

Support Vector Machines



Algorithm

- Trade off



Example

Mass



Lets starts by imagining we measured mass of people of employees who are obese



Example

Age

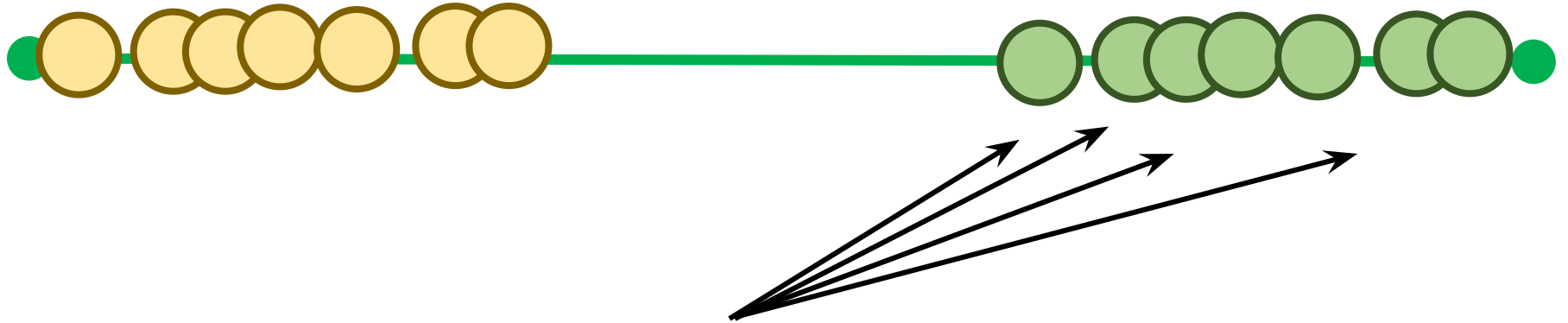


Yellow represent people who are not obese



Example

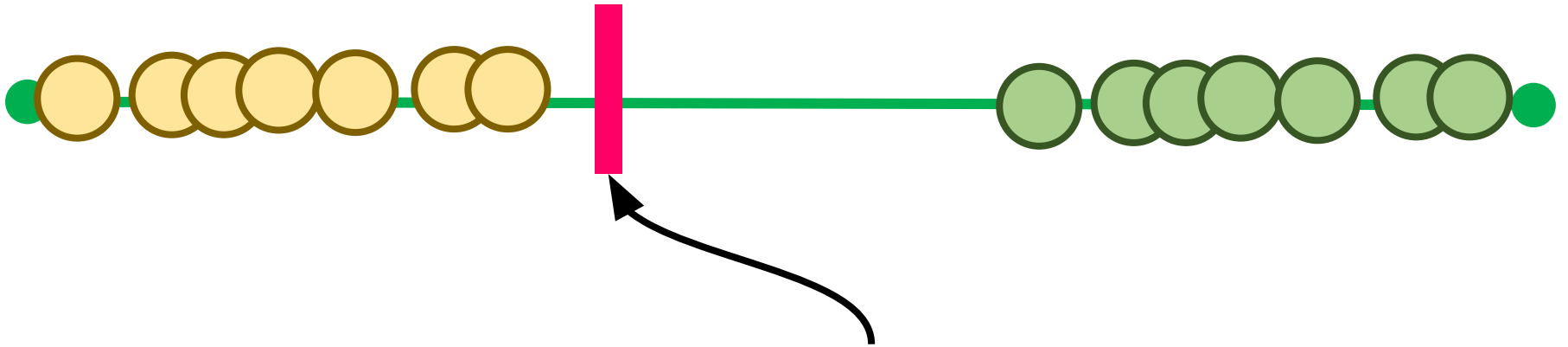
Age



Green represent people who
are obese



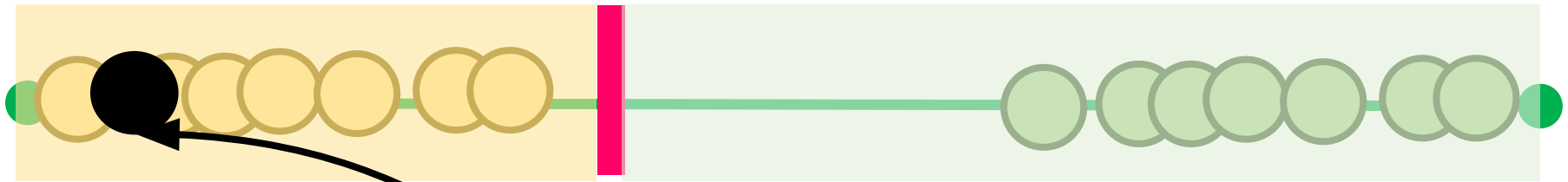
Example



- Based on the observation we can pick a threshold



Case-1



- For a new observation on left side of the threshold point ?



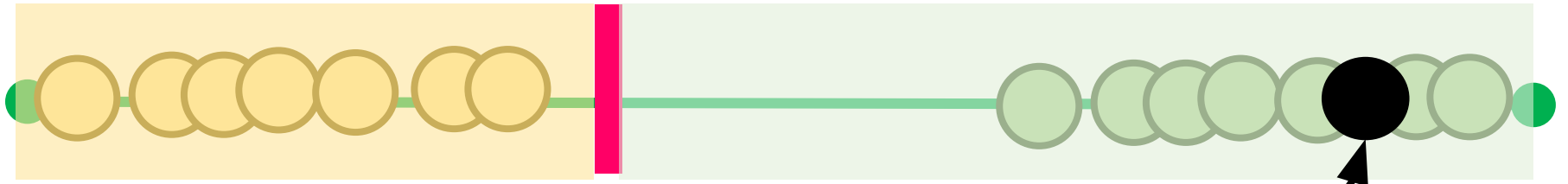
Case-1



- We can classify it as not obese



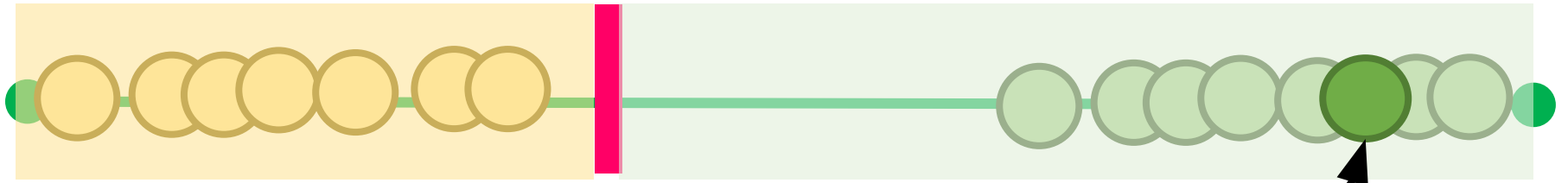
Case-2



- For a new observation on right side or more mass than the threshold point ?



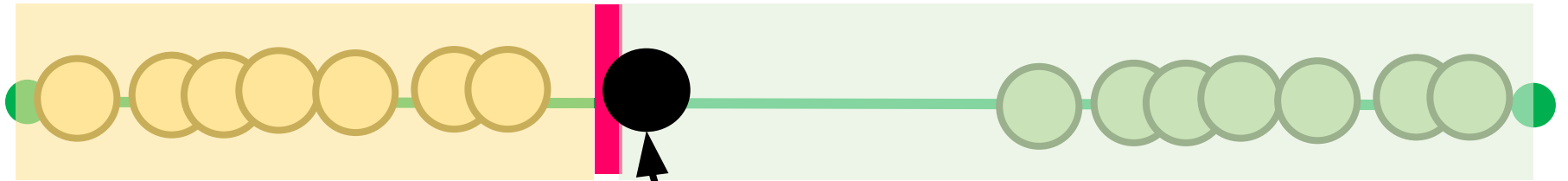
Case-2



- We can classify as “obese”



Case-3



- What if let's say new mass came just above the threshold mass ??



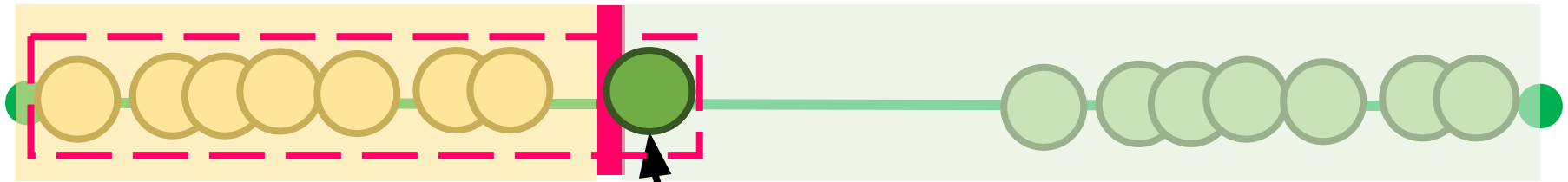
Case-3



- It is classify as "obese"



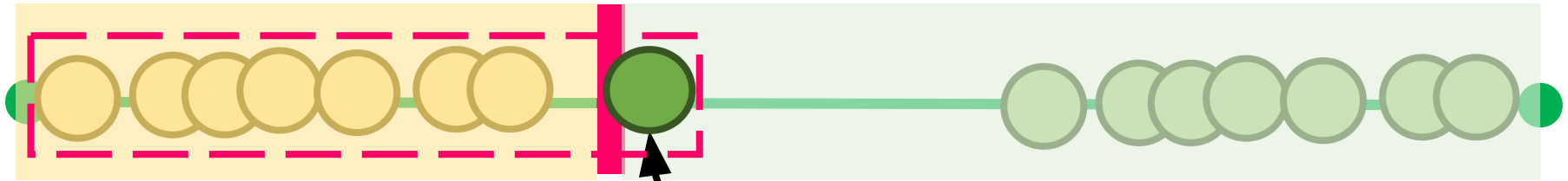
Case-3



- It is classify as "obese"
- It doesn't make sense, because it is much closer to the observation that are **not obese**



Case-3

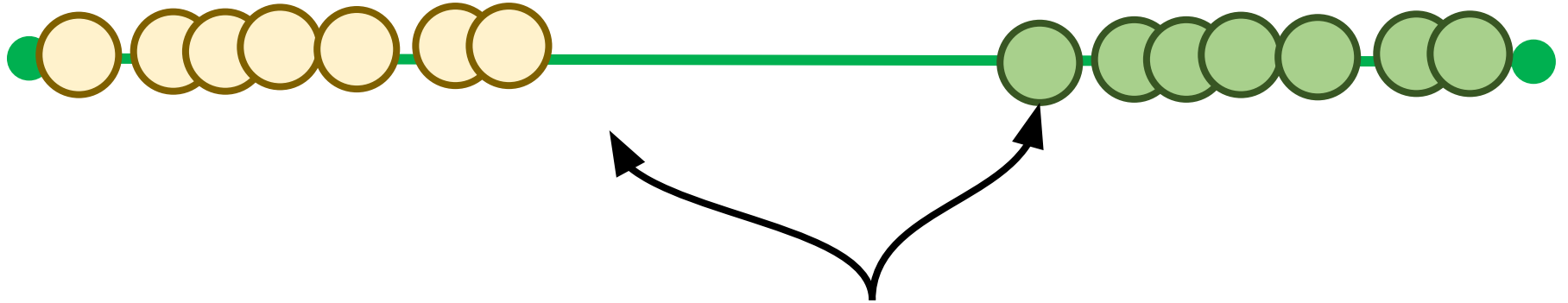


- So, this threshold is lame

Can we do better ??



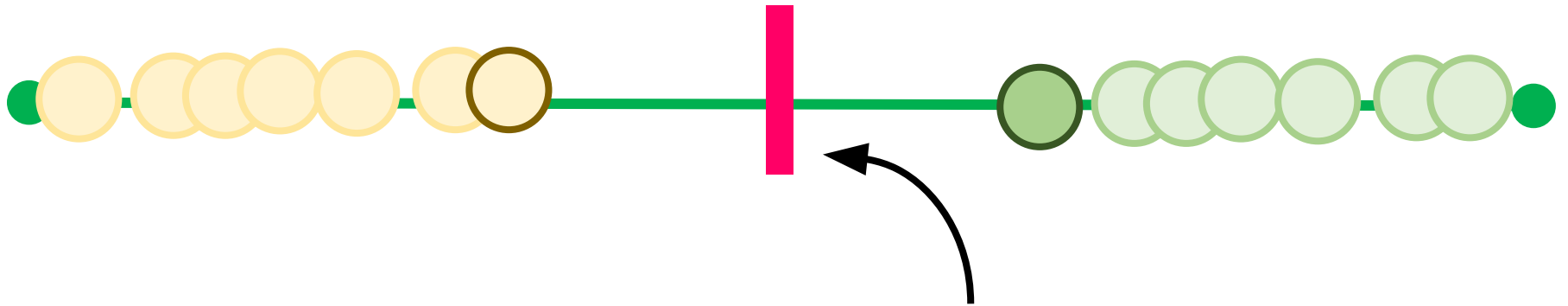
Remedy



We will focus on the observations on the edges of each cluster



Remedy

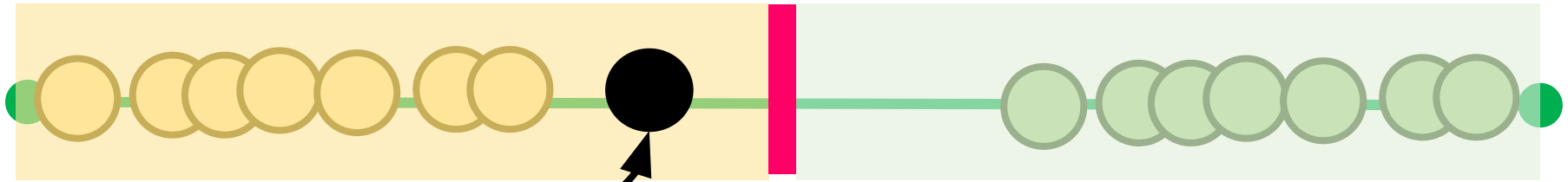


Use mid point between them as threshold

- ✓ select a threshold such a way that it should have equidistant from the vector to allow maximum margin



Case-3

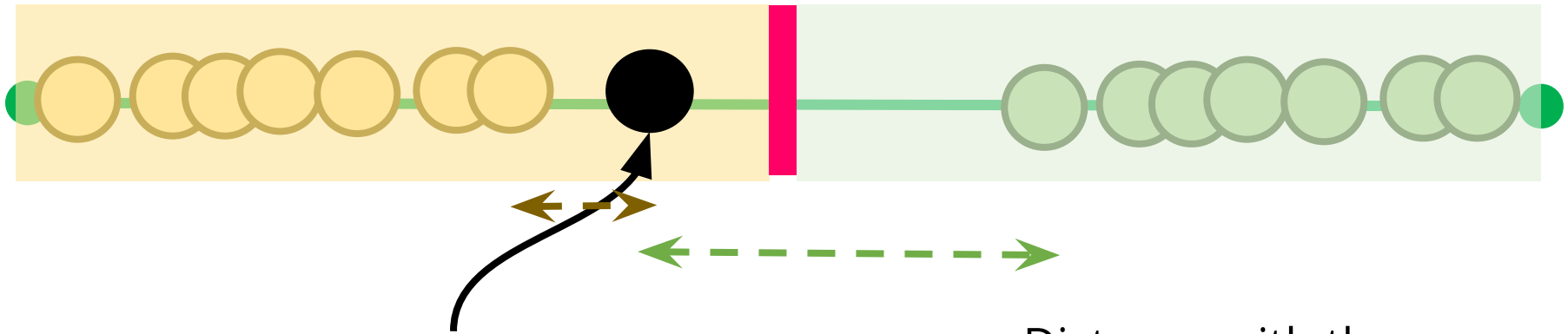


- What if let's say new mass came just above the threshold mass??

- Distance with the edge of not obese is less



Case-3

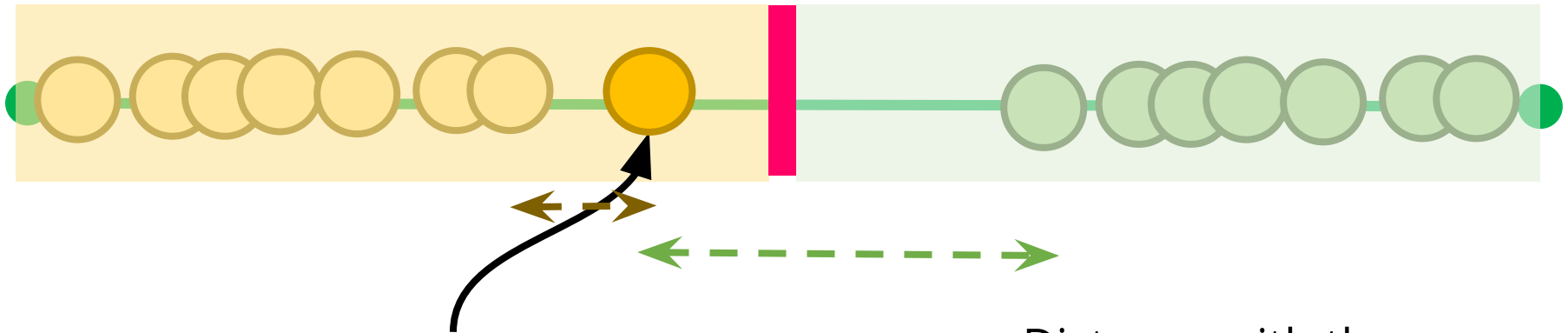


- What if let's say new mass came just above the threshold mass ??

- Distance with the edge of not obese is less than the distance for having a obese hence it will classify as "not obese"



Case-3

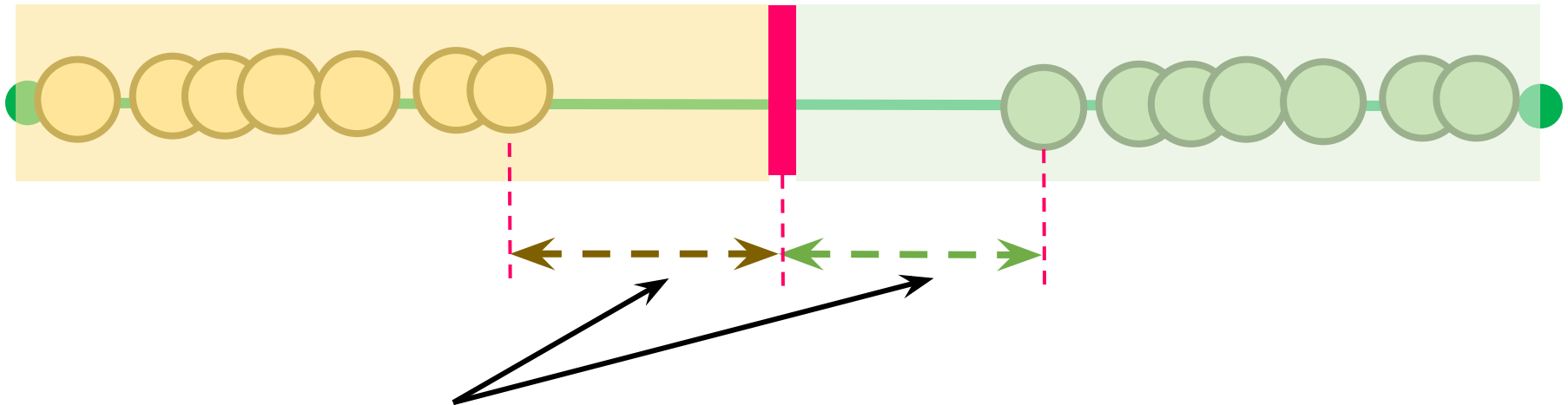


- Classify as “not obese”

- Distance with the edge of not obese is less than the distance for having obese hence it will classify as “not obese”



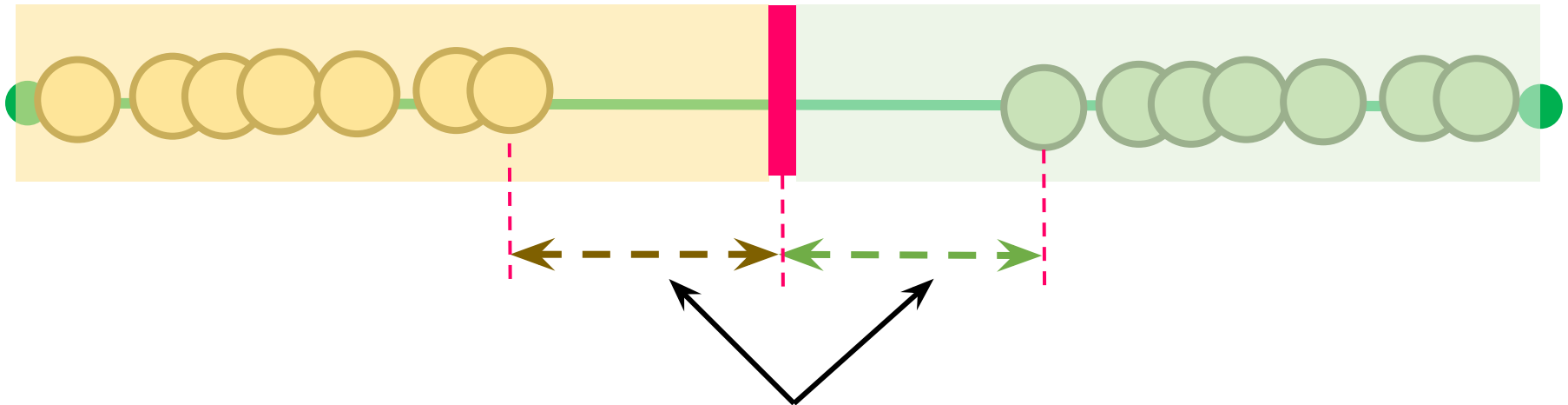
Terminology



- The shortest distance between the observations and threshold is called **margin**



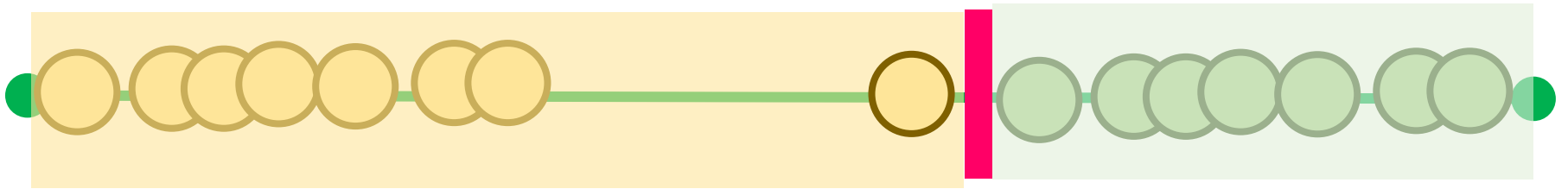
Terminology



- When we are using the threshold that gives us the largest margin to make classification is called **Maximum Margin Classifier**



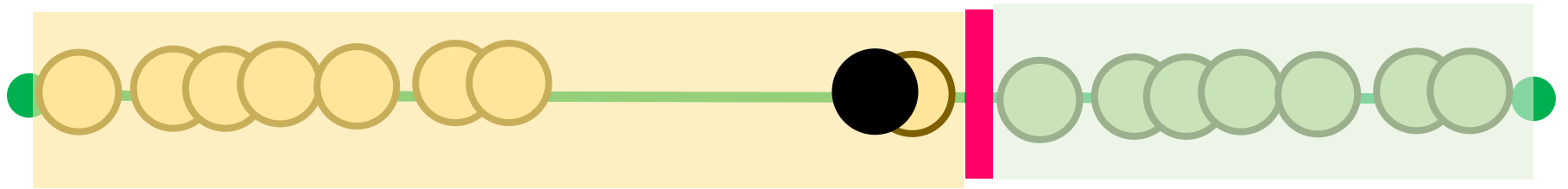
Case-4



- **Maximum Margin Classifier**, create a margin between two closest points



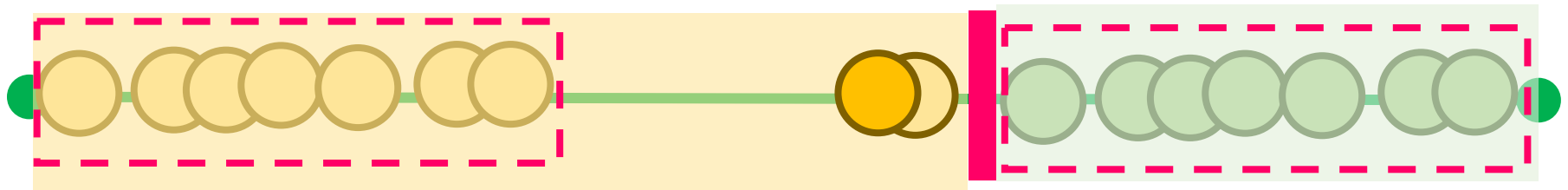
Case-4



- Maximum Margin Classifier classifies this points a “not obese”
- ❖ Note: most of the green points are closes to the predictor.



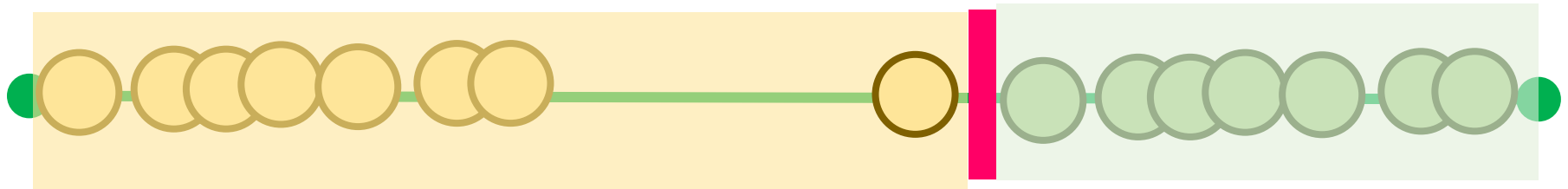
Case-4



- Maximum Margin Classifier classifies this points a “not obese”
- ❖ Note: most of the green points are closes to the predictor.



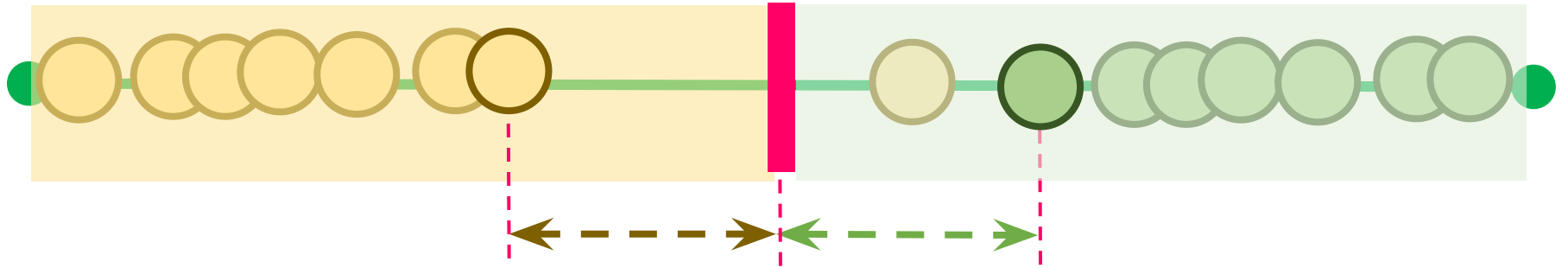
Case-4 - Remedy



- **Threshold should not so sensitive to outlier**
 - ✓ **Allow misclassifications.**



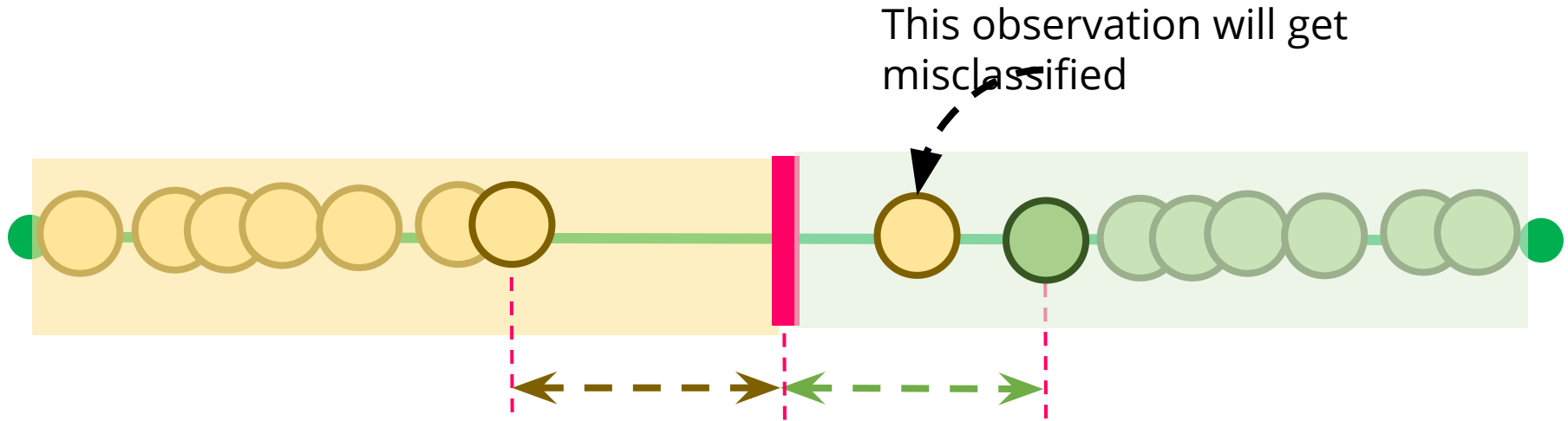
Case-4 - Solution



- If you put threshold halfway between these two observations



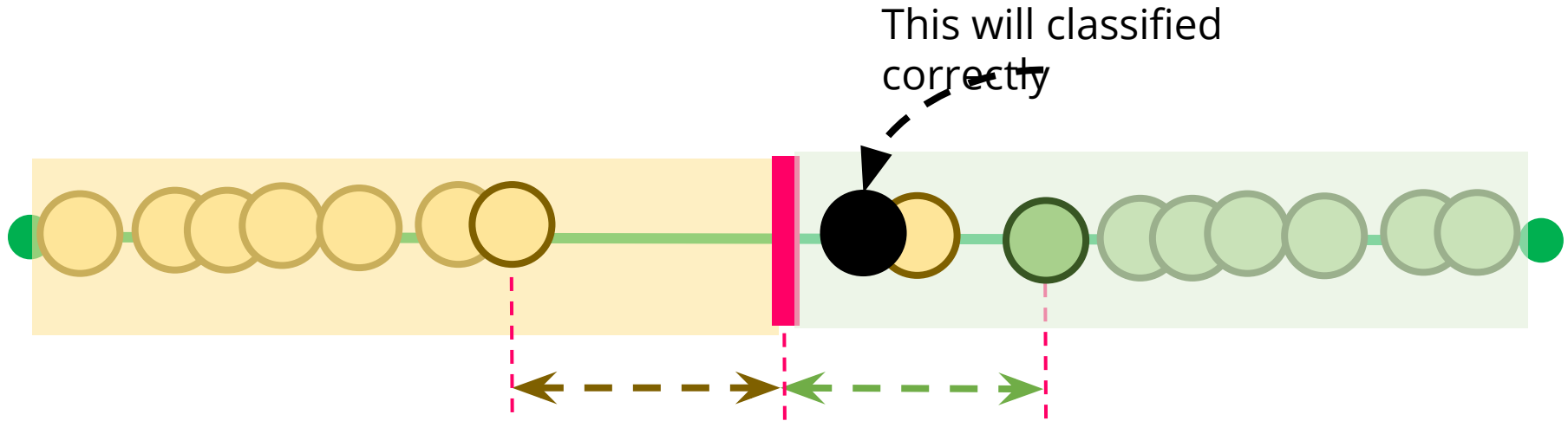
Case-4 - Solution



- Few observation might get misclassified



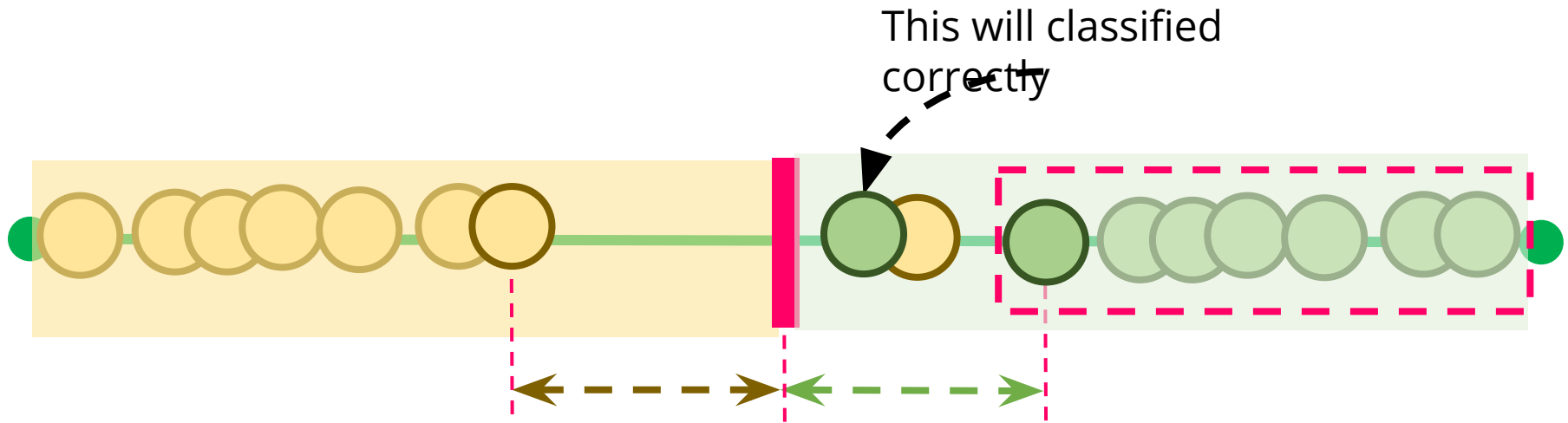
Case-4 - Solution



- For new observation it will classify correctly



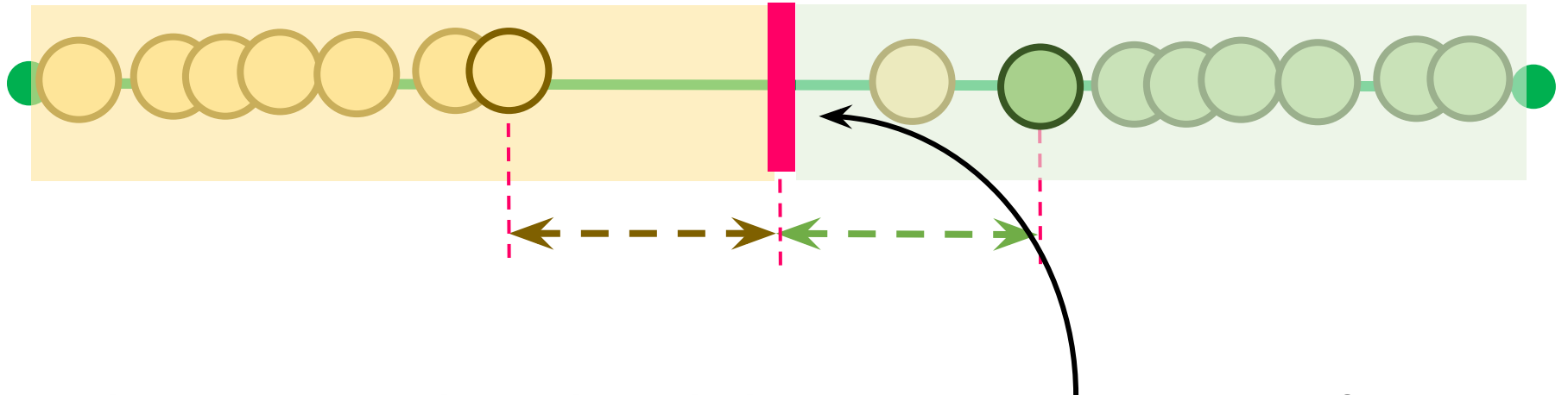
Case-4 - Solution



- For new observation it will classify correctly



Case-4 - Solution



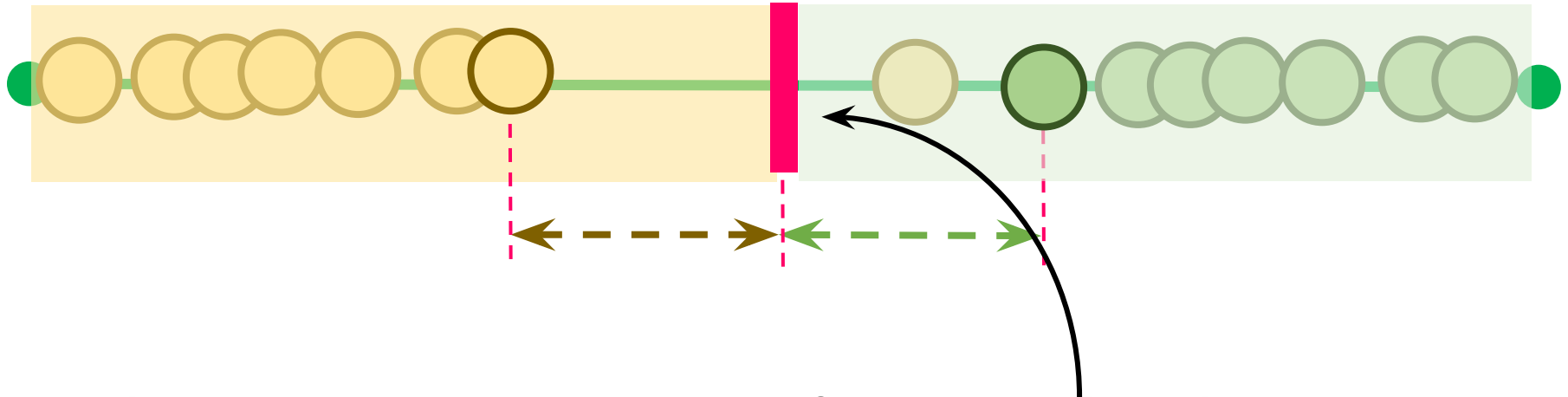
- Choosing a threshold that allows misclassification is an example of Bias/Variance Tradeoff



Soft Margin



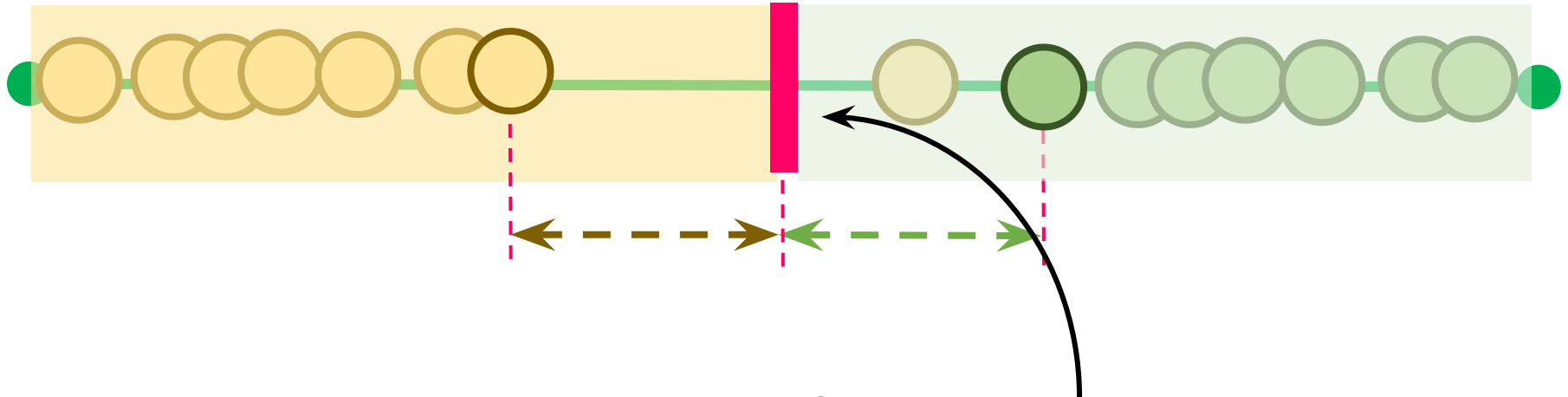
Soft Margin



- When we allow misclassification, the distance between the observations and the threshold is called **Soft Margin**



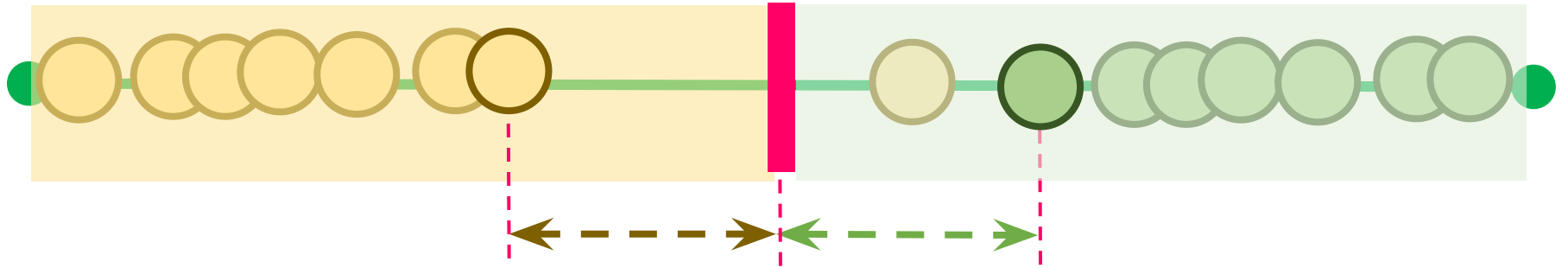
Soft Margin



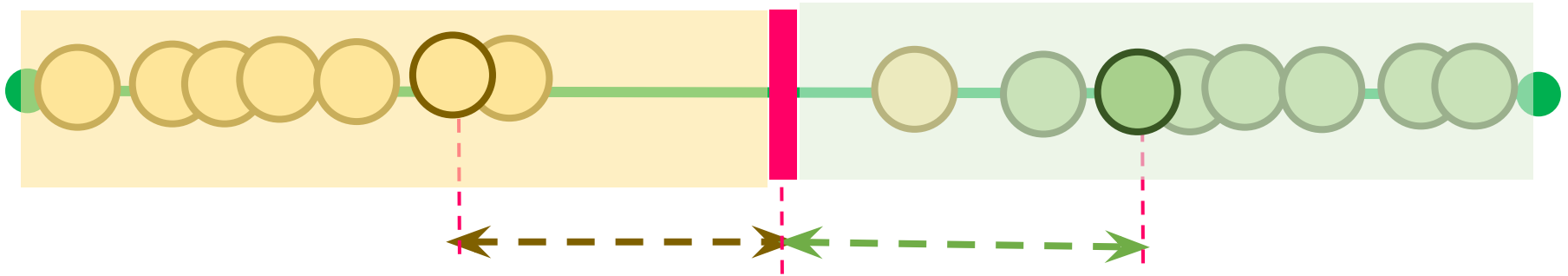
- When we allow misclassification, the distance between the observations and the threshold is called **Soft Margin**



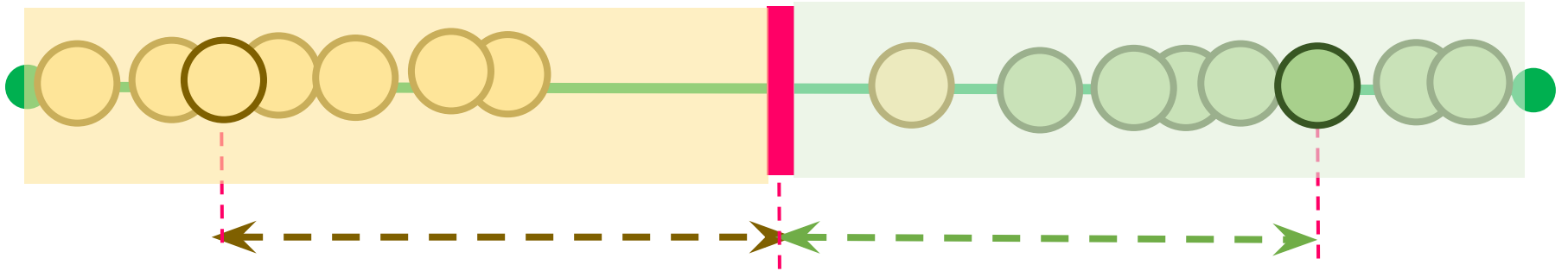
How to determine Soft Margin



How to determine Soft Margin



How to determine Soft Margin

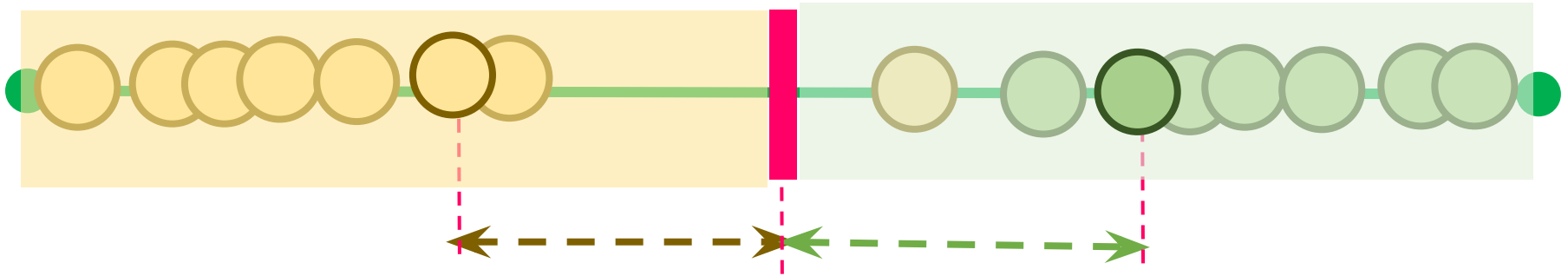


How to determine Soft Margin

- We use Cross Validation to determine how many misclassifications and observations to allow inside of the Soft Margin to get the best classification.



Cross Validation for Soft Margin



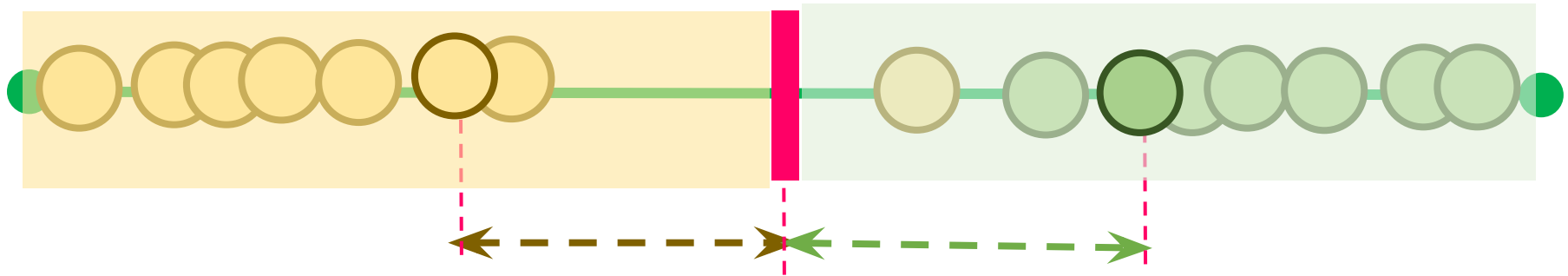
- If Cross Validation determined that it was the best Soft Margin.
 - There will be one misclassified
 - Two observation will be correctly classified to be within the **soft margin**.



Soft Margin Classifier or Support Vector Classifier



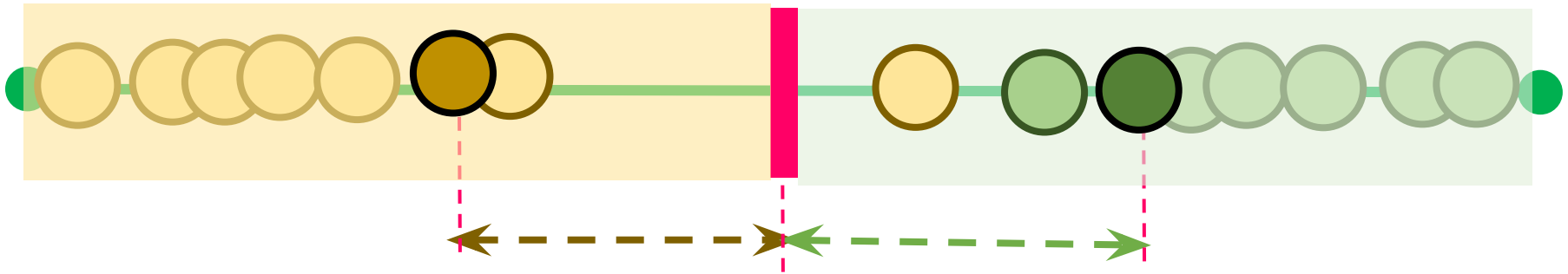
Soft Margin Classifier



- When we use a Soft Margin to determine the location of a threshold which is called Soft Margin Classifier also known as Support Vector Classifier to classify observation.



Soft Margin Classifier



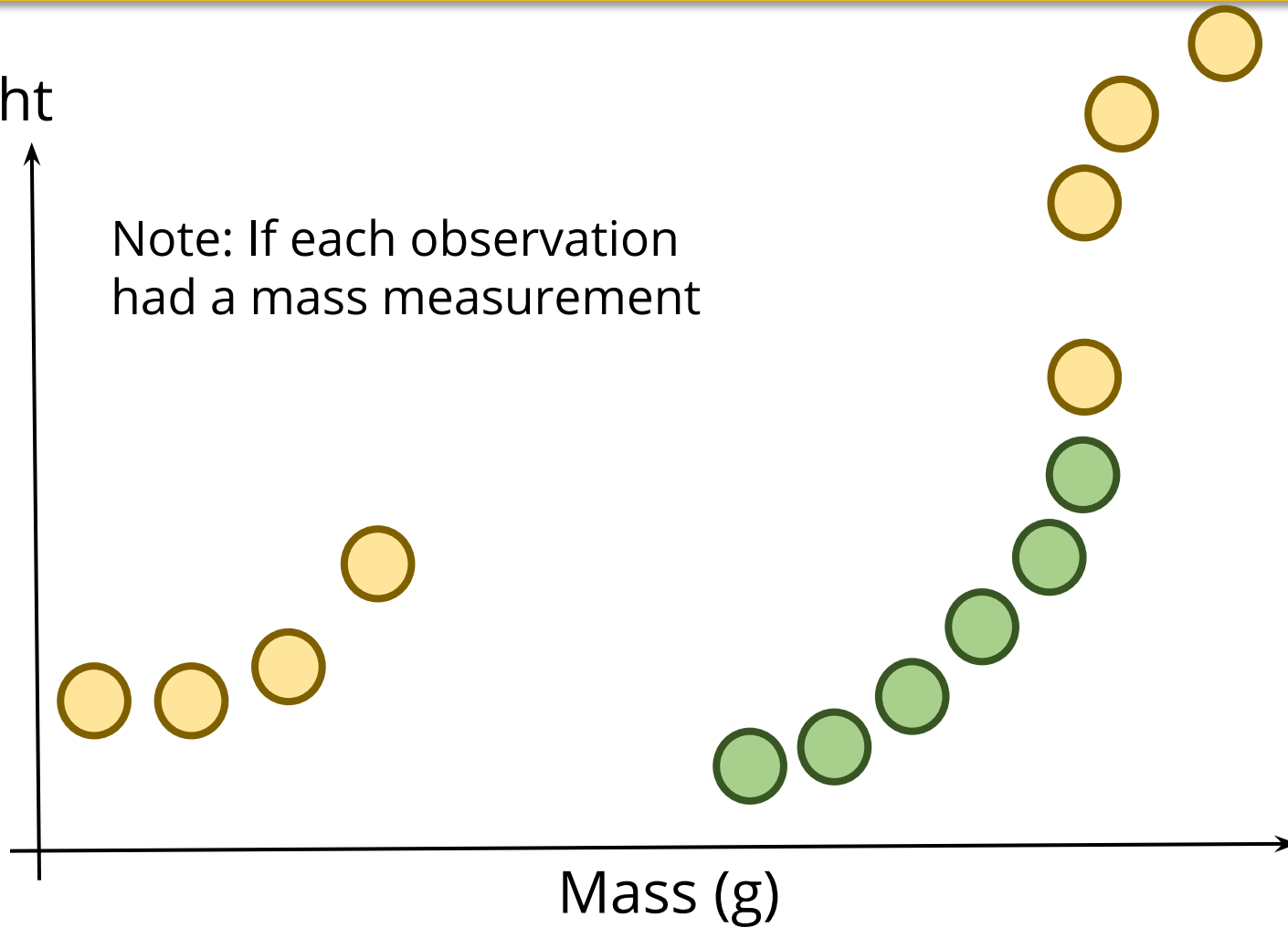
- The name Support Vector Classifier comes from the fact that the observations on the edge and within the **Soft Margin** are called **Support Vectors**



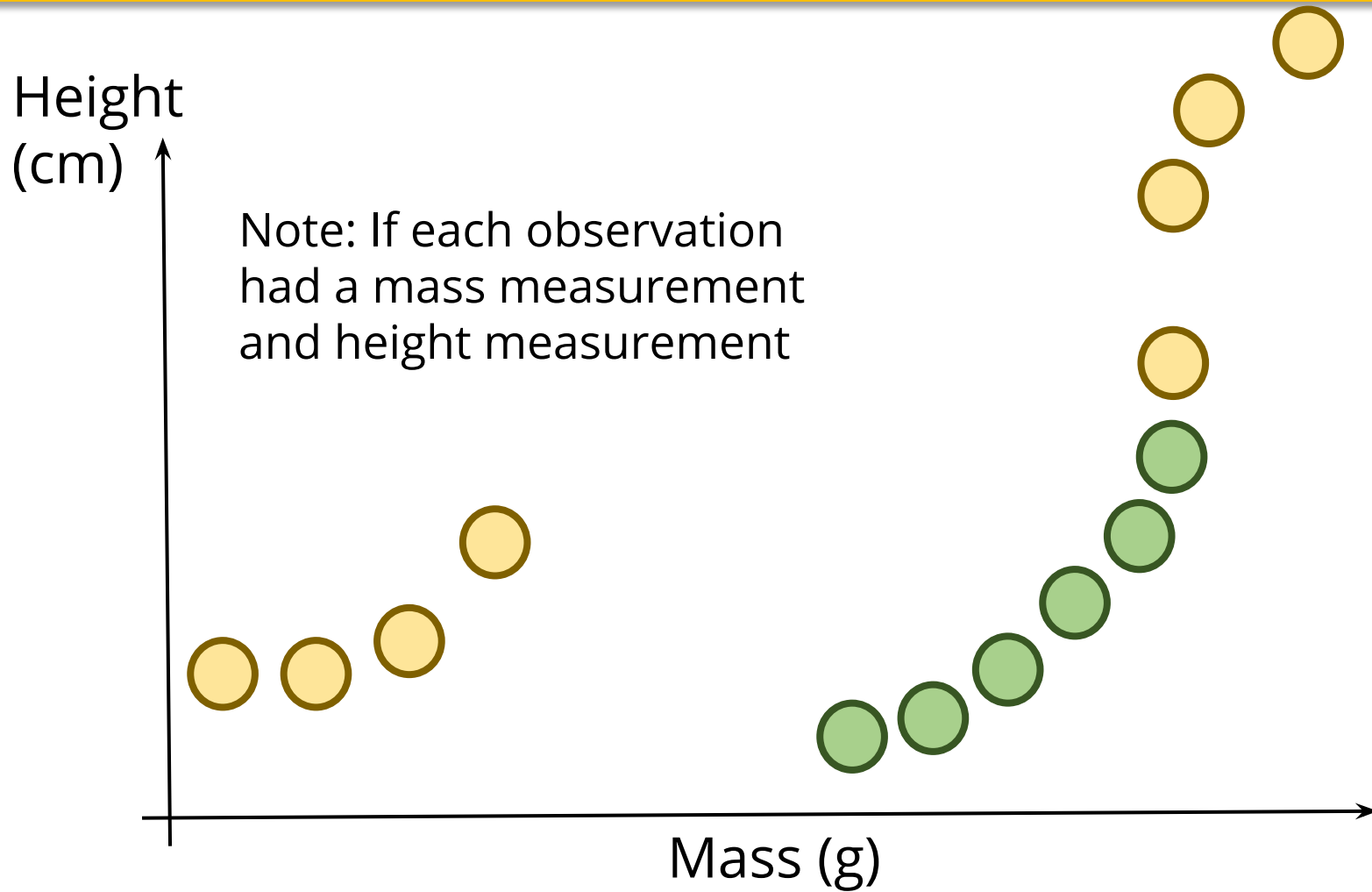
2D

Height
(cm)

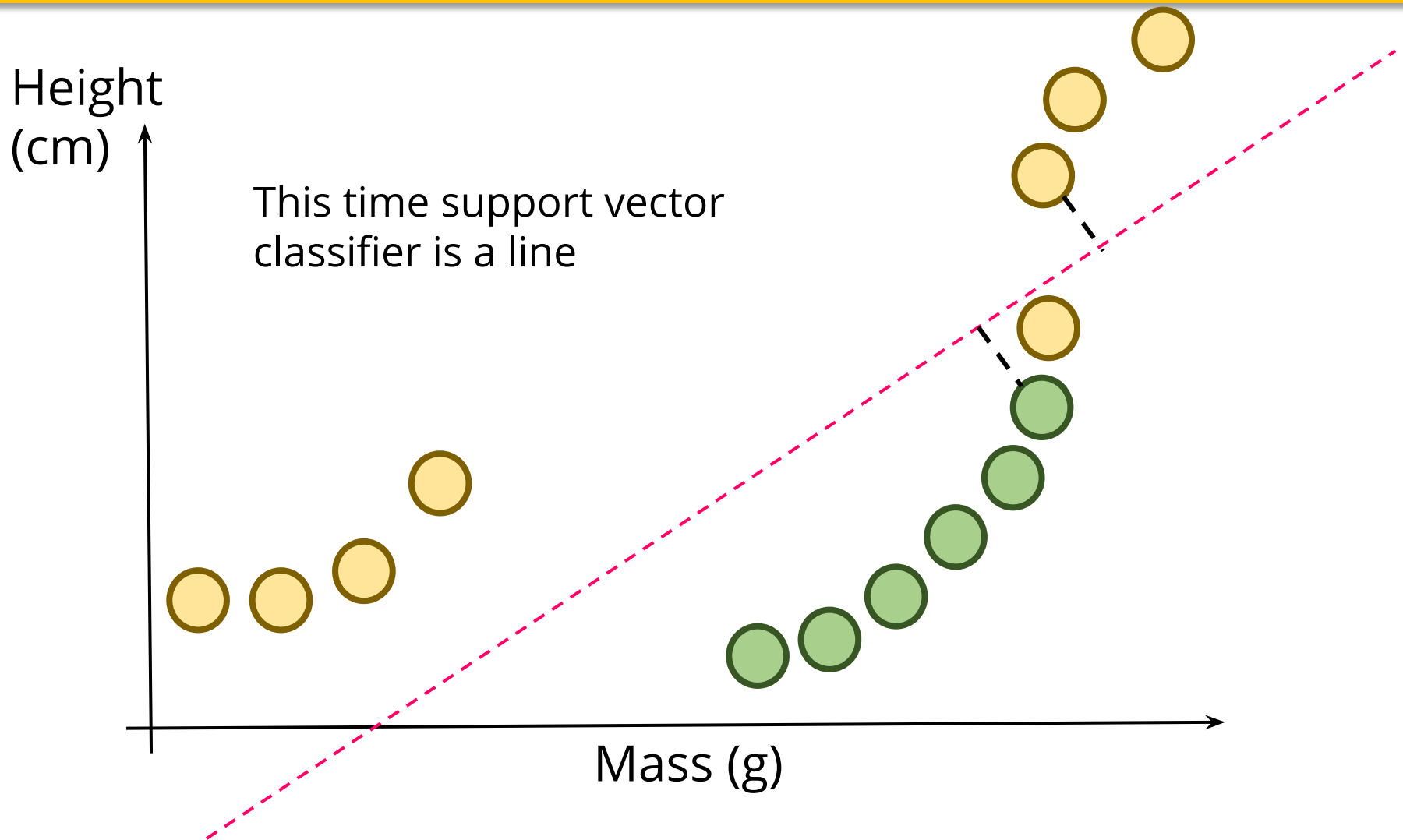
Note: If each observation
had a mass measurement



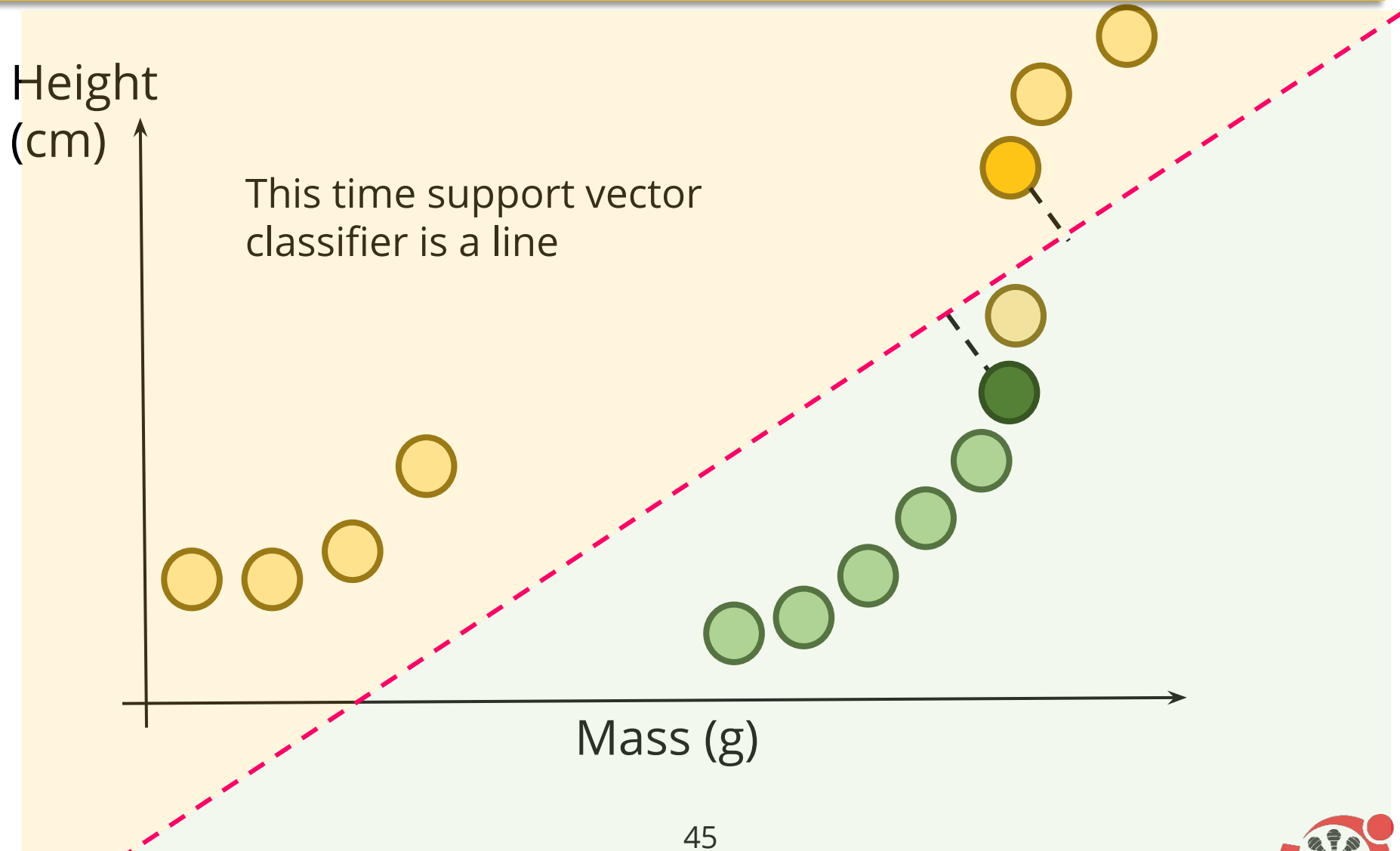
2-Dimension Data



2-Dimension Data



2-Dimension Data



2-Dimension Data

Height
(cm)

and, in this case, the Soft
Margin is measure from
these two points.

Mass (g)

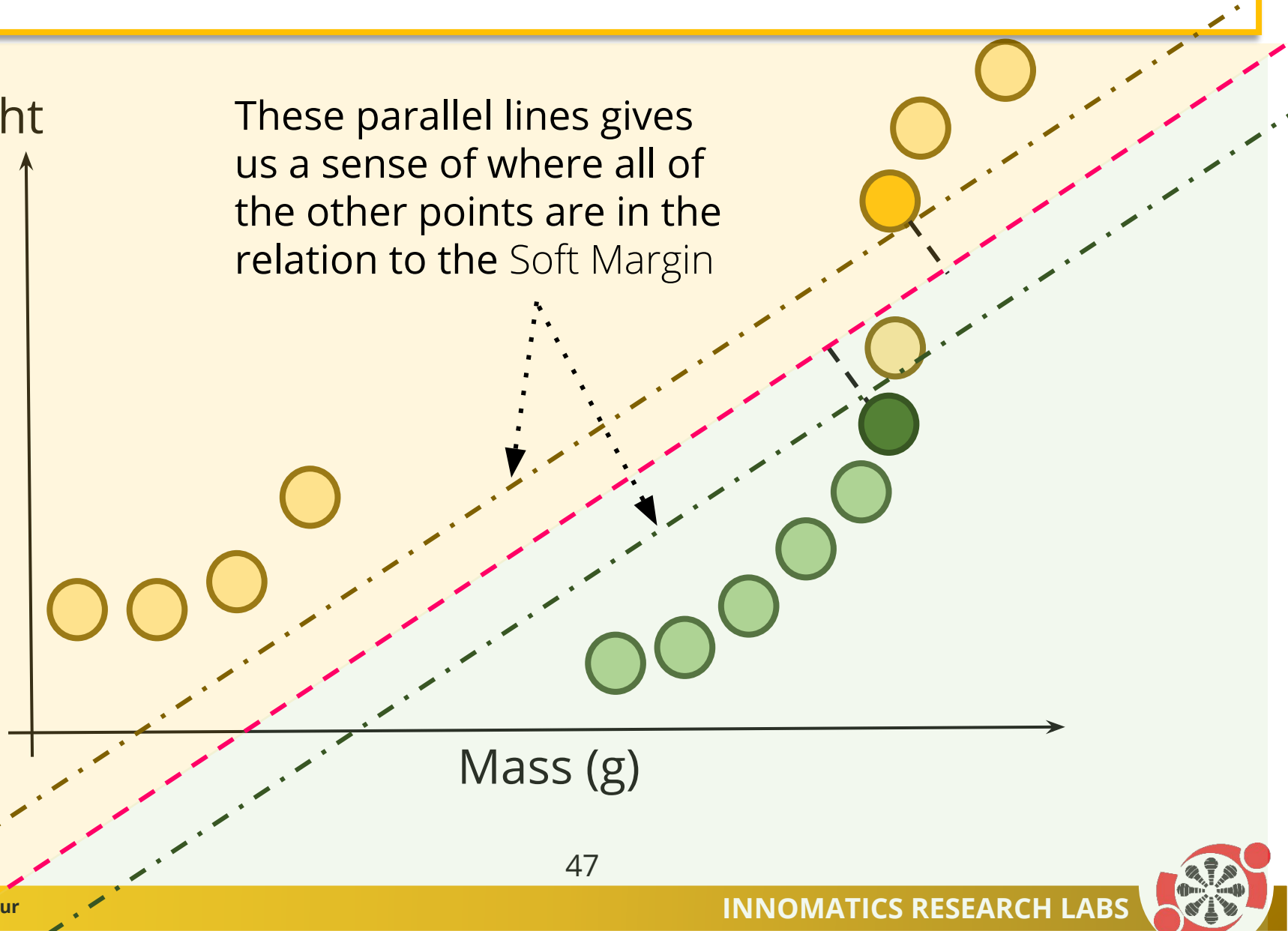
46



2-Dimension Data

Height
(cm)

These parallel lines gives
us a sense of where all of
the other points are in the
relation to the Soft Margin



2-Dimension Data

Height (cm)

These observation are outside the Soft Margin

Mass (g)

48



2-Dimension Data

Height (cm)

These observation are inside the Soft Margin and misclassified

Mass (g)

49



Support Vector Classifiers

- Support Vector Classifiers seem pretty cool because they can handle outliers.
- They allow misclassifications, they can handle overlapping classifications.



Case-5

Dosage
(mg)



Yellow : Drug Not Cured

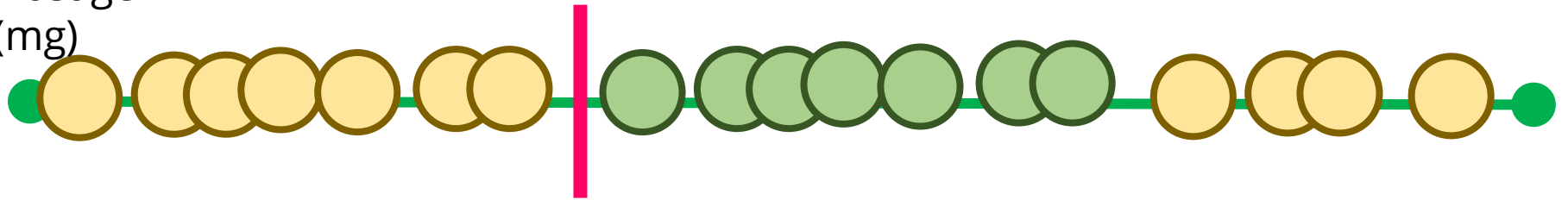
Green: Drug Cured

- What if this was our training data and we have tons of overlap ?



Case-5

Dosage
(mg)



Yellow : Drug Not Cured

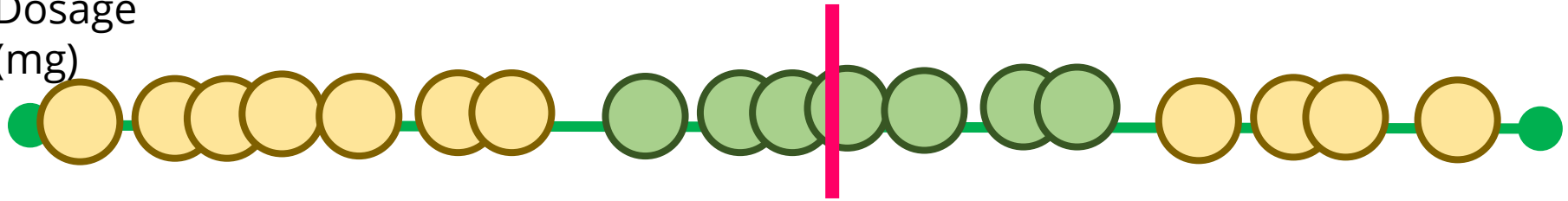
Green: Drug Cured

- Support Vector Classifiers are only semi-cool, since they don't perform well with type of data



Case-5

Dosage
(mg)



Yellow : Drug Not Cured

Green: Drug Cured

- Support Vector Classifiers are only semi-cool, since they don't perform well with type of data



Support Vector Machines



Case -5

- Since Maximal Margin Classifier and Support Vector Classifiers can't handle this data



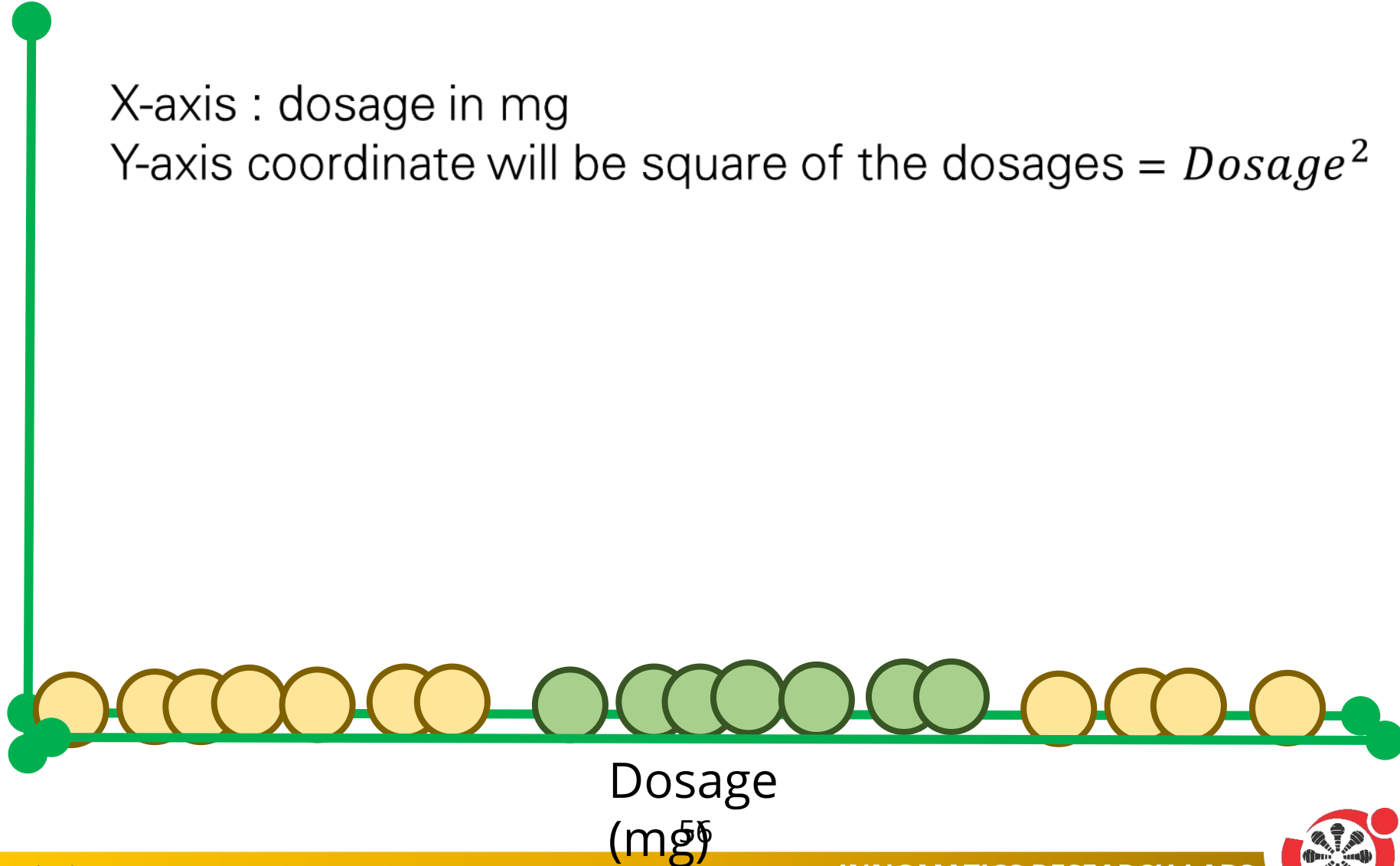
- Let's start by getting get an intuitive sense of the main ideas behind Support Vector Machines



Case-5

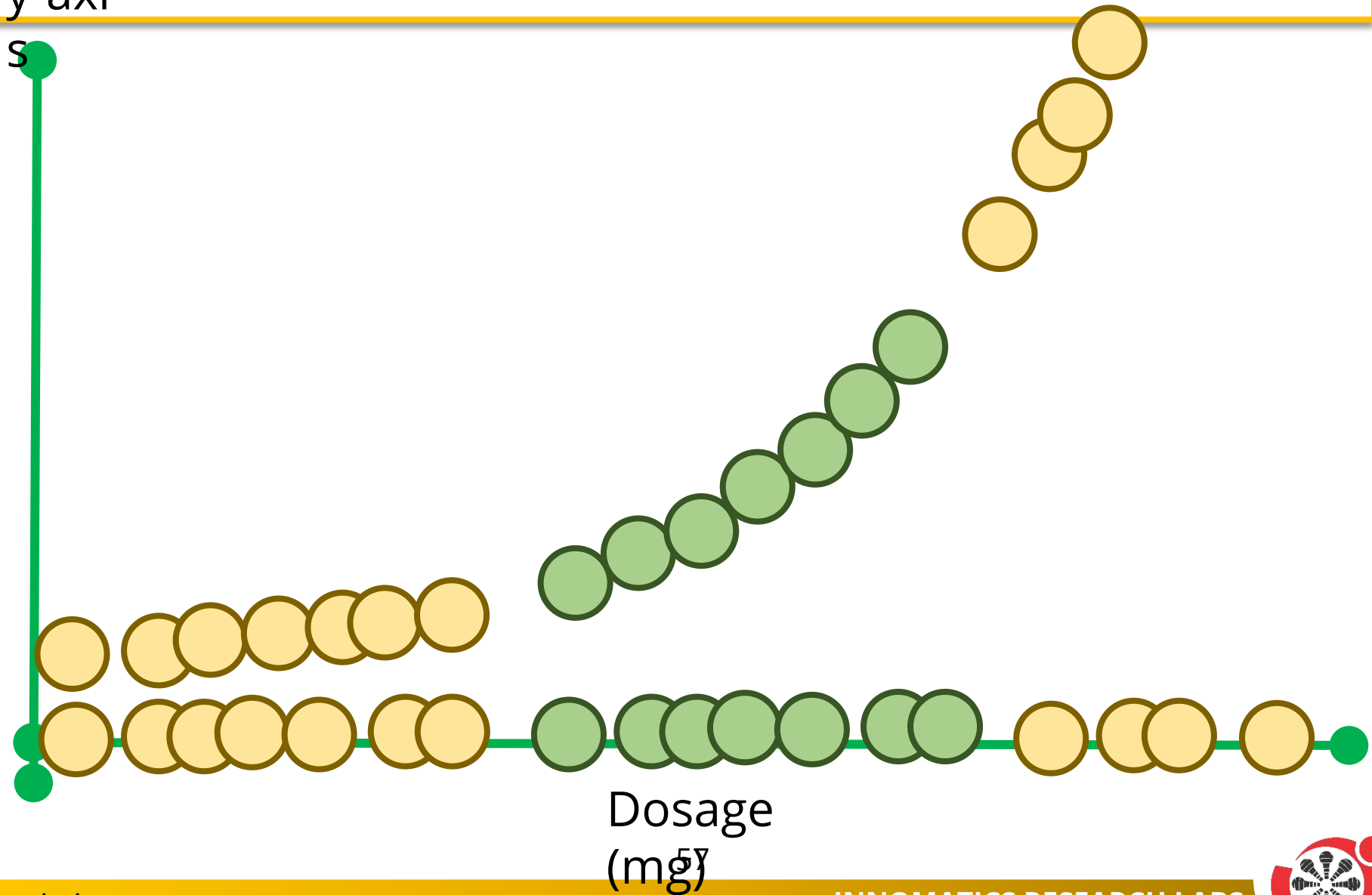
X-axis : dosage in mg

Y-axis coordinate will be square of the dosages = $Dosage^2$



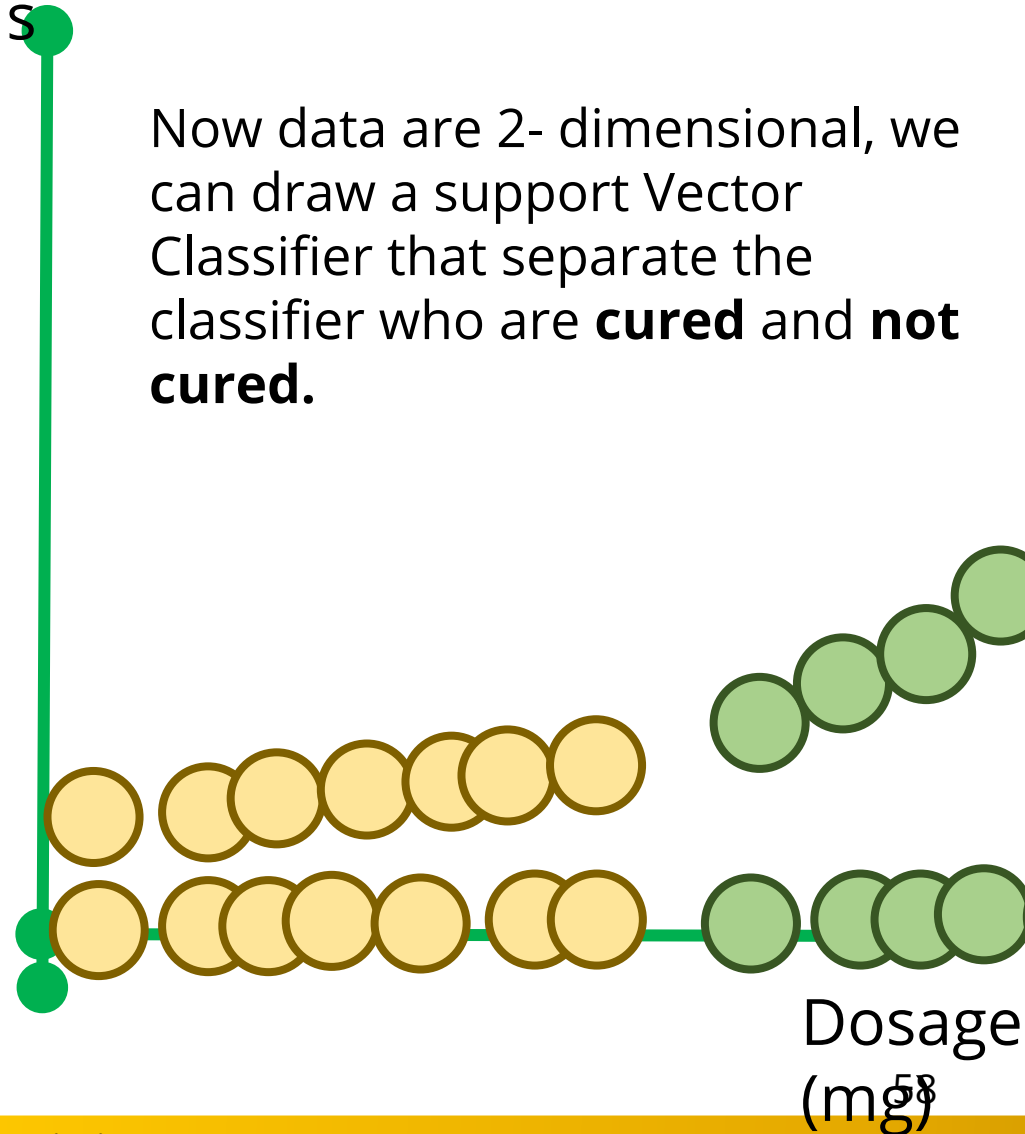
Case-5

y-axi



Case-5

y-axi

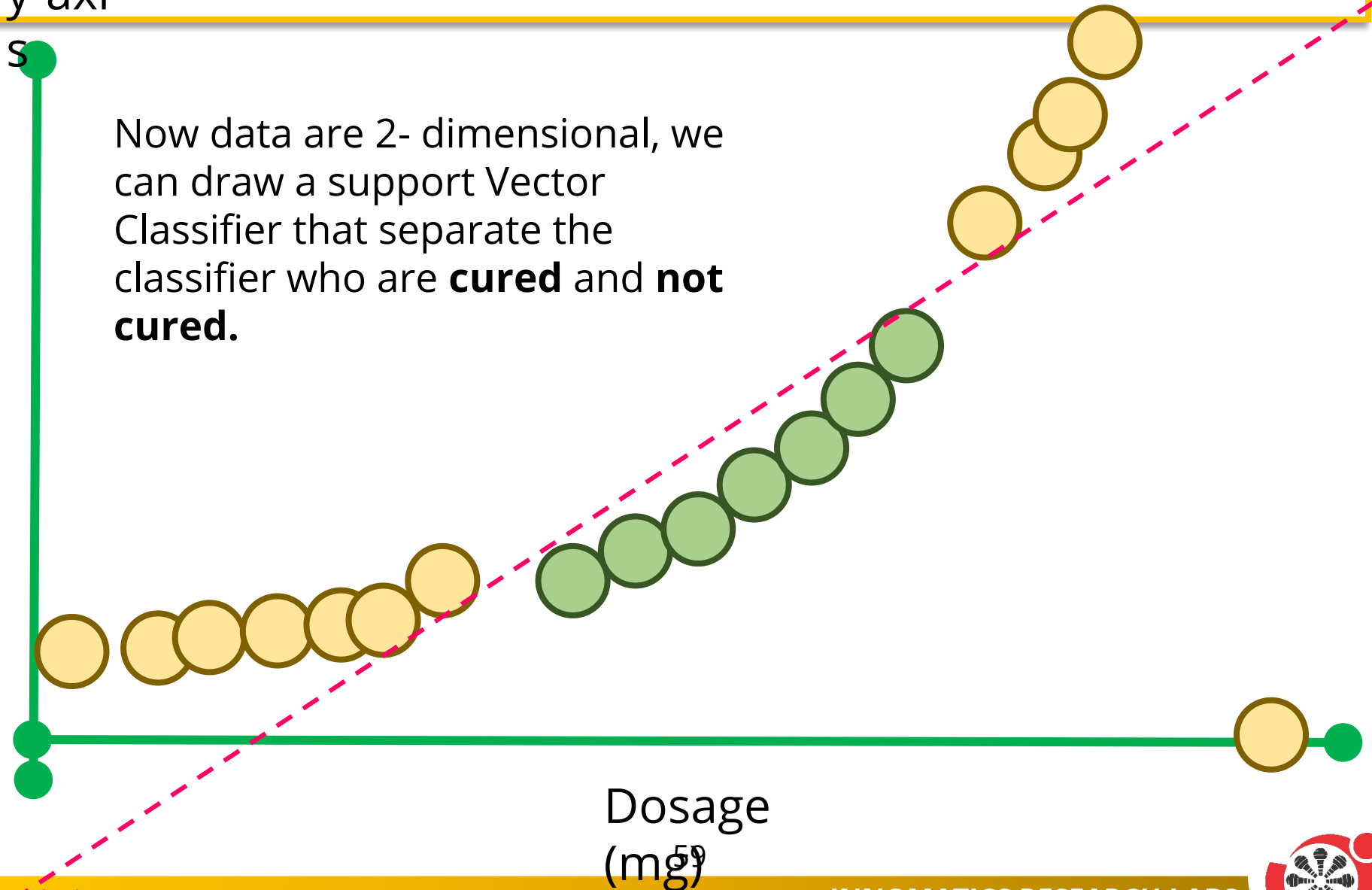


Case-5

y-axi

S

Now data are 2- dimensional, we can draw a support Vector Classifier that separate the classifier who are **cured** and **not cured**.

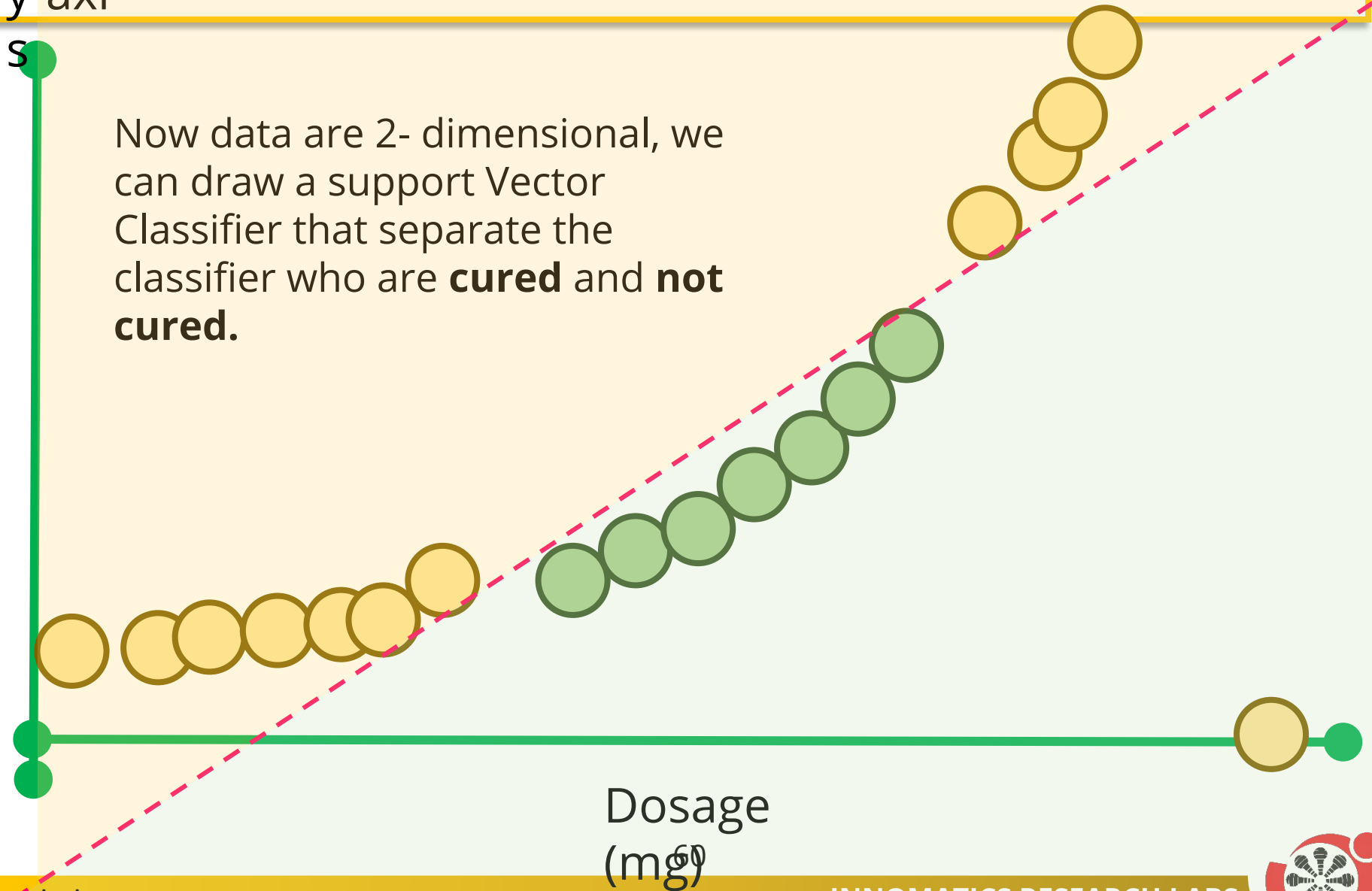


Case-5

y-axi

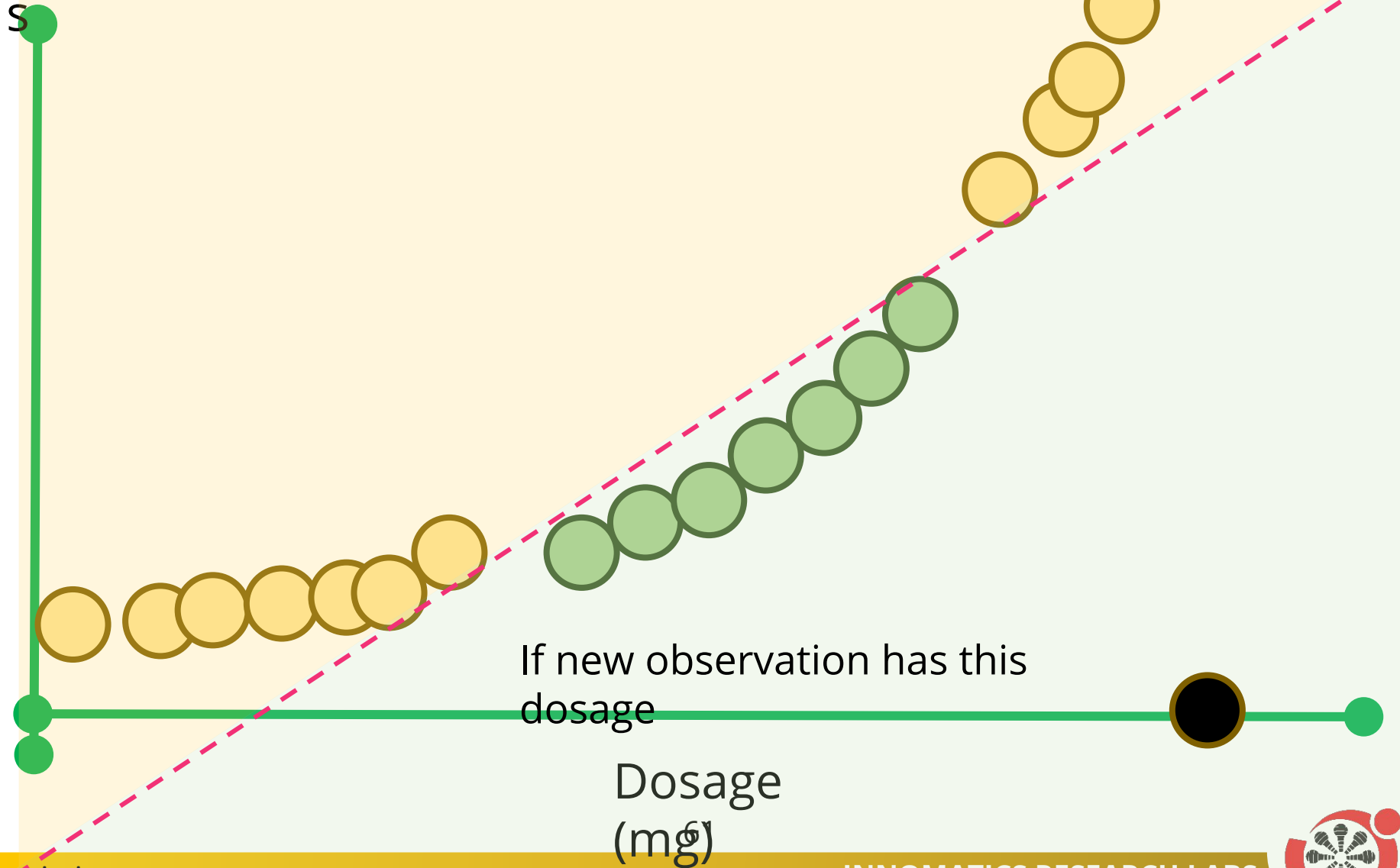
S

Now data are 2- dimensional, we can draw a support Vector Classifier that separate the classifier who are **cured** and **not cured**.



Case-5

y-axi



Case-5

y-axi

S

Classify the observation as not cured.

Square the Dosage

Dosage
(mg)



Support Vector Machines

The main idea of support vector machine is

1. Start with data in a relatively low dimension
2. Move the data into a higher dimension
3. Find a support vector classifier that separate the higher dimension data into two groups



Transform the data ?

- How do we decide how to transform the data ?

To make mathematics possible, Support Vector Machines use something called Kernel Functions to systematically find Support Vector Classifier in higher dimensions.



