

Linear Regression

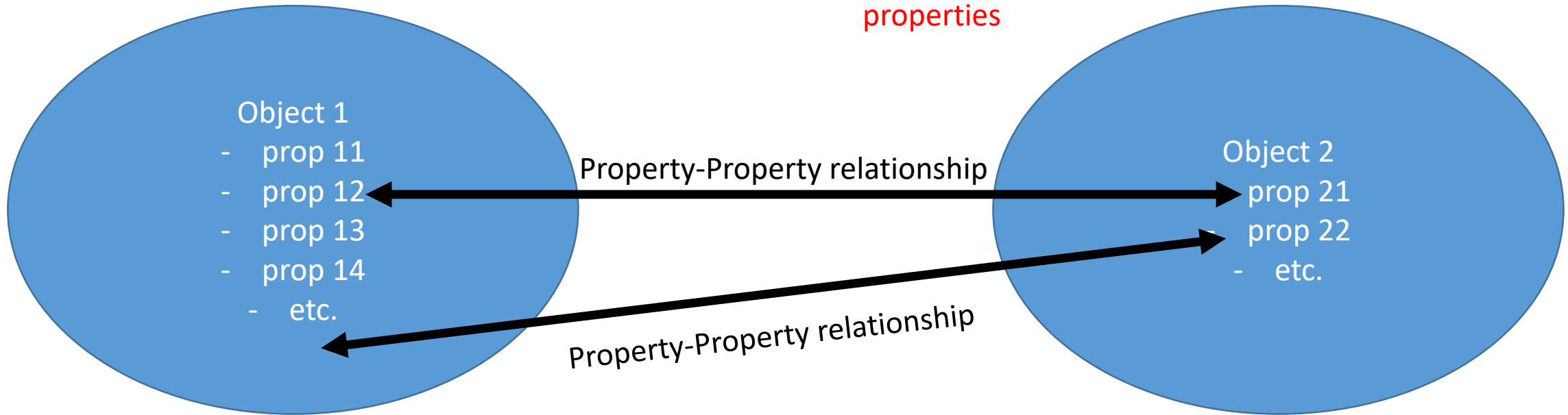
Dr. Kalidas Y., IIT Tirupati

In this lecture you will learn about LOSS Function and SOLVER formulation

Objects can be ANY... literally ANY..! concept in the world!!

(1) Identify objects and properties within each object

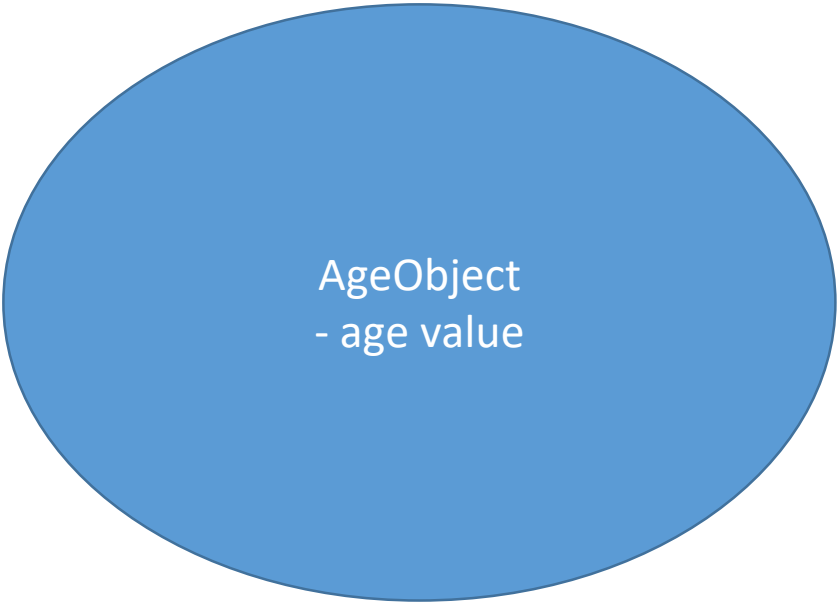
(2) A rough understanding of which properties relate to which other properties



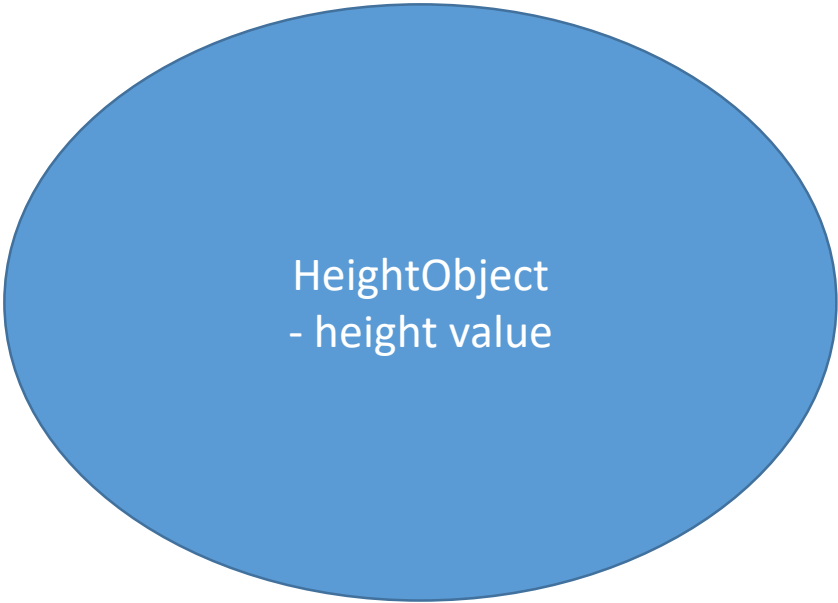
(3) Vector representation of objects

*Convert <noun/pronoun/etc> → <Noun>objects,
e.g. car -> CarObject, he -> PersonObject etc.*

*<verb> → <Verb>-er, <Verb>-able objects,
e.g. walk -> Walk-er or Walk-able, talk -> Talk-er, Talk-able*




AgeObject
- age value



HeightObject
- height value

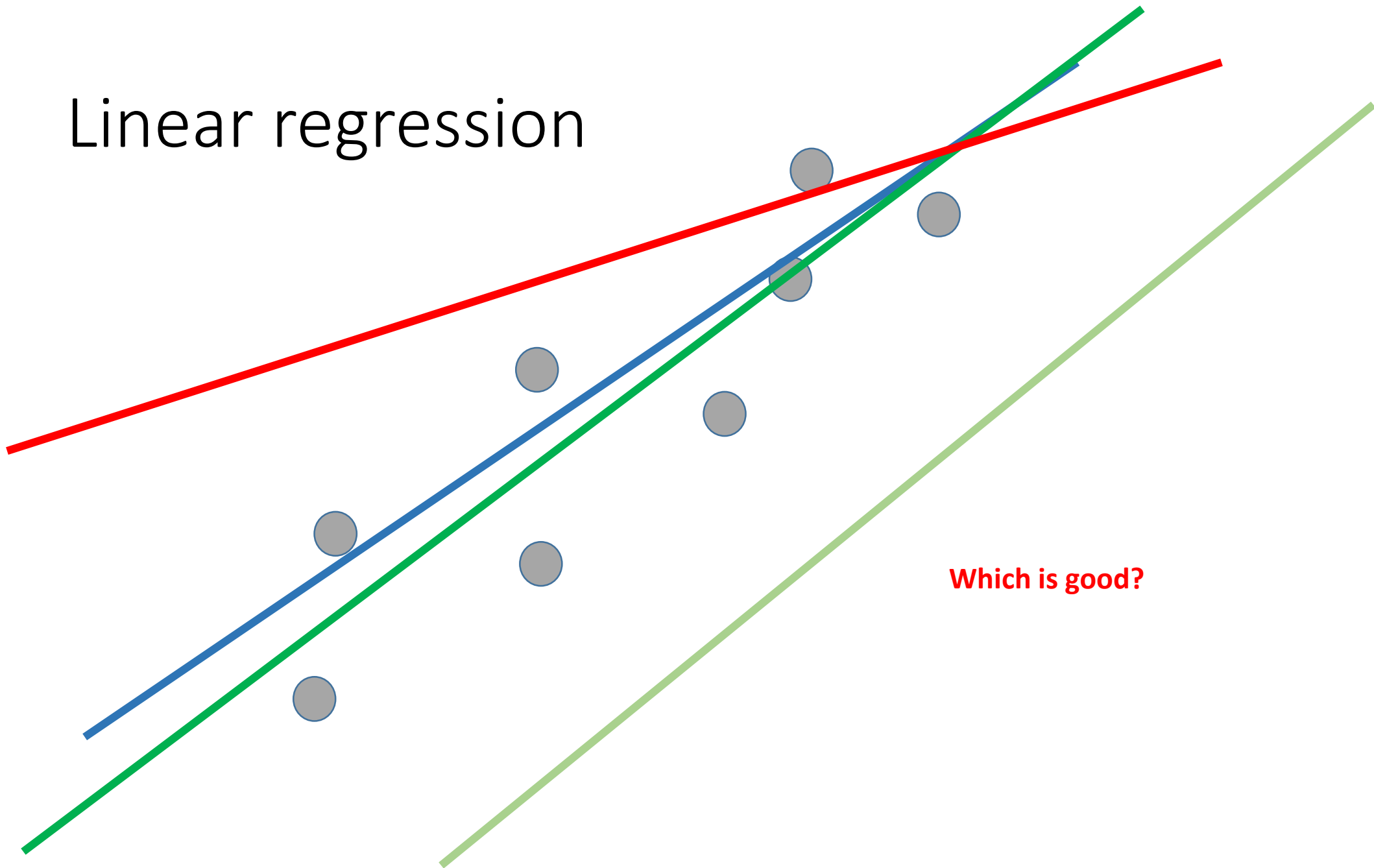


AudioRecordingTimeDurationObject
- time value

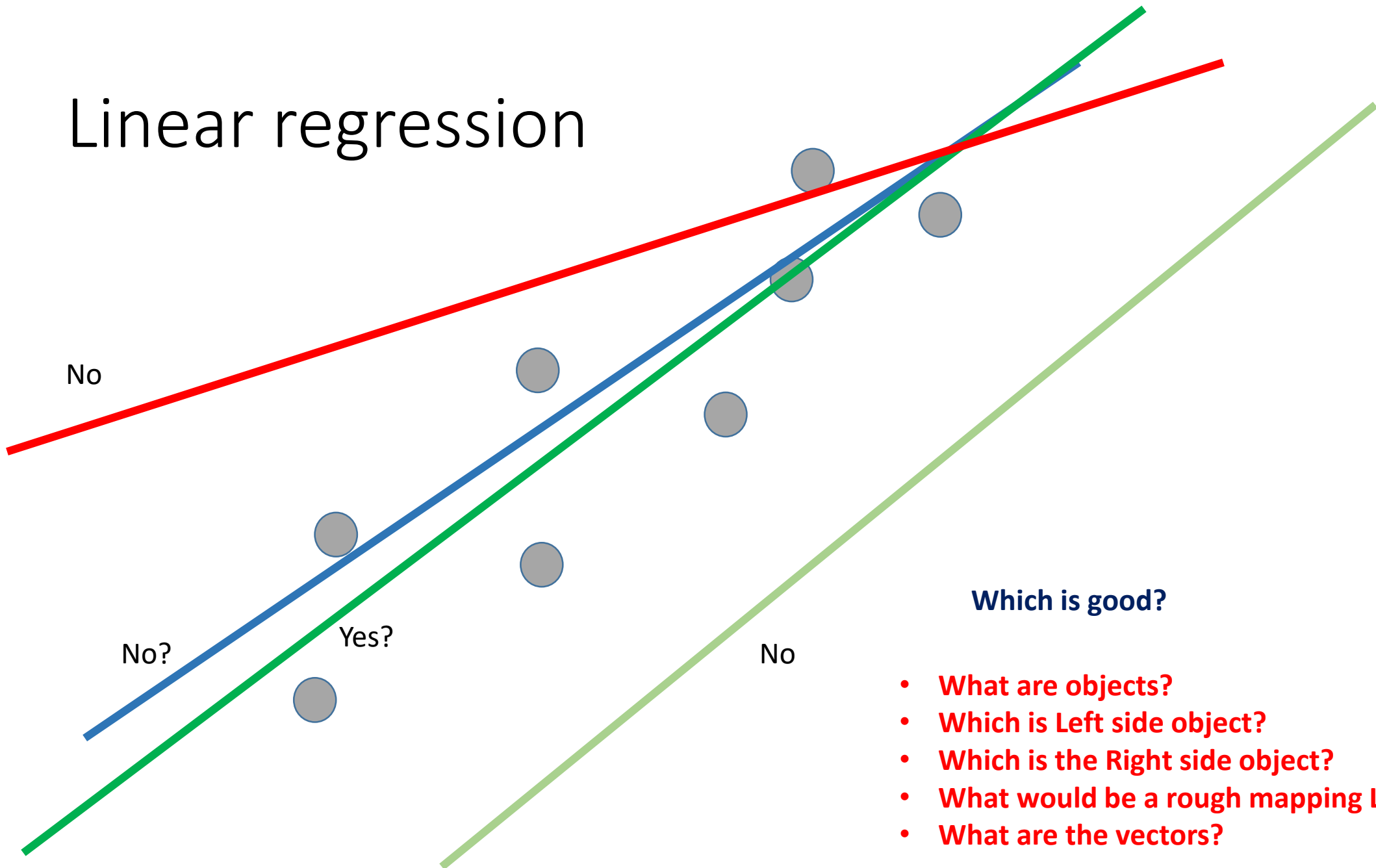


AudioRecordingFileSizeObject
- file size value

Linear regression

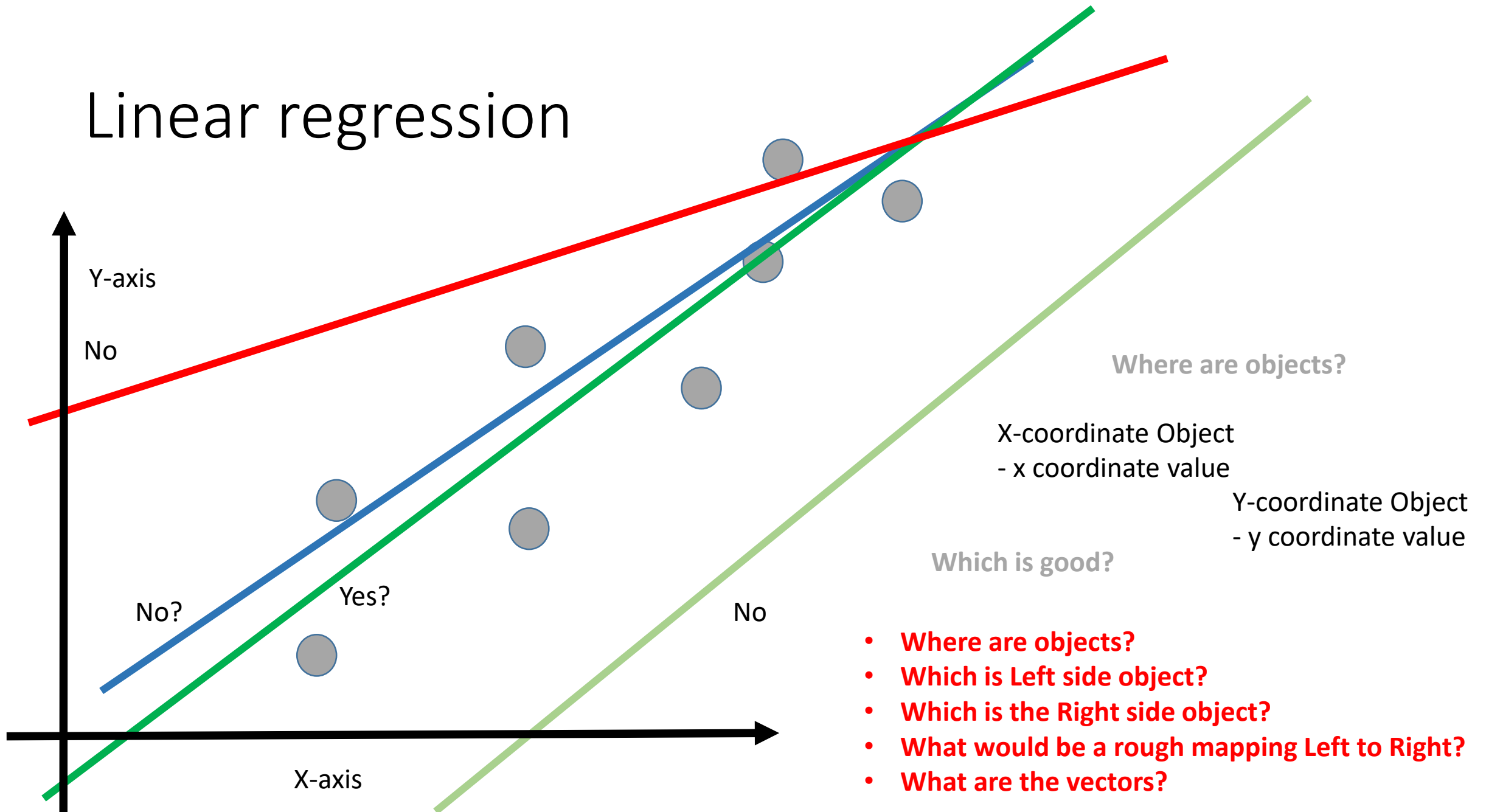


Linear regression



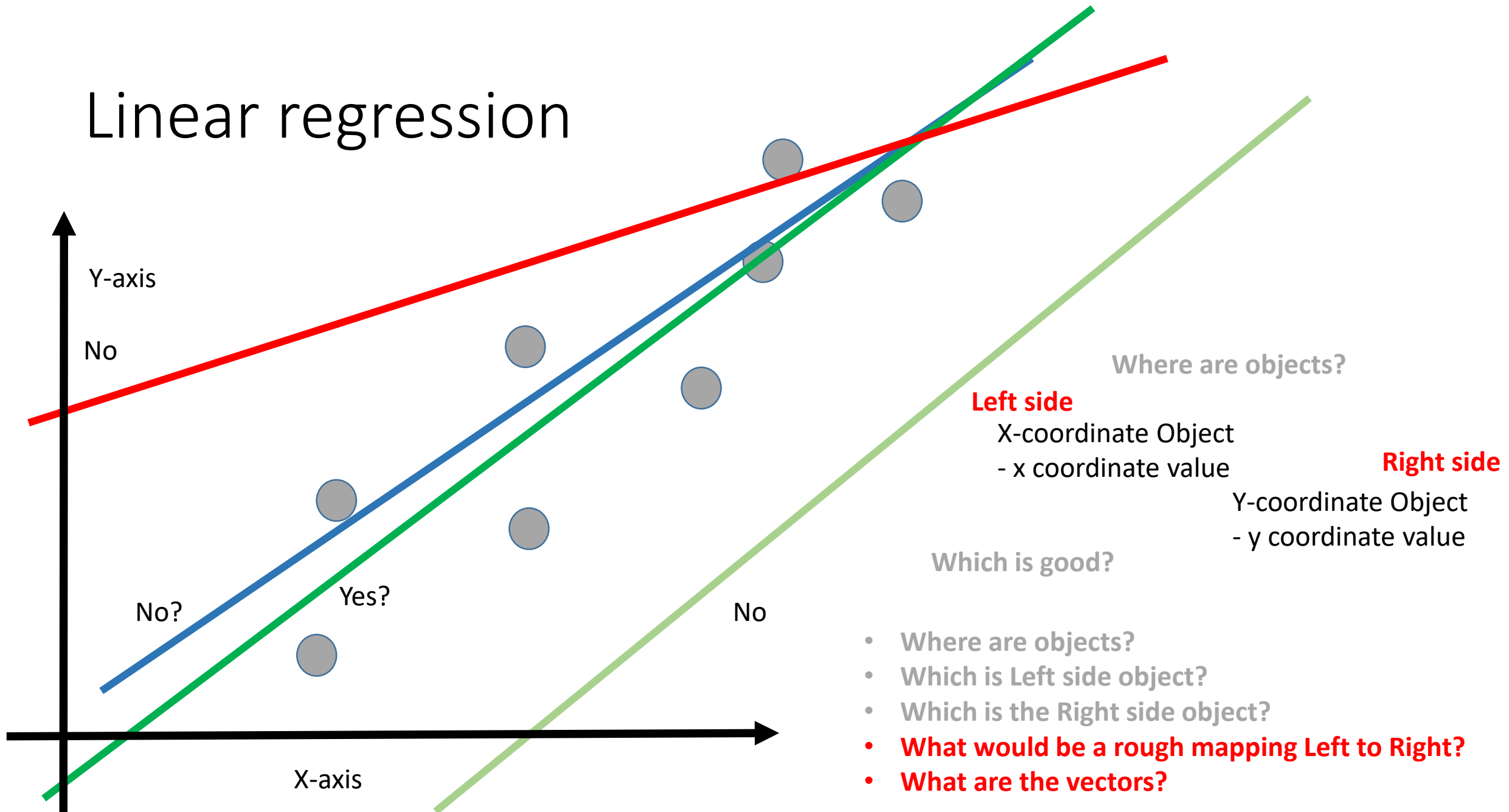
- What are objects?
- Which is Left side object?
- Which is the Right side object?
- What would be a rough mapping Left to Right?
- What are the vectors?

Linear regression

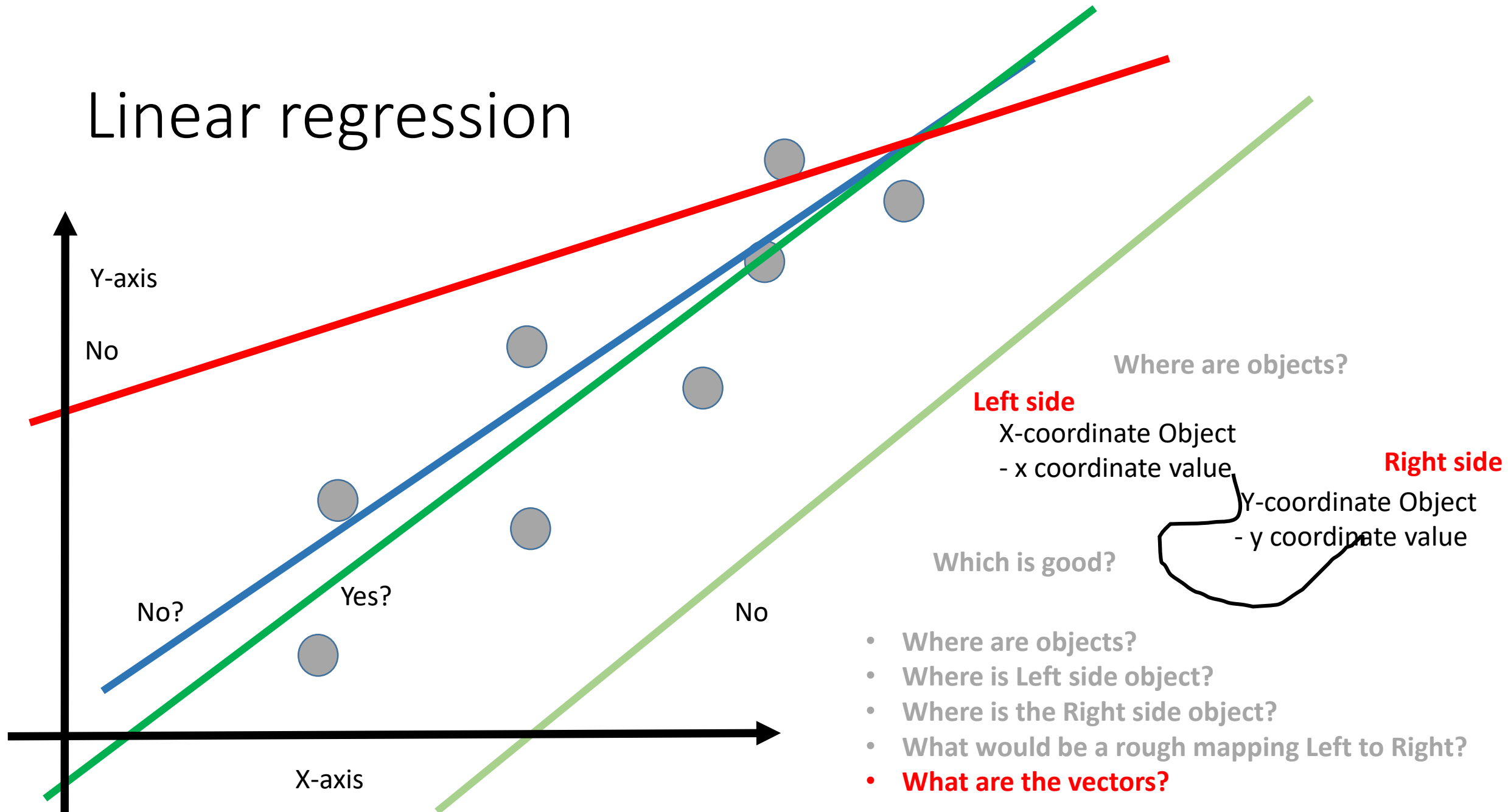


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Linear regression

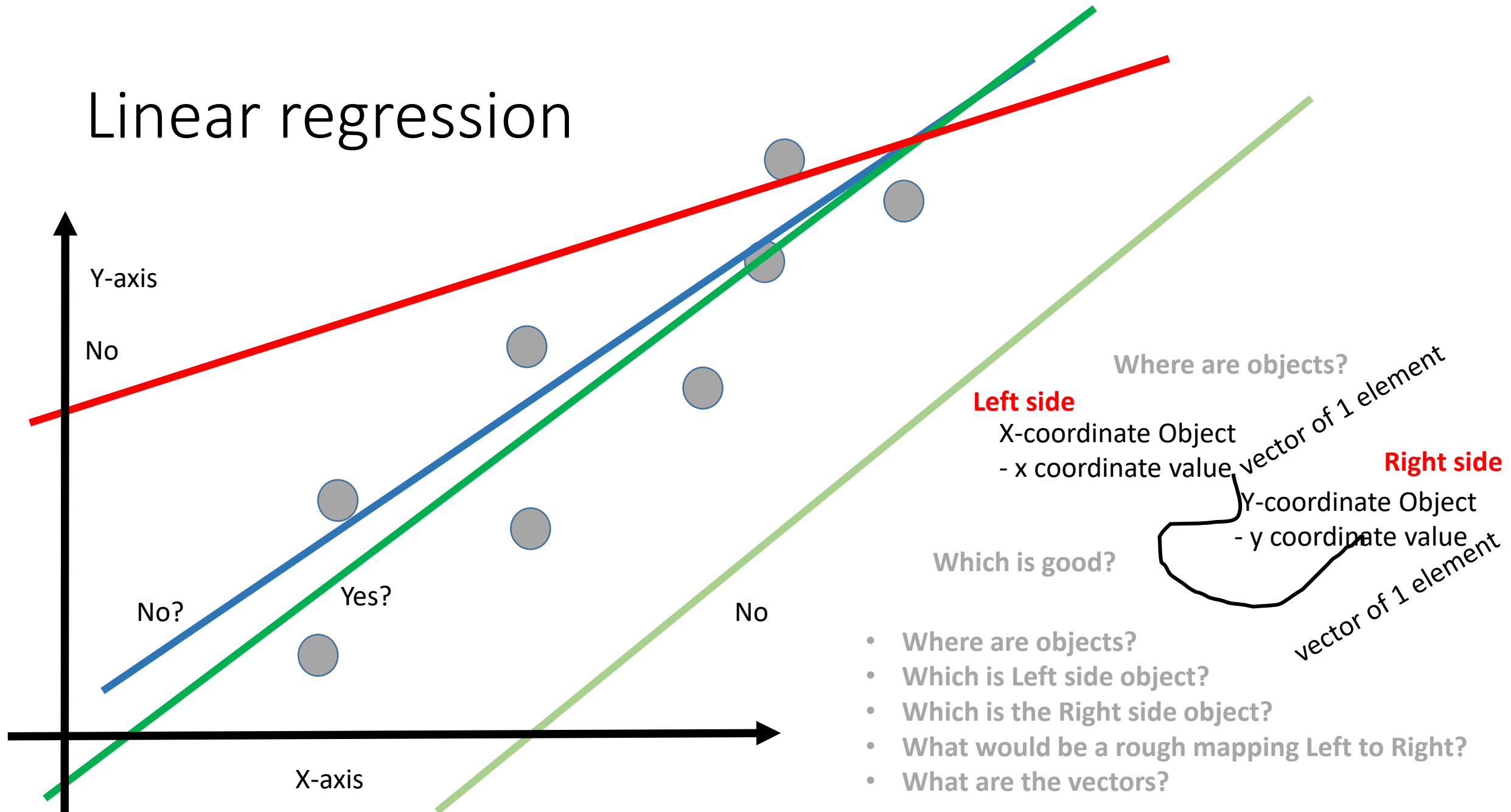


Linear regression

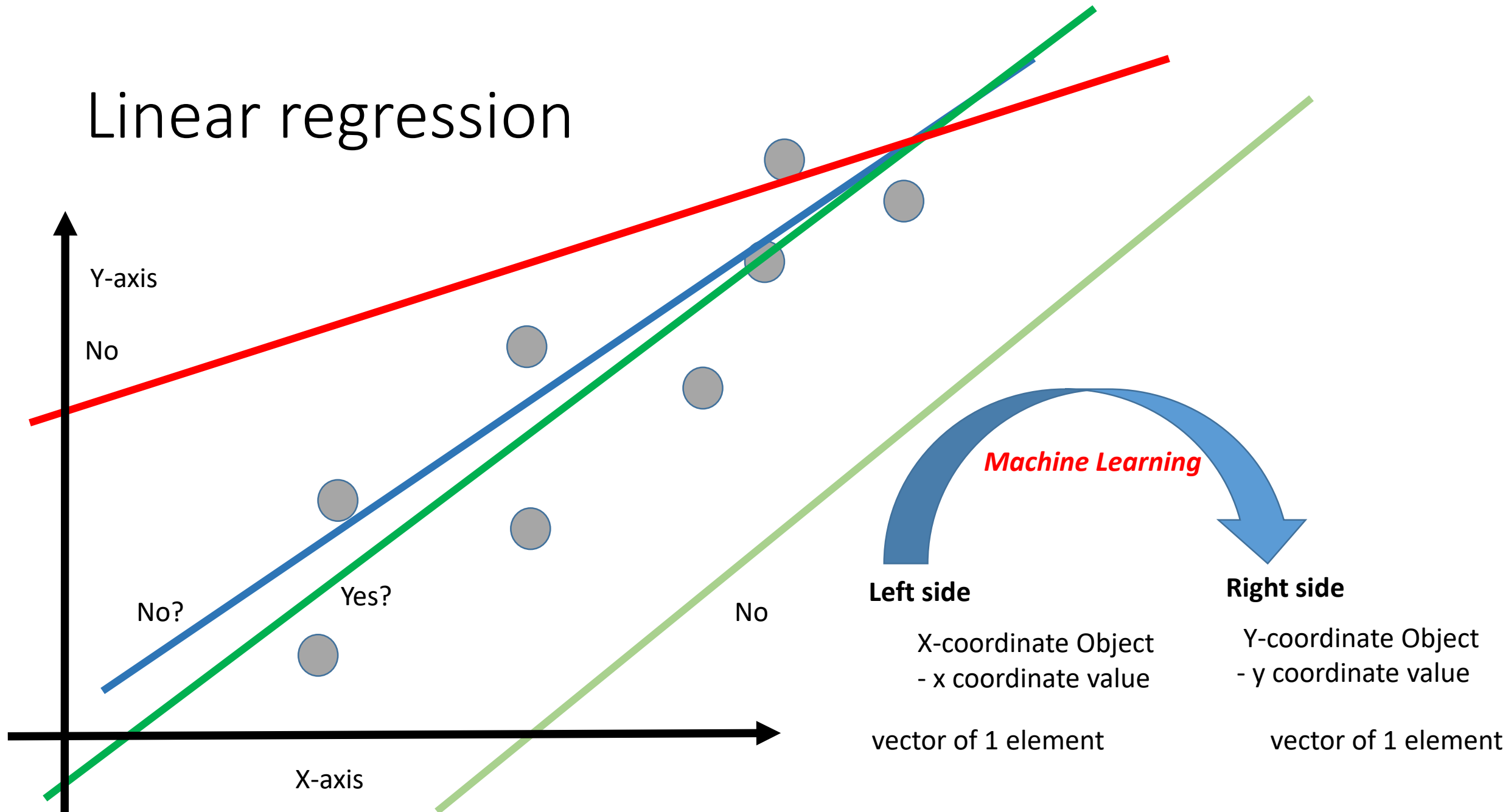


- Where are objects?
- Where is Left side object?
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- **What are the vectors?**

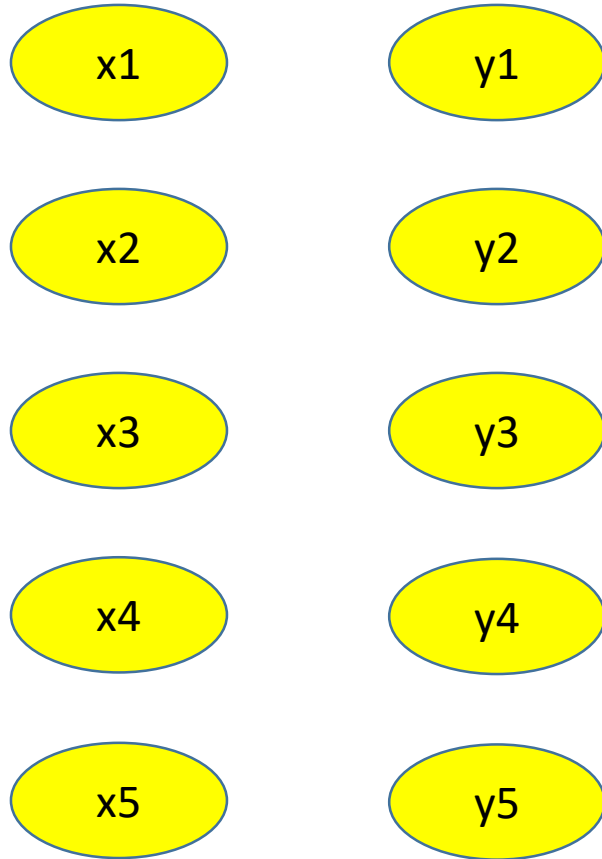
Linear regression



Linear regression



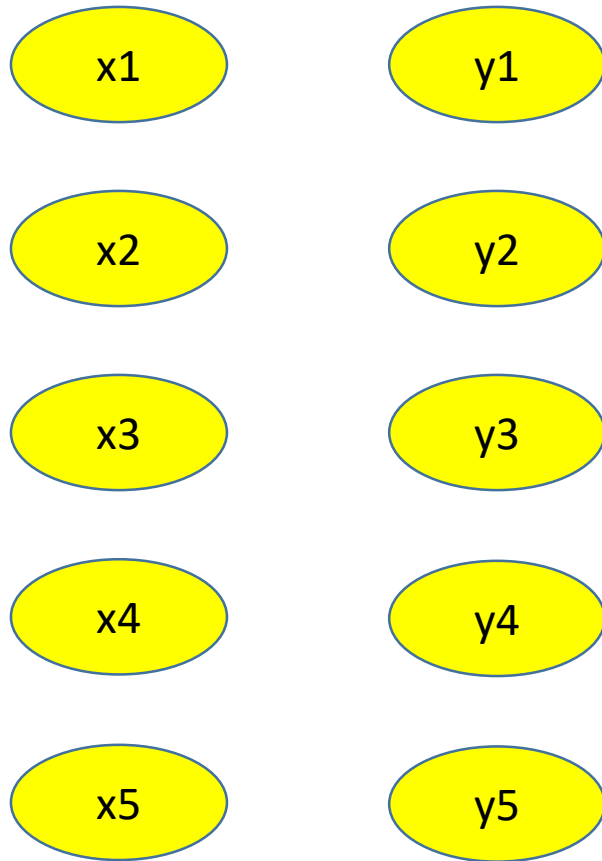
Representation



Mapping

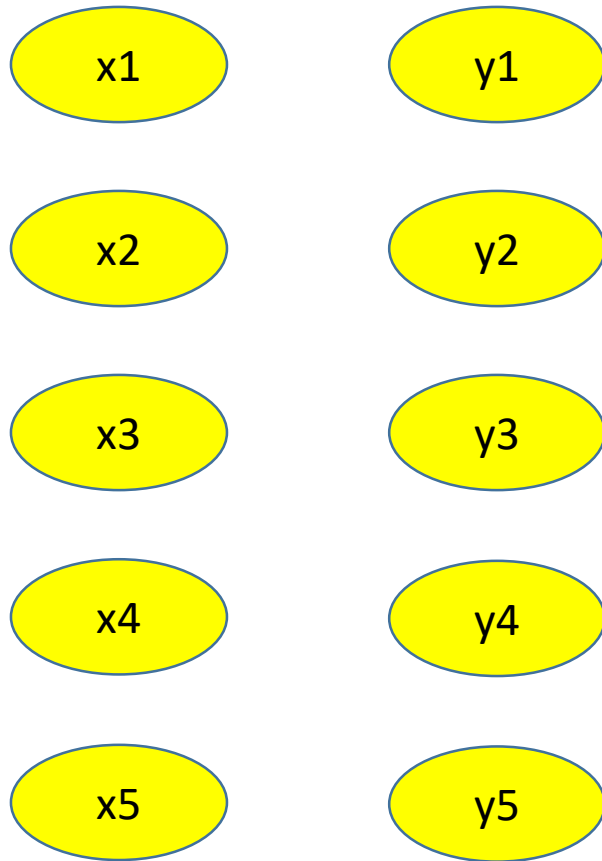
x_i vector to y_i vector

Representation



X	Y
	Target or Label
x1	y1
x2	y2
x3	y3
x4	y4
x5	y5

Representation



Mapping

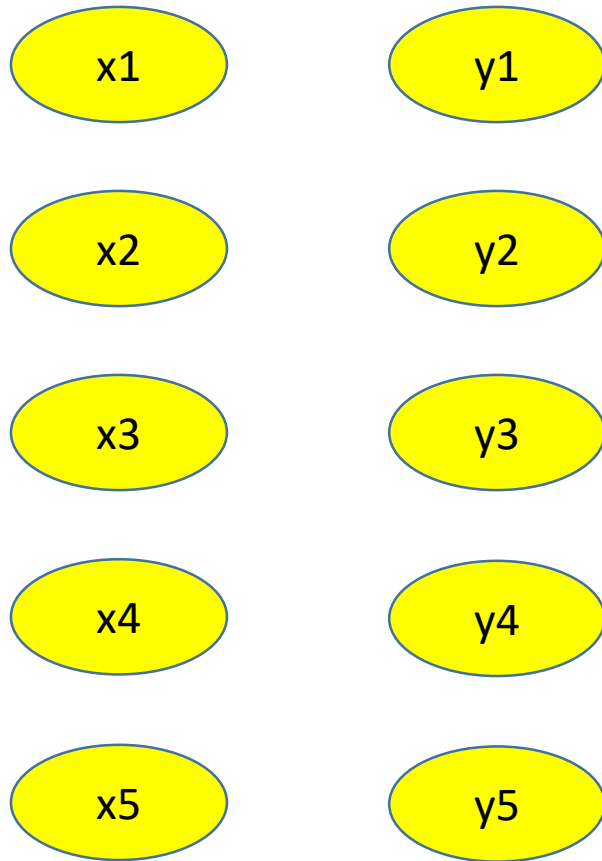
x_i vector to y_i vector

List notation

$$X = [x_i]_{i \in [1..5]}$$

$$Y = [y_i]_{i \in [1..5]}$$

Representation



Mapping

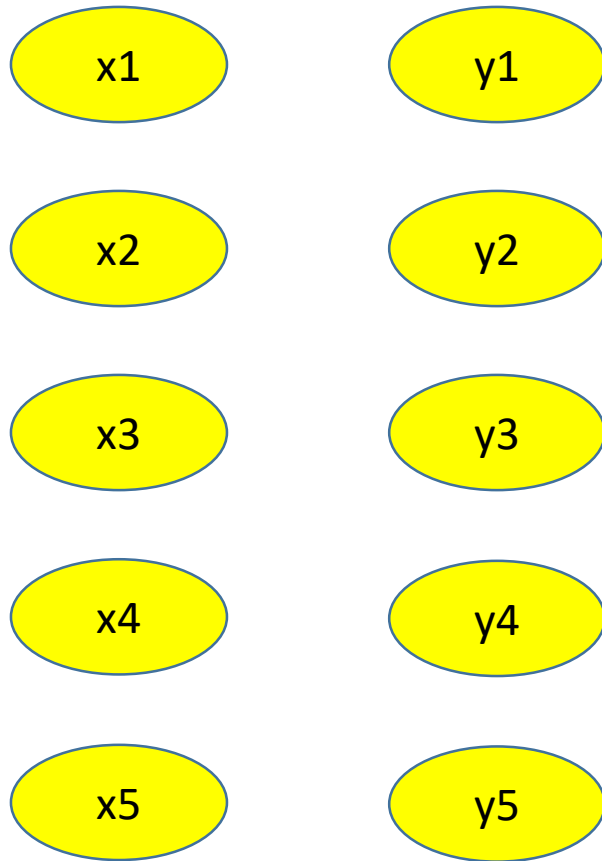
x_i vector to y_i vector

List notation

X

Y

Representation



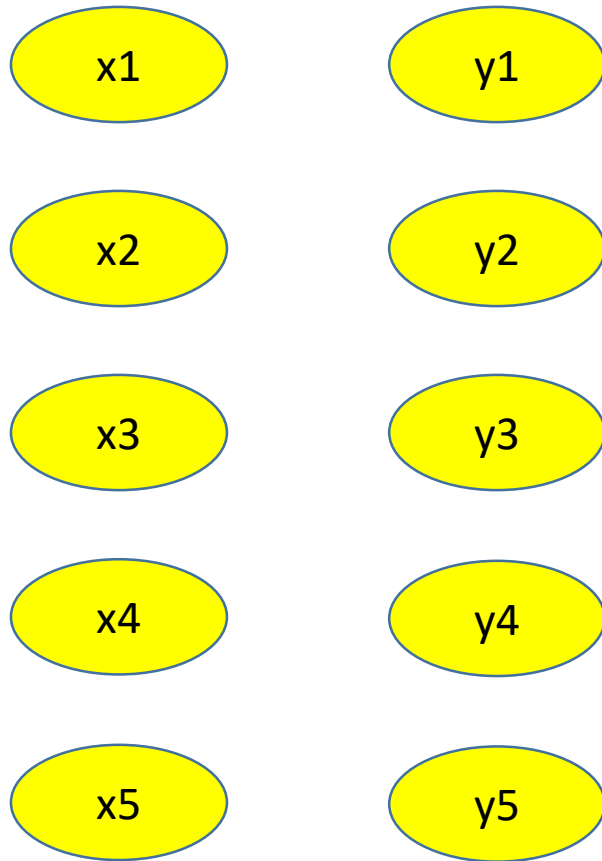
Mapping

x_i vector to y_i vector

List notation

$$Y = f(X)$$

Representation



Mapping

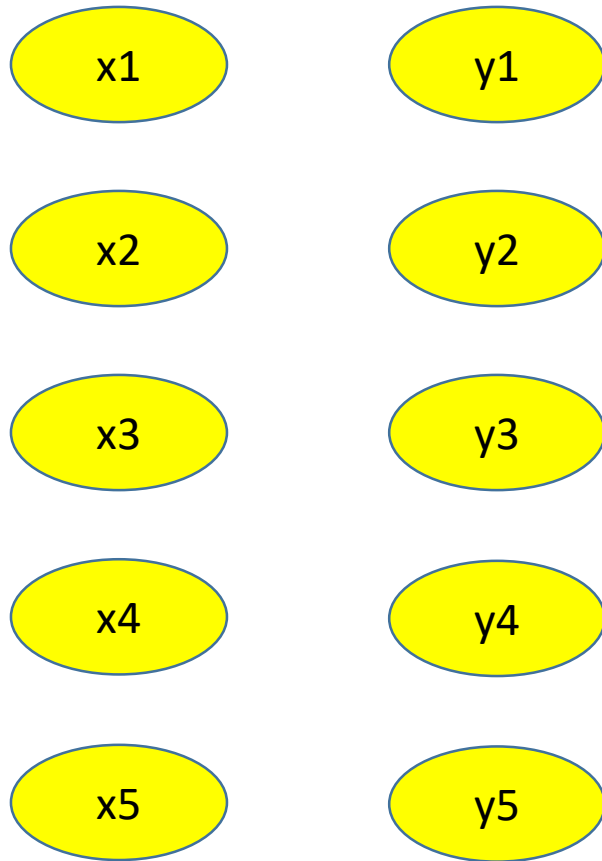
x_i vector to y_i vector

List notation

$$Y = f(X)$$

$f()$ is called model

Representation



Mapping

x_i vector to y_i vector

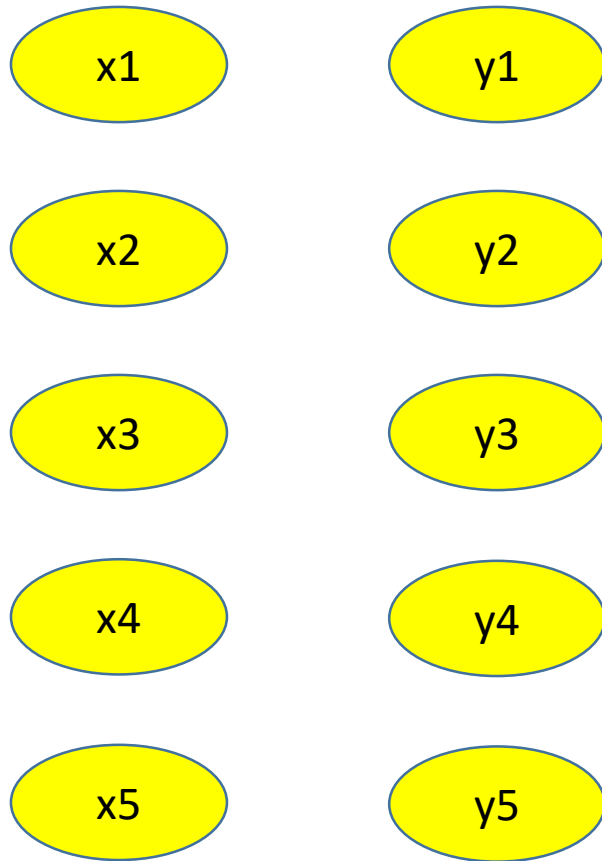
List notation

$$Y = f(X)$$

$f()$ is called model

model's fit(X, Y)

Representation



Mapping

x_i vector to y_i vector

List notation

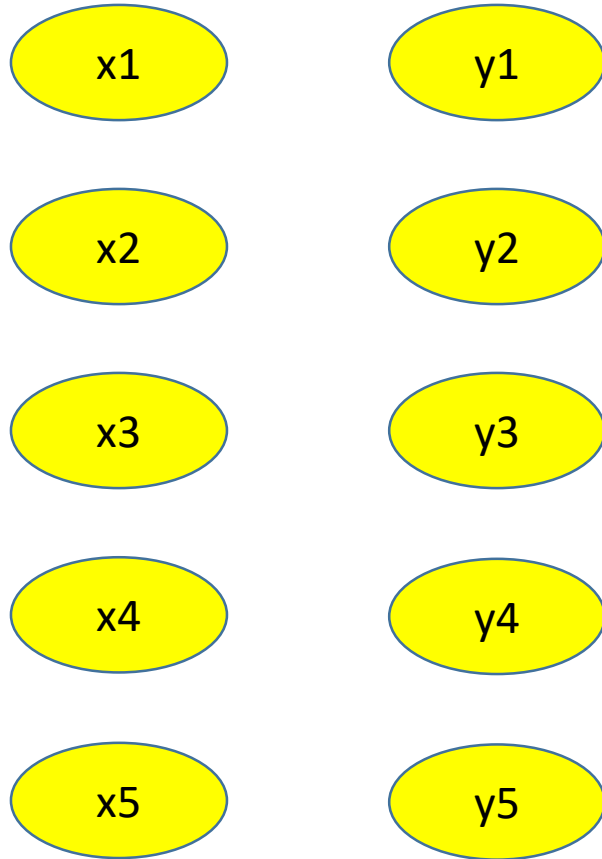
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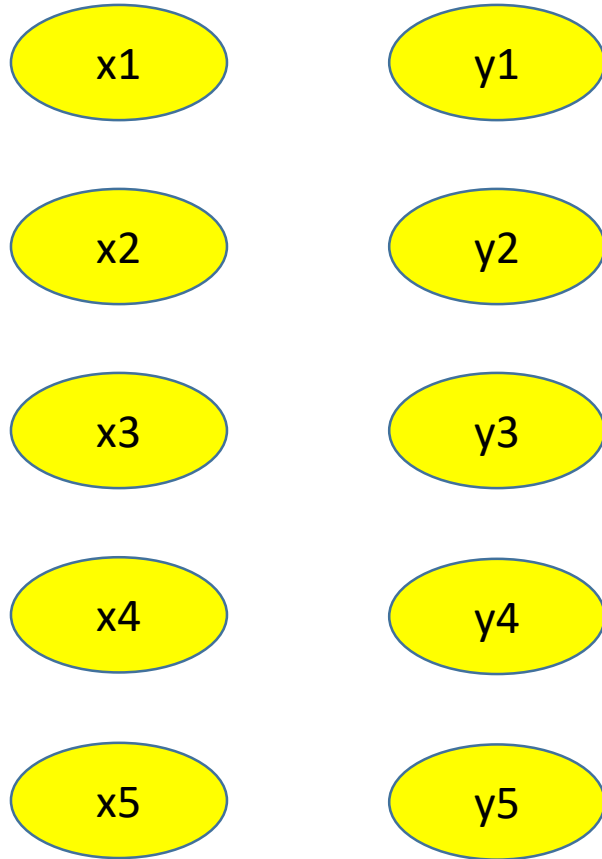
model's predict(**X^{new}**)

Left side (X) \rightarrow Machine Learning \rightarrow Right side (Y)



PREDICT..
Predict Y (right side), Given X (left side)

Left side (X) \rightarrow Machine Learning \rightarrow Right side (Y)



$y = x^2?$ or..
 $y = x^3?$ or..
 $y = 3x + 34?$ or..
 $y = -67x^2 + 45?$ or..
?????
?????

Left side (X) → Machine Learning → Right side (Y)

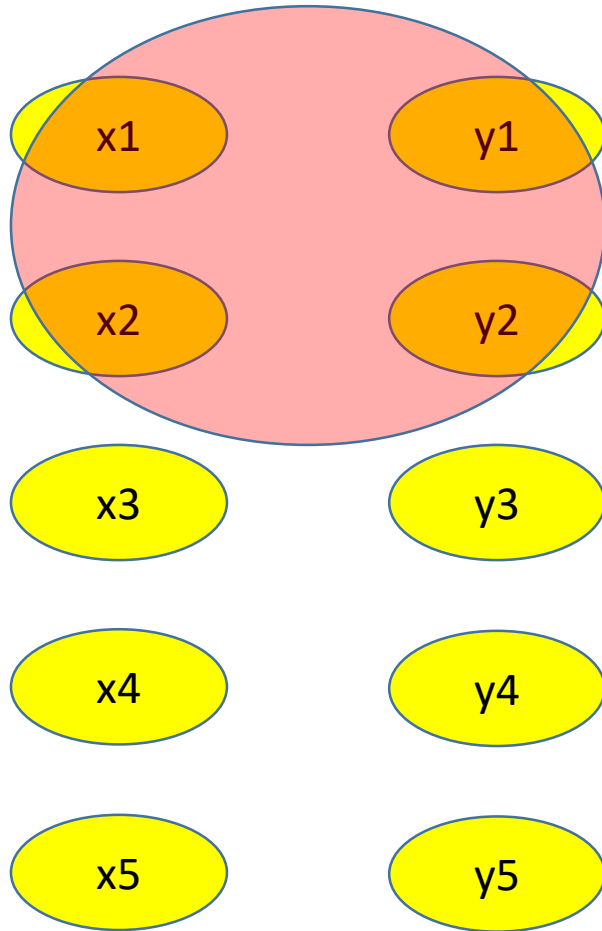
Line...

passing through two points (x1,y1) and (x2,y2)

$$y = m x + c$$

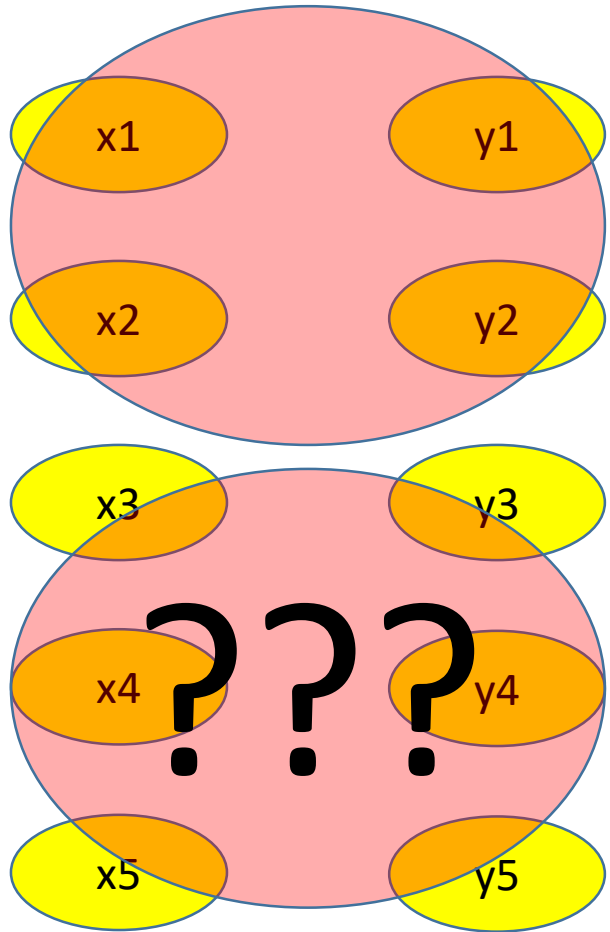
$$\frac{y - y_1}{x - x_1} = \frac{y_2 - y_1}{x_2 - x_1}$$

$$y = \frac{y_2 - y_1}{x_2 - x_1} * x + \left(y_1 - x_1 * \frac{y_2 - y_1}{x_2 - x_1} \right)$$



Linear Regression

Left side (X) \rightarrow Machine Learning \rightarrow Right side (Y)



Line passing through two points (x1,y1) and (x2,y2)

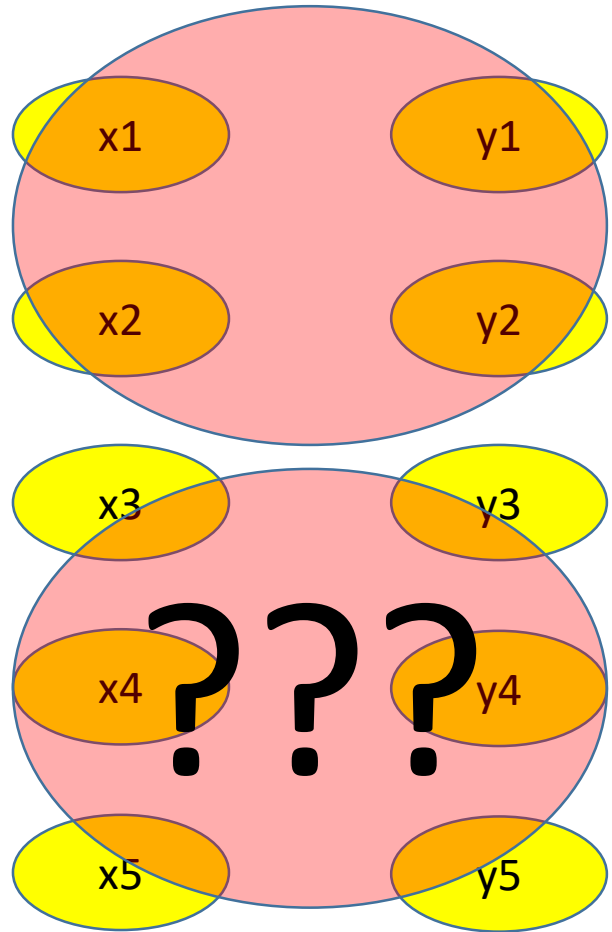
$$y = m x + c$$

$$\frac{y - y1}{x - x1} = \frac{y2 - y1}{x2 - x1}$$

$$y = \frac{y2 - y1}{x2 - x1} * x + \left(y1 - x1 * \frac{y2 - y1}{x2 - x1} \right)$$

Linear Regression

Left side (X) \rightarrow Machine Learning \rightarrow Right side (Y)



Line passing through two points (x_1, y_1) and (x_2, y_2)

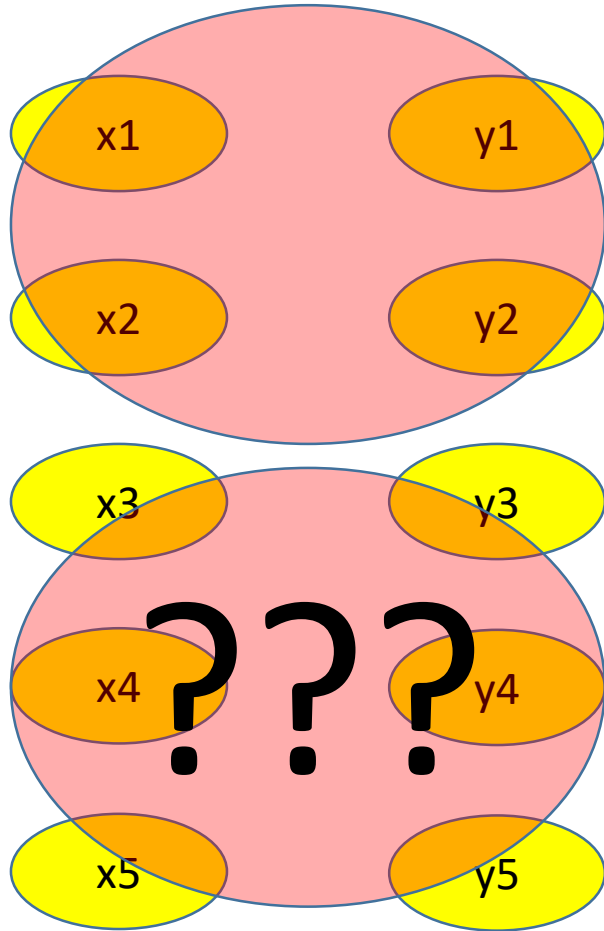
$$y = \frac{y_2 - y_1}{x_2 - x_1} * x + \left(y_1 - x_1 * \frac{y_2 - y_1}{x_2 - x_1} \right)$$

Substitute $(x, y) = (x_3, y_3)$

Substitute $(x, y) = (x_4, y_4)$

...and then do what!!??

Left side (X) \rightarrow Machine Learning \rightarrow Right side (Y)
 Line passing through two points (x_1, y_1) and (x_2, y_2)



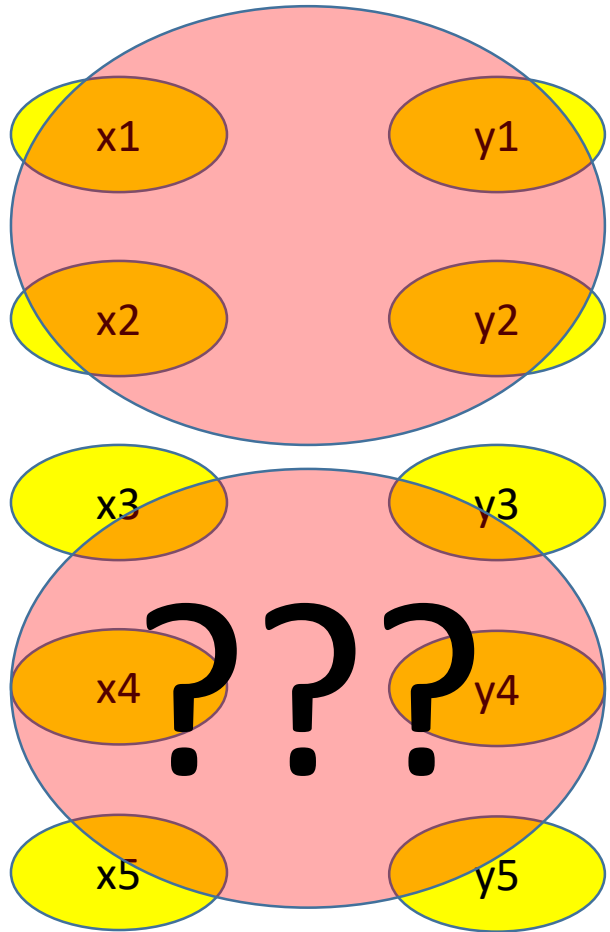
$$y = \frac{y_2 - y_1}{x_2 - x_1} * x + \left(y_1 - x_1 * \frac{y_2 - y_1}{x_2 - x_1} \right)$$

Substitute $(x, y) = (x_3, y_3)$
 Substitute $(x, y) = (x_4, y_4)$

Need goodness measure!
Need badness measure!
Need quality measure!

Linear Regression

Left side (X) \rightarrow Machine Learning \rightarrow Right side (Y)

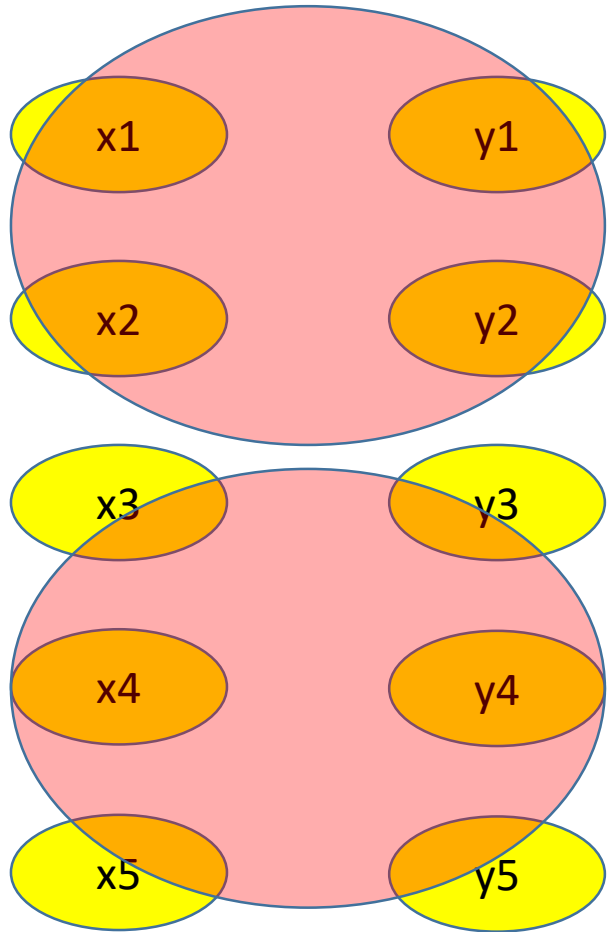


Line passing through two points (x_1, y_1) and (x_2, y_2)

$$y = \frac{y_2 - y_1}{x_2 - x_1} * x + \left(y_1 - x_1 * \frac{y_2 - y_1}{x_2 - x_1} \right)$$

Linear Regression

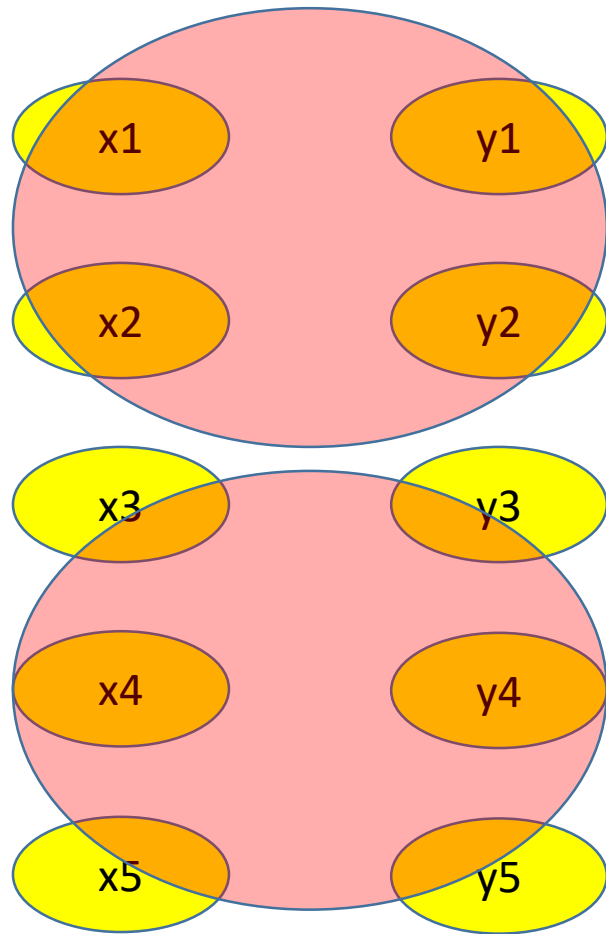
Left side (X) \rightarrow Machine Learning \rightarrow Right side (Y)



Equation of Line :- $y = m * x + c$

Need goodness or badness measure!

Left side (X) \rightarrow Machine Learning \rightarrow Right side (Y)



Equation of Line :- $y = m * x + c$

$$y1 = m * x1 + c ?$$

$$y2 = m * x2 + c ?$$

...

$$y5 = m * x5 + c ?$$

???

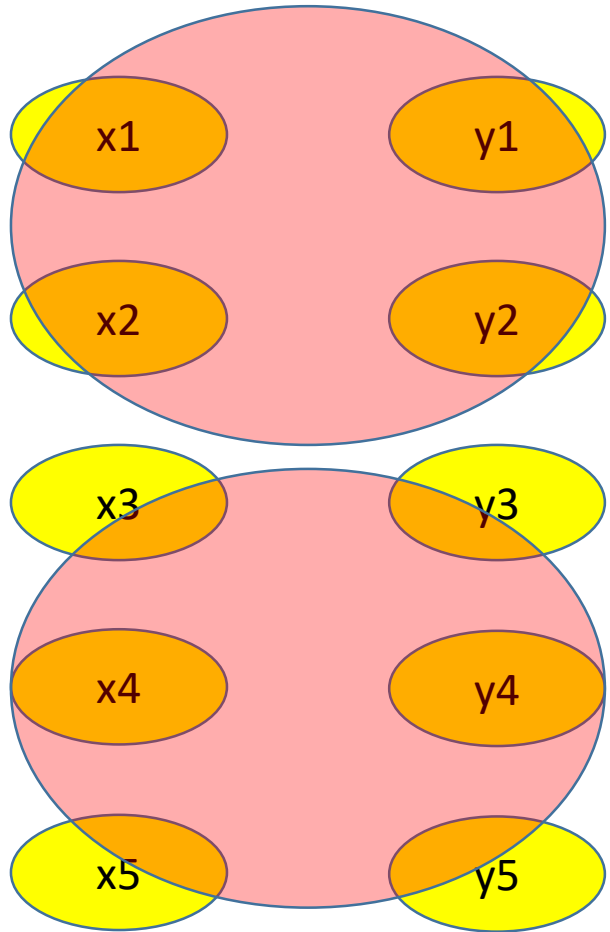
Left side = Exactly same as = Right side ???

Exactly can they be same?

For any value of m and c

What is learning here?

Left side (X) \rightarrow Machine Learning \rightarrow Right side (Y)



Equation of Line :- $y = m * x + c$

$$y1 = m * x1 + c ?$$

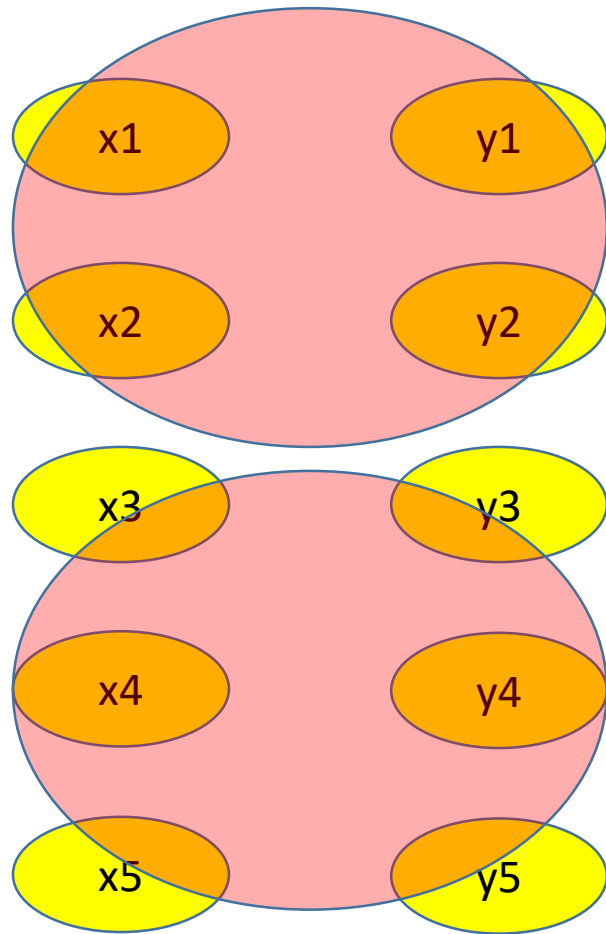
$$y2 = m * x2 + c ?$$

...

$$y5 = m * x5 + c ?$$

What could be a badness measure?...

Left side (X) \rightarrow Machine Learning \rightarrow Right side (Y)



Equation of Line :- $y = m * x + c$

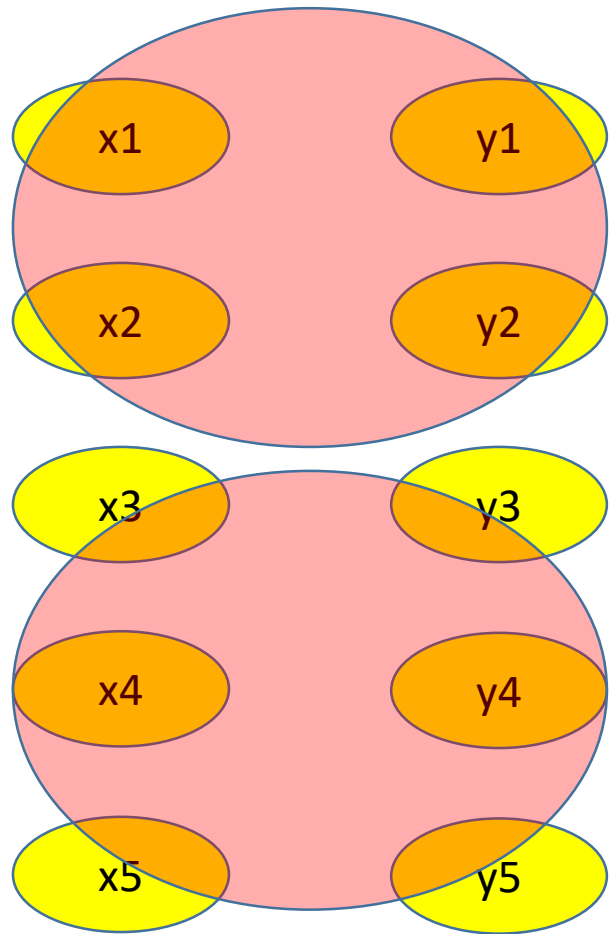
Badness for (x1,y1) :- $(y1 - (m * x1 + c))^2$

Badness for (x2,y2) :- $(y2 - (m * x2 + c))^2$

...

Badness for (x5,y5) :- $(y5 - (m * x5 + c))^2$

Left side (X) \rightarrow Machine Learning \rightarrow Right side (Y)

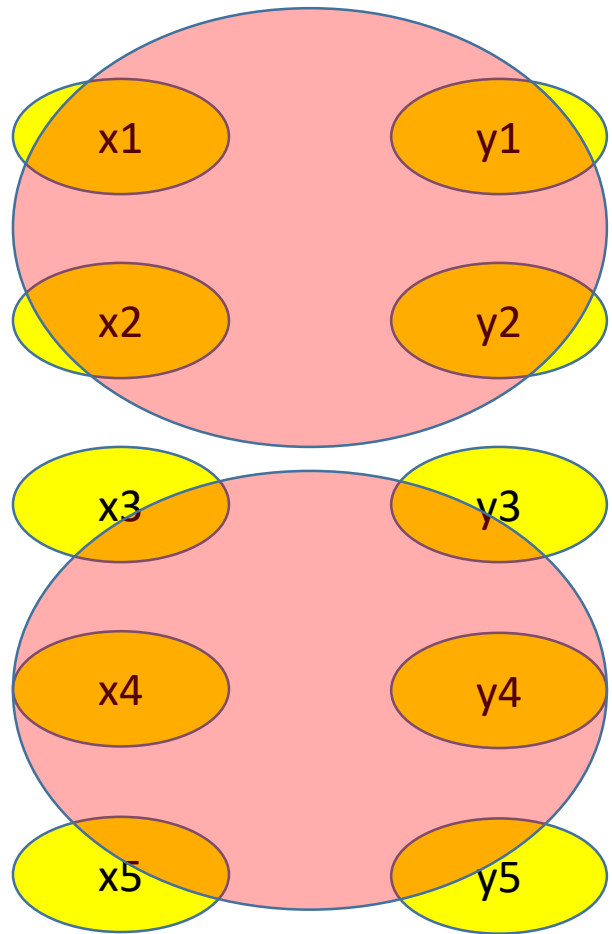


Equation of Line :- $y = m * x + c$

$$L(m, c, X, Y) = \sum_{i=1}^{i=5} (y_i - (m * x_i + c))^2$$

LOSS FUNCTION
ERROR FUNCTION

Left side (X) \rightarrow Machine Learning \rightarrow Right side (Y)



Equation of Line :- $y = m * x + c$

Actual.. Ground truth..

Prediction

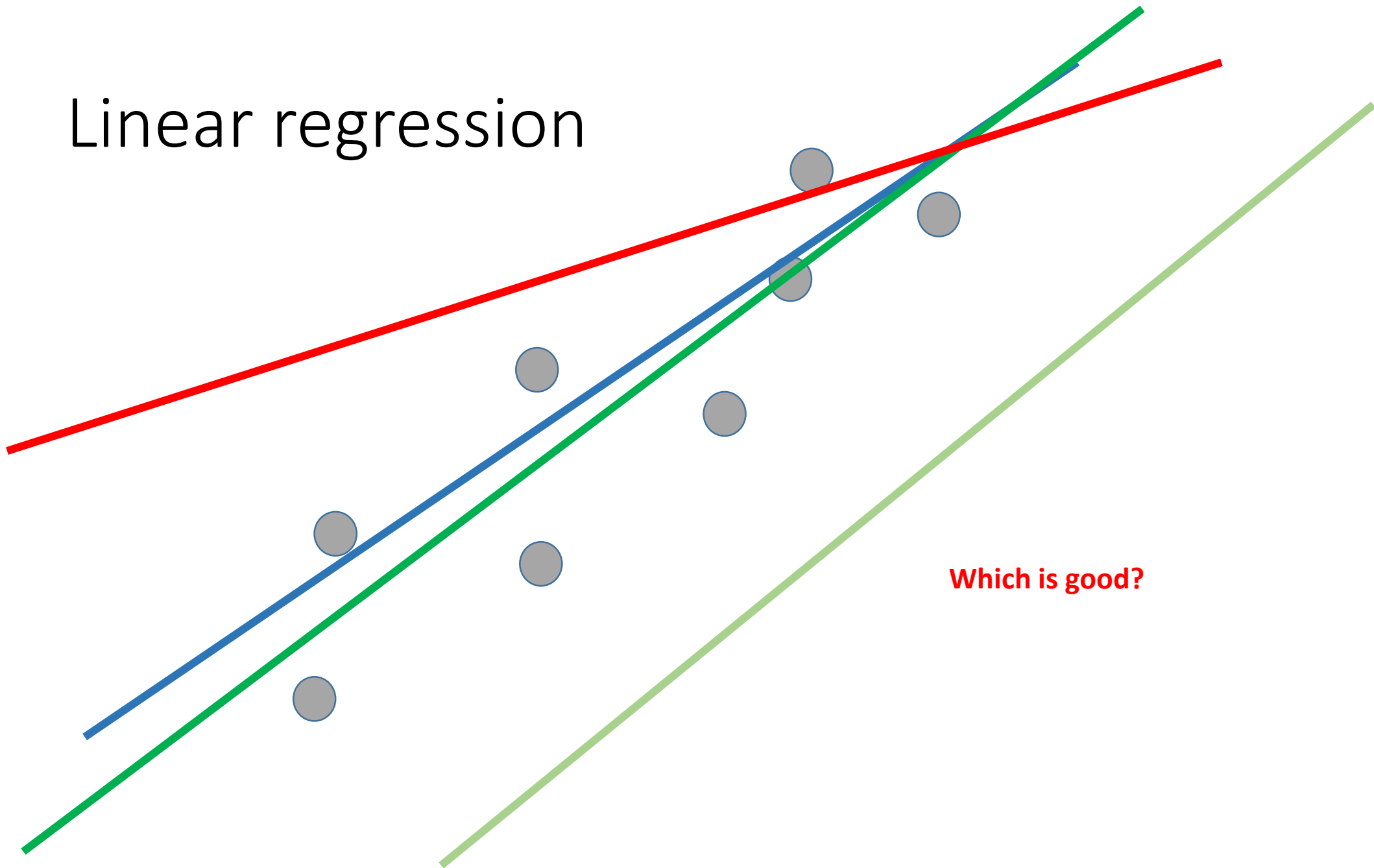
$$L(m, c) = \sum_{i=1}^{i=5} (y_i - (m * x_i + c))^2$$

LOSS FUNCTION

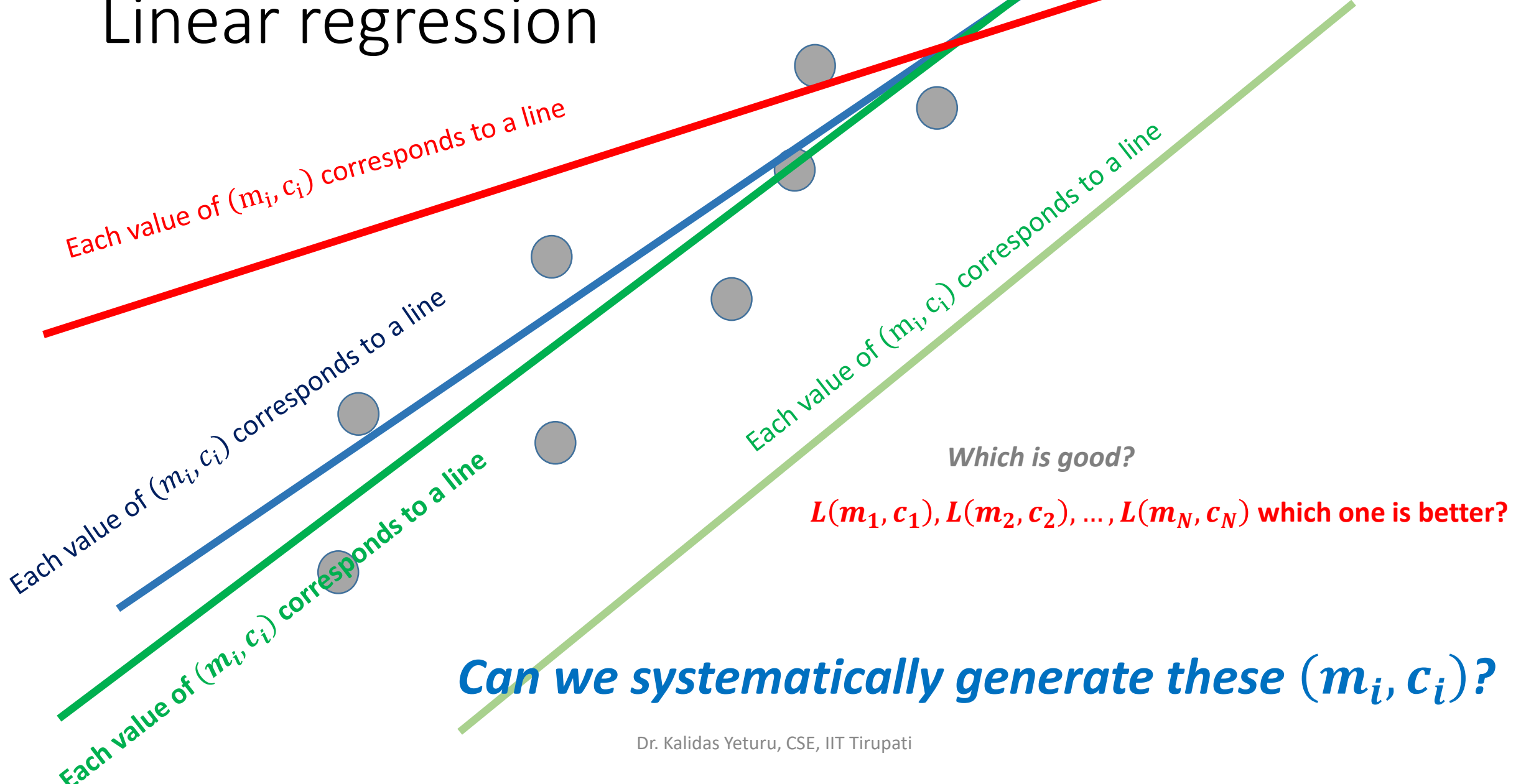
PARAMETERS

REGRESS..
prediction to return to.. actual

Linear regression



Linear regression



What are the different ways?

2nd argument is
the *list of Parameters*

BruteForceSolver(*L*, [*m1*, *c1*])

minval = +10000.0

FOR *m* ∈ [−100, ..., +100]

FOR *c* ∈ [−100, ..., +100]

Compute *v* = *L*(*m*, *c*)

IF *v* < *minval*:
 v = *minval*
 m1 = *m*,
 c1 = *c*

1st argument is the *Loss function*

Questions...

- -100 to +100, who gave the range?
- What is the step size?
- What if the solution is highly fine, (3.451, -89.1123)?
- Can we speed up?

What are the different ways?

2nd argument is
the *list of Parameters*

RandomSolver(*L*, [*m1*, *c1*])

minval = +10000.0

FOR ITER= 1:100000

FOR m = RAND(-100, 100)

FOR c = RAND(-100, 100)

Compute $v = L(m, c)$

IF $v < minval$:
 $v = minval$
 $m1 = m$,
 $c1 = c$

1st argument is the *Loss function*

Questions...

- -100 to +100, who gave the range?
- What is the step size?
- What if the solution is highly fine, (3.451, -89.1123)?
- Can we speed up?

What are the different ways?

GradientSolver(*L*, [*m1*, *c1*], *gradL*)

2nd argument is
the *list of Parameters*

1st argument is the *Loss function*

3rd argument is
the *gradient function*

???