Machine Learning od podstaw

Michał Lipka SAP
20 Listopada, 2019

PUBLIC

THE BEST RUN SAP

Hack Your Career

Fit yourself in IT – Rozegraj swoją rekrutację

15.10.2019
Marek Nawa
Maciej Ogrodnik

Getting started with OAUTH 2.0

29.10.2019
Tomasz Miler

Machine Learning od podstaw

20.11.2019
Michał Lipka

Building a city with SCRUM - Workshop

12.12.2019
Michał Drzewiecki

SAP Labs Poland

Top ecommerce, marketing, billing

Development: Go, Java, Cloud Native solutions

> 400 pracowników

Najlepszy Pracodawca w rankingu AON

Jedno z 20 centrów SAP’s Labs Network

Agenda:

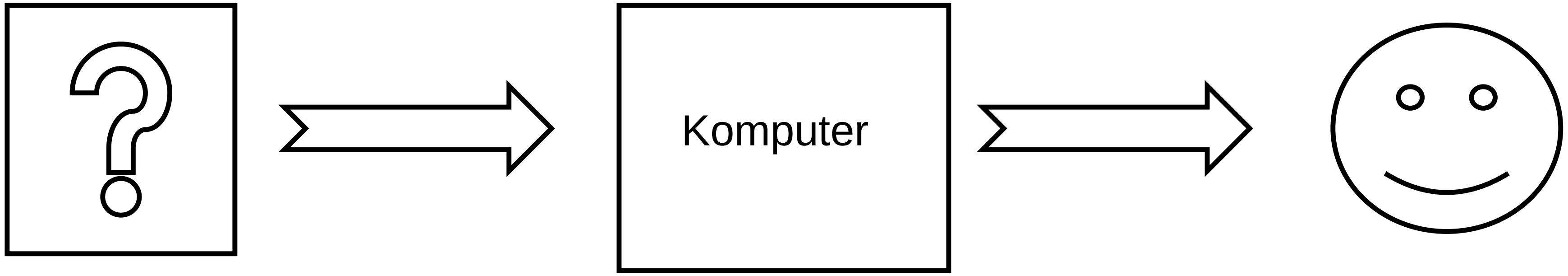
- Co to tak w ogóle jest machine learning?
- Sposoby uczenia
- Reprezentacja modelu: hipoteza, funkcja kosztu, gradient prosty
- Regresja liniowa
- Klasyfikacja
- Sieci neuronowe

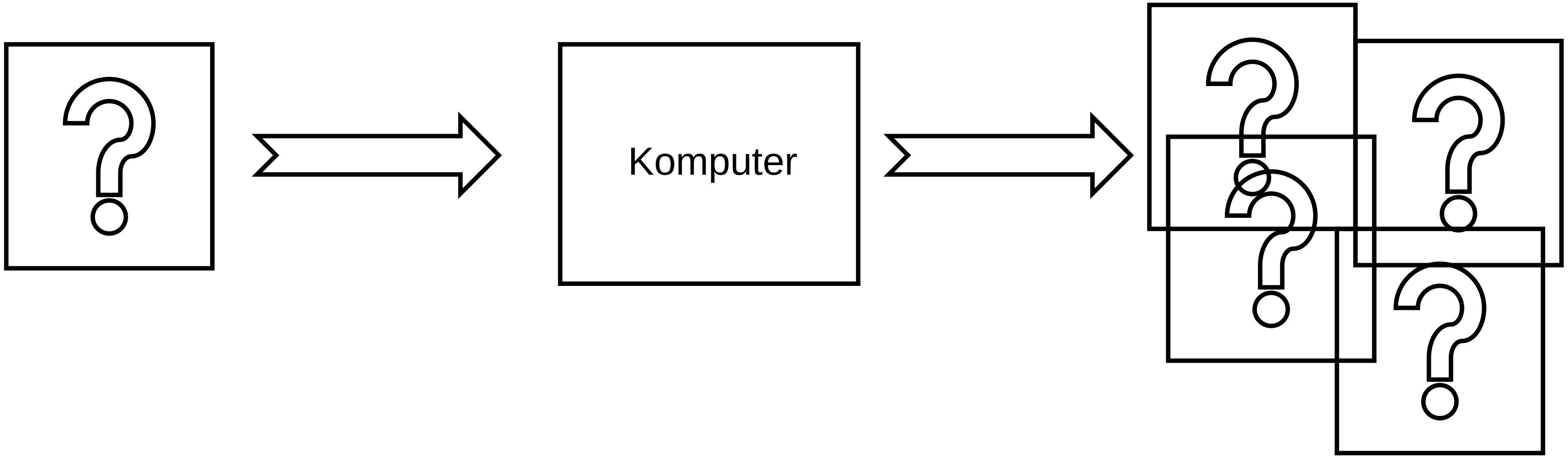
”The field of study that gives computers the ability to learn without being explicitly programmed."

Arthur Samuel

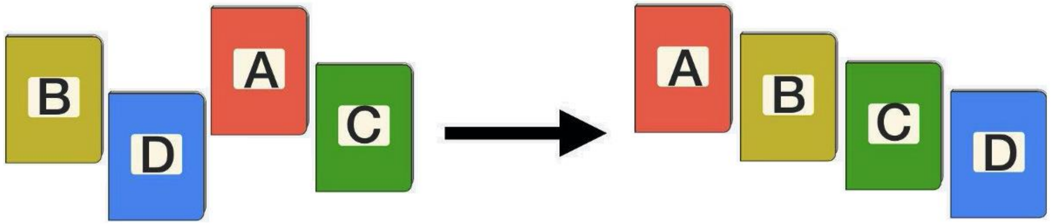
"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E.”

Tom M. Mitchell

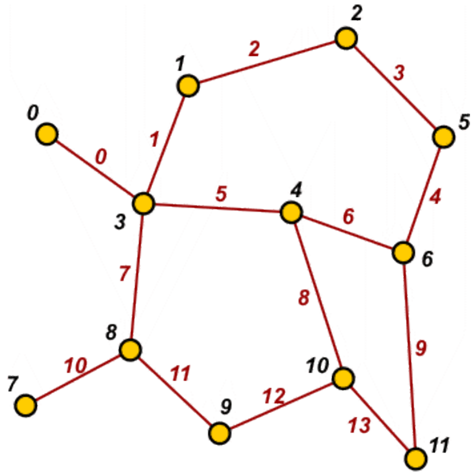

Komputer


Komputer

Sortowanie tablic



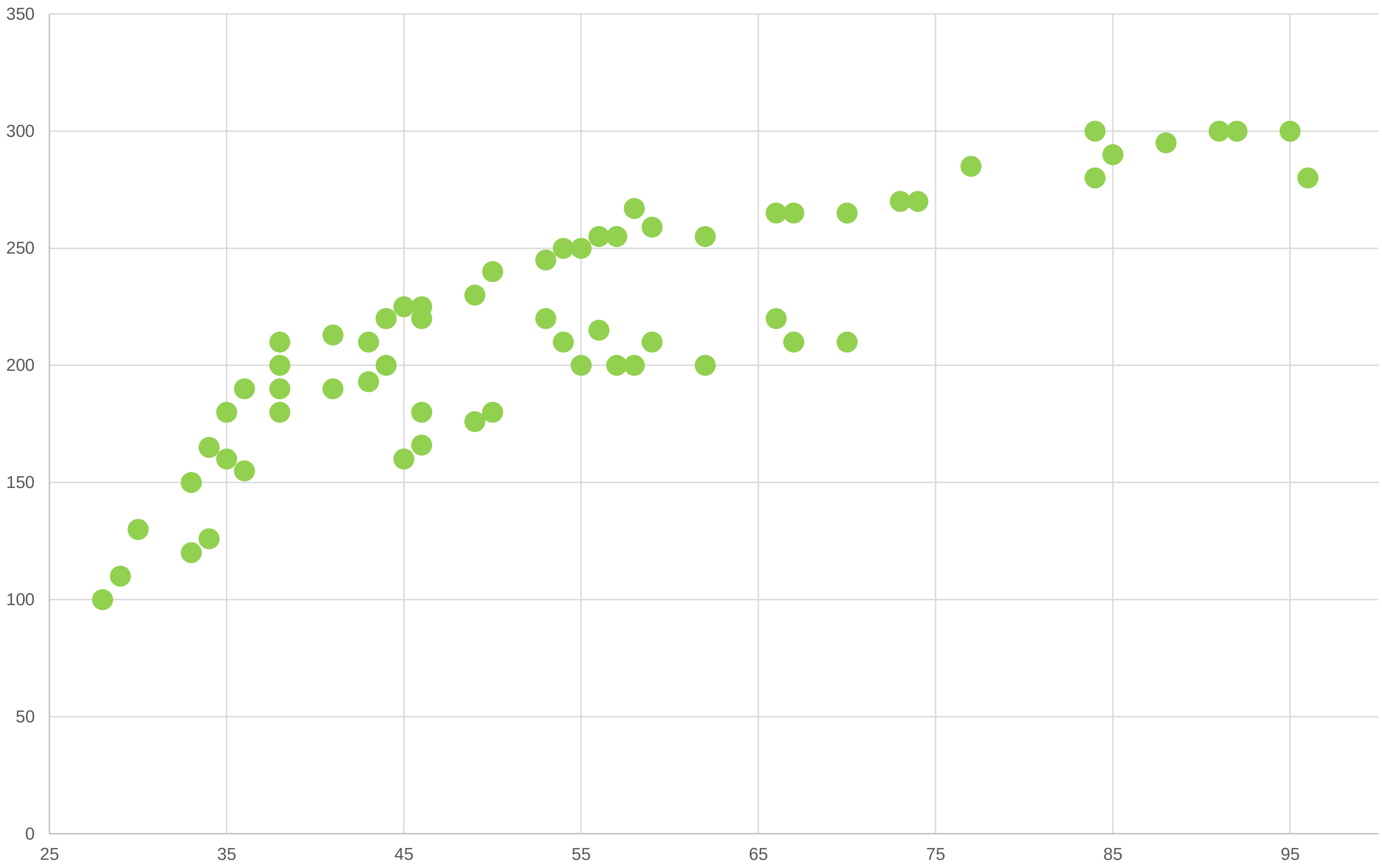
Teoria grafów



Rodzaje uczenia:

- Nadzorowane
- Nienadzorowane
- Inne: drzewa decyzji, uczenie przez wzmacnianie

Hipoteza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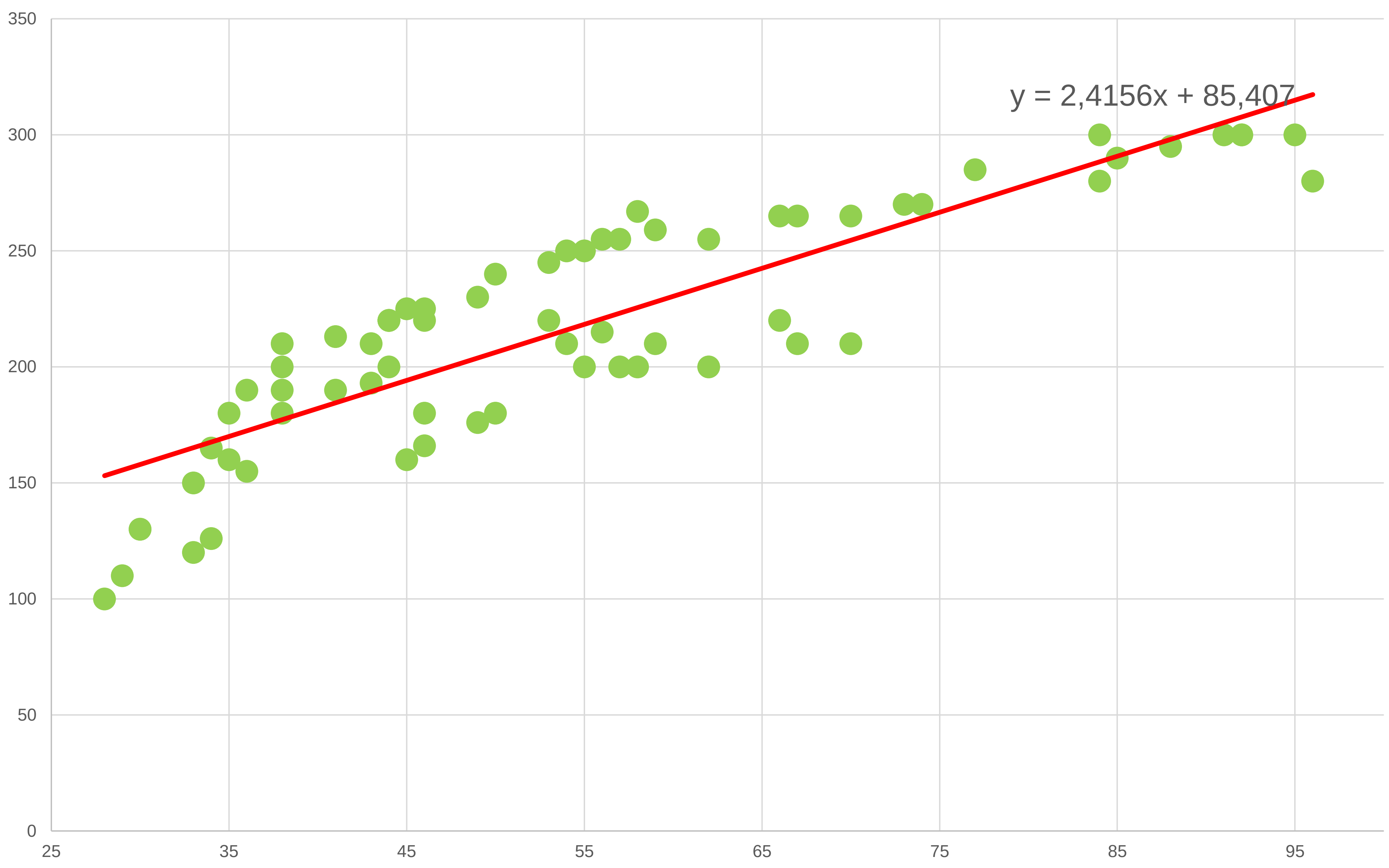
Regresja liniowa

Hipoteza $h_\theta(x) = \theta_0 + \theta_1 x$

$$h_\theta(x) = \theta_0 + \theta_1 x$$

	X (rozmiar w m2)	Y (cena w tyś)
$x^{(1)}, y^{(1)}$	28	100
$x^{(2)}, y^{(2)}$	29	110
$x^{(3)}, y^{(3)}$	31	130
$x^{(4)}, y^{(4)}$	31	133
$x^{(i)}, y^{(i)}$	…	…


y = 2,4156x + 85,407
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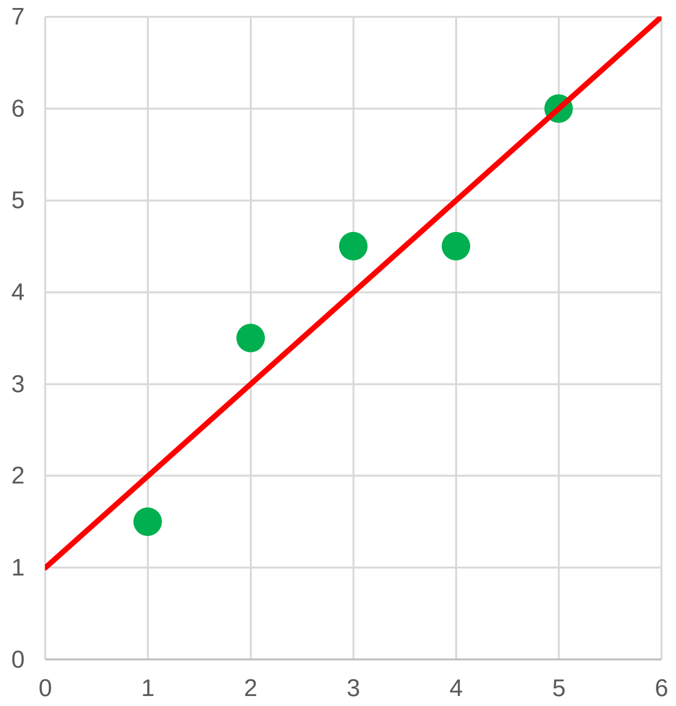
Dwa pytania:

- skąd wiemy, że dana prosta jest „dobra” ?
- jak ją policzyć?

Funkcja kosztu $J(\theta)$



$$h_\theta(x) = \theta_0 + \theta_1 x$$

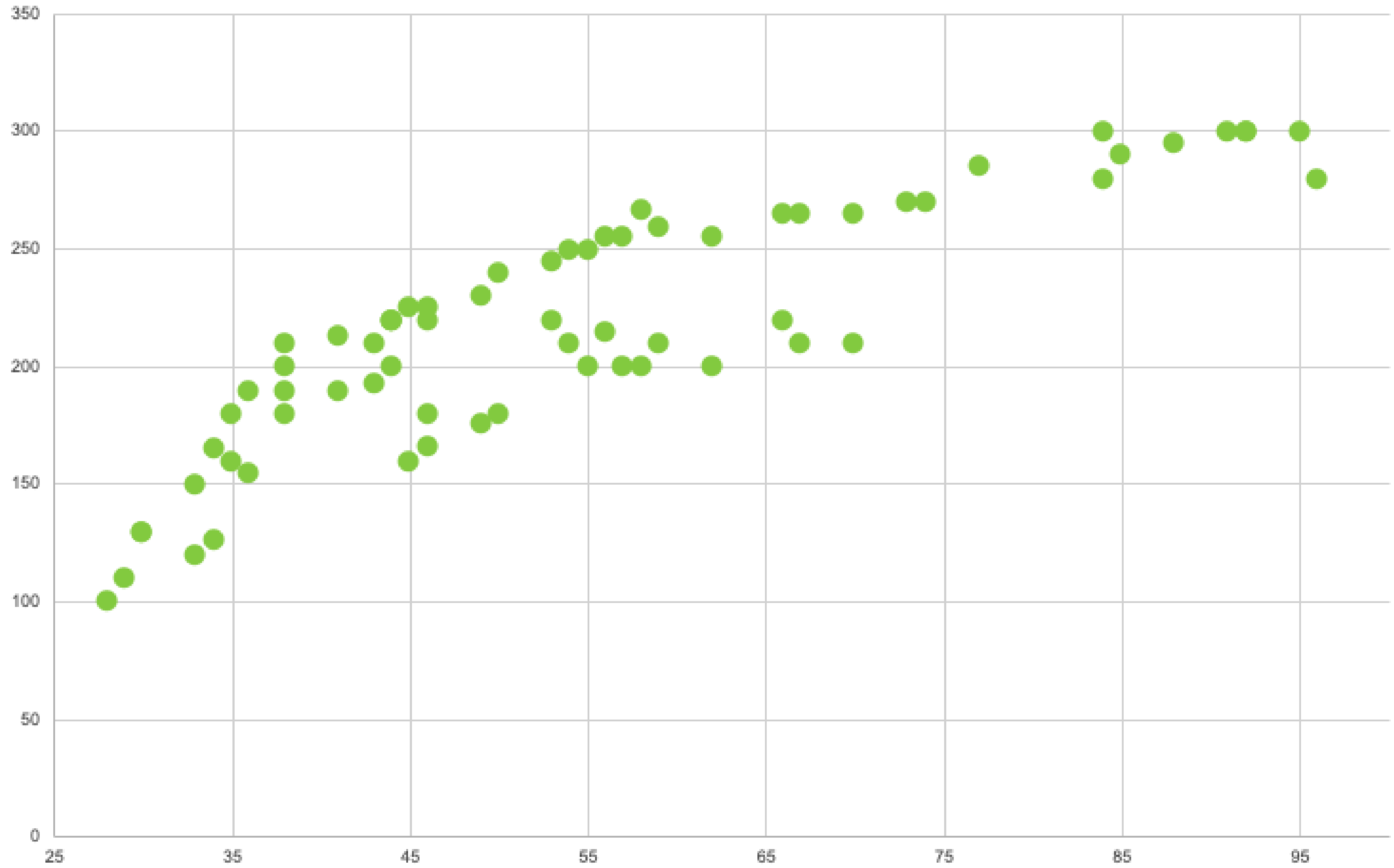
$$J(\theta_0, \theta_1) = \qquad h_\theta\left(x^{(i)}\right) - y^{(i)}$$

$$J(\theta_0, \theta_1) = \frac{1}{m}\sum_{i=1}^{m}\left(h_\theta\left(x^{(i)}\right) - y^{(i)}\right)$$

$$J(\theta_0, \theta_1) = \frac{1}{2m}\sum_{i=1}^{m}\left(h_\theta\left(x^{(i)}\right) - y^{(i)}\right)^2$$

$$\underset{(\theta_0, \theta_1)}{\text{minimaze}}\, J(\theta_0, \theta_1)$$

Jak wygląda proces uczenia?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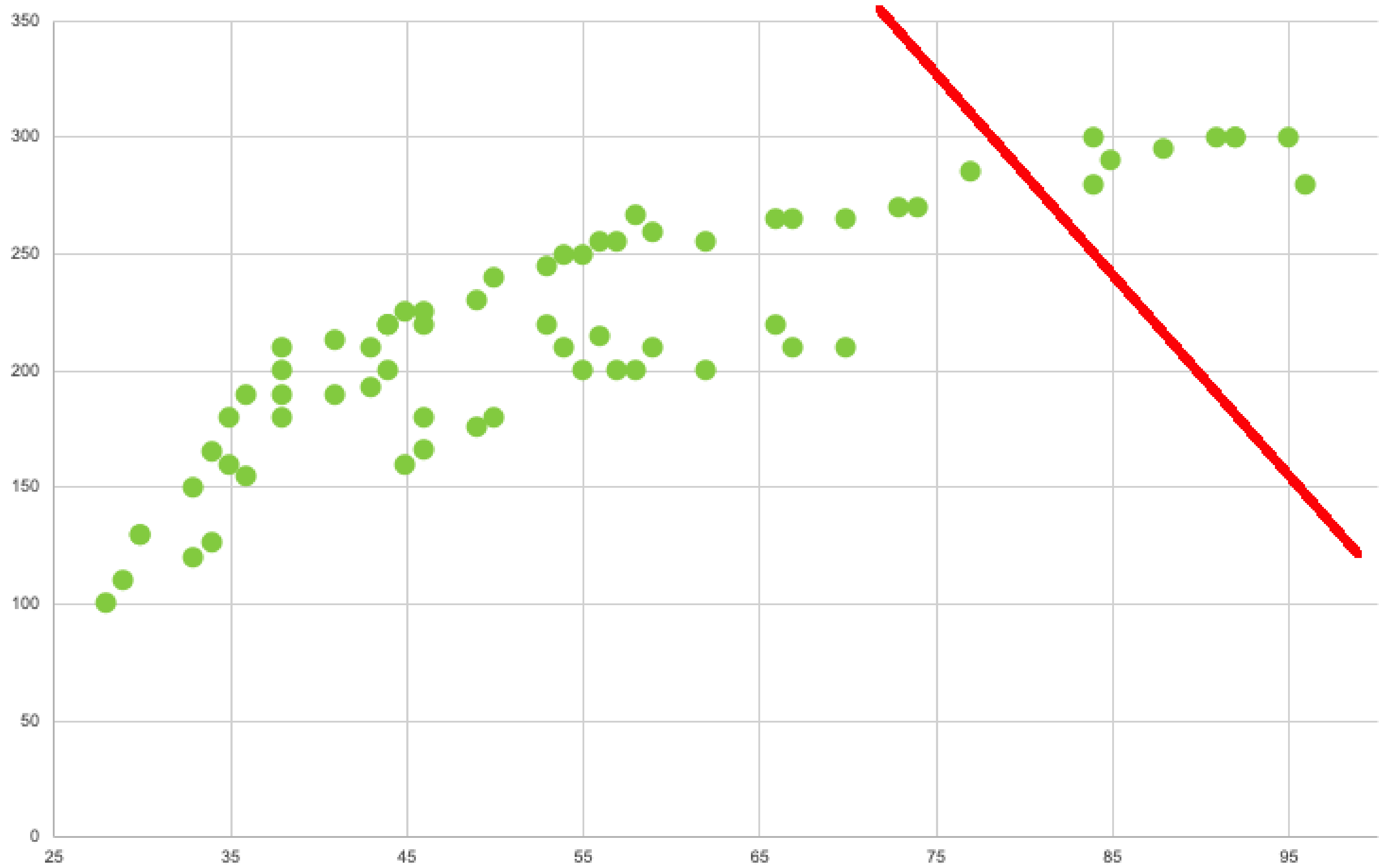

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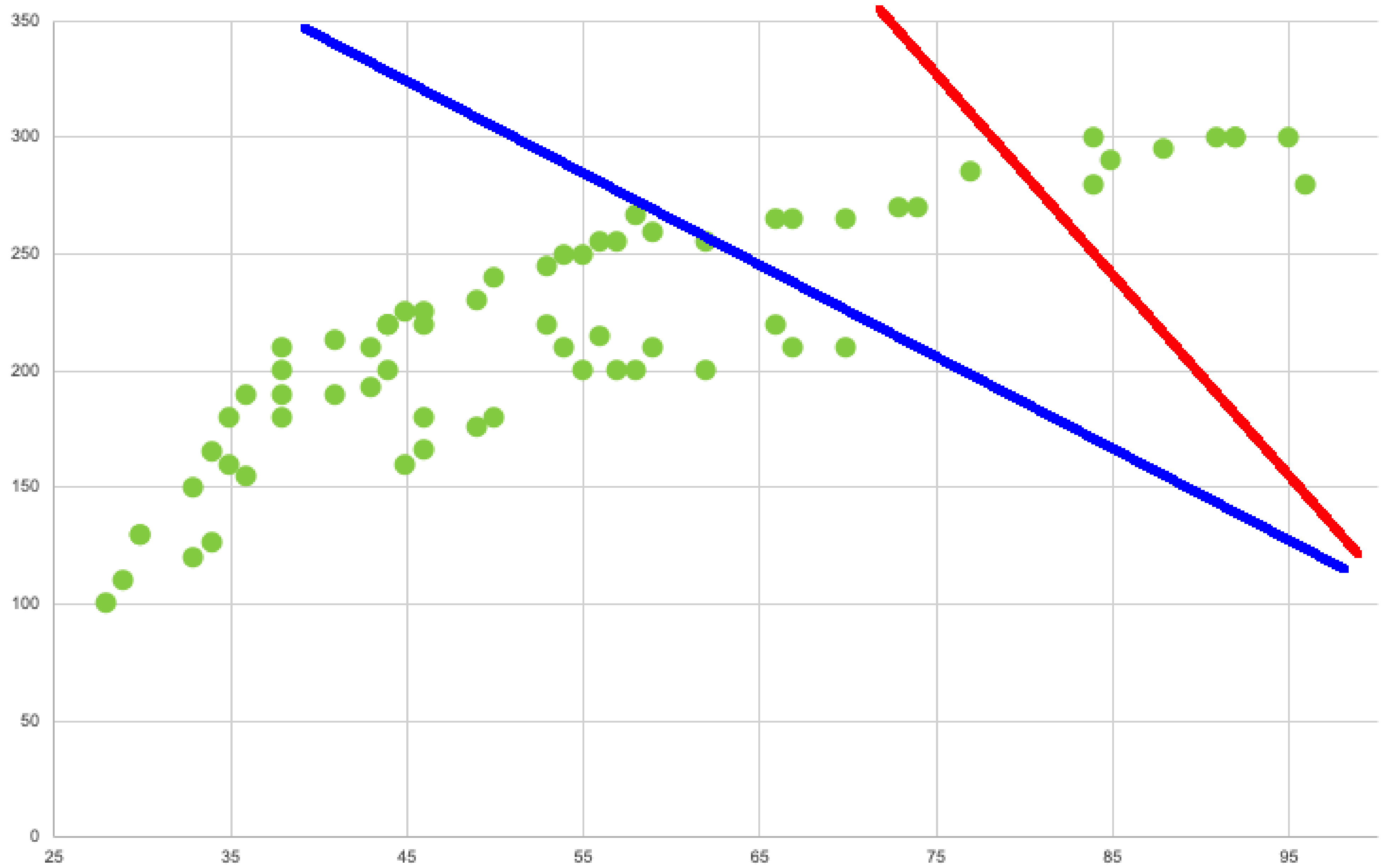
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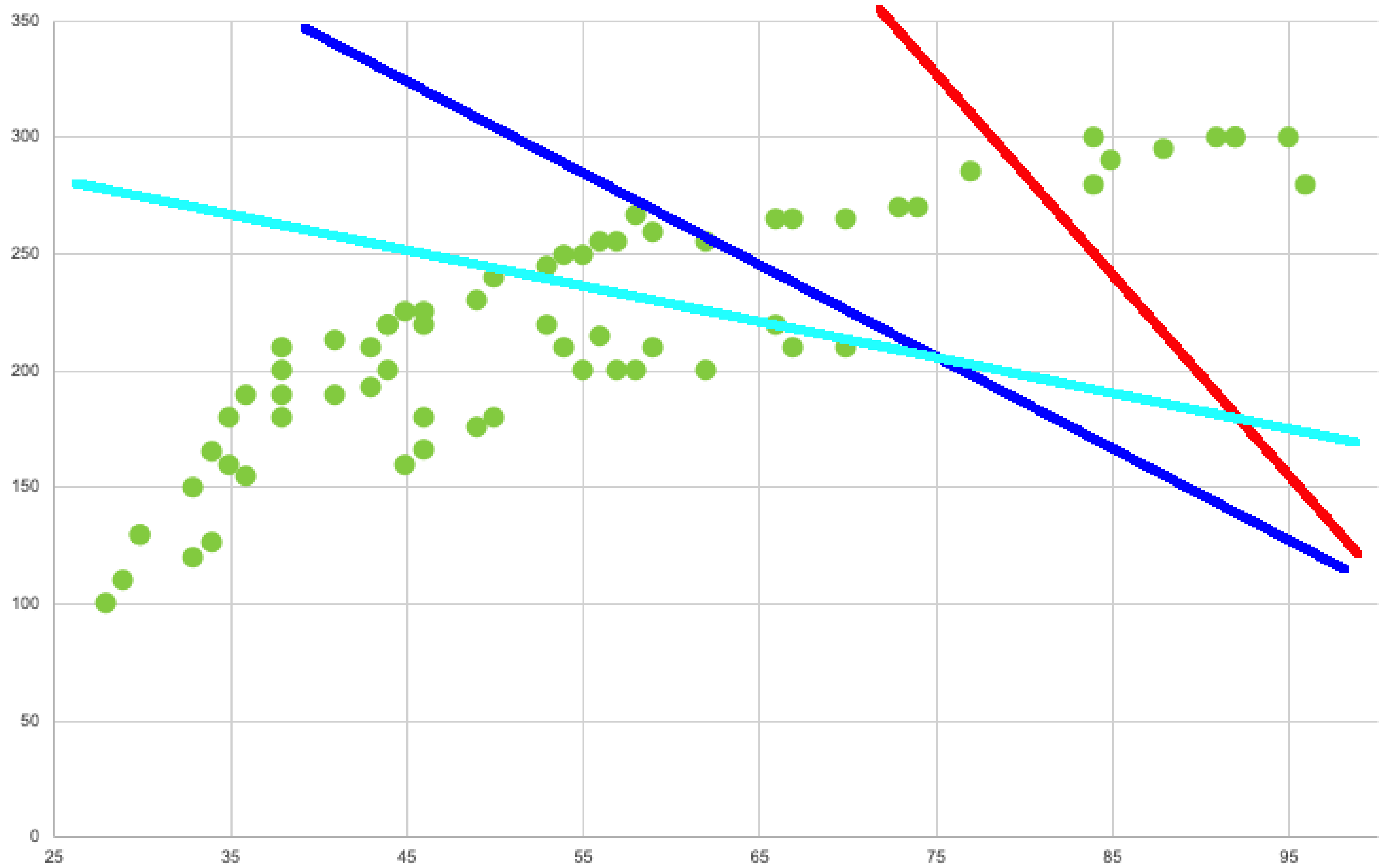
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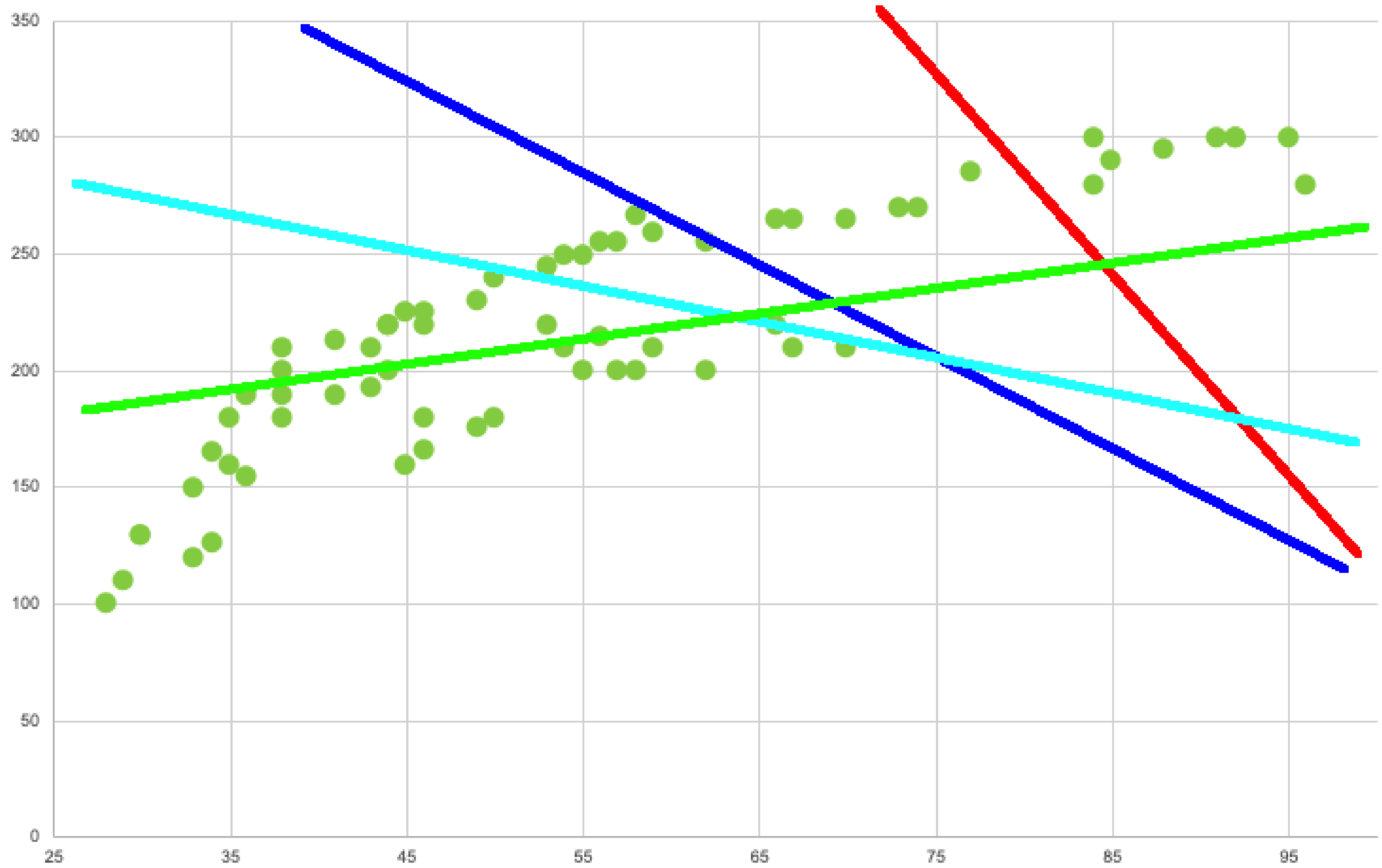
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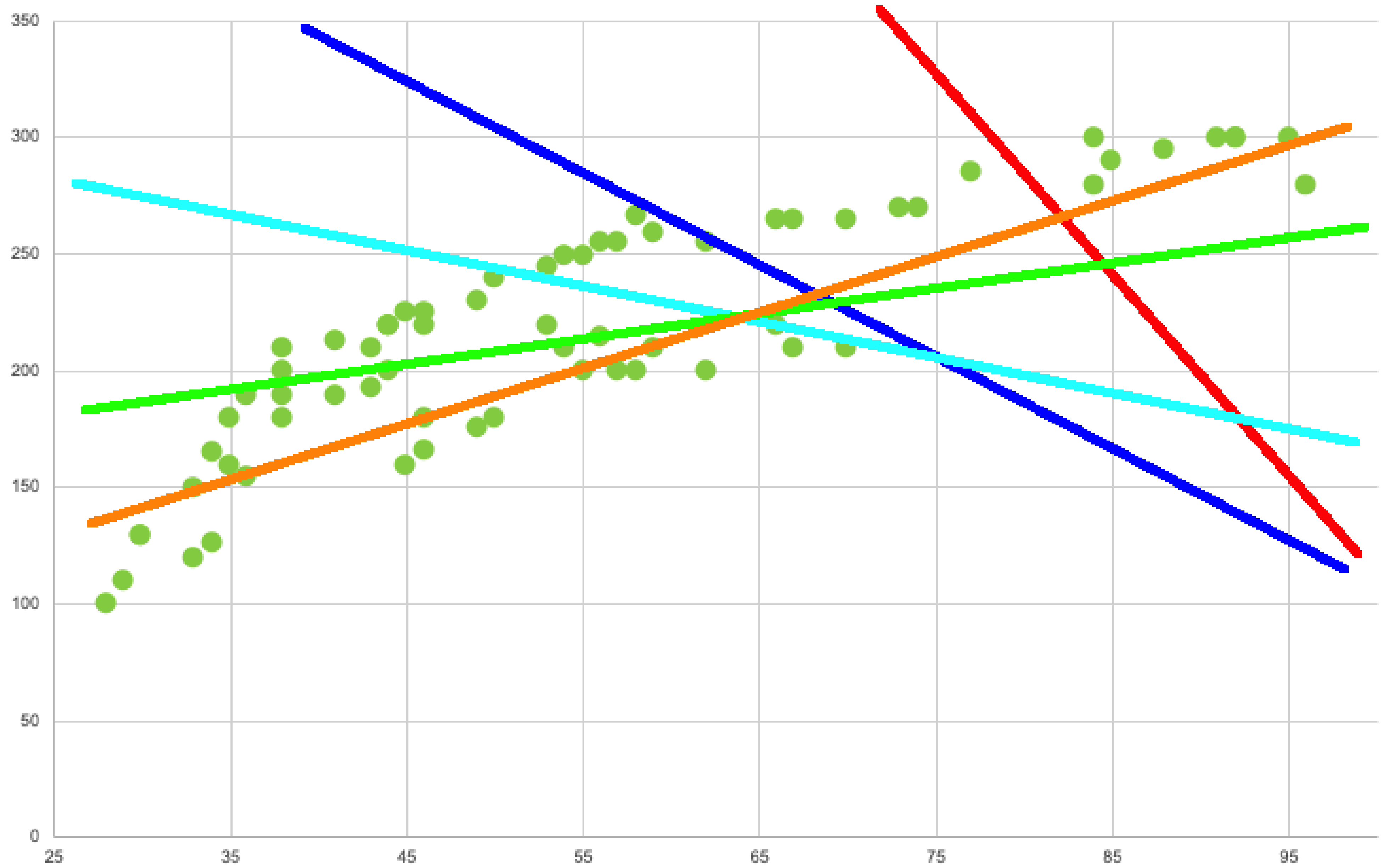
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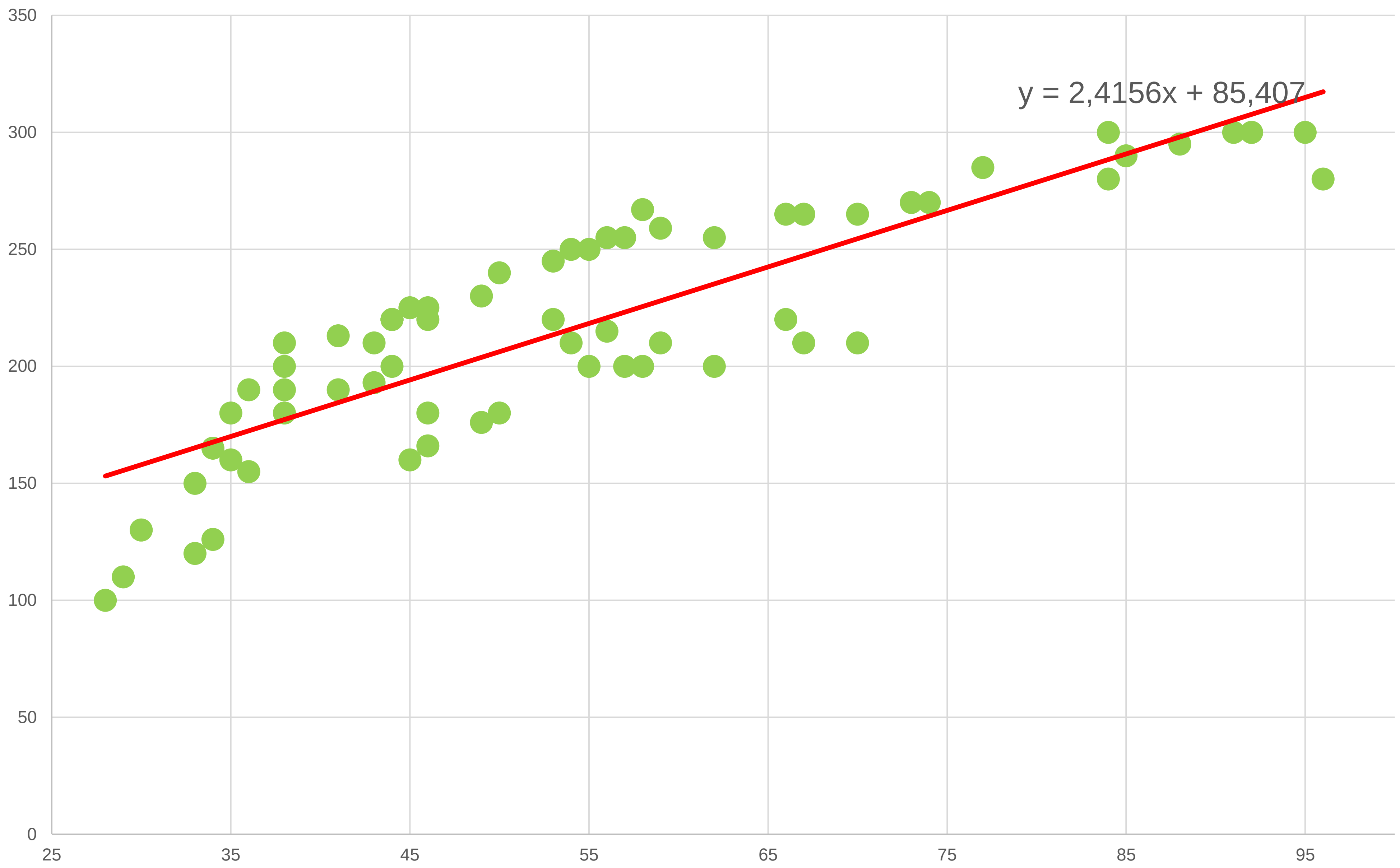

y = 2,4156x + 85,407
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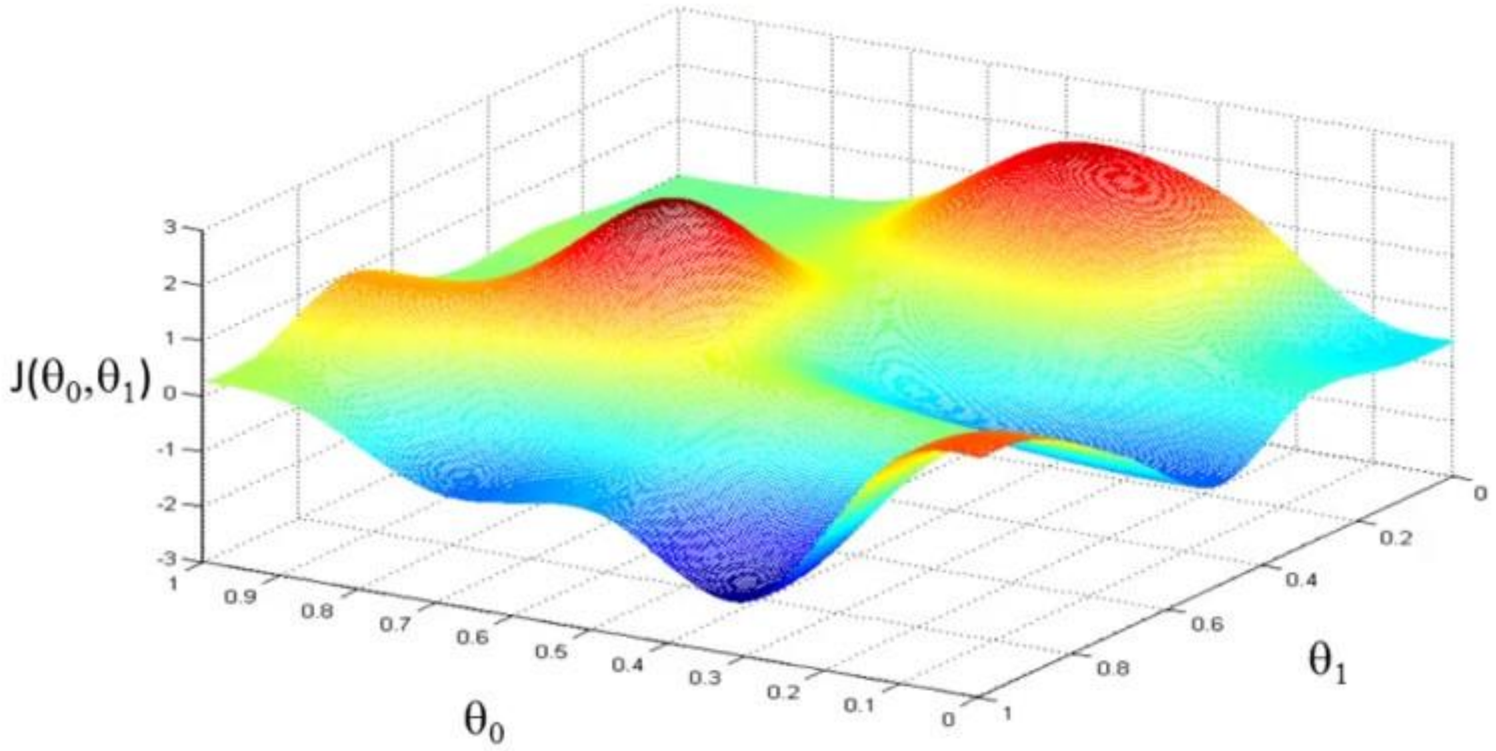
Gradient prosty


$J(\theta_0,\theta_1)$
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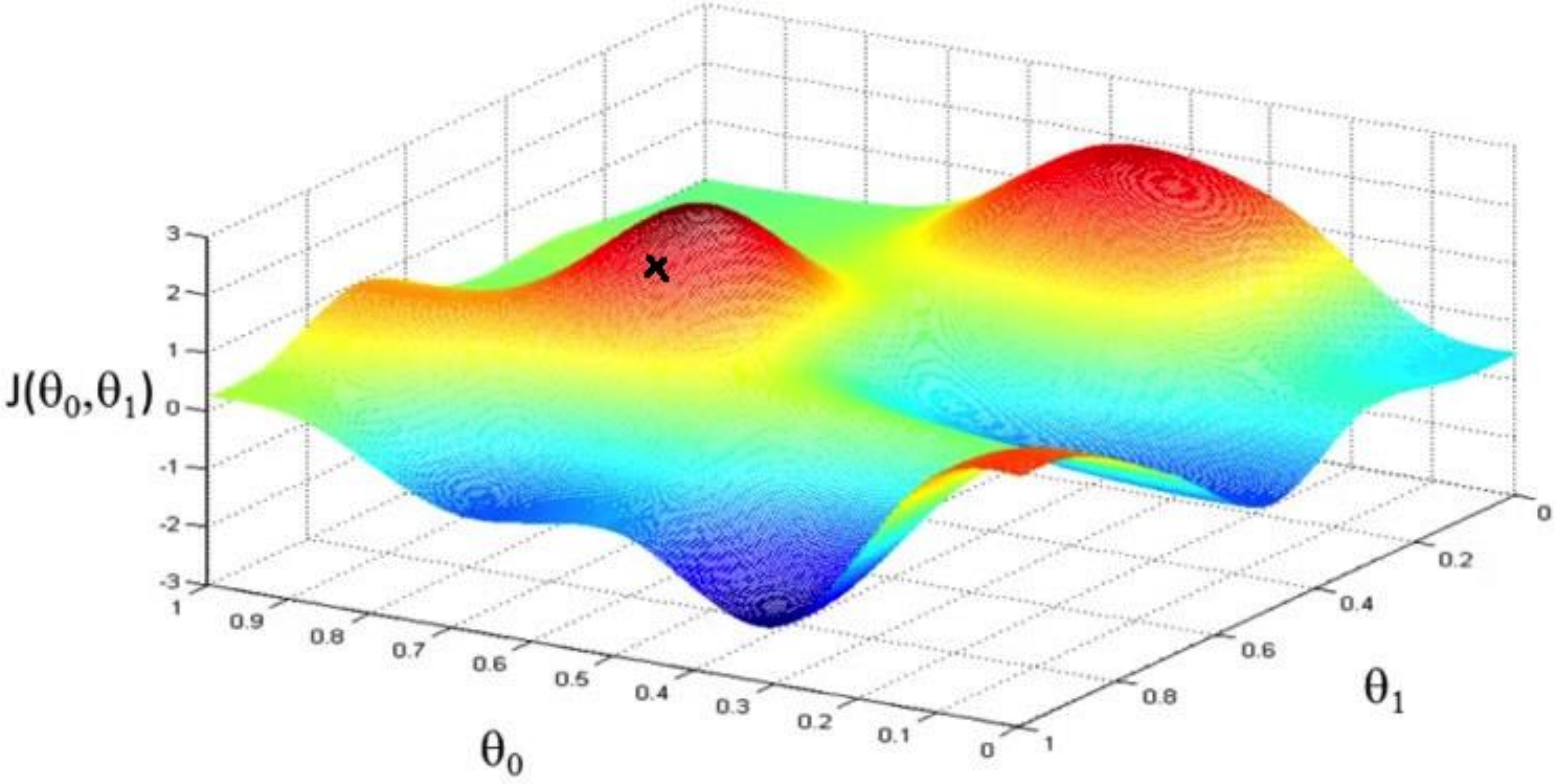
θ_1



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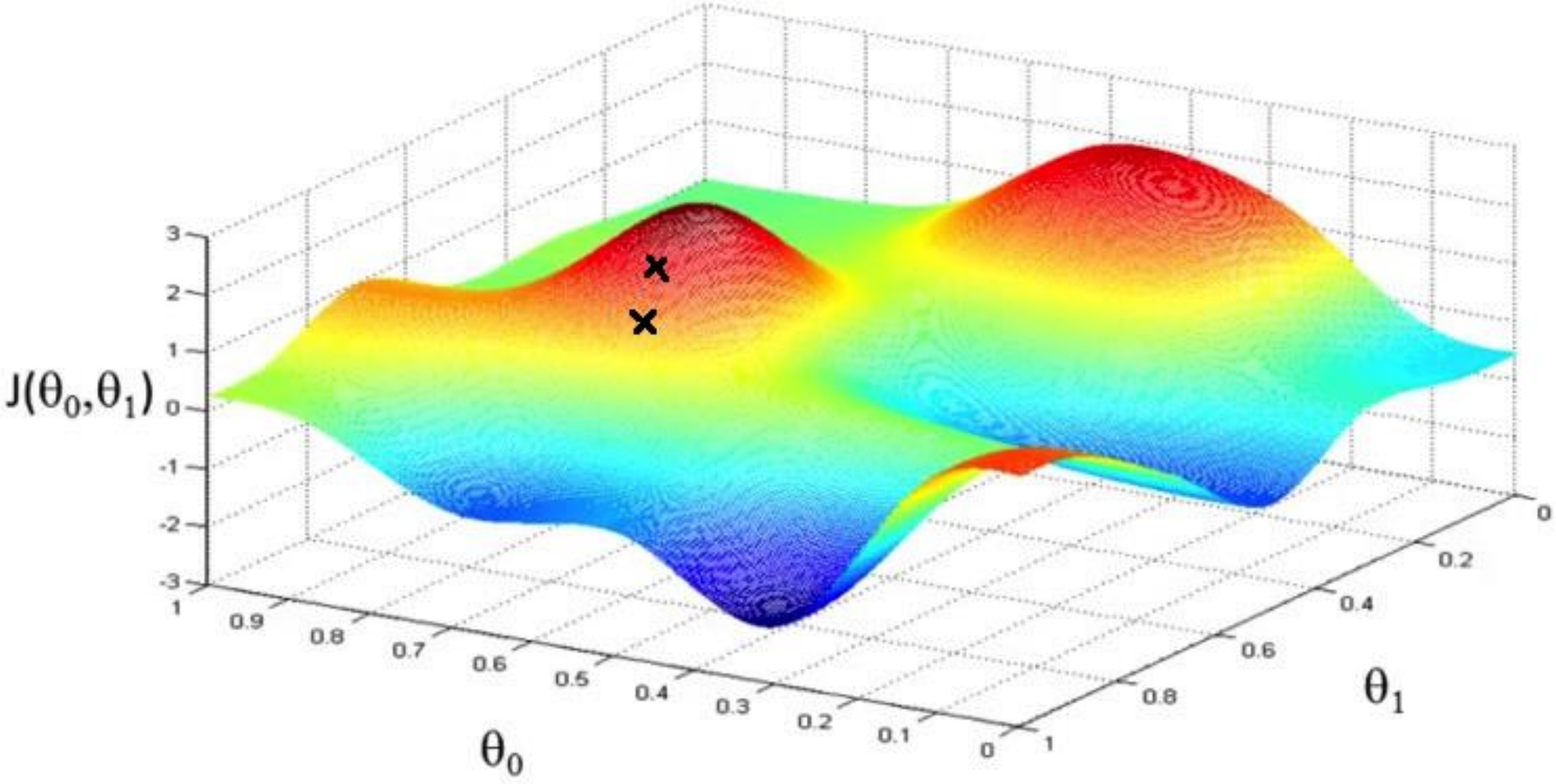

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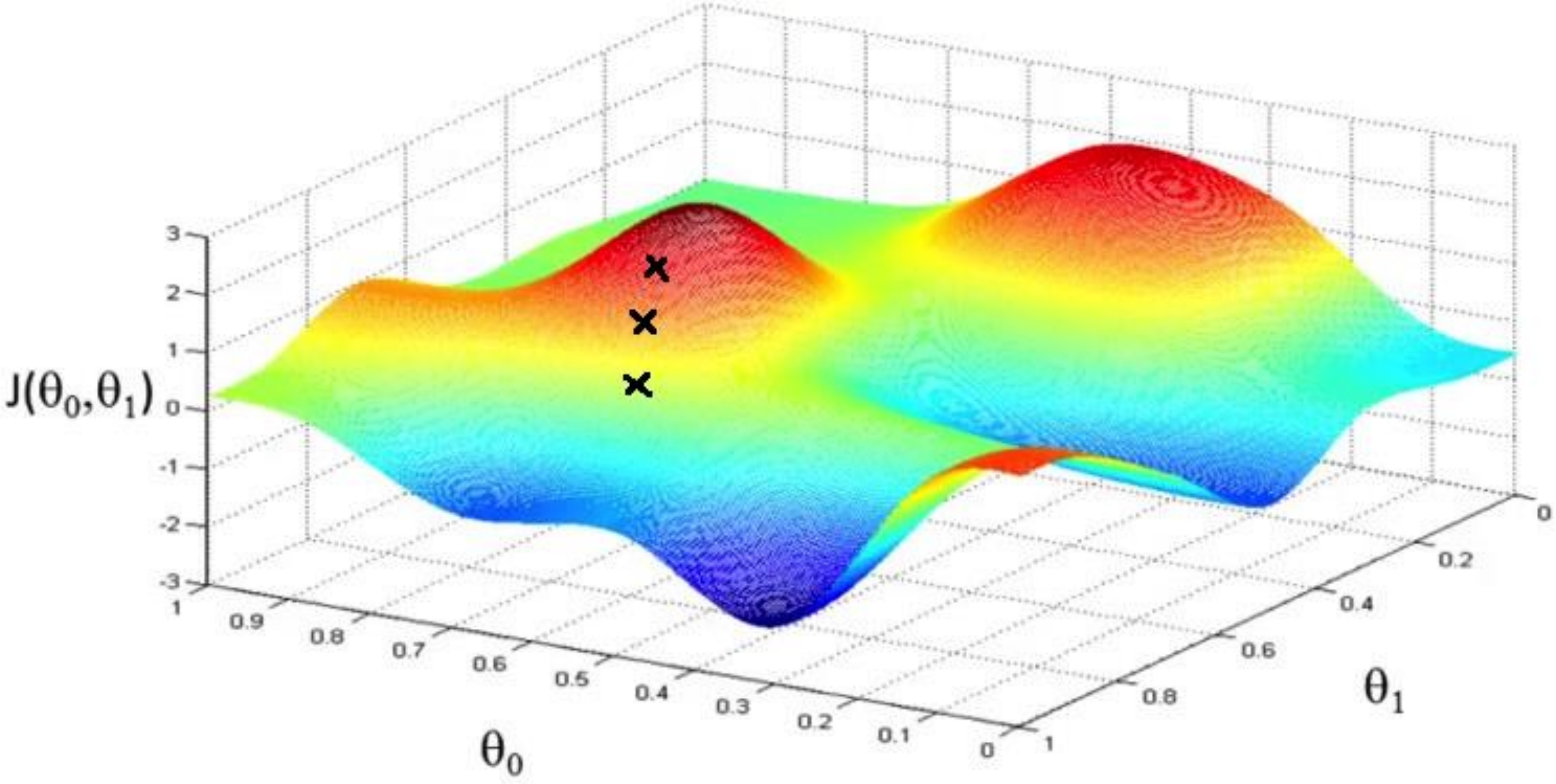

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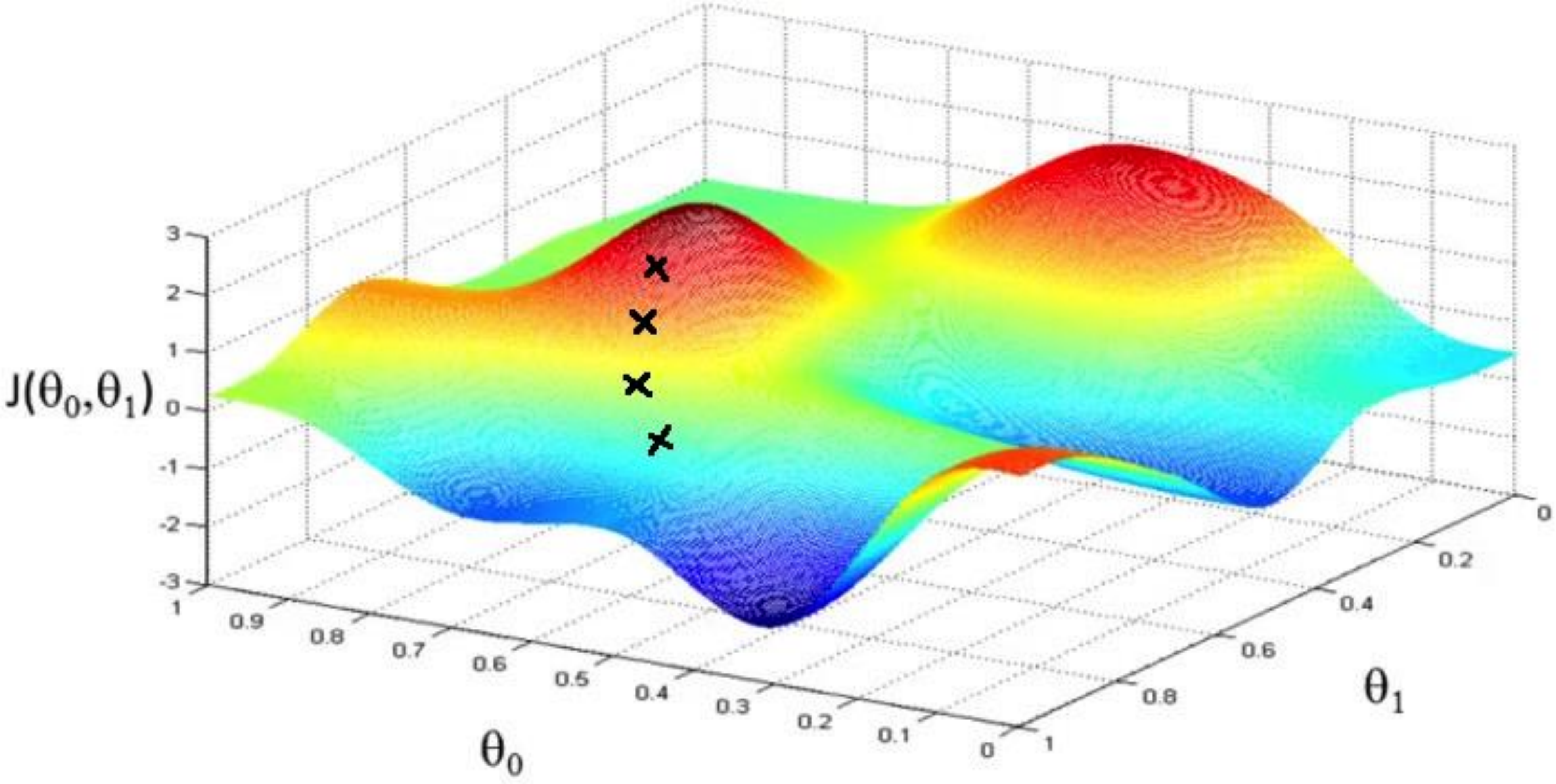

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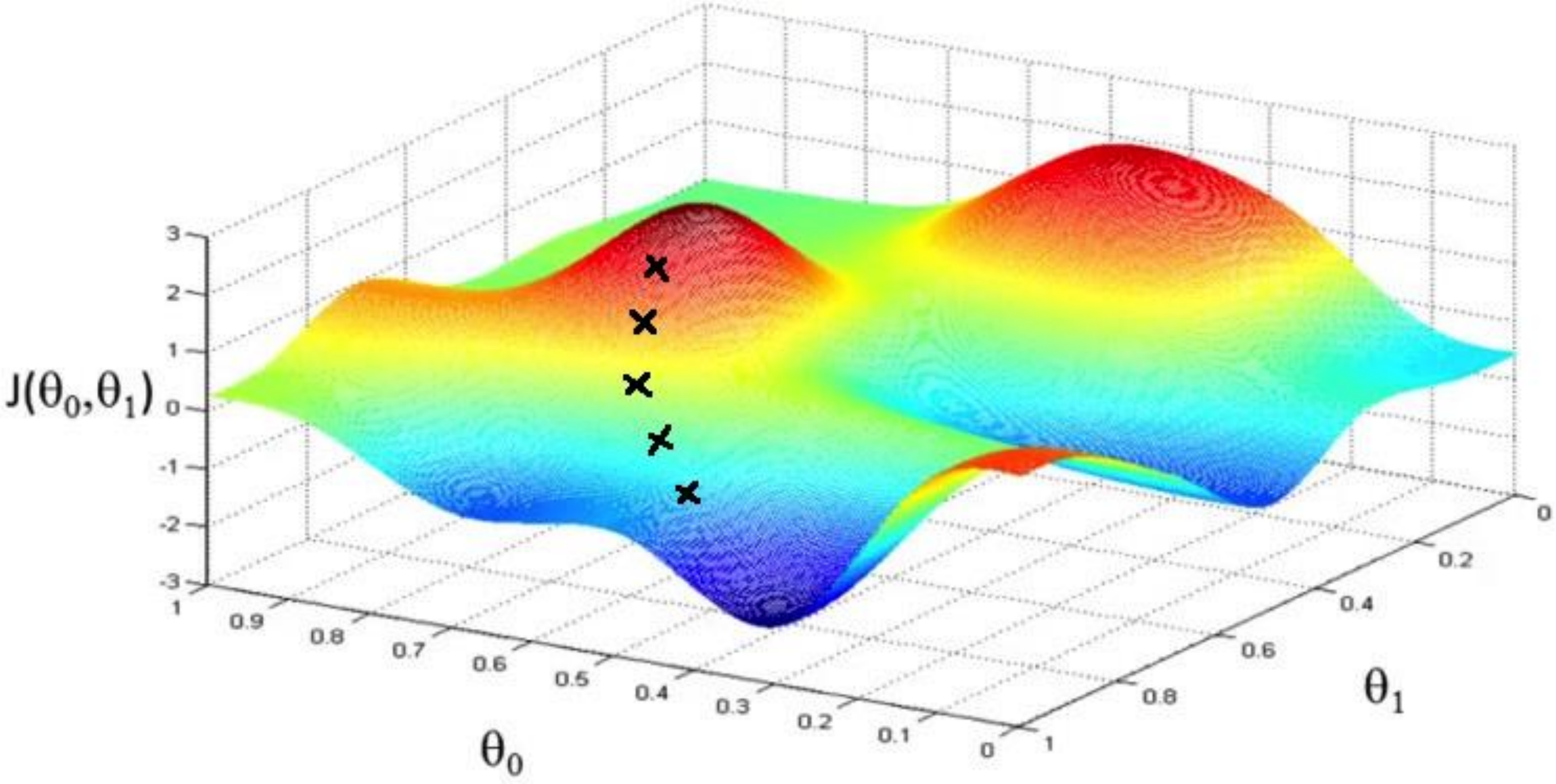

J(θ0,θ1)
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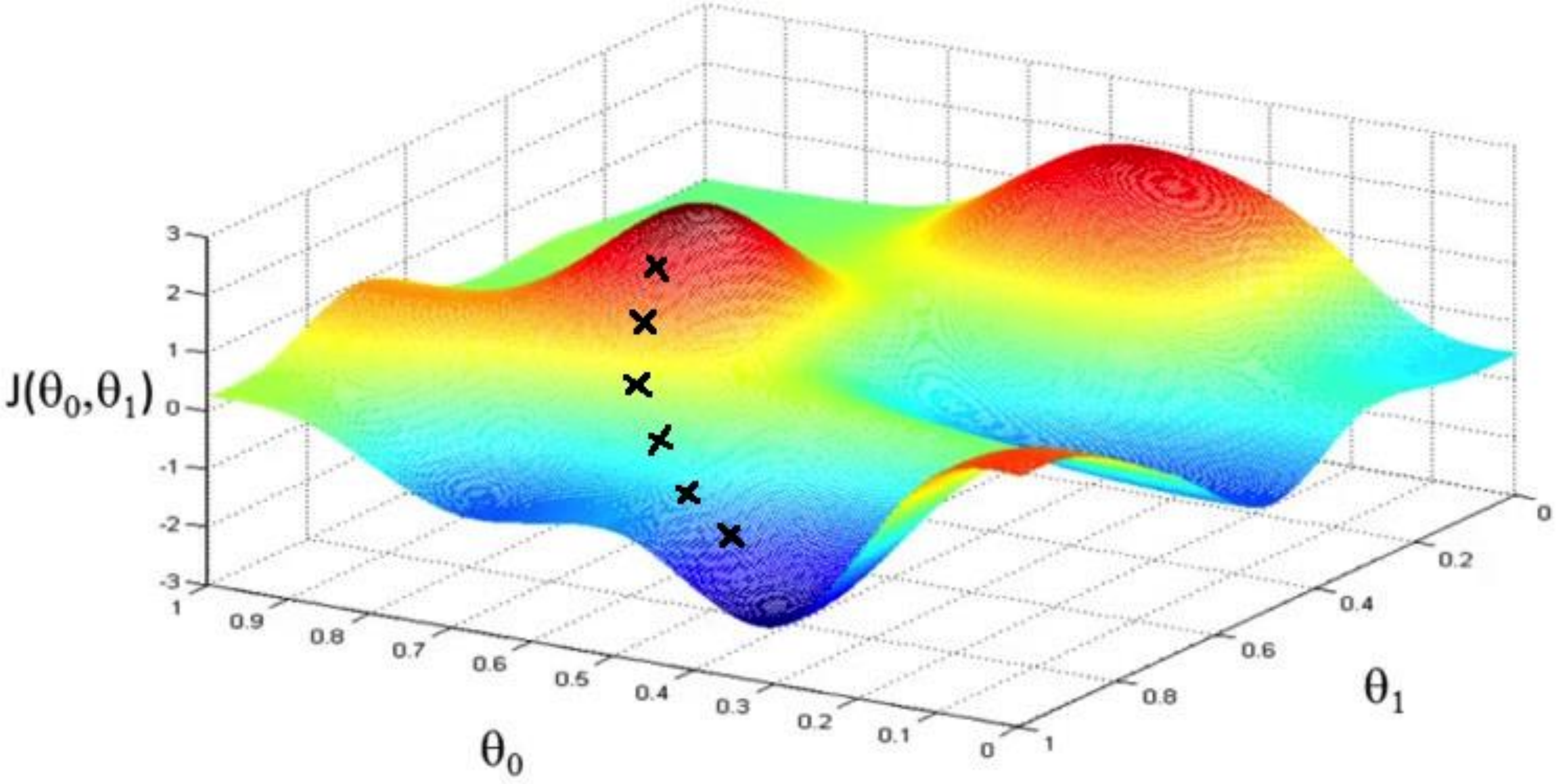
θ1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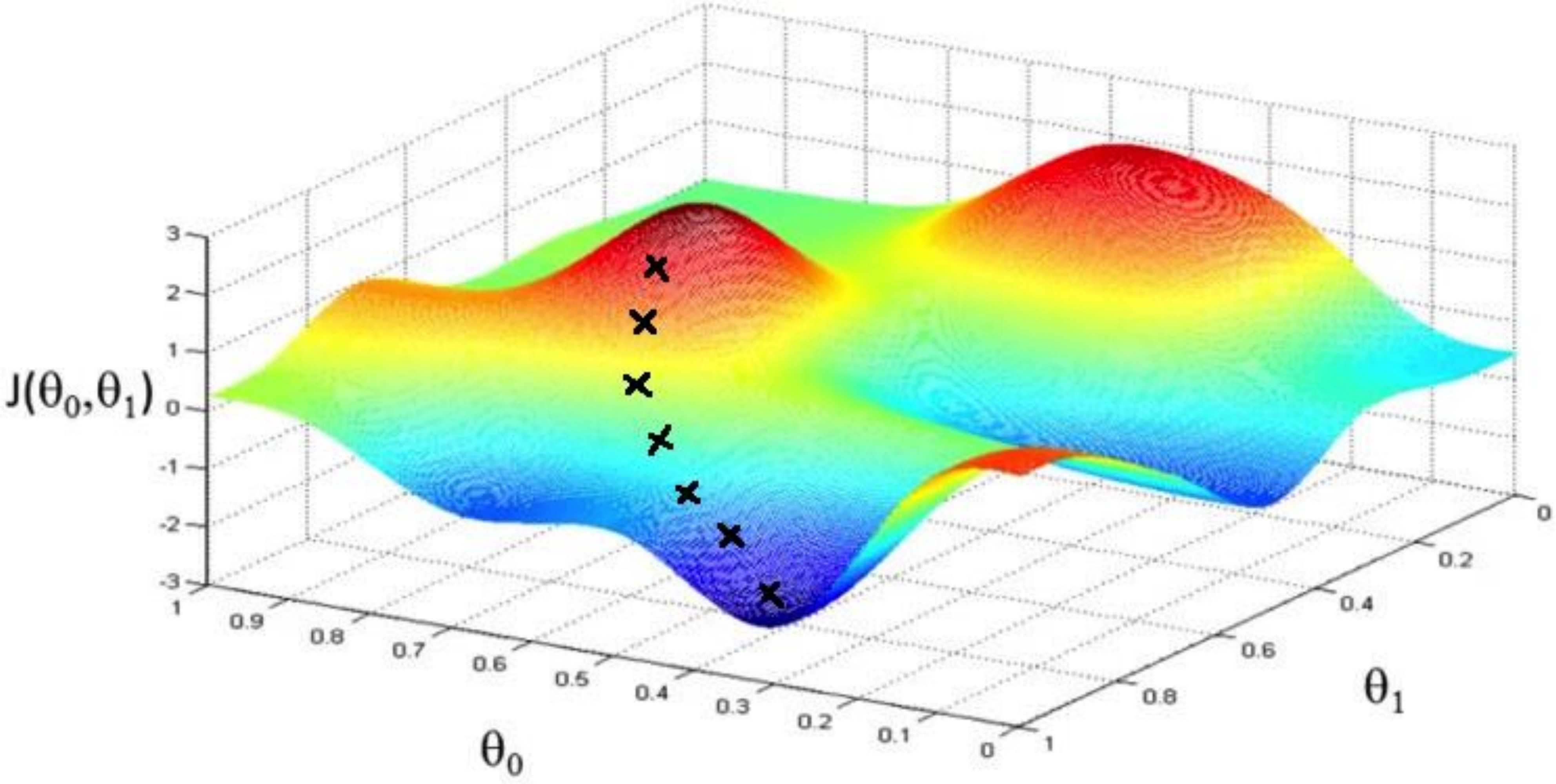

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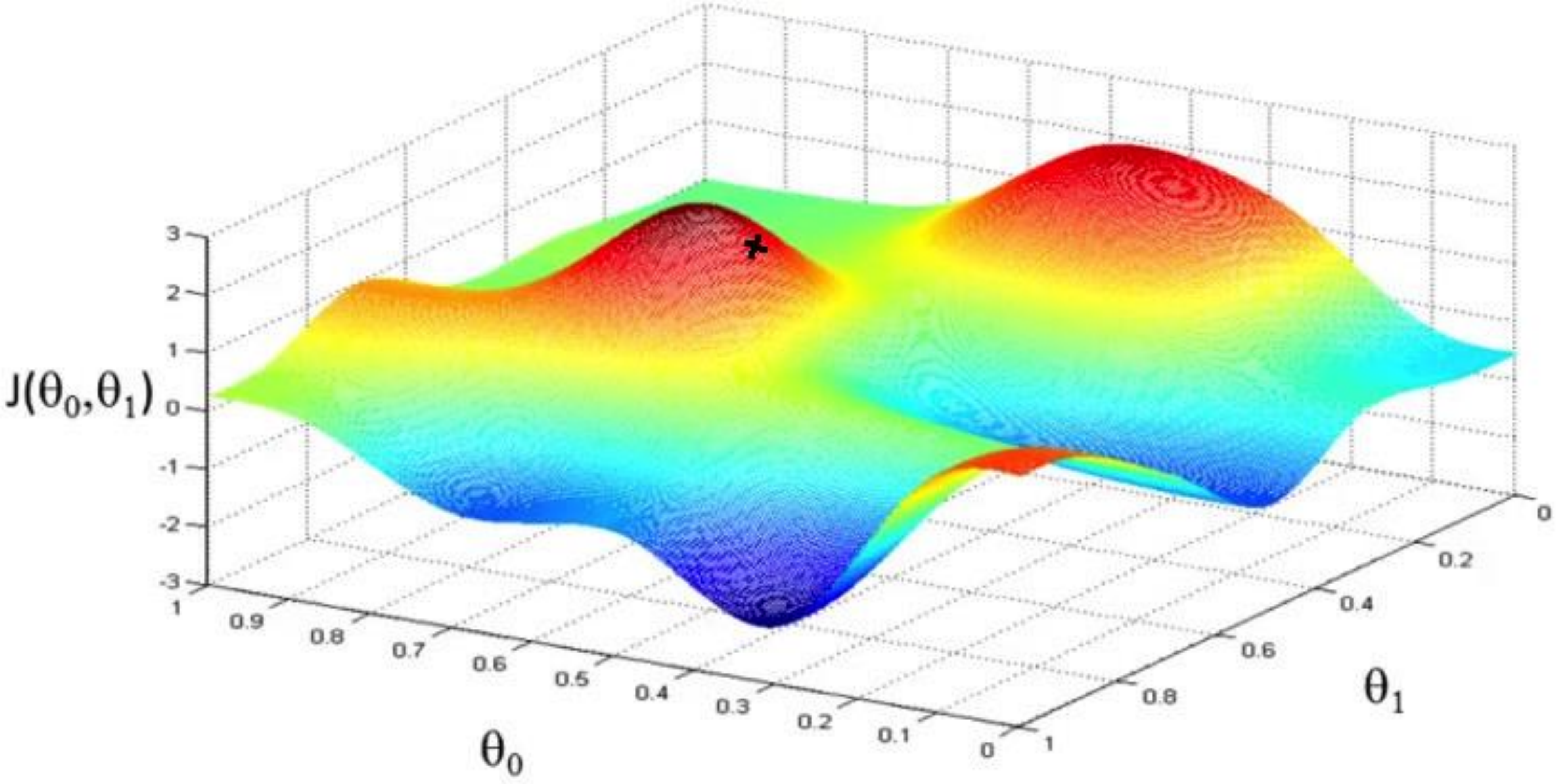

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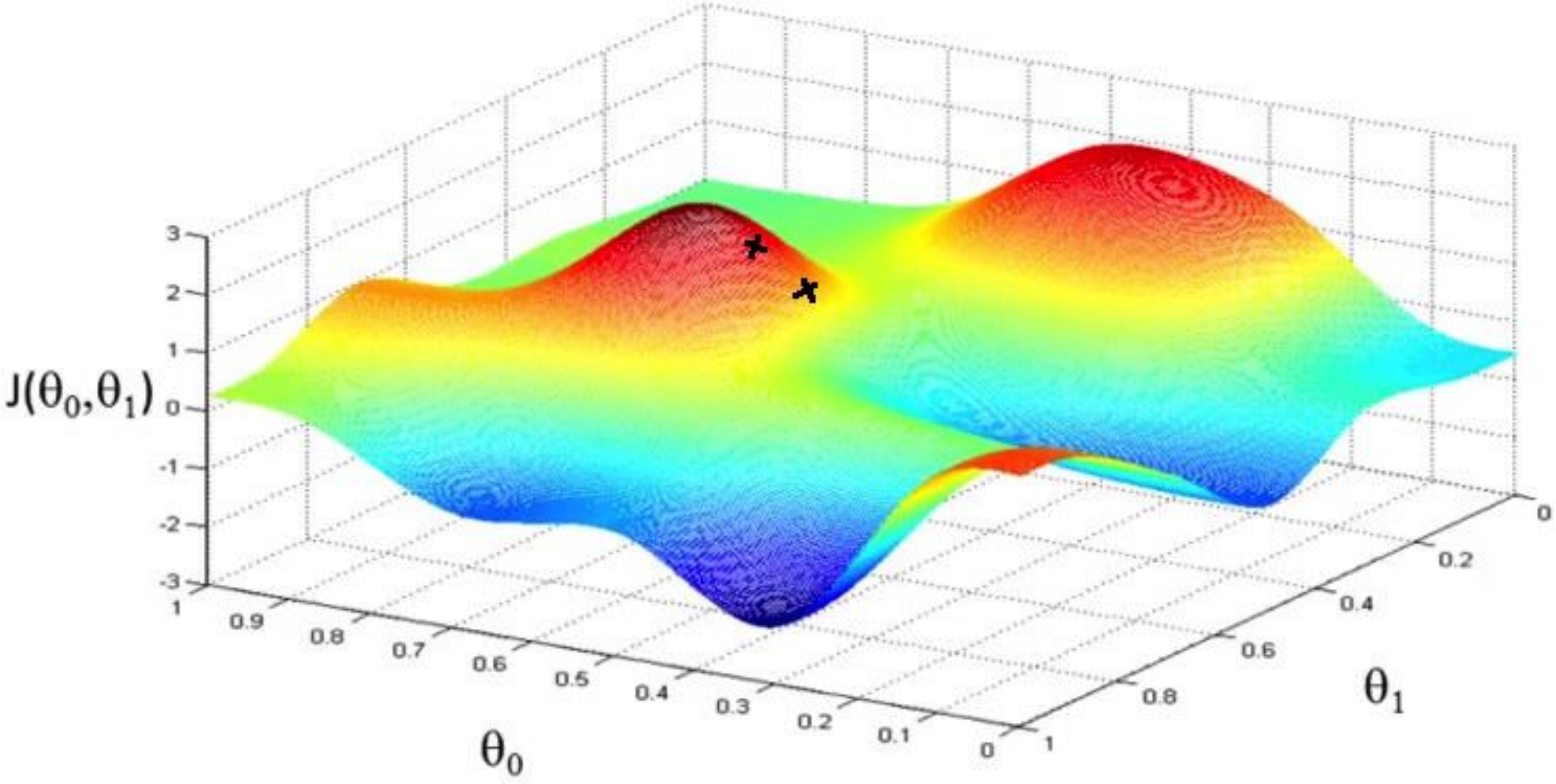

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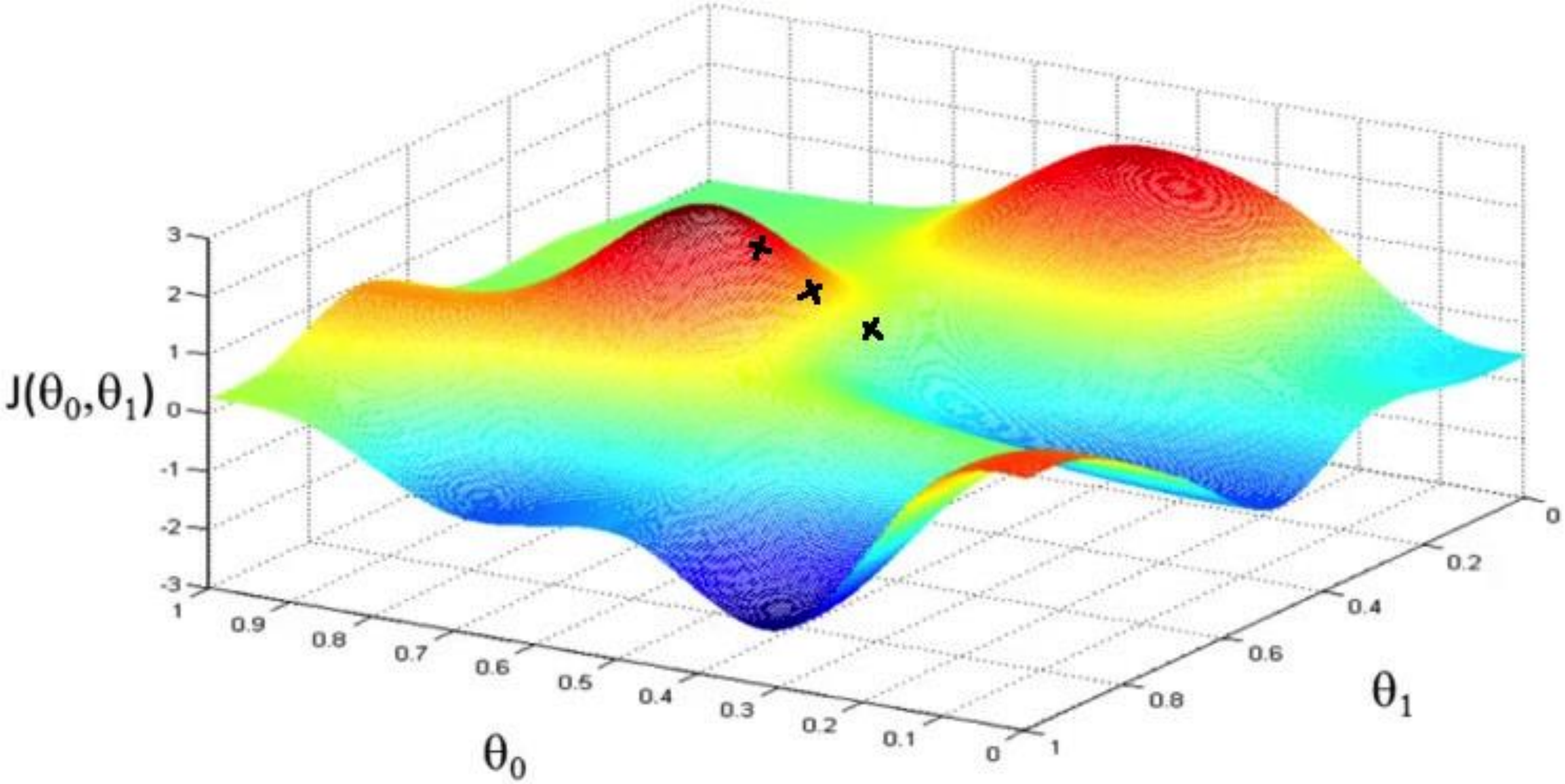
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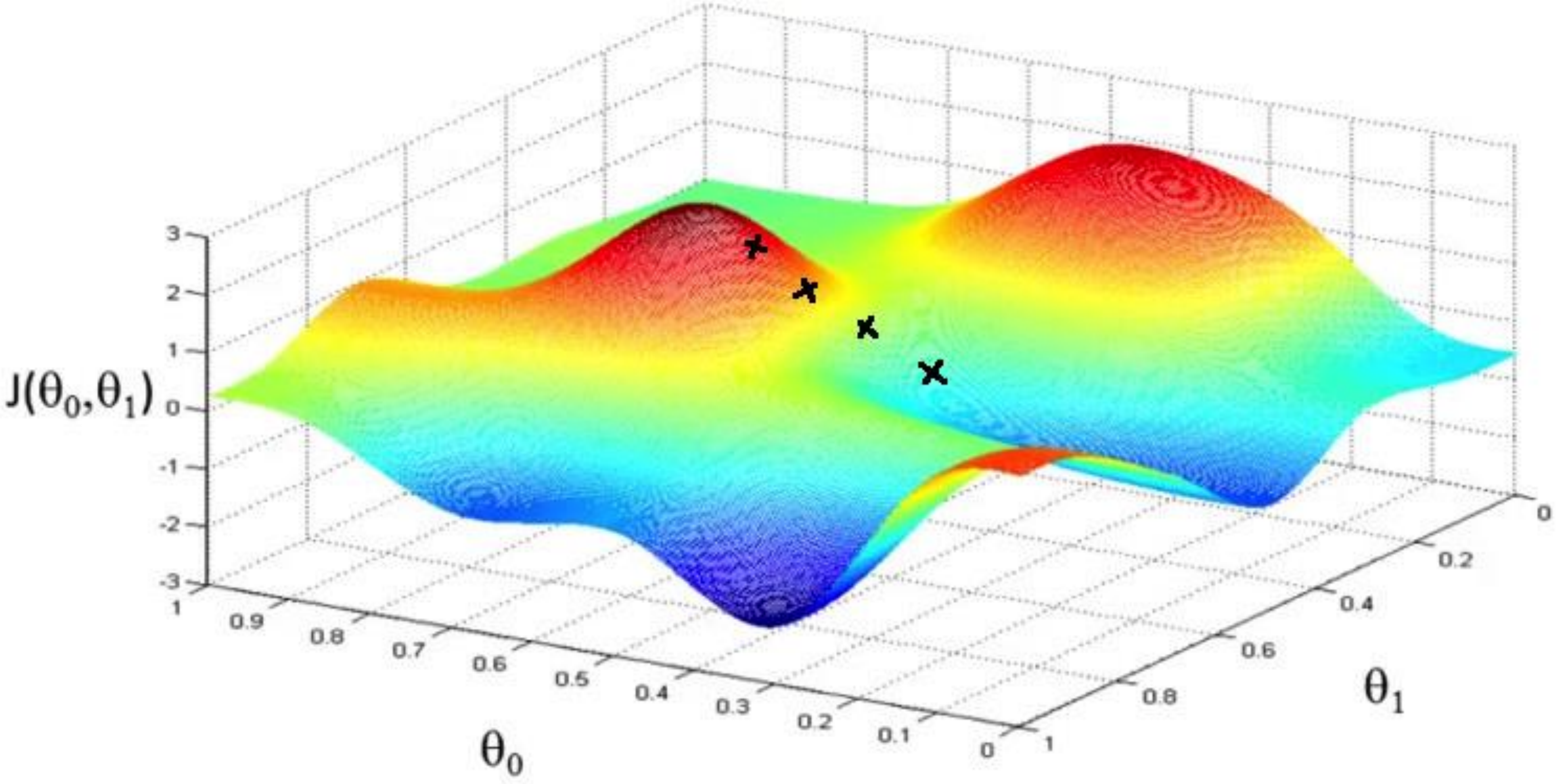

$J(\theta_0,\theta_1)$
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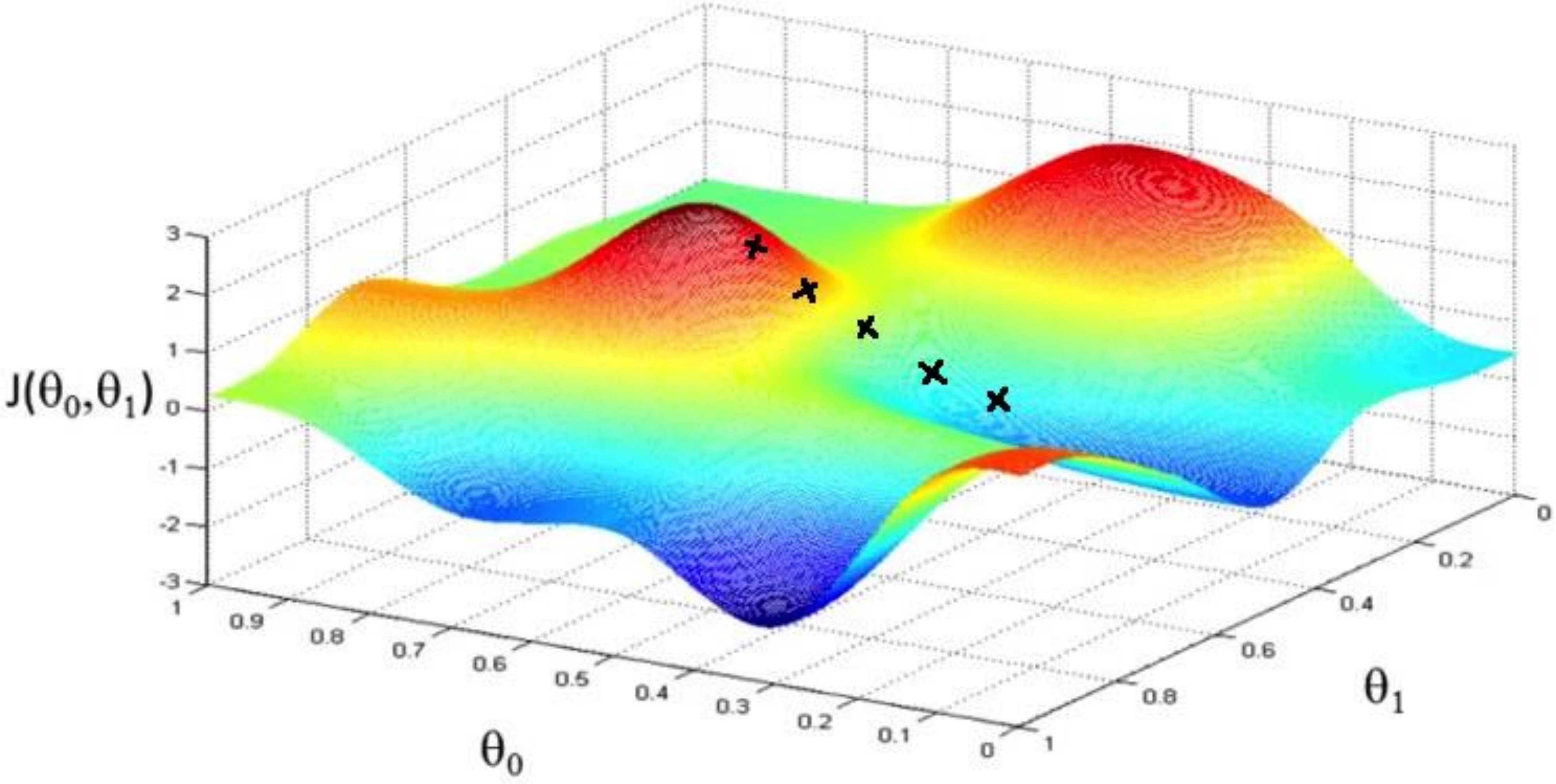

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$J(\theta_0,\theta_1)$
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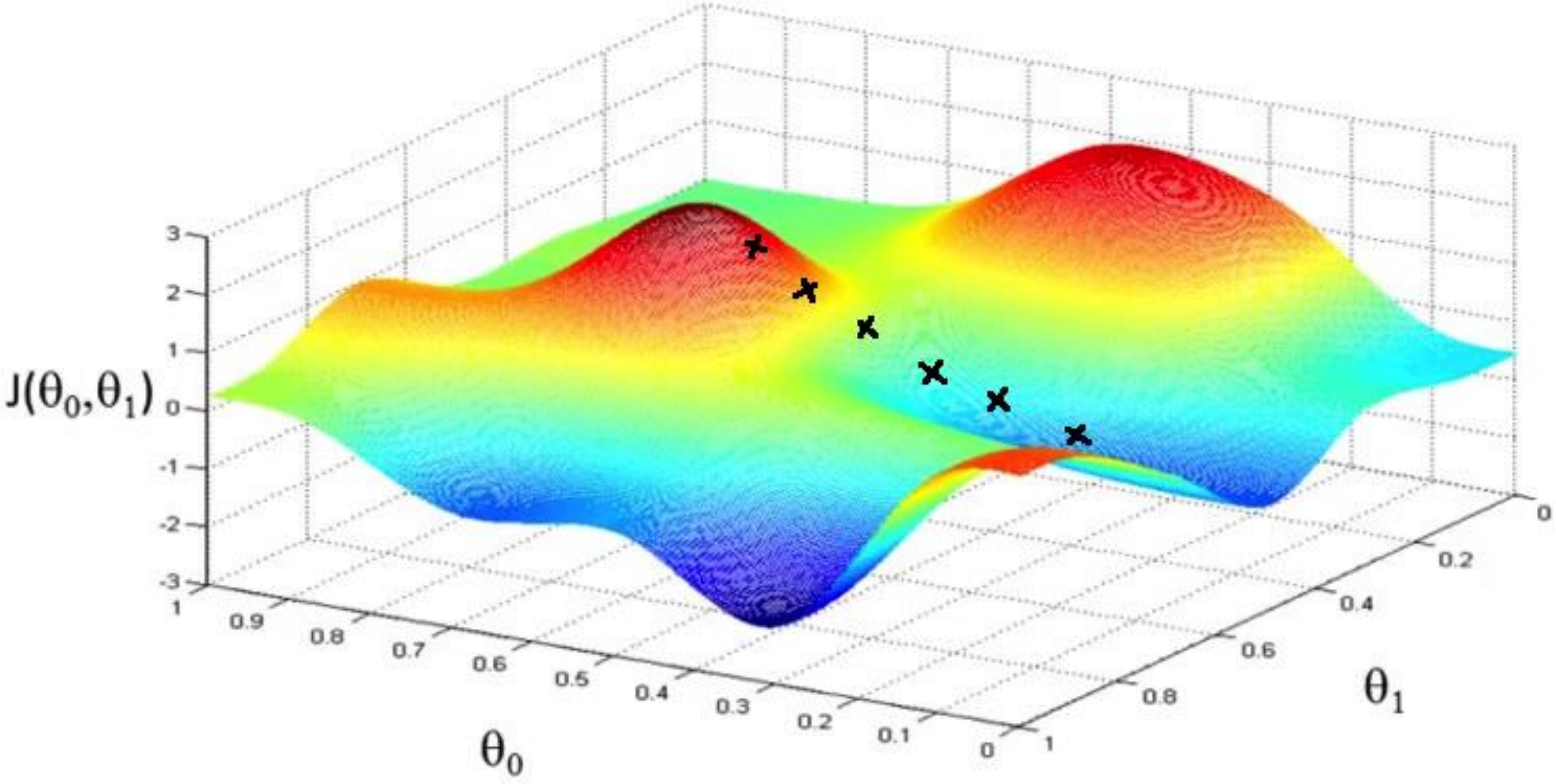

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$J(\theta_0,\theta_1)$
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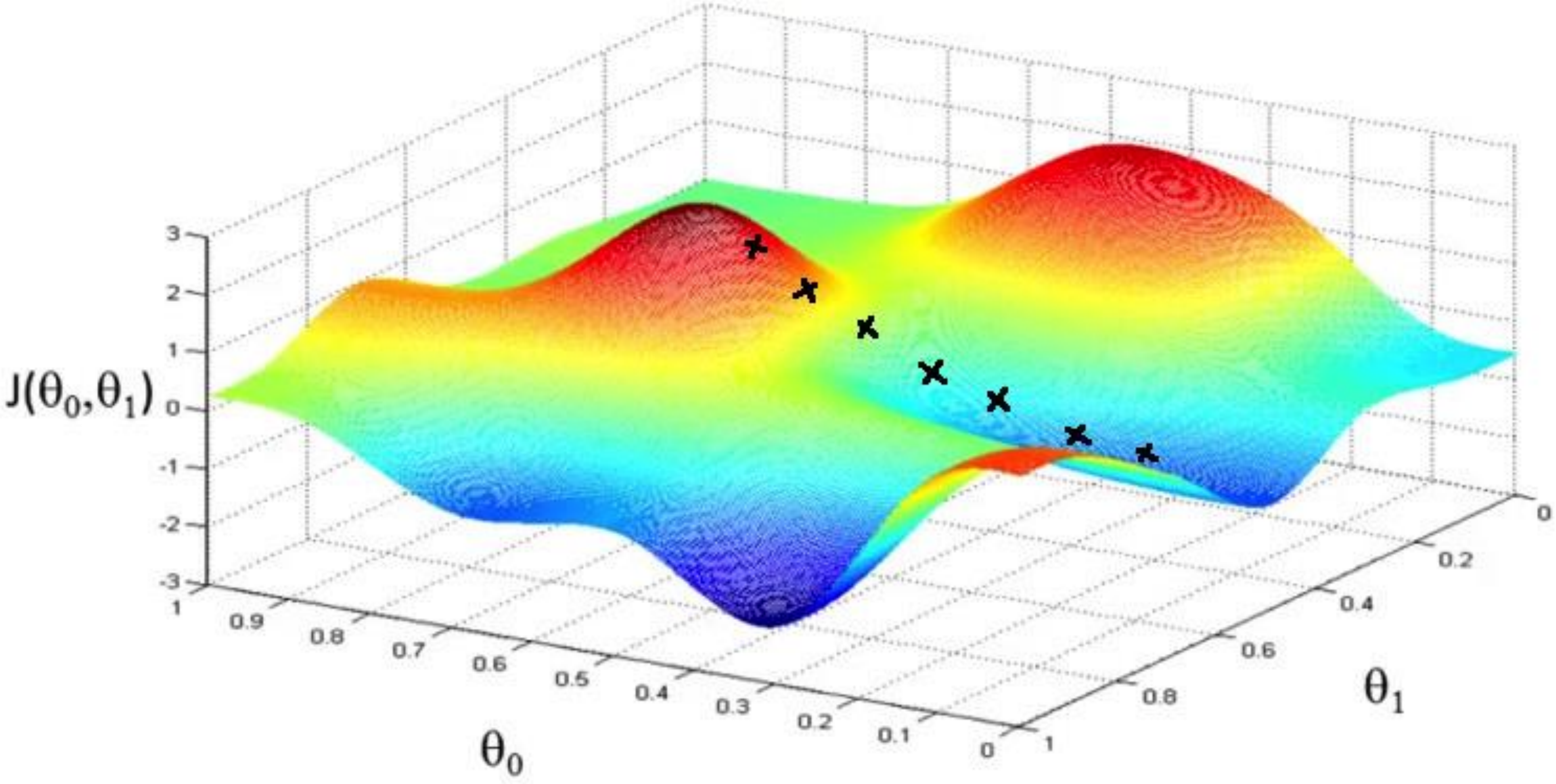
θ_1



$J(\theta_0,\theta_1)$
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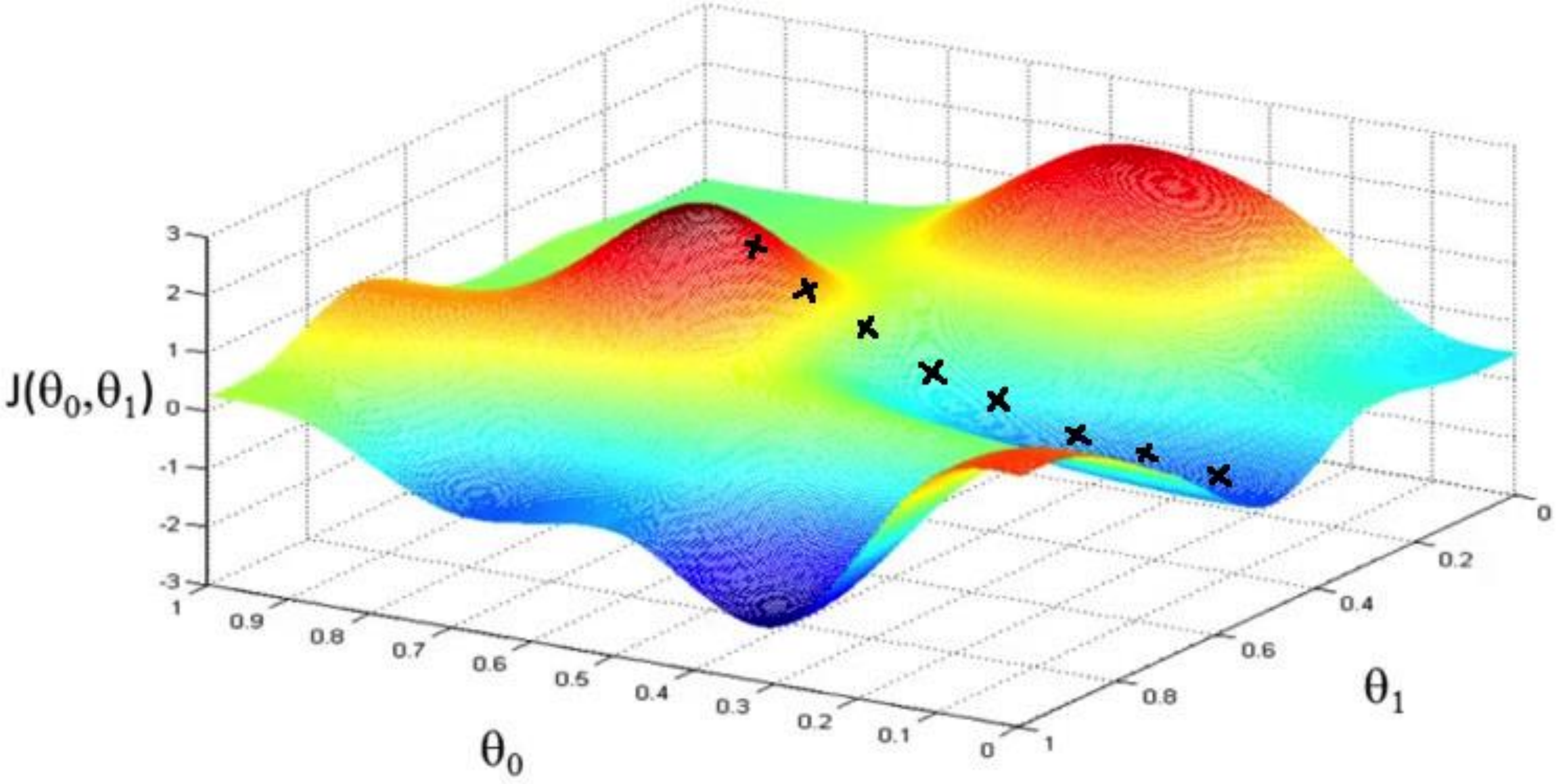
$J(\theta_0,\theta_1)$
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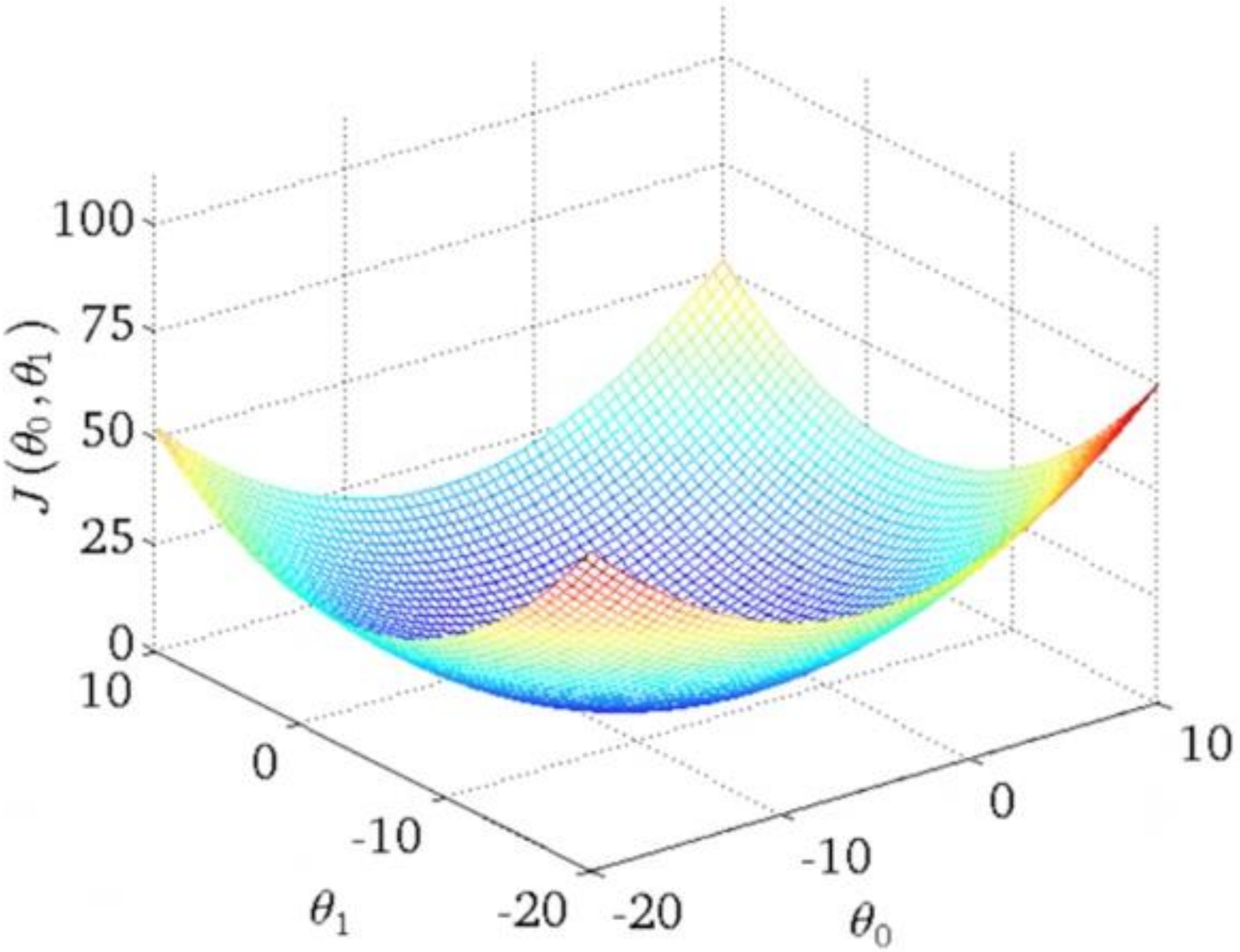
θ_1


100
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25
0
$J(\theta_0, \theta_1)$
10
0
-10
-20
θ_1
-20
-10
0
10
θ_0

Gradient prosty

- Zaczynami z dowolnymi θ_0, θ_1
- Zmieniamy θ_0, θ_1 tak żeby $J(\theta)$ się zmniejszało

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1)$$

$$\theta_0 := \theta_0 - \alpha \frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)})$$

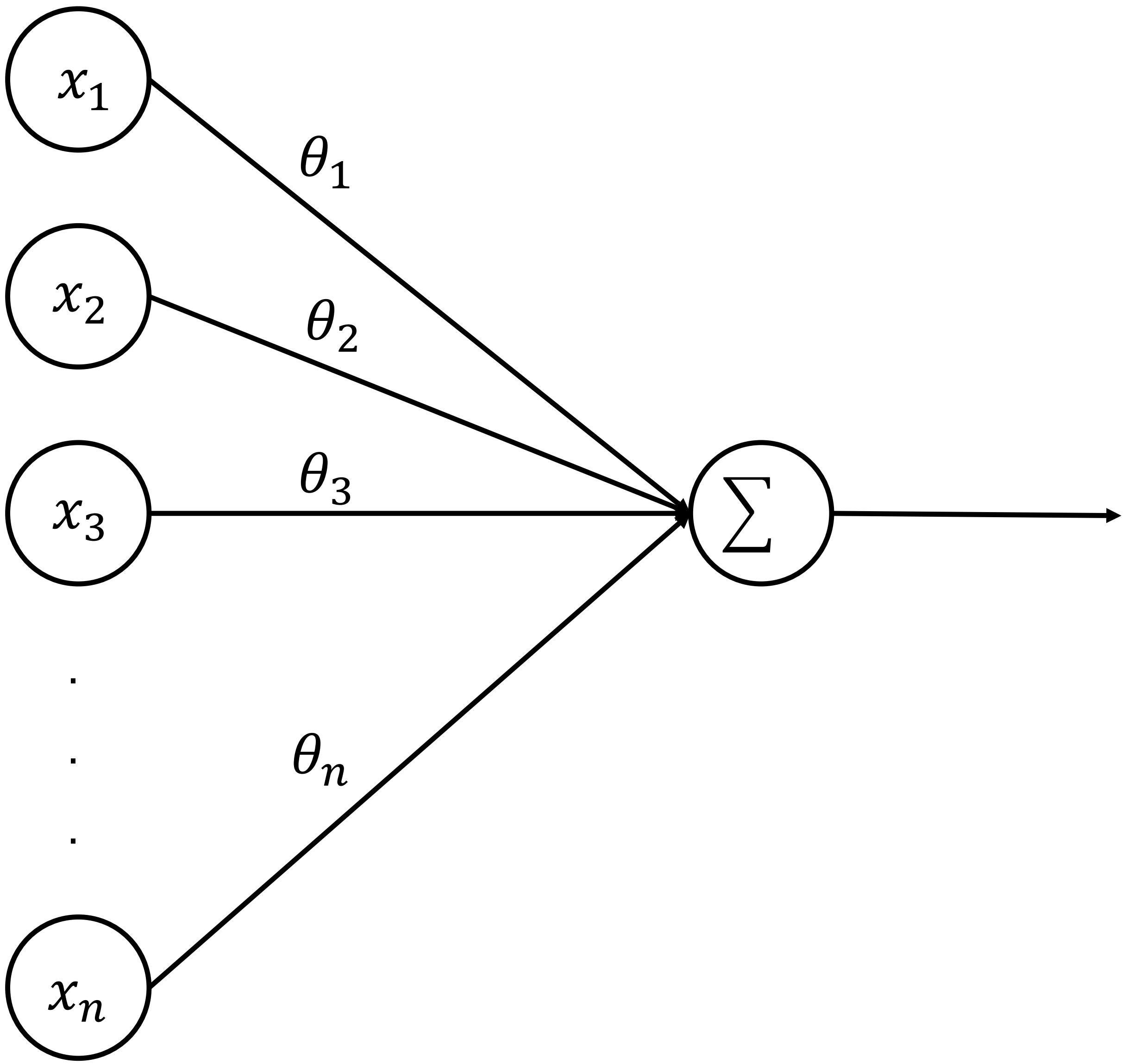
$$\theta_1 := \theta_1 - \alpha \frac{1}{m} \sum_{i=1}^{m} ((h_\theta(x^{(i)}) - y^{(i)}) * x^{(i)})$$

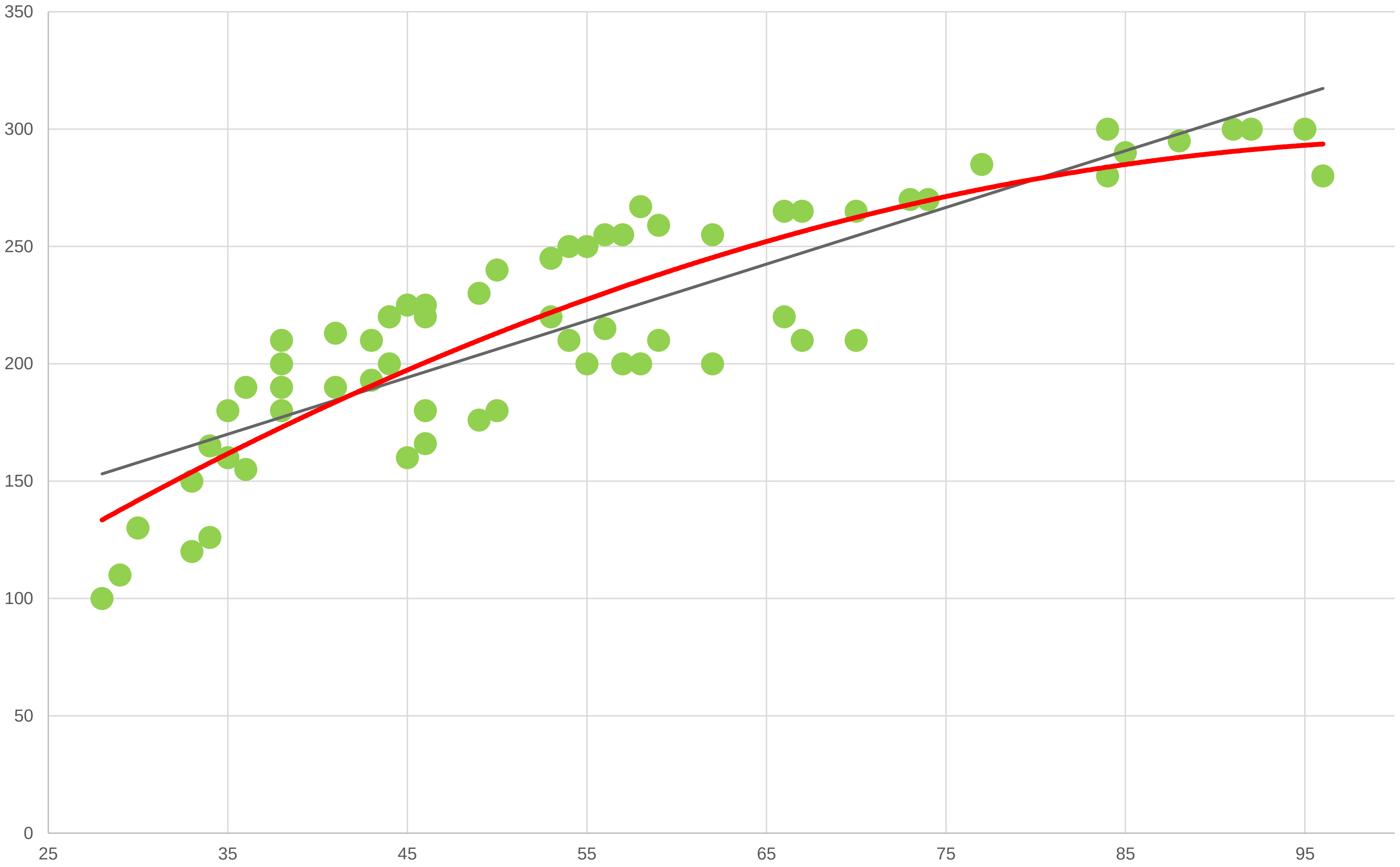
Wiele atrybutów

$$h_\theta(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \ldots + \theta_n x_n$$

$$h_\theta(x) = \theta_0 x_0 + \theta_1 x_1 + \theta_2 x_2 + \ldots + \theta_n x_n$$ gdzie: $x_0 = 1$

$$h_\theta(x) = \theta^T x \qquad x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \qquad \theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \vdots \\ \theta_n \end{bmatrix}$$


x_1
x_2
x_3
x_n
θ_1
θ_2
θ_3
θ_n
$\sum$


350
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45
55
65
75
85
95

Nieliniowa hipoteza

$$h_\theta(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_1^2$$

$$h_\theta(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_1^2 + \theta_2 x_1 x_2 + \theta_2 x_2 + \theta_2 x_2^2$$

Klasyfikacja

Regresja logistyczna

$$h_\theta(x) = g(\theta^T x)$$

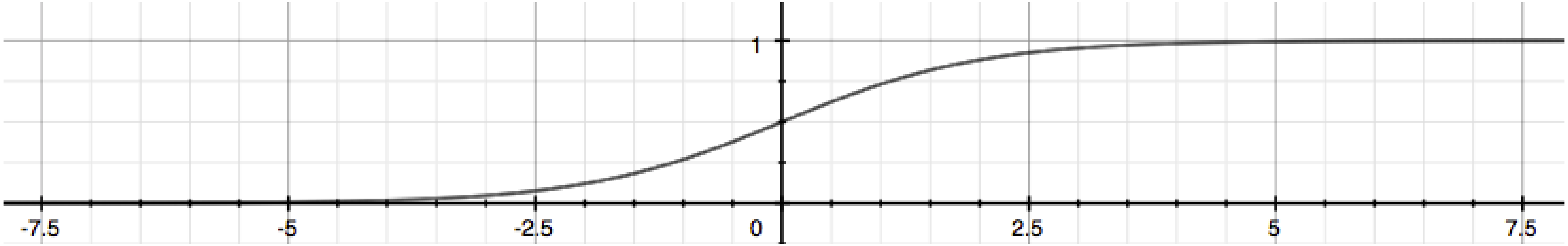
$$z = \theta^T x$$

$$g(z) = \frac{1}{1 + e^{-z}}$$

$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}$$

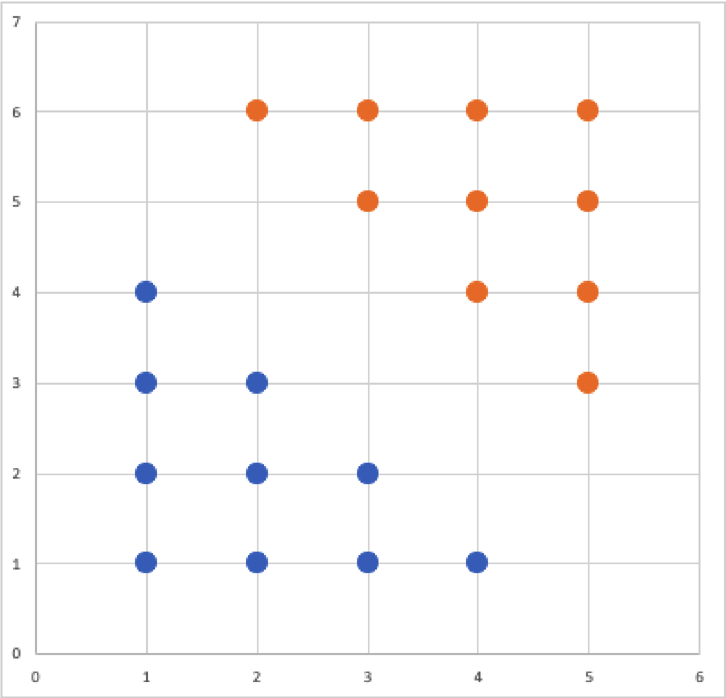
Funkcja logistyczna

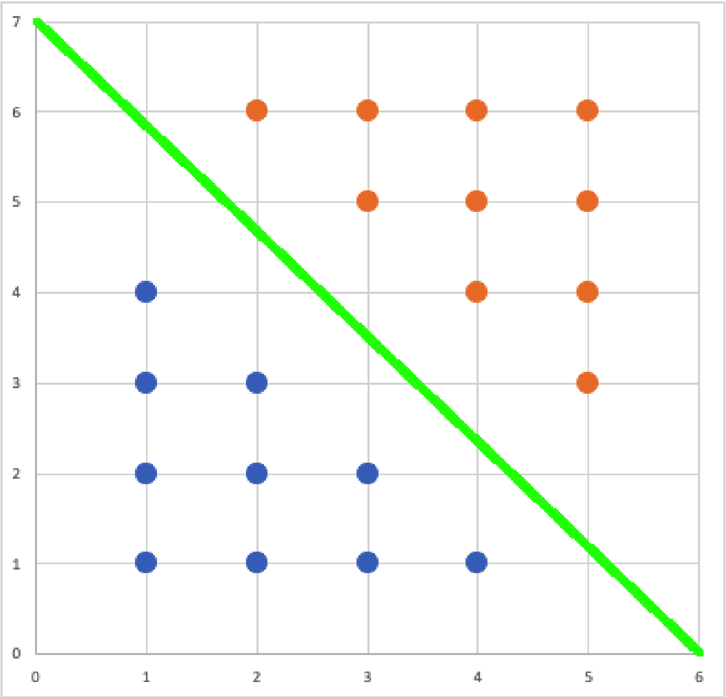
$$g(z) = \frac{1}{1 + e^{-z}}$$



$$h_\theta(x) = g(\theta^T x)$$

$$h_\theta(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2) \qquad \theta_0 = 7, \theta_1 = -1, \theta_2 = 1$$





Funkcja kosztu dla regresji logistycznej:

$$J(\theta) = \frac{1}{m}\sum_{i=0}^{m} \mathrm{Cost}(h_\theta(x^{(i)}), y^{(i)})$$

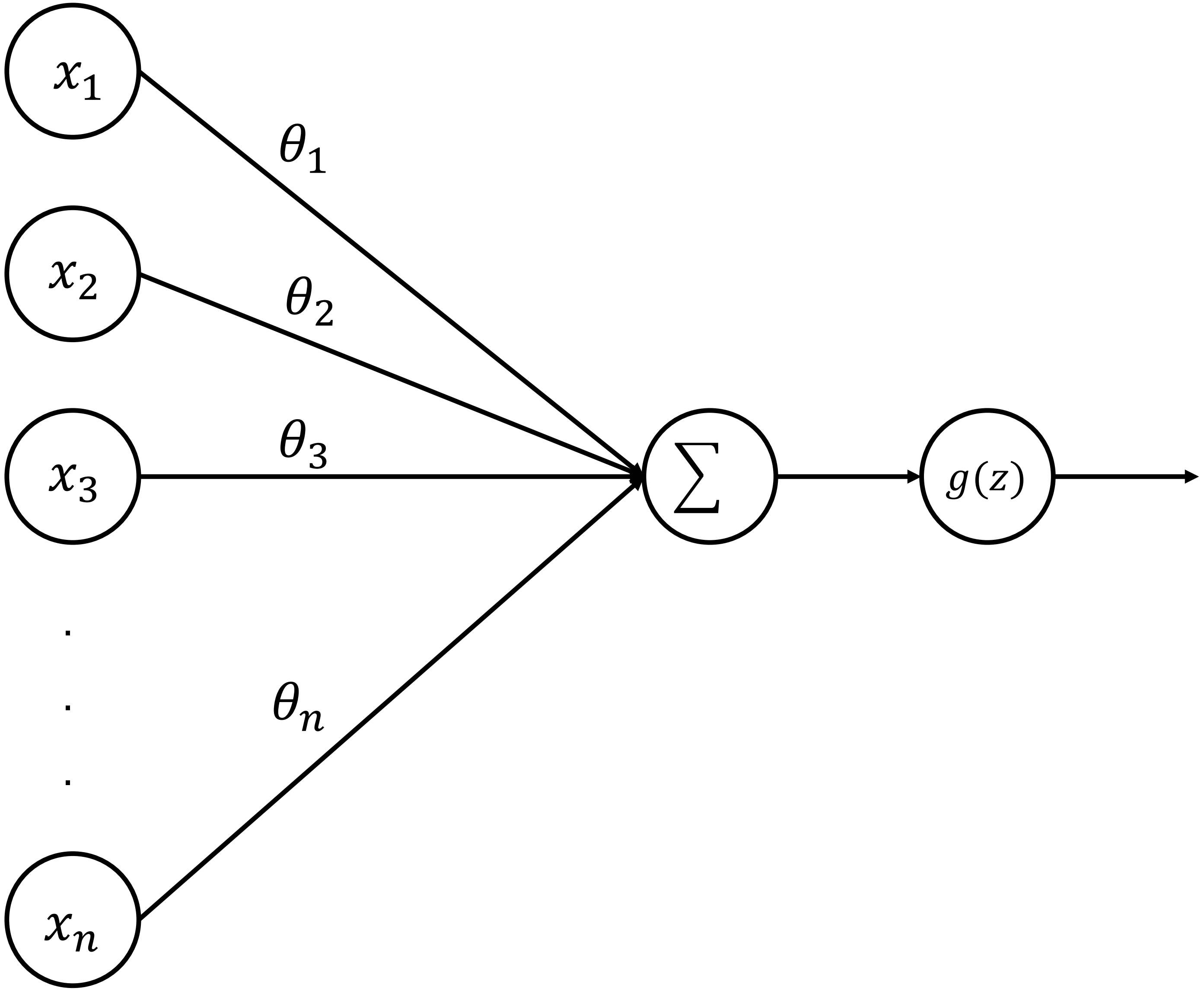
$$\mathrm{Cost}(h_\theta(x), y) = \begin{cases} -\log(h_\theta(x)) & y = 1 \\ -\log(1 - h_\theta(x)) & y = 0 \end{cases}$$

$$J(\theta) = -\frac{1}{m}\sum_{i=0}^{m}\left[y^{(i)}\log\left(h_\theta(x^{(i)})\right) + (1 - y^{(i)})\log\left(1 - h_\theta(x^{(i)})\right)\right]$$

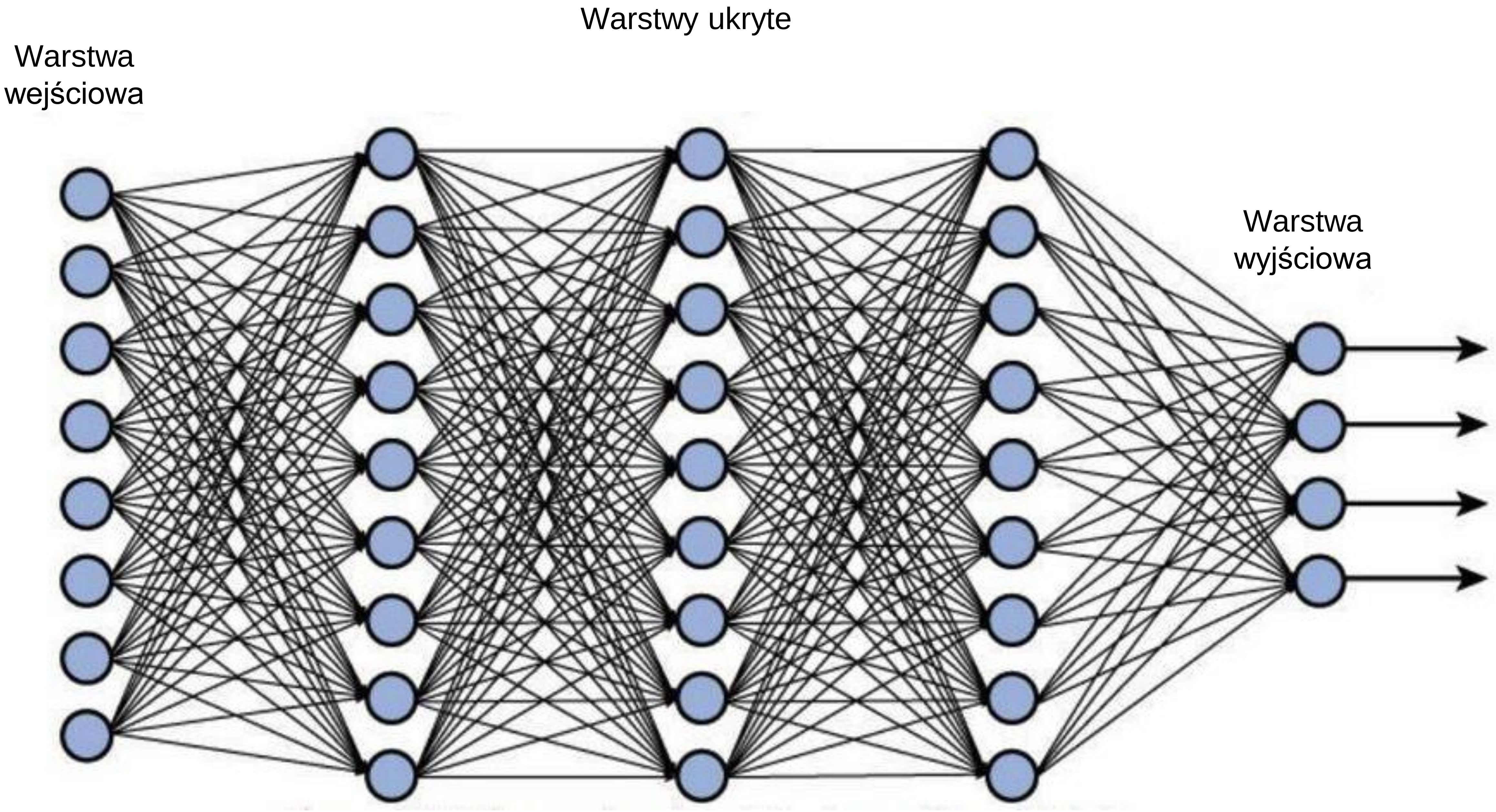
Gradient prosty

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

$$\theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^{m} \left(\left(h_\theta \left(x^{(i)} \right) - y^{(i)} \right) * \, x^{(i)} \right)$$


x_1
x_2
x_3
.
.
.
x_n
θ_1
θ_2
θ_3
θ_n
$\sum$
$g(z)$

Sieci neuronowe


Warstwy ukryte
Warstwa wejściowa
Warstwa wyjściowa

Funkcja kosztu sieci neuronowej:

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}\sum_{k=1}^{K}\left[y_k^{(i)} log\left(\left(h_\theta\left(x^{(i)}\right)\right)_k\right) + (1 - y_k^{(i)}) log\left(1 - \left(h_\theta\left(x^{(i)}\right)\right)_k\right)\right]$$

https://www.coursera.org/learn/machine-learning/

Dziękuję.

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