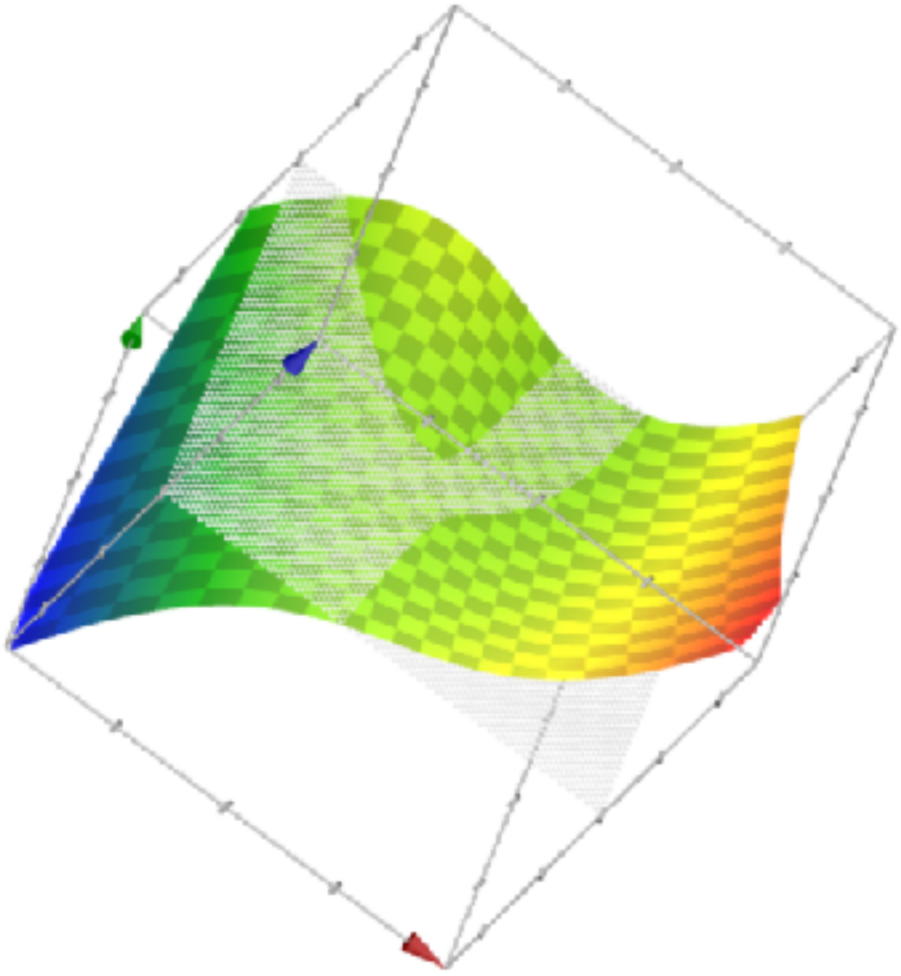

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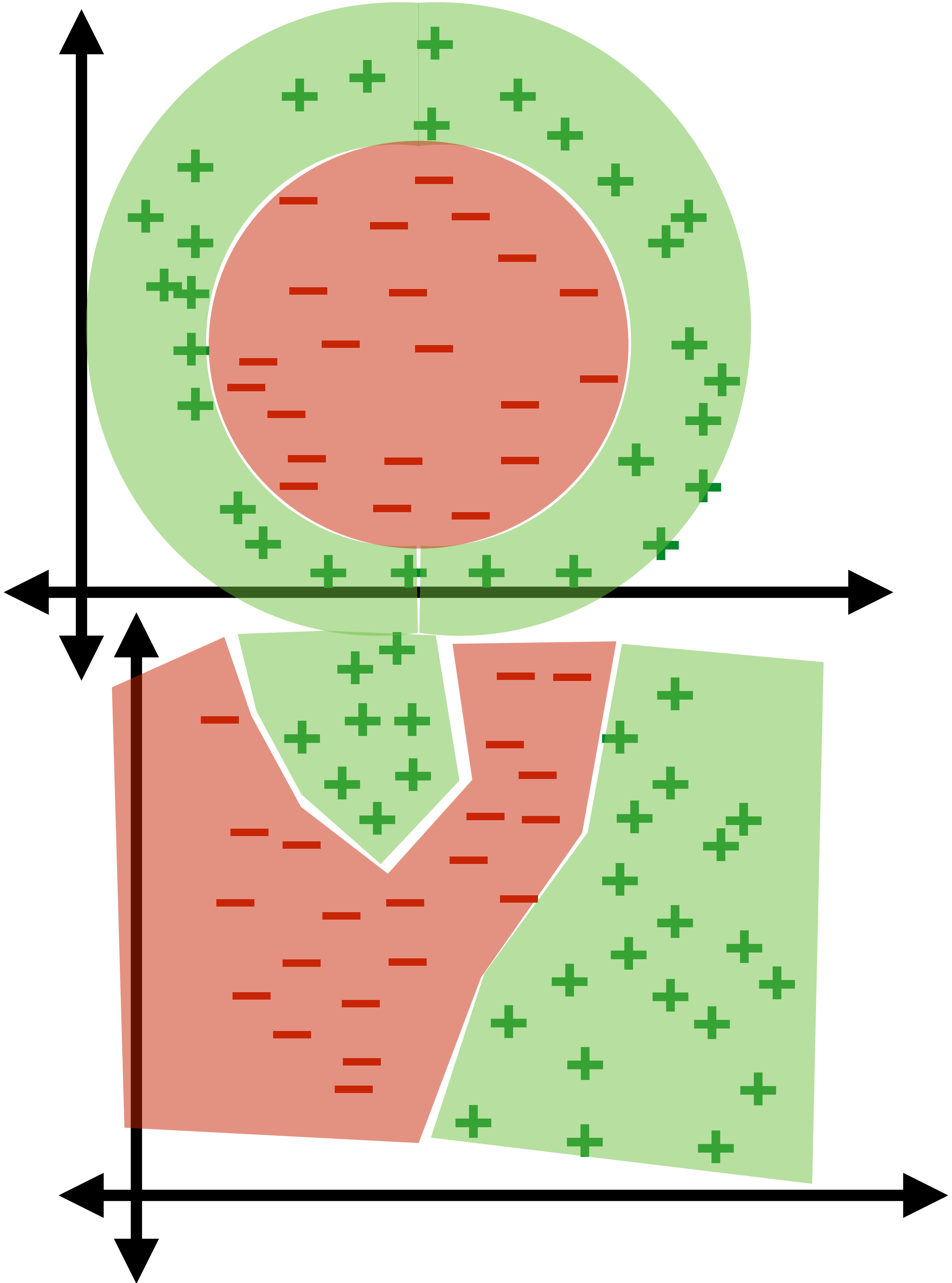
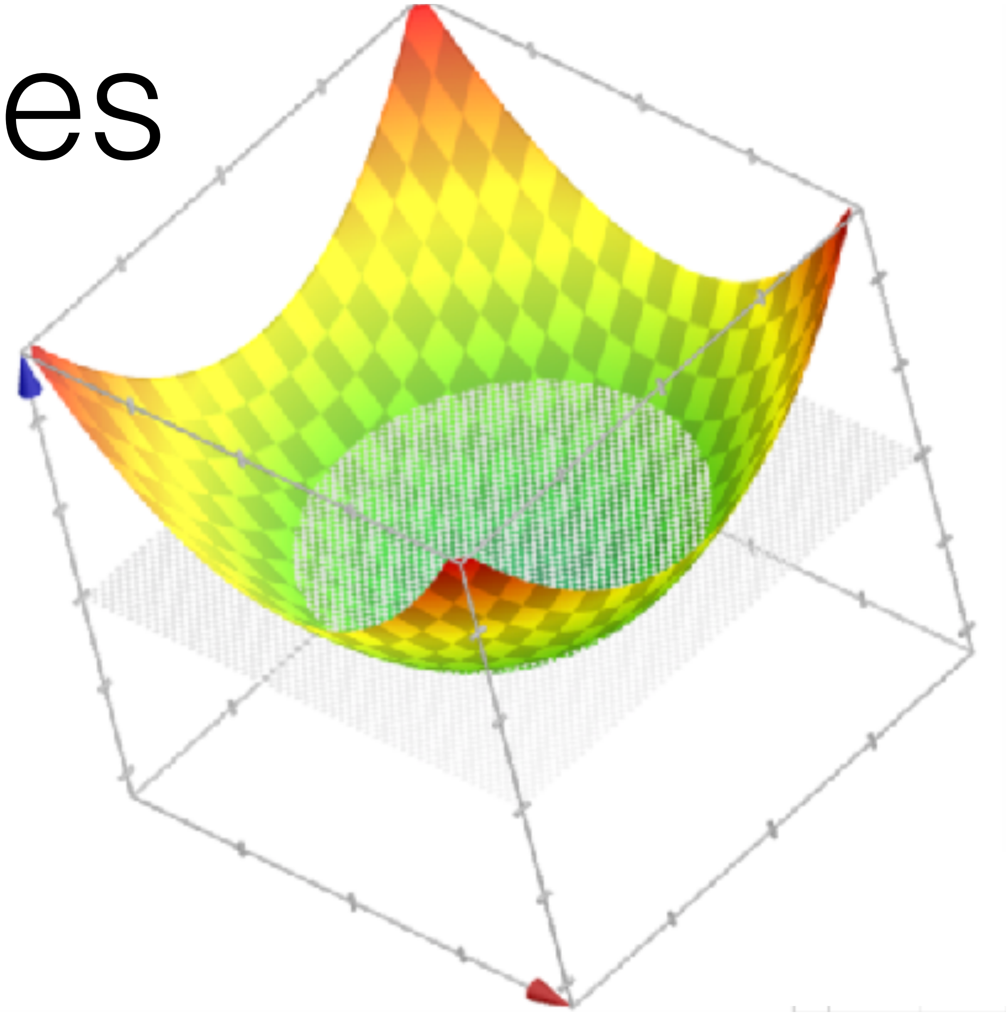
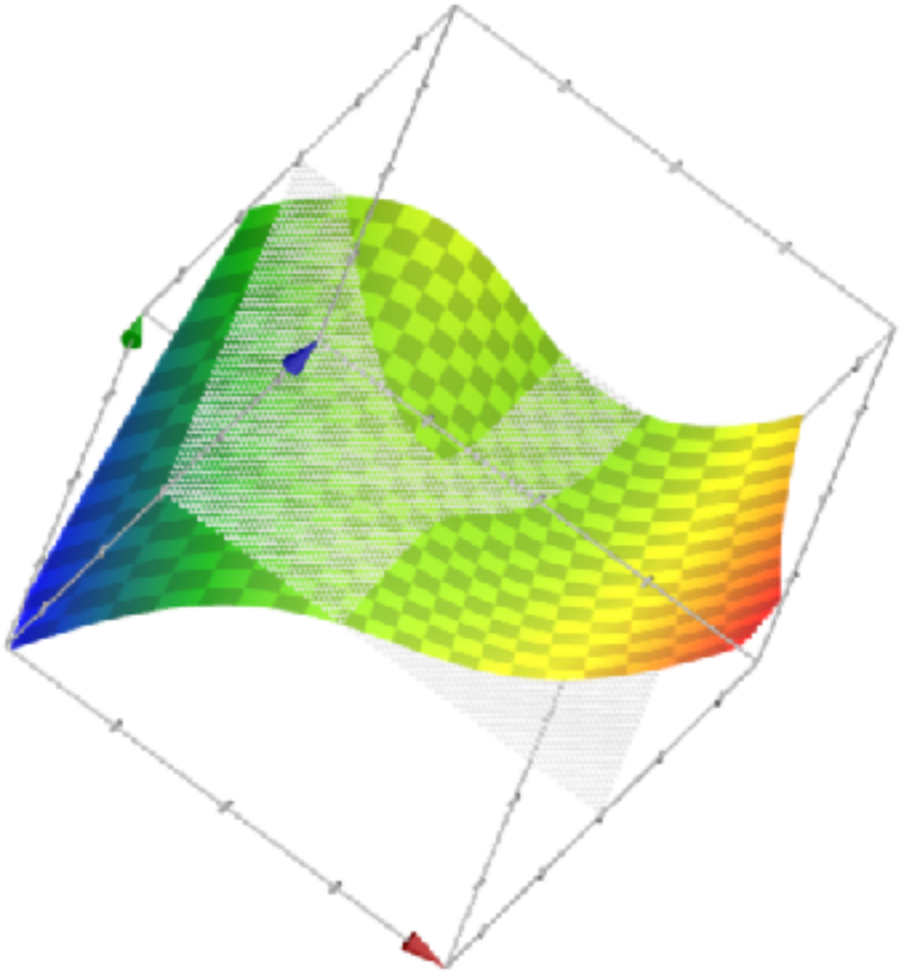
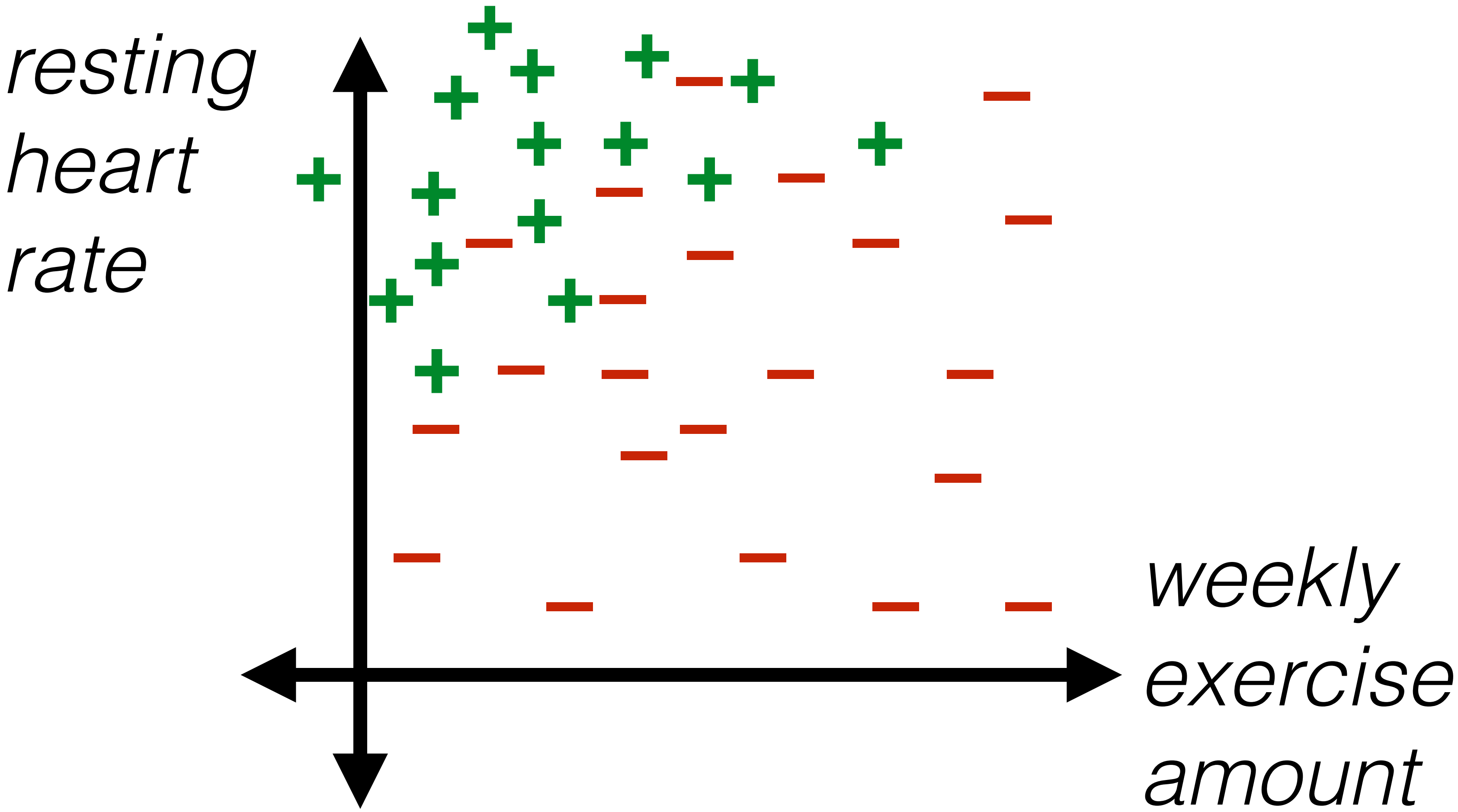






Nonlinear boundaries



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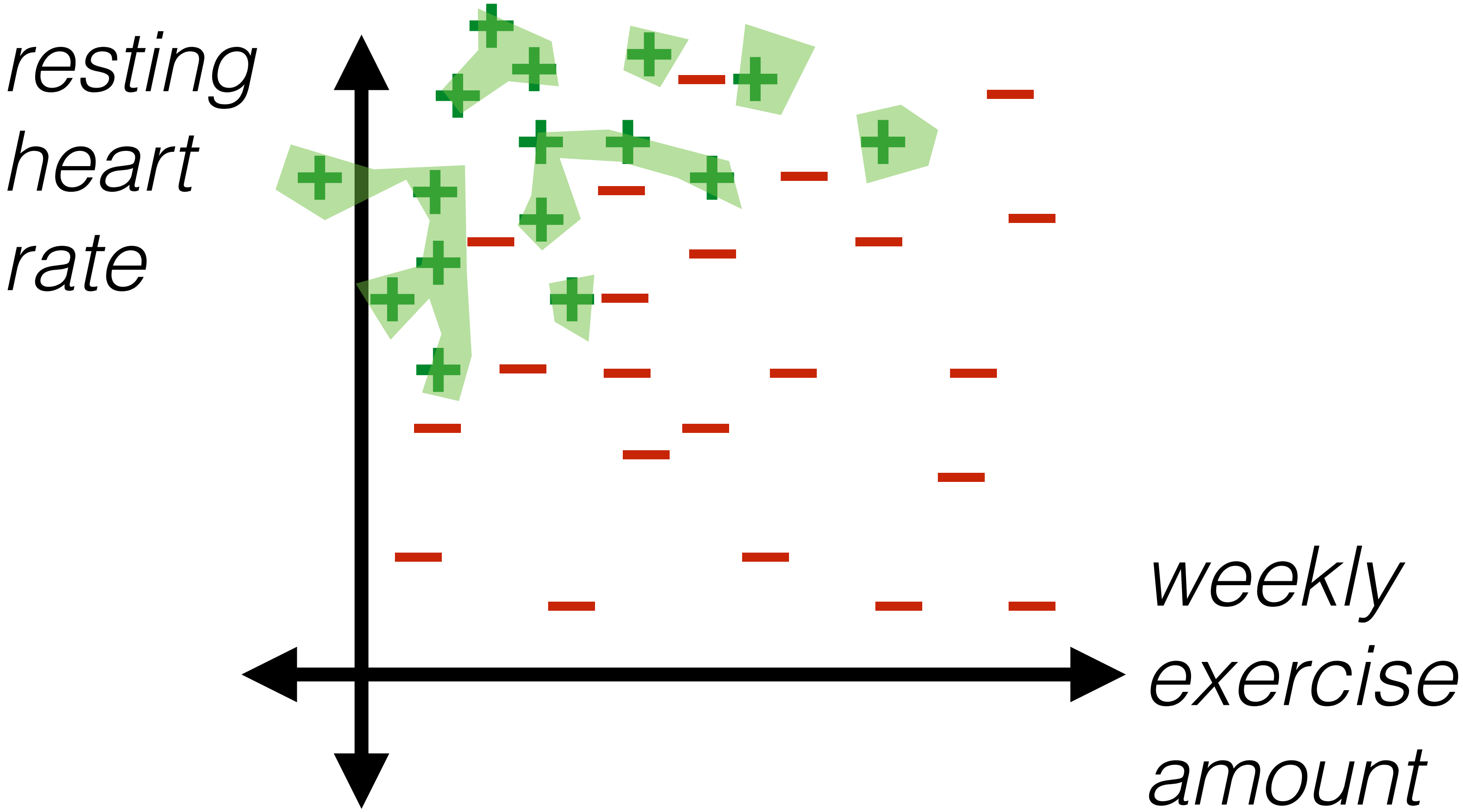
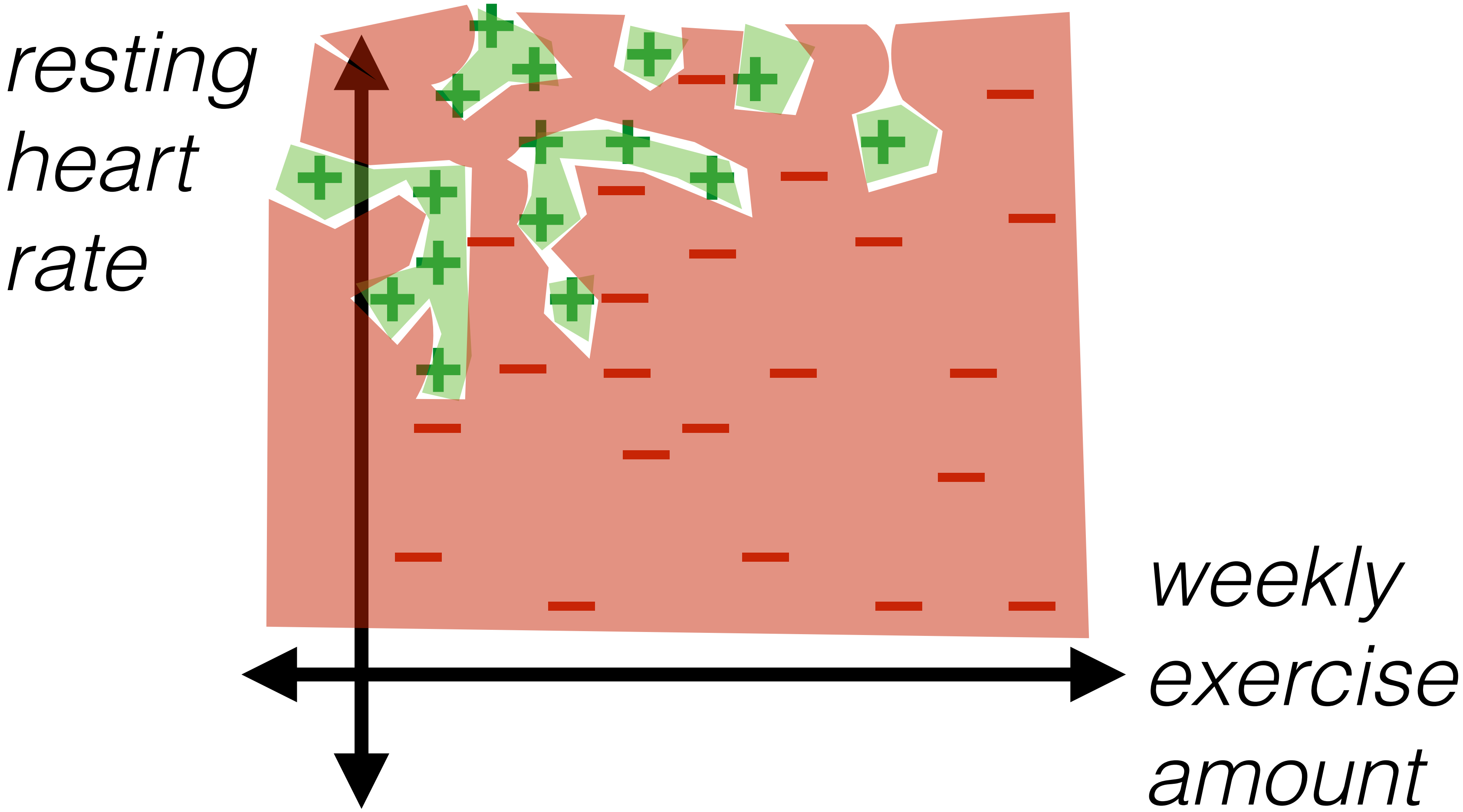


Nonlinear boundaries



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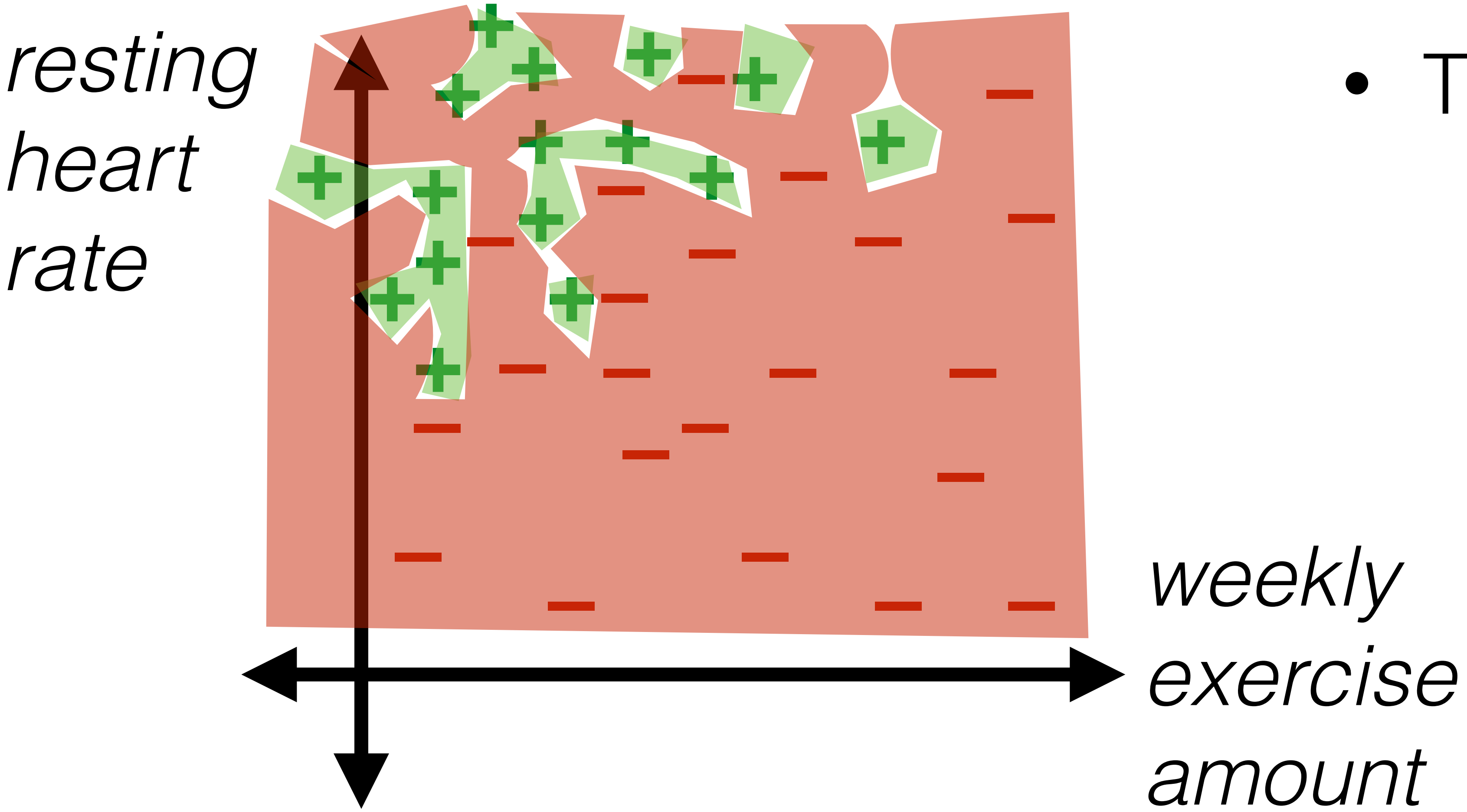
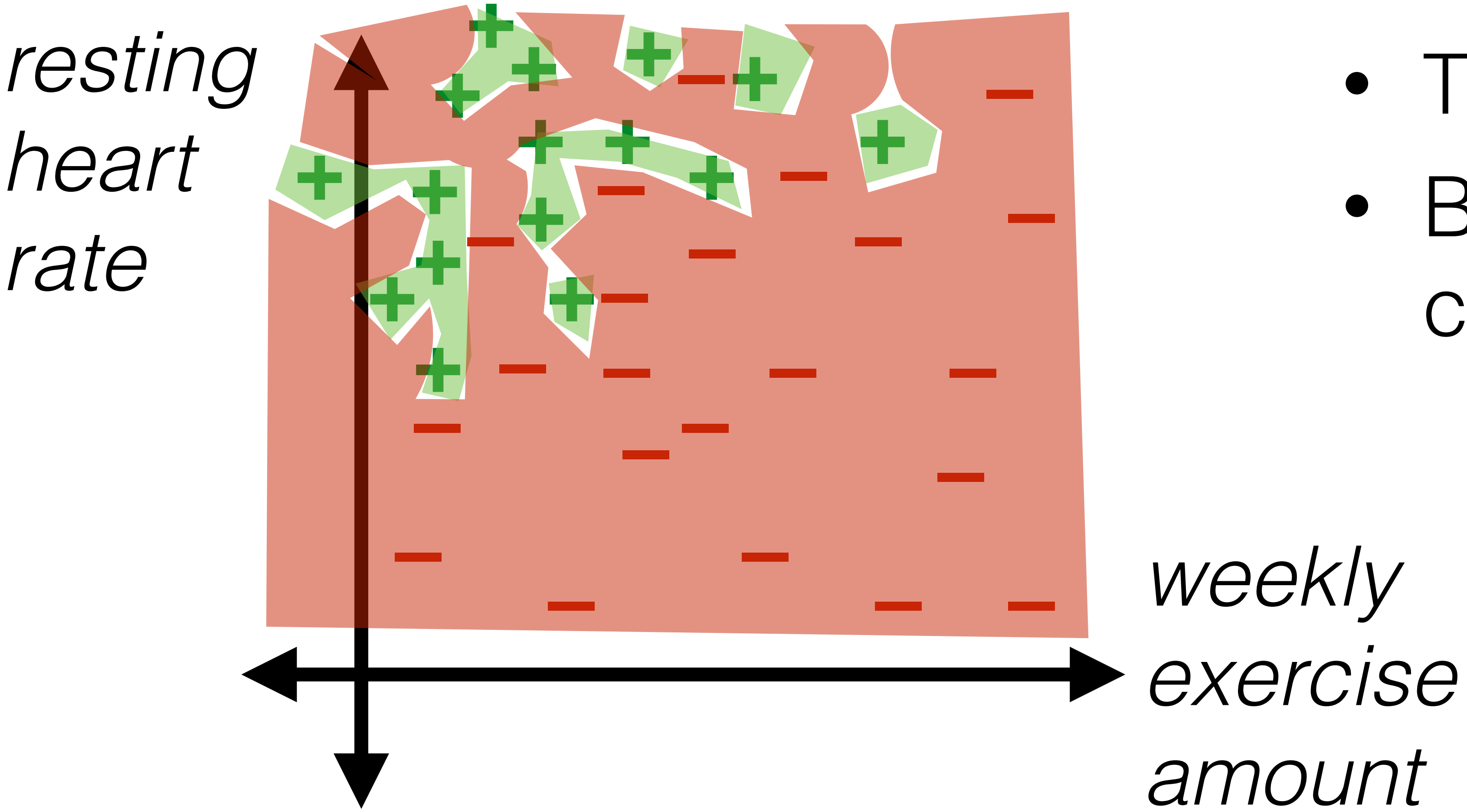


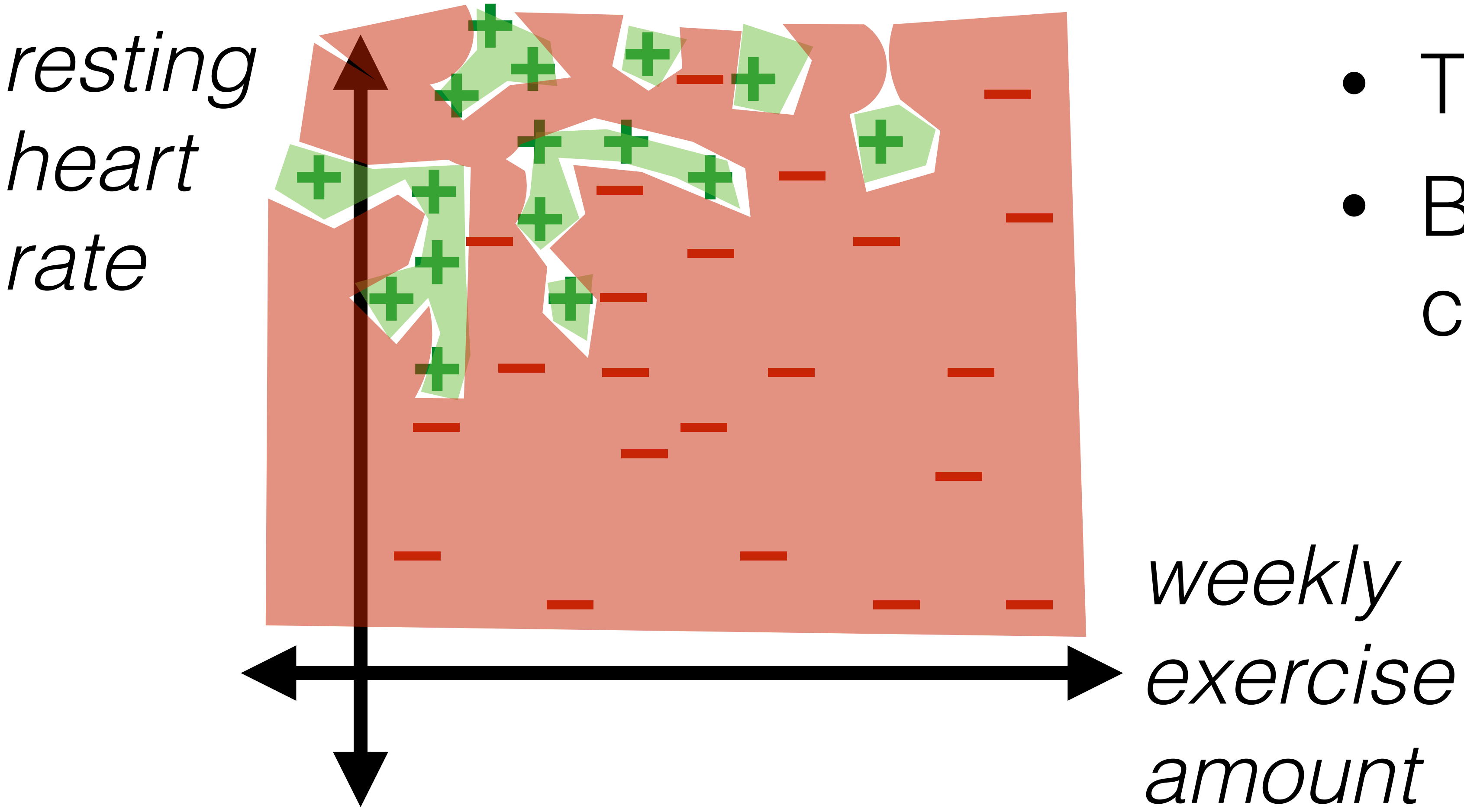
- Training error is 0!

Nonlinear boundaries



- Training error is 0!
- But seems like our classifier is overfitting

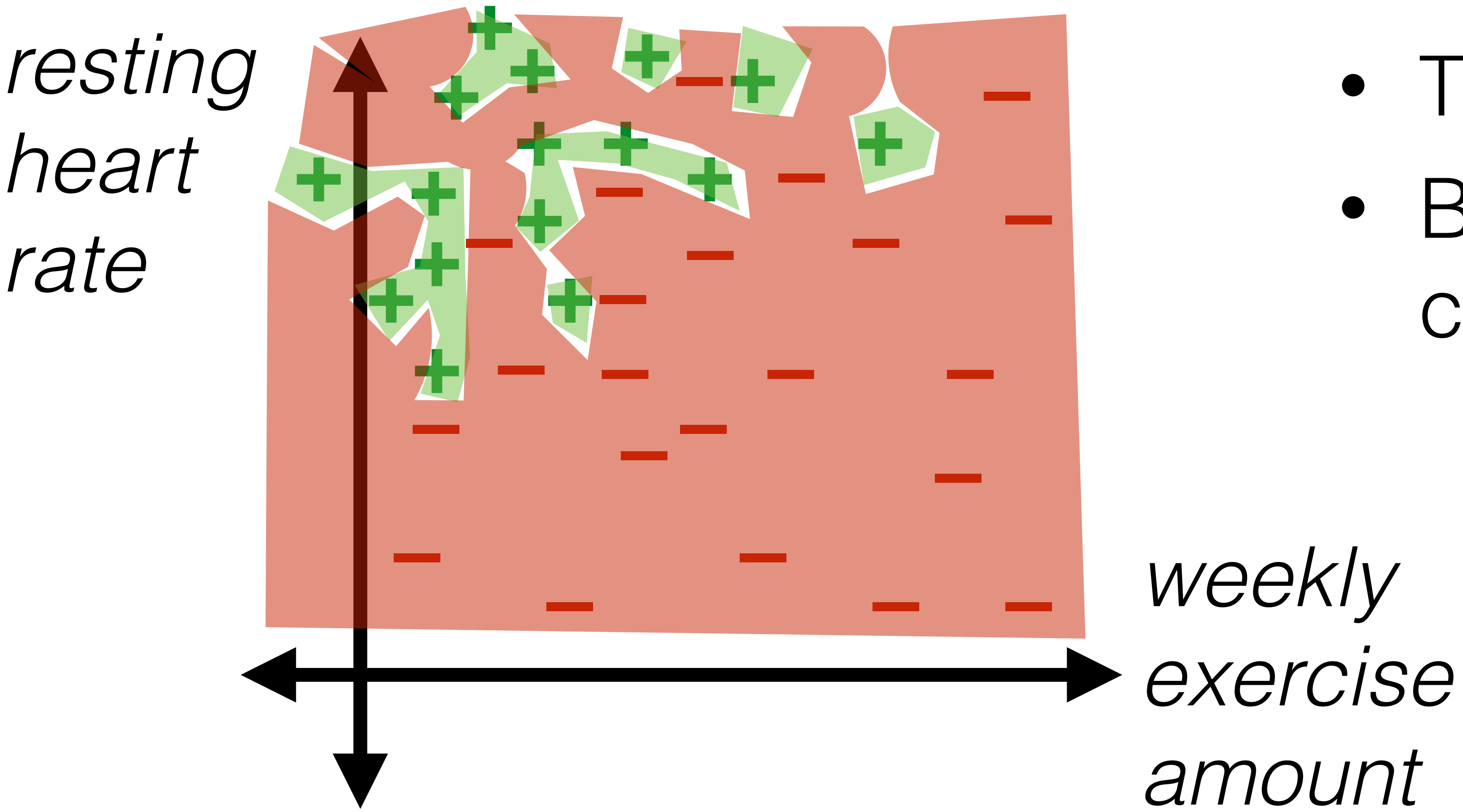
Nonlinear boundaries



- Training error is 0!
- But seems like our classifier is overfitting

- How can we detect overfitting?

Nonlinear boundaries



- Training error is 0!
- But seems like our classifier is overfitting

- How can we detect overfitting?
- How can we avoid overfitting?

Evaluation of a learning algorithm

- How good is our learning algorithm on data like ours?

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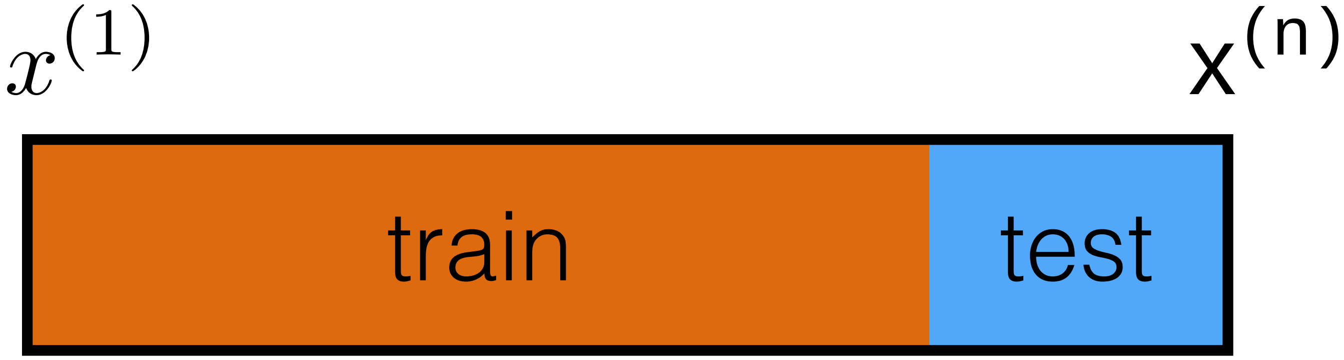

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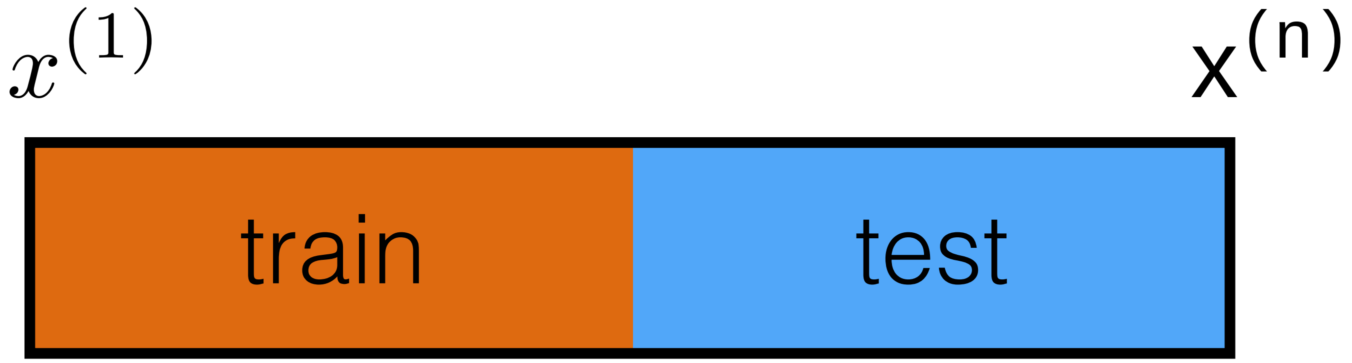

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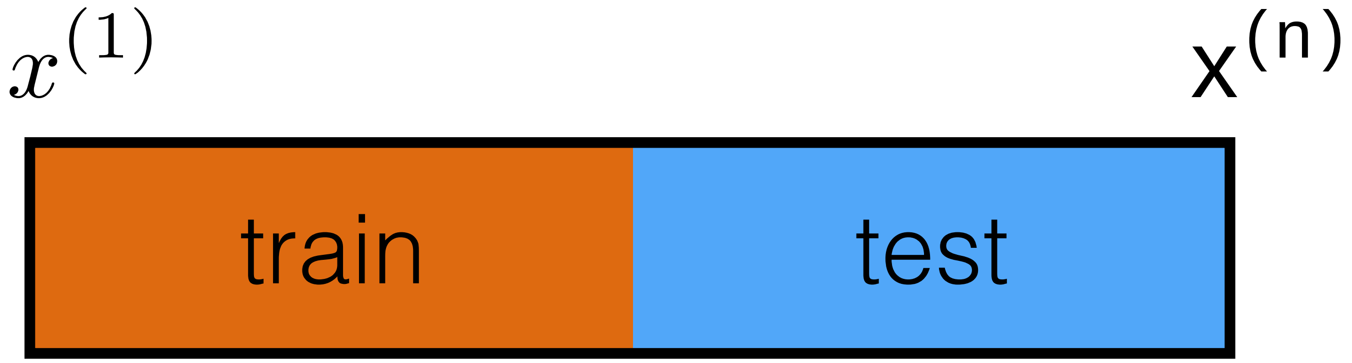

- Idea: use full data for training and then report training error
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  - More training data: closer to training on full data

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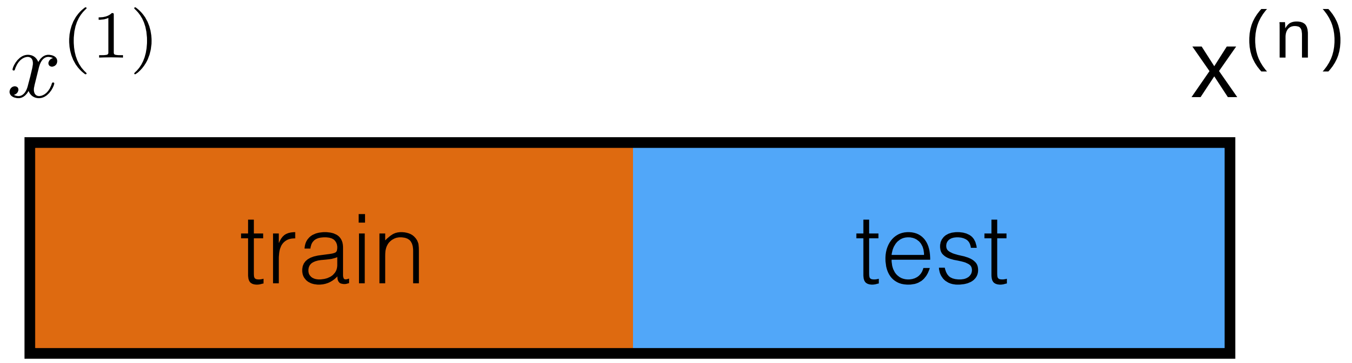

- Idea: use full data for training and then report training error
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  - More training data: closer to training on full data
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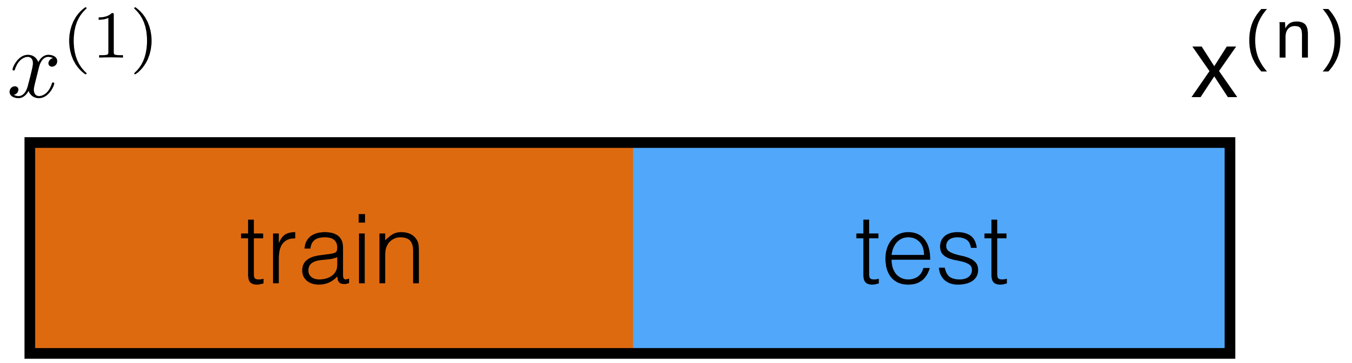

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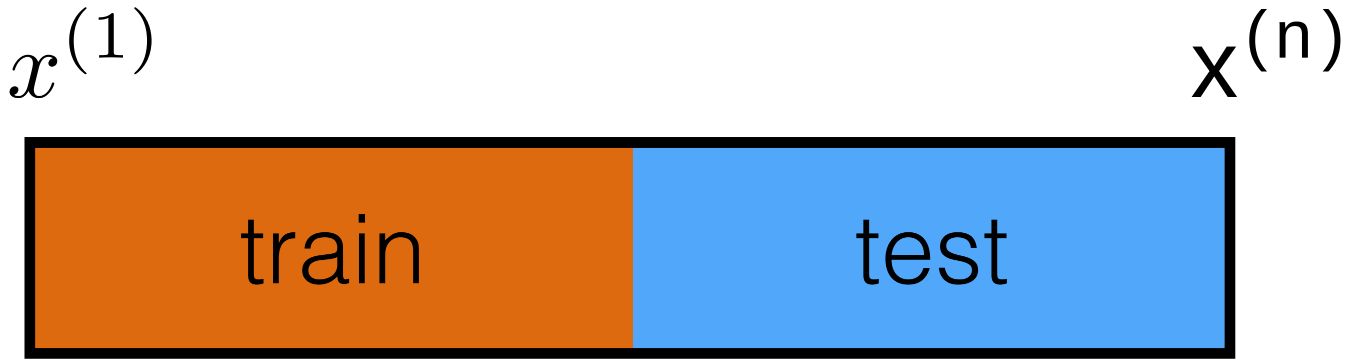

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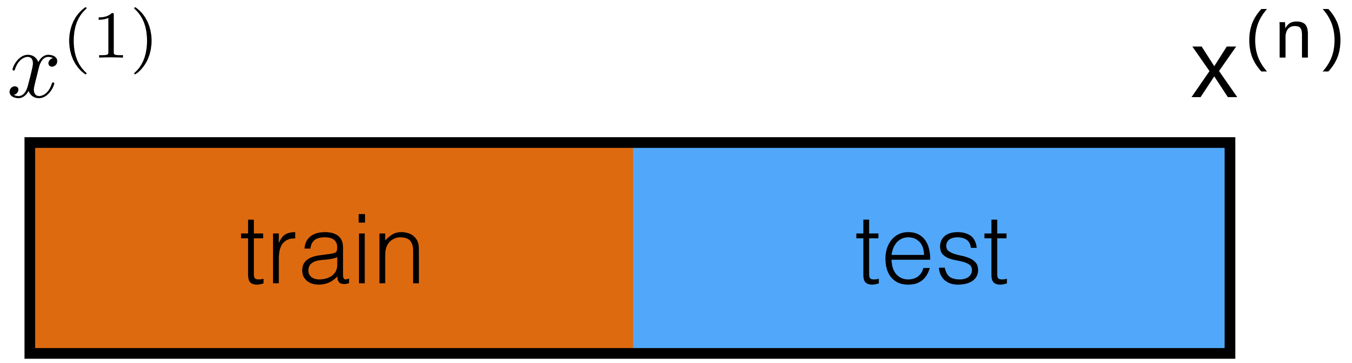

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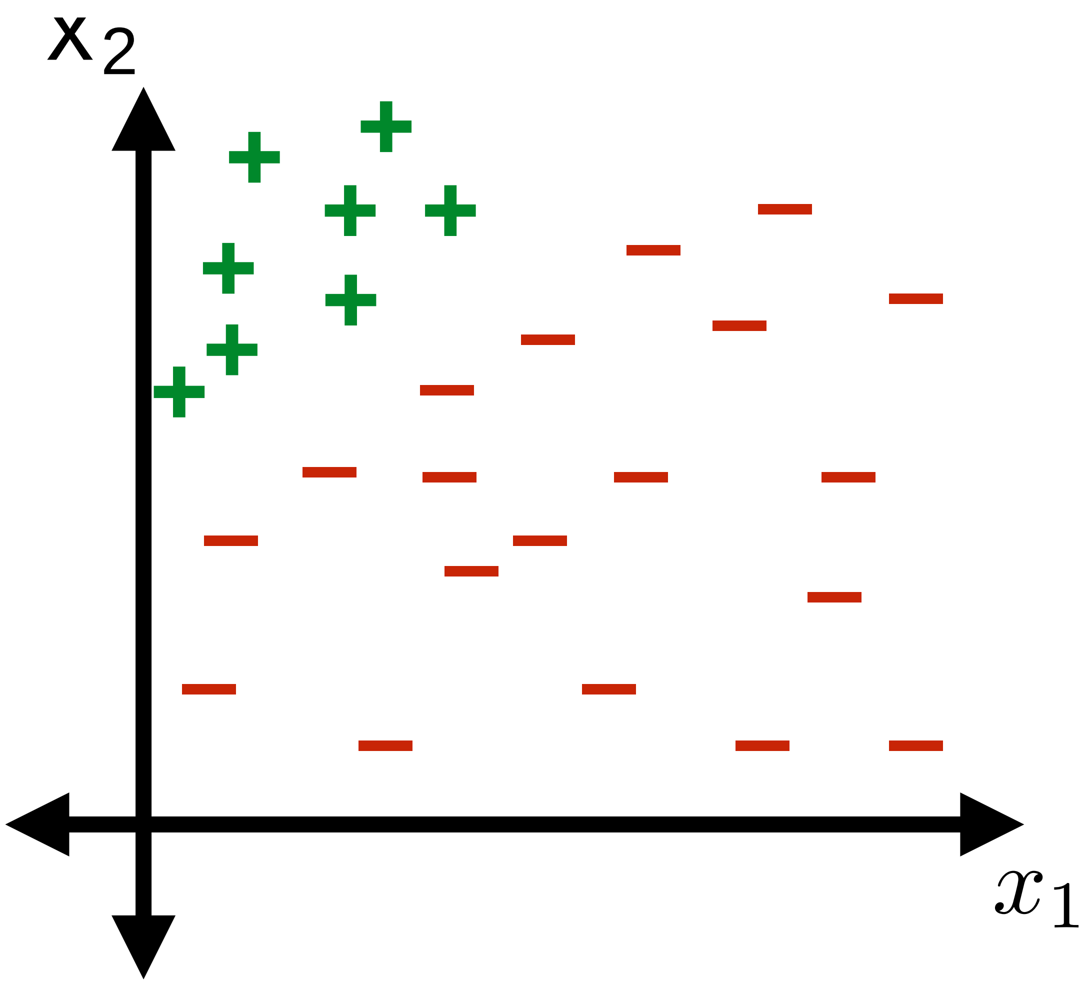

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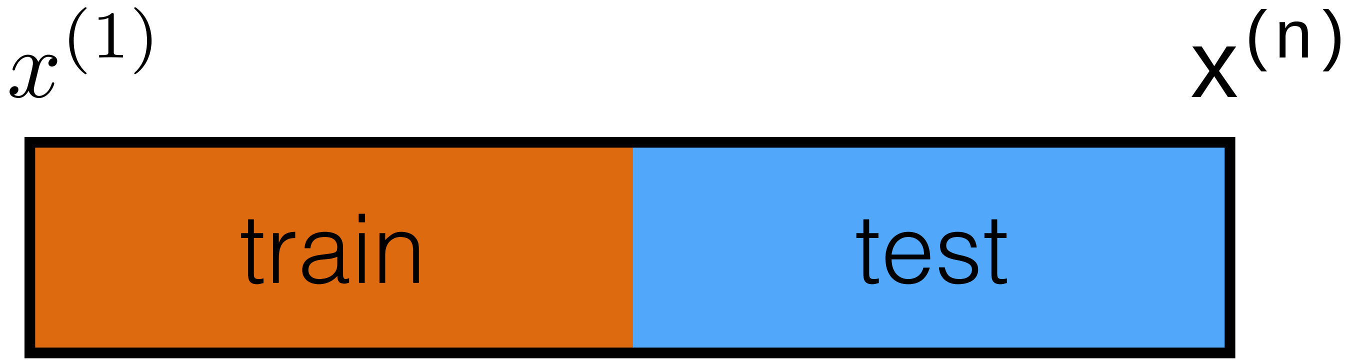

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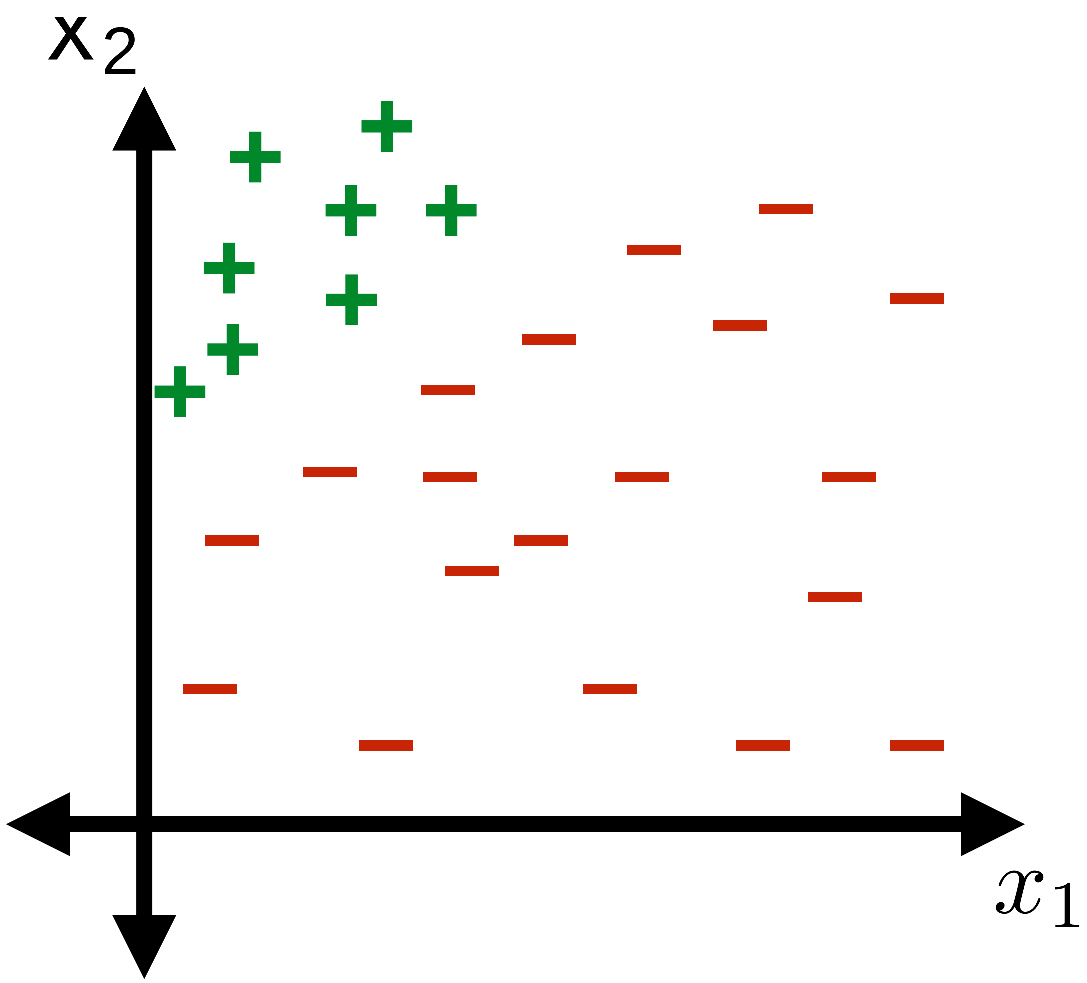

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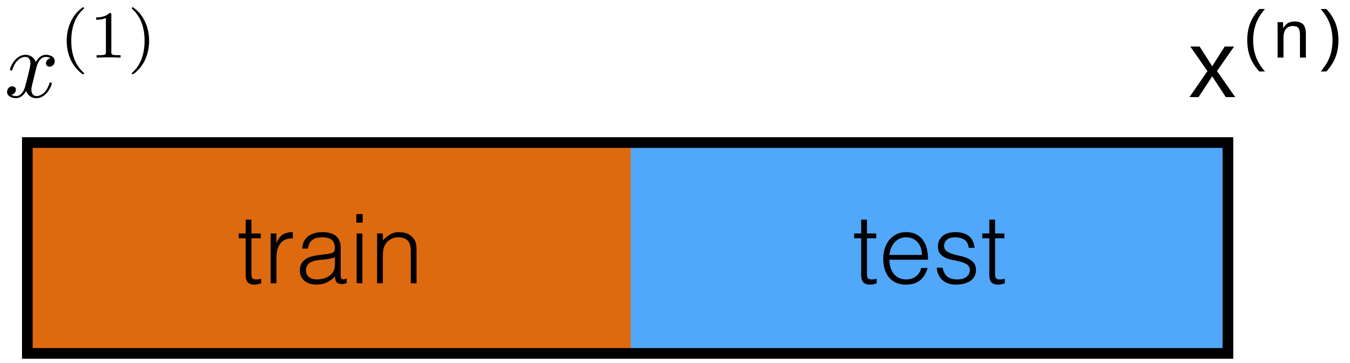

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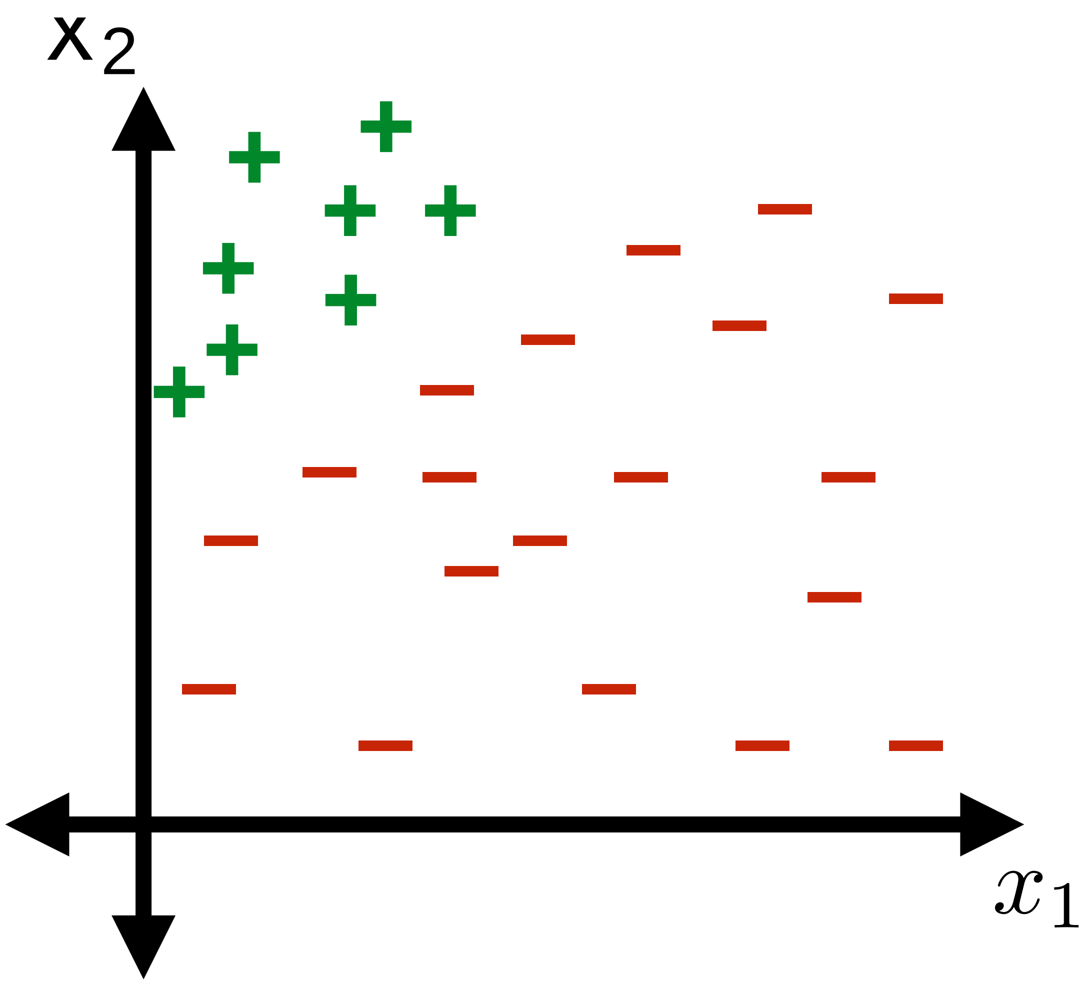

Evaluation of a learning algorithm

```
Cross-validate( $\mathcal{D}_n$ , k )
```

Evaluation of a learning algorithm

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Cross-validate($\mathcal{D}_n$ , k )
    Divide $D_n$ into k chunks $D_{n,1}$,...,$D_{n,k}$ (of
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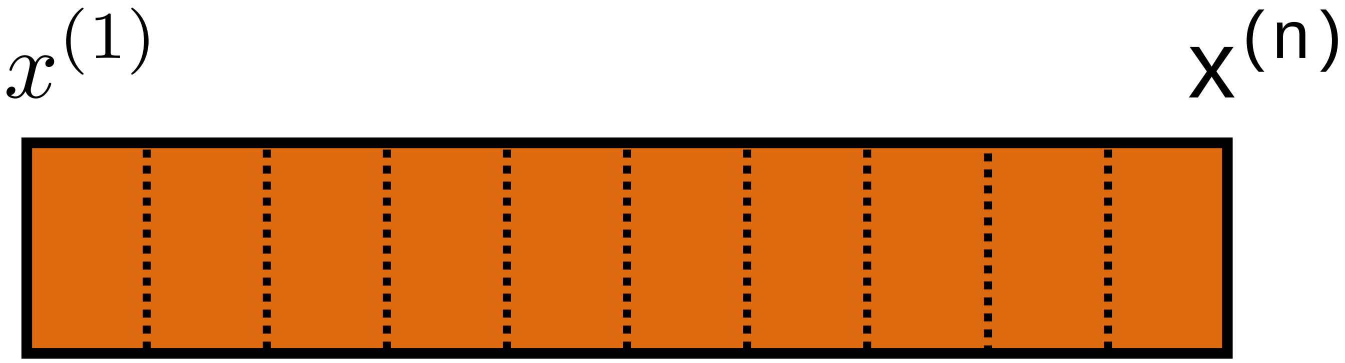

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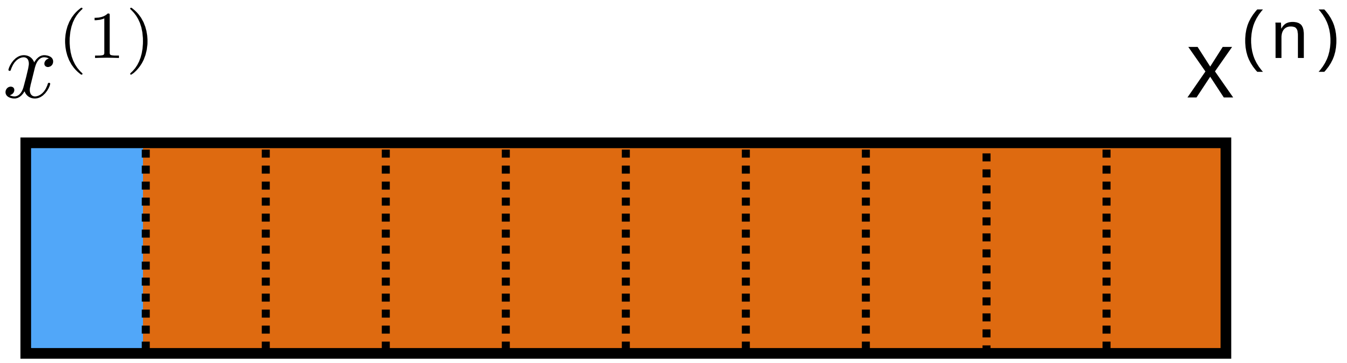

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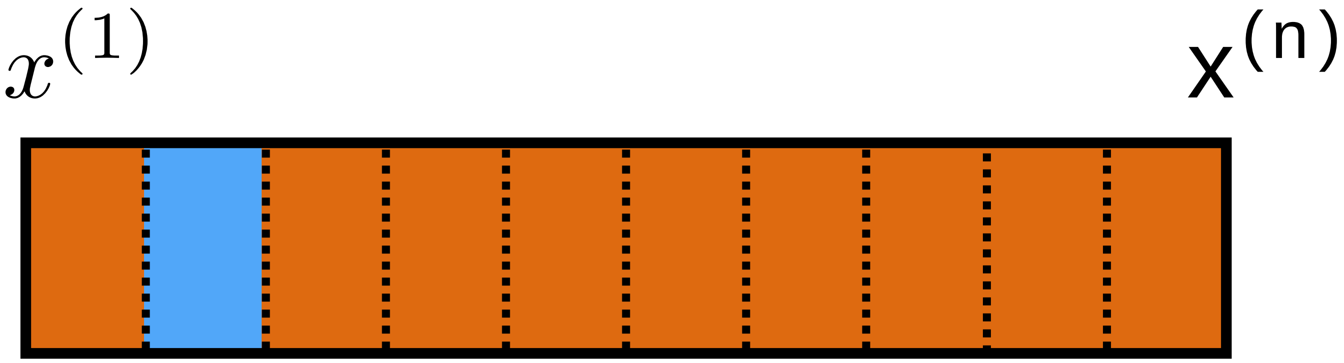

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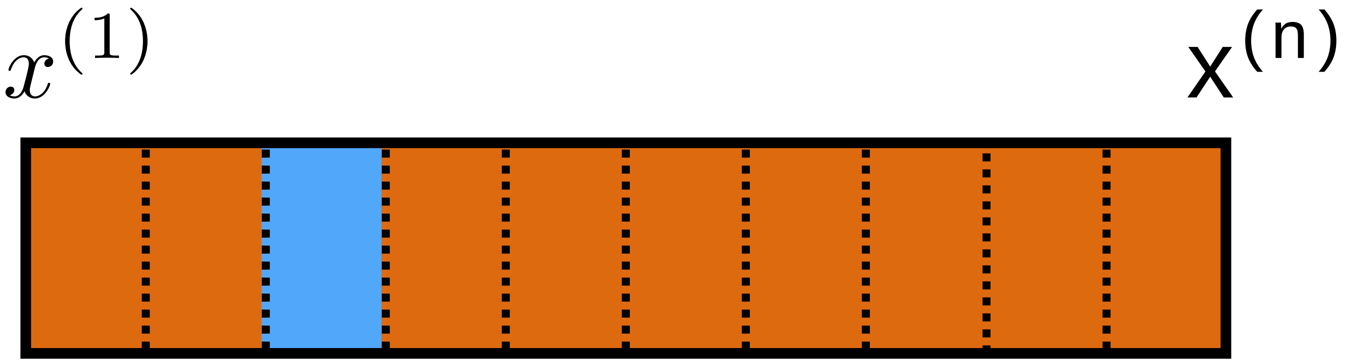

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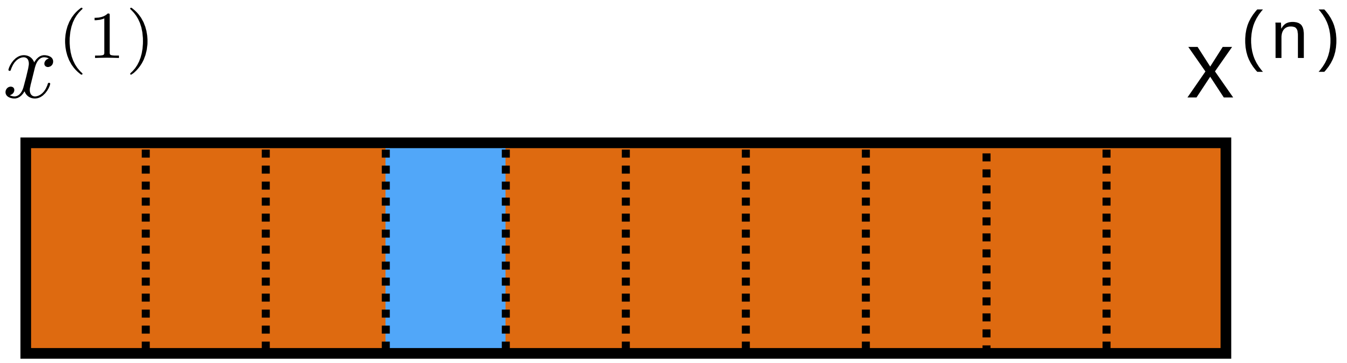

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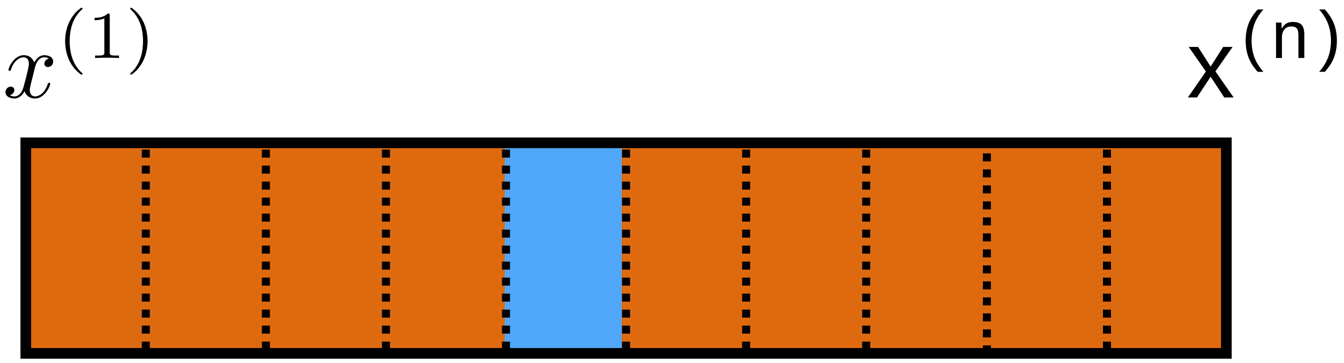

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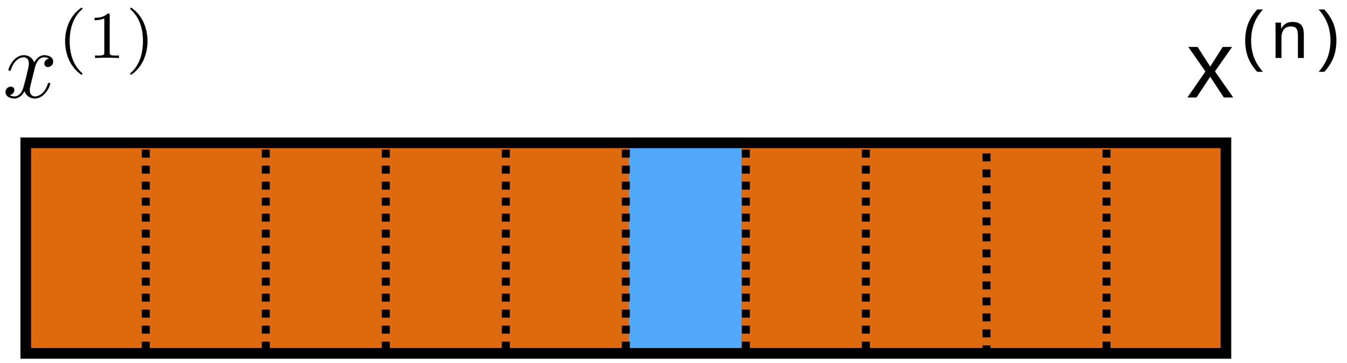

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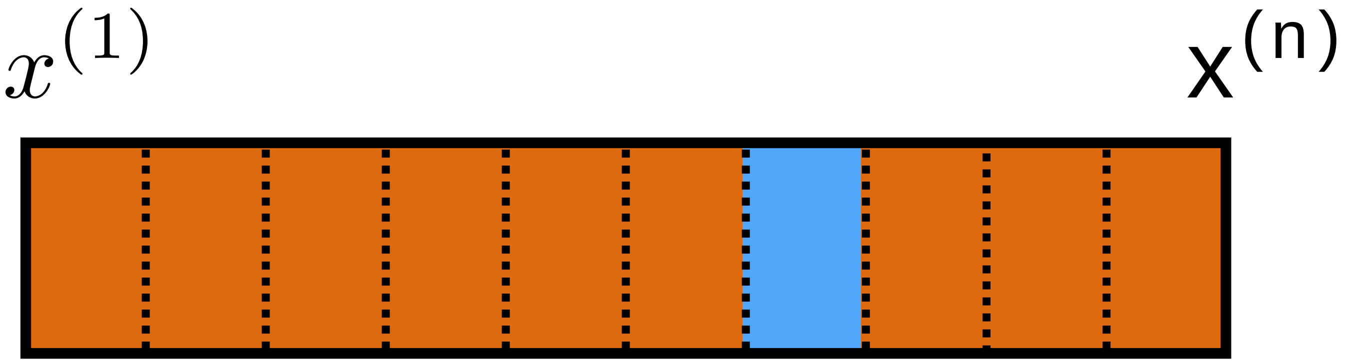

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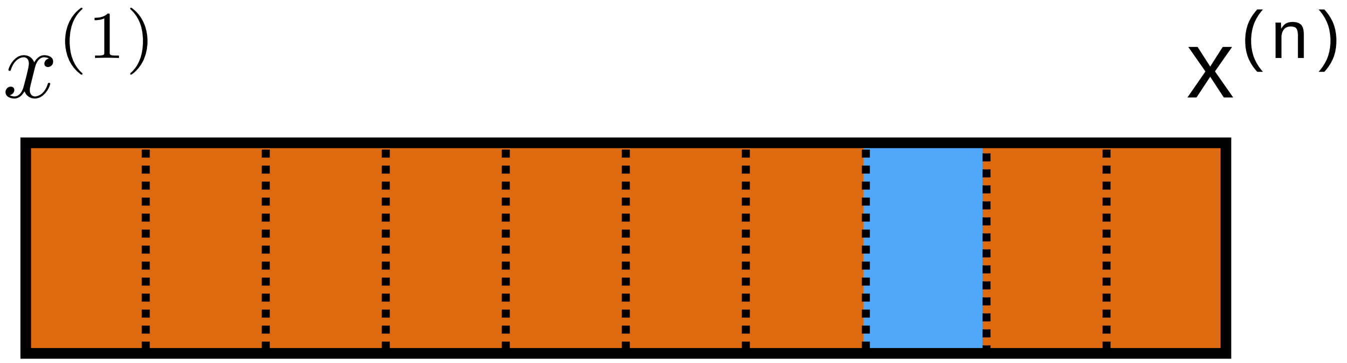

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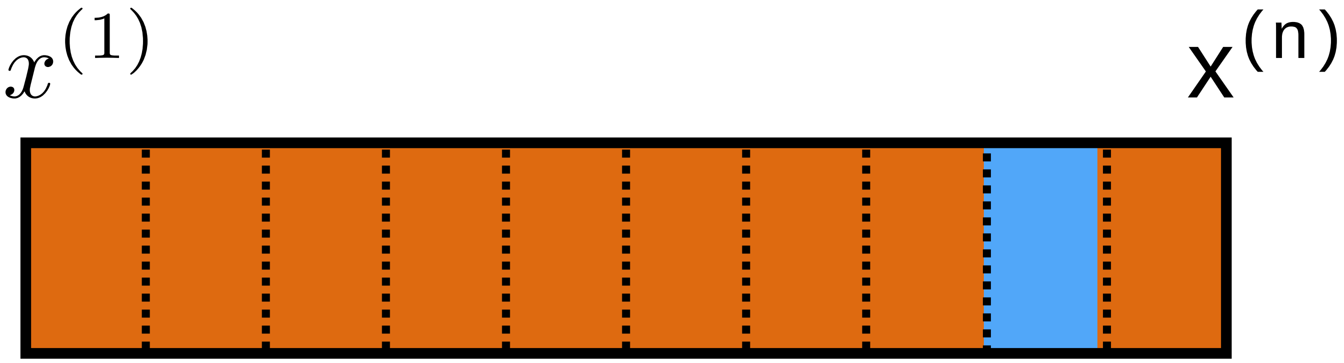

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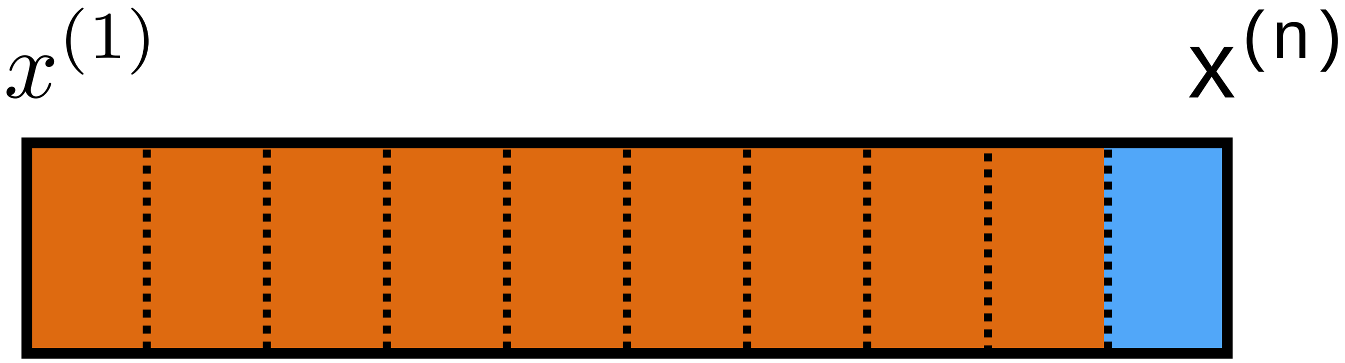

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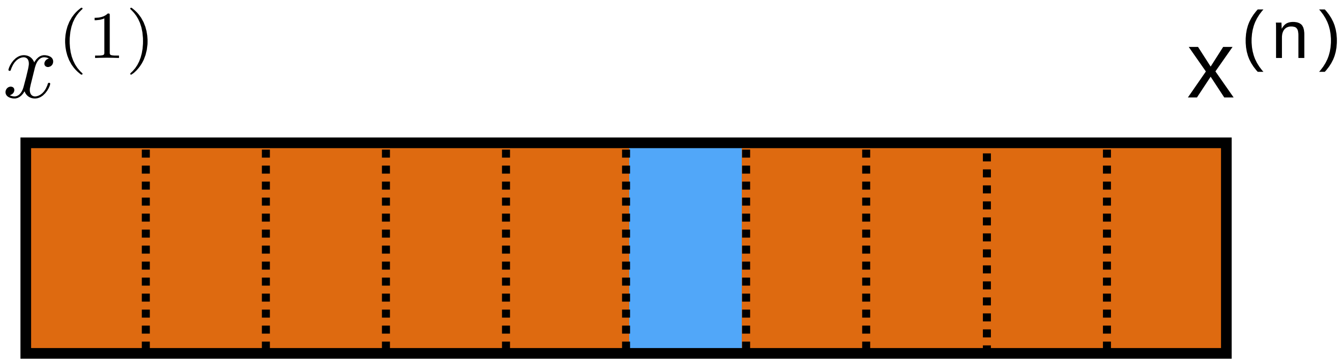

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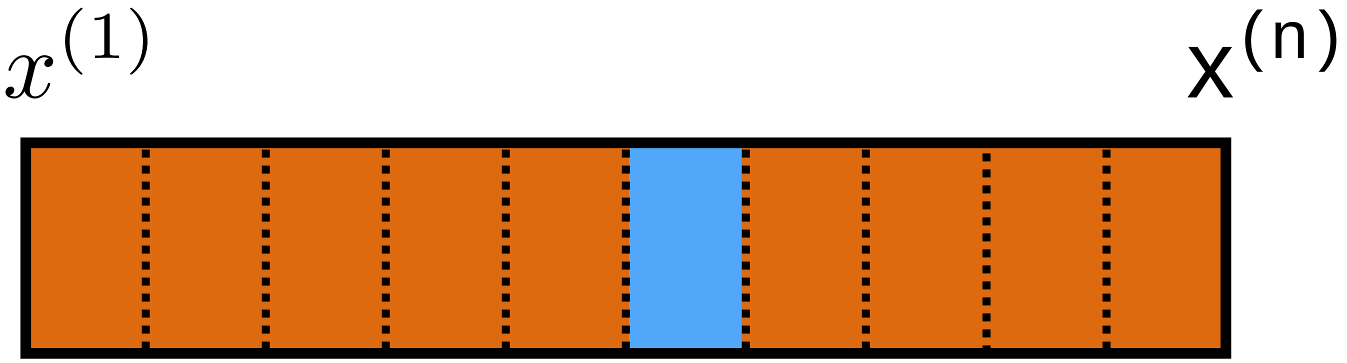

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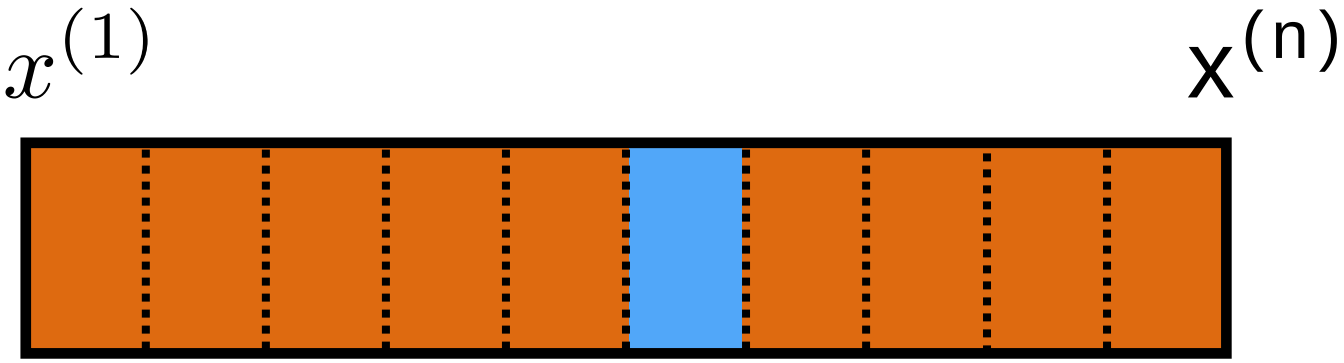

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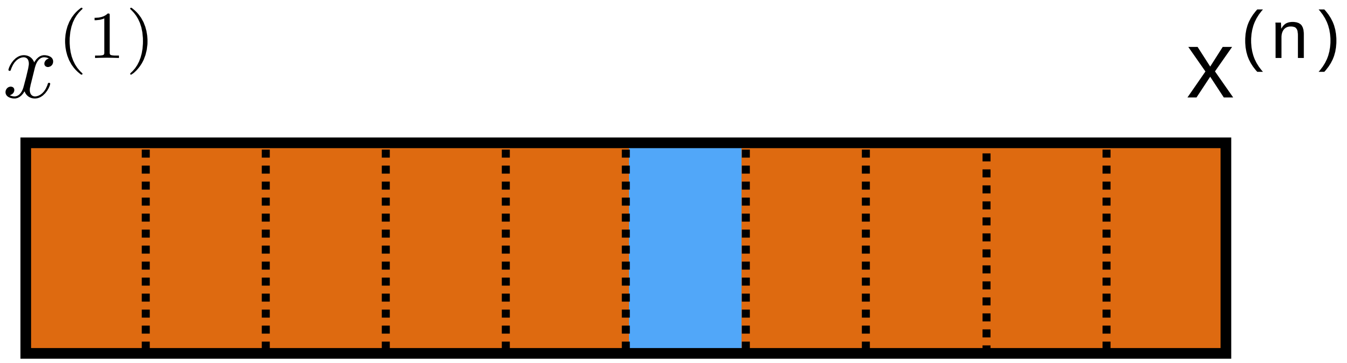

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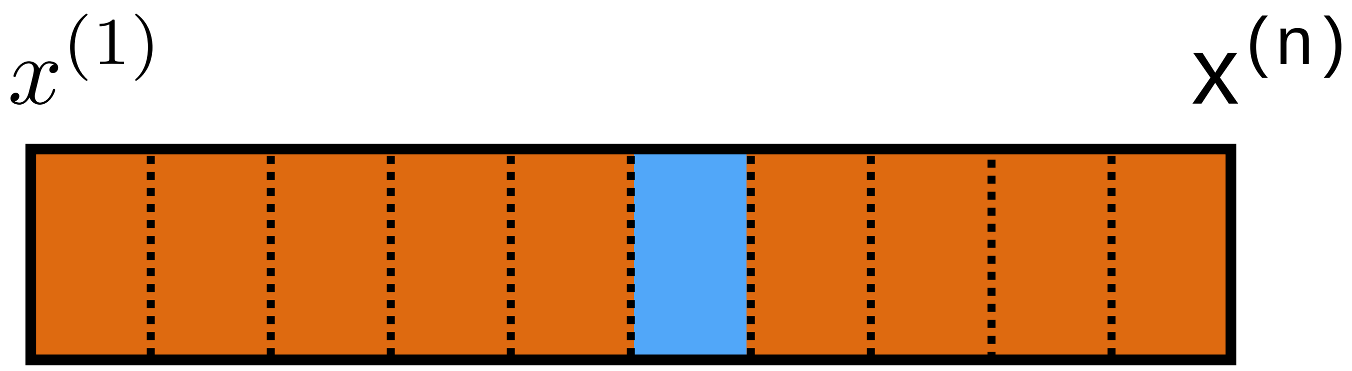

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- Again, good idea to shuffle order of data first

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