

Day - 87, Feb 25, 2025 (Mugh 13, 2081)

- ① The Second Derivative (Newton's Method and Leibniz Notation)
- ② Hessian and Hessian Matrix
- ③ Hessian Matrix and Concavity
- ④ Newton's Method for two variables
- ⑤ Graphs and Conceptual figures, Motives and Eigen Values
- ⑥ Examples on the Newton's Method [Optimization Problems]

Source: Calculus for Machine Learning and Data Science offered by DeepLearning AI in Coursera

[Derivative of a derivative - Second Derivative]

Newton's method:

$$x_{k+1} = x_k - \frac{g'(x_k)}{(g'(x_k))'}$$

$\rightarrow ??$

Second Derivative

Leibniz Notation:

$$\frac{d^2 f(x)}{dx^2} = \frac{d}{dx} \left(\frac{d f(x)}{dx} \right)$$

Lagrange Notation: $f''(x)$ as Second Derivative and $f'(x)$ is
the first Derivative.

$x \rightarrow$ distance

$v \rightarrow$ velocity

$a \rightarrow$ acceleration

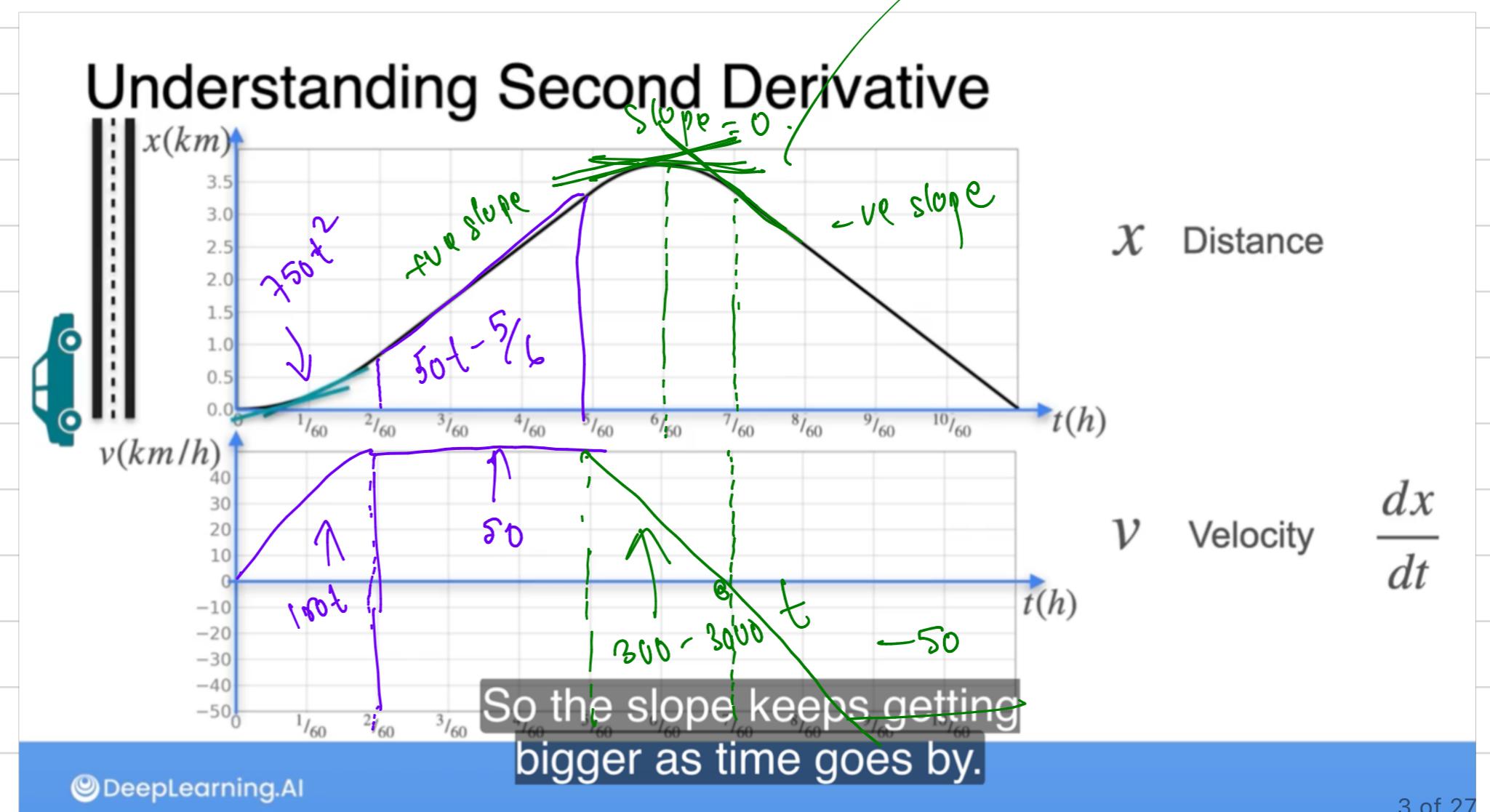
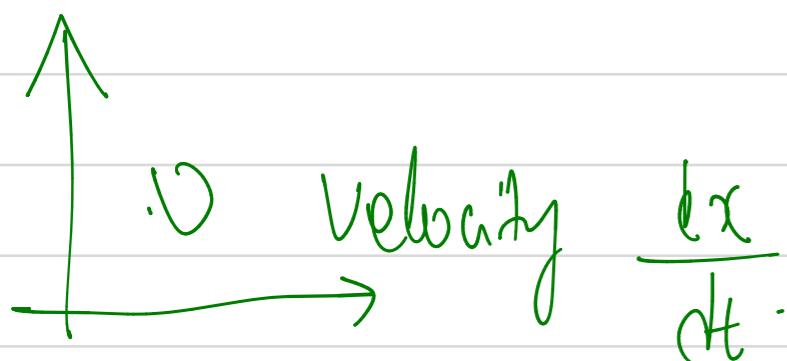
$$\frac{dx}{dt}$$

$$\frac{dv}{dt} = \frac{d^2x}{dt^2}$$

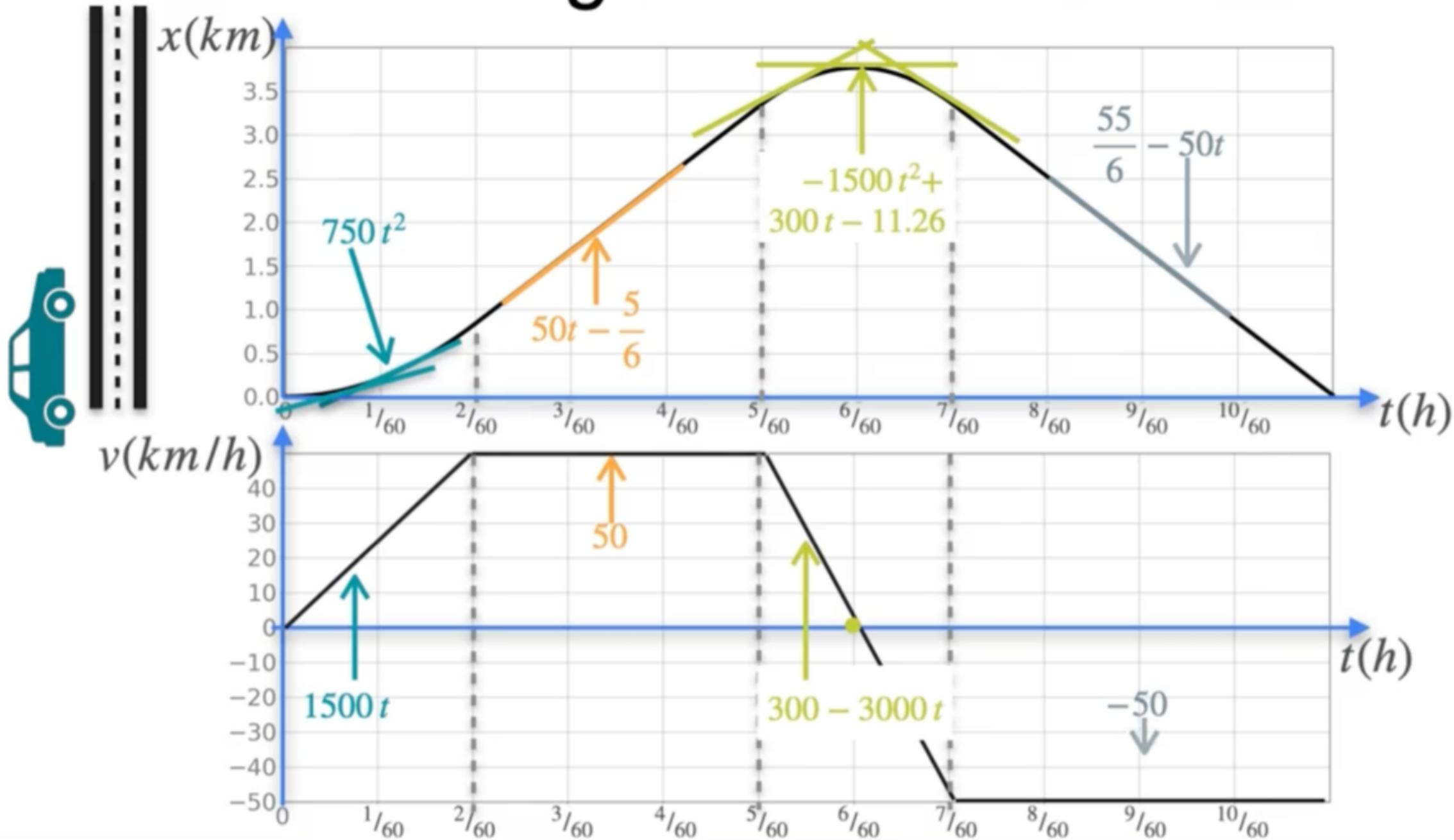
$$0 \rightarrow \frac{da}{dt}$$

$$d = \frac{dv}{dt}$$

$$150t^2 + 30t - 11.16$$



Understanding Second Derivative



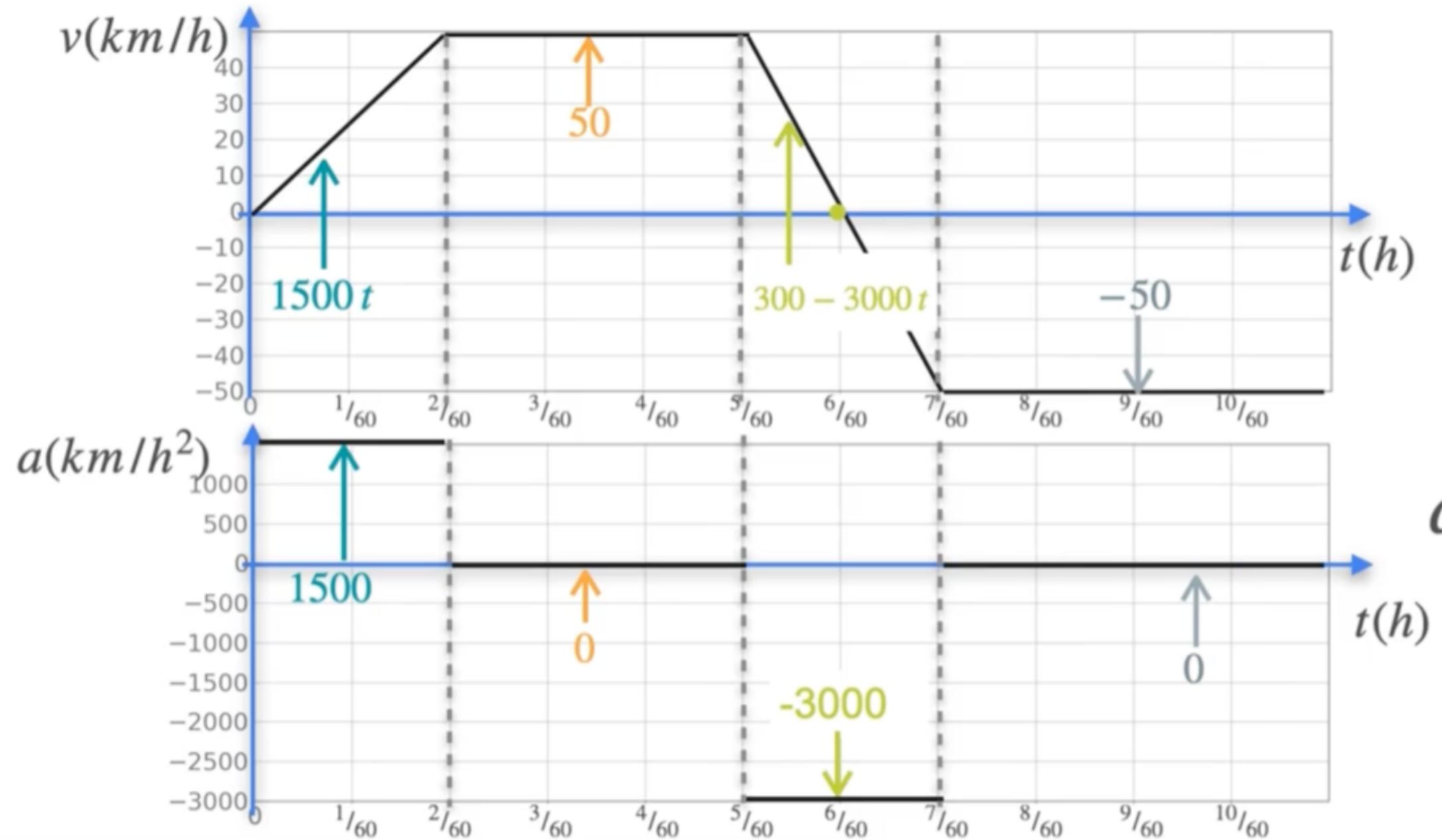
x Distance

v Velocity

$$\frac{dx}{dt}$$

If the second derivative of a function $f(x)$ i.e. $f''(x)$ or $\frac{d^2}{dx^2} f(x)$ is equal to 0 for every value of x , what can we say about $f(x)$?

Understanding Second Derivative



v Velocity

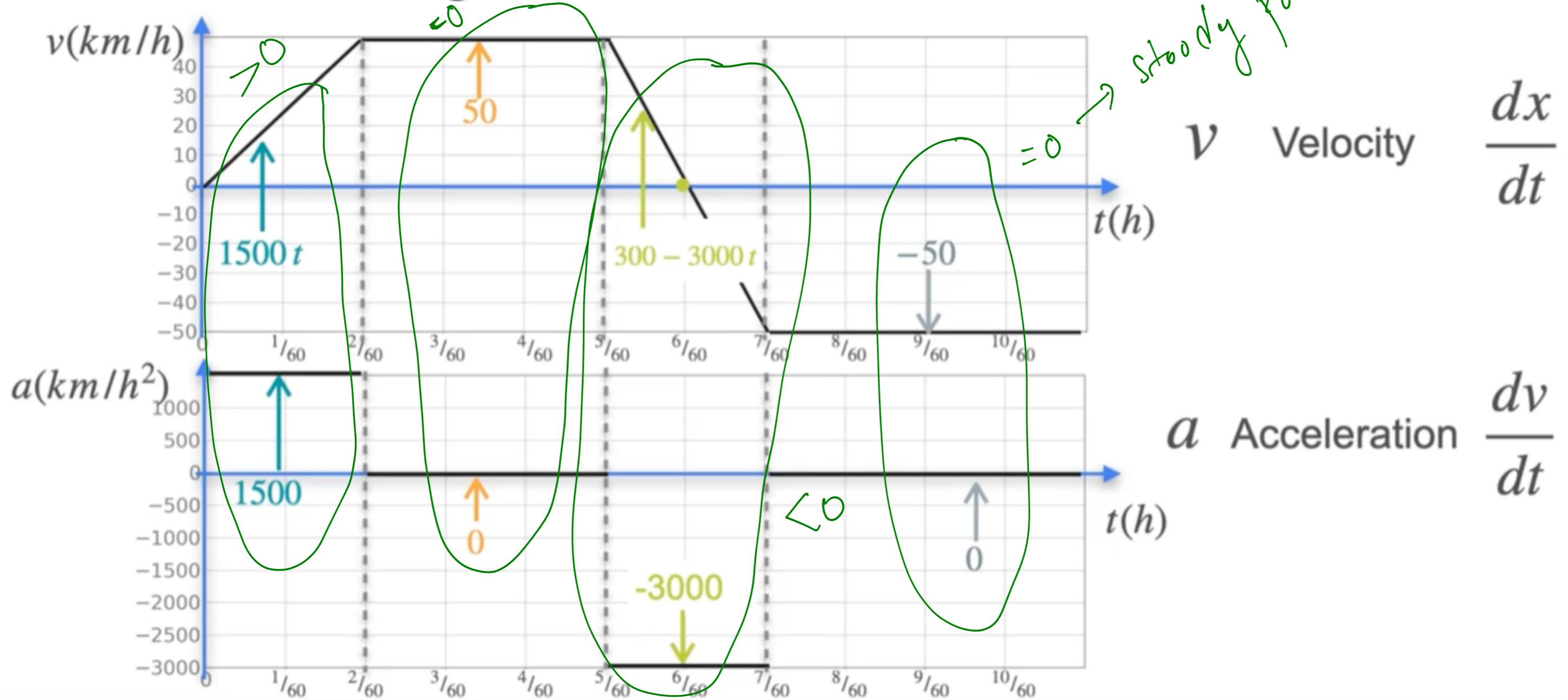
$$\frac{dx}{dt}$$

a Acceleration

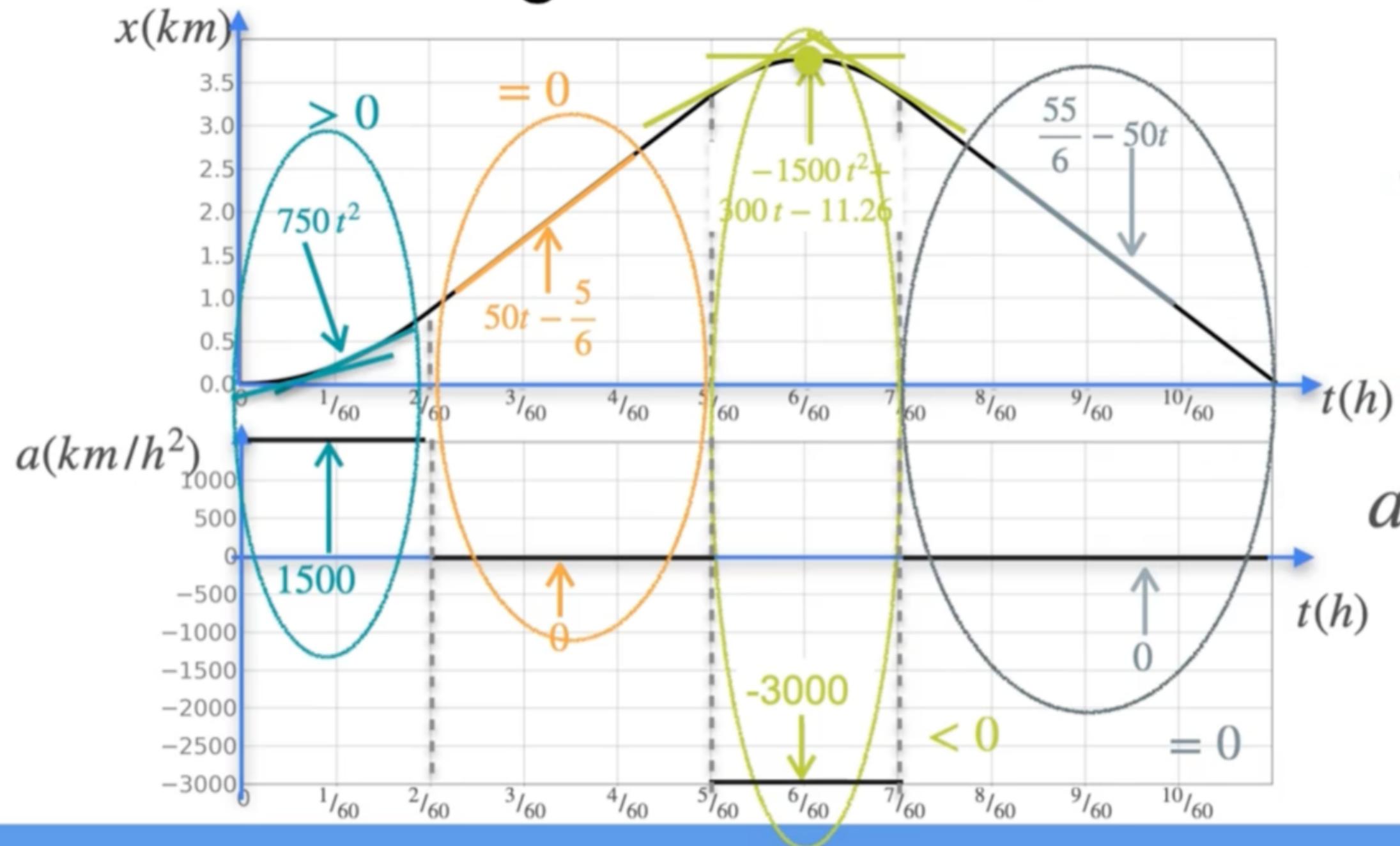
$$\frac{dv}{dt}$$

⇒ We can say $f'(x)$ is a line because $f'(x)$ is constant means it must be a line (either horizontal or not)!

Understanding Second Derivative



Understanding Second Derivative



x Distance
Second derivative tells us about the curvature

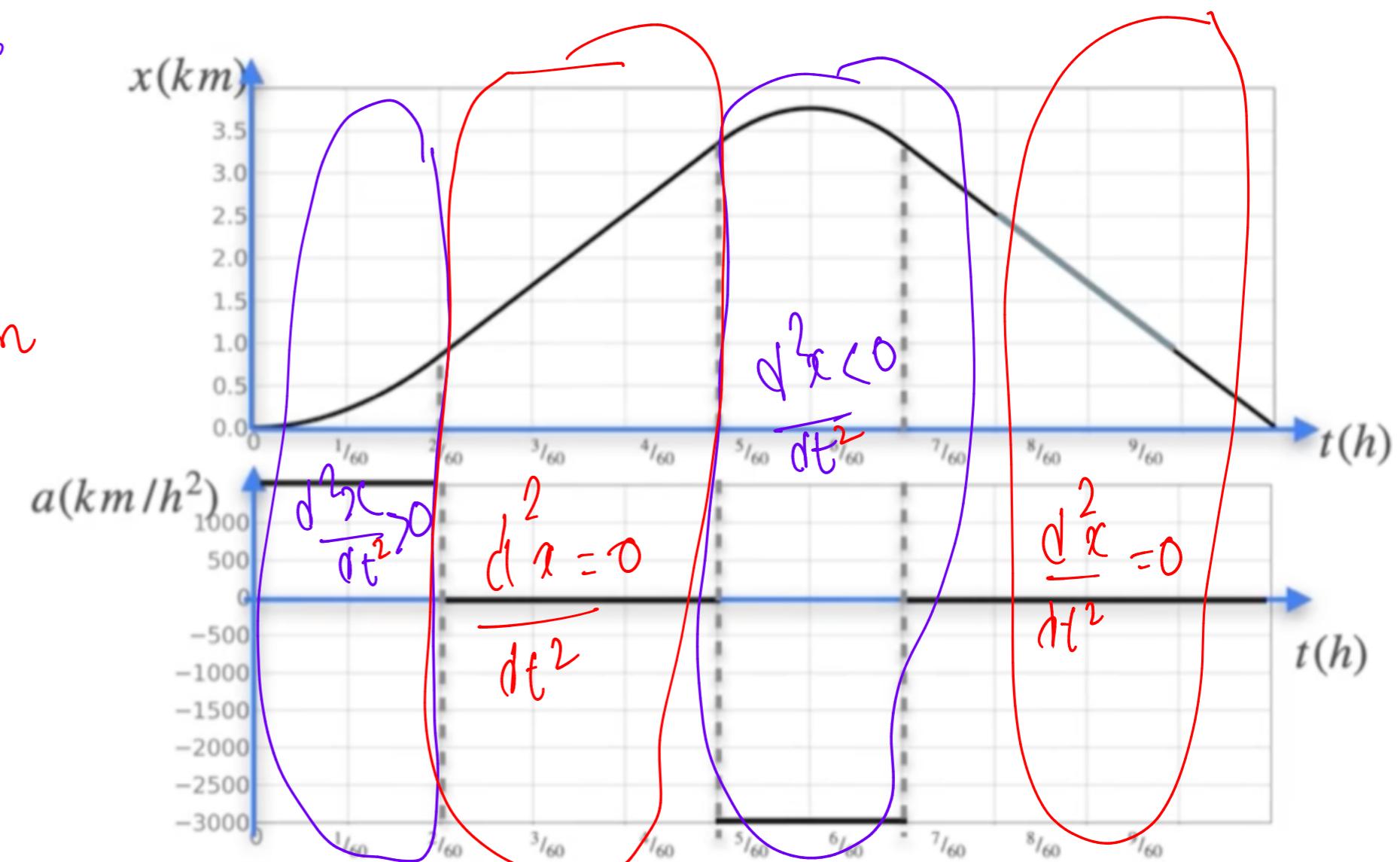
a Acceleration $\frac{d^2x}{dt^2}$

Curvature

$\frac{d^2 x}{dt^2} > 0$ Concave up or convex

$\frac{d^2 x}{dt^2} < 0$ Concave down

$\frac{d^2 x}{dt^2} = 0$ Need More Information!



Curvature

$$\frac{d^2x}{dt^2} > 0$$

Concave up or convex

$$\frac{d^2x}{dt^2} < 0$$

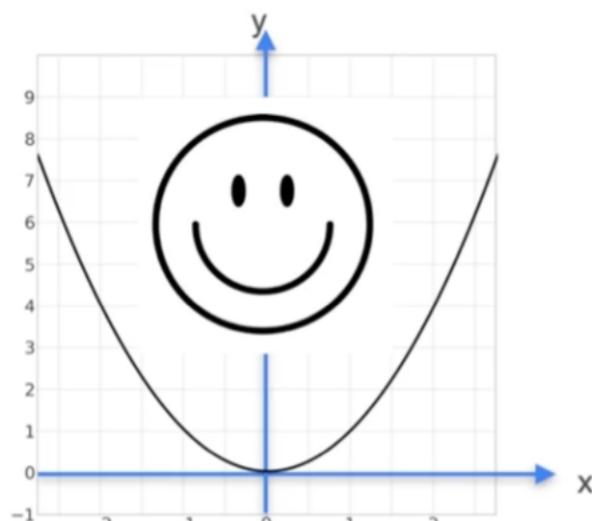
Concave down

$$\frac{d^2x}{dt^2} = 0$$

Need more information

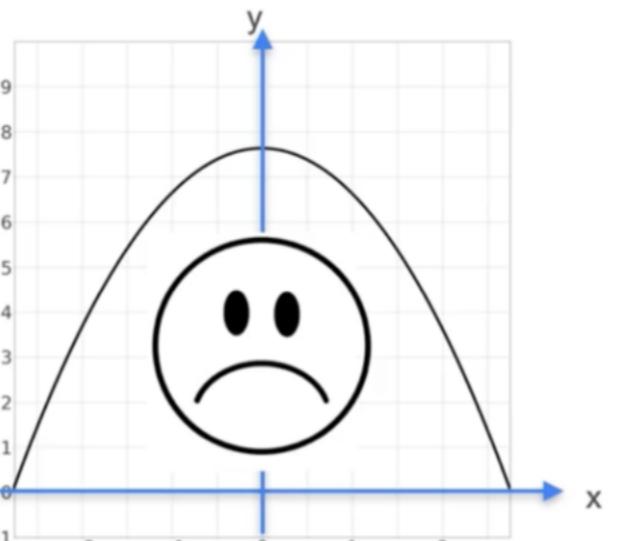


Curvature



Concave up or convex

$$f''(0) > 0$$



Concave down

$$f''(0) < 0$$

$\frac{d^2 f}{dx^2}$ tells max or min.

$$f' = (x_1, y) = (0, 0)$$

Are the candidates for

maximum or minimum.

But How do we

Know maximum or minimum?

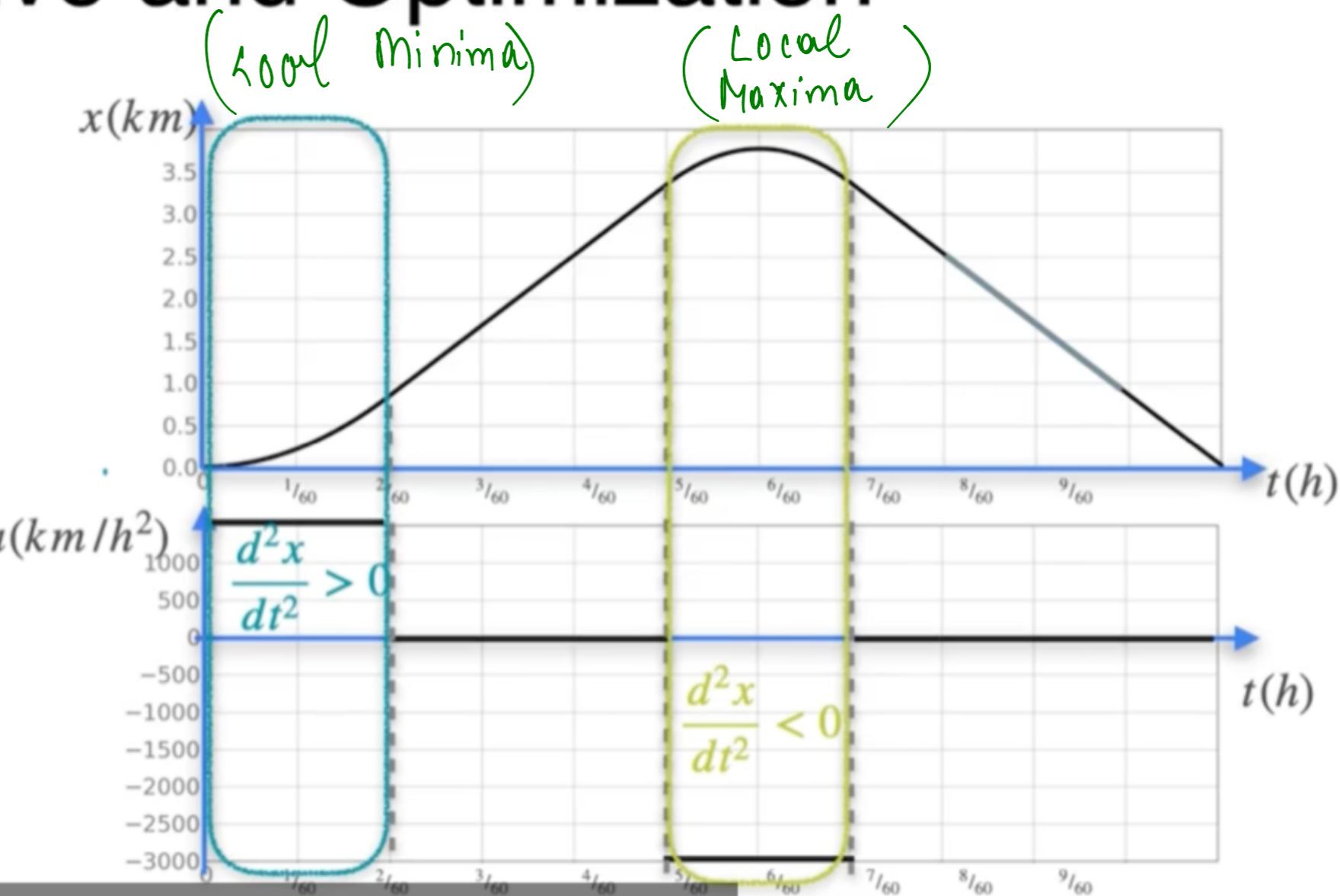
Answer is the second derivative tells us.

Second Derivative and Optimization

$$\frac{d^2x}{dt^2} > 0 \quad (\text{local minima})$$

$$\frac{d^2x}{dt^2} < 0 \quad (\text{local maxima})$$

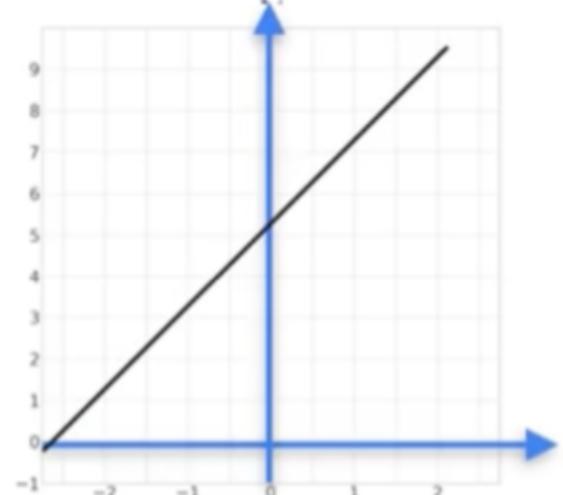
$$\frac{d^2x}{dt^2} = 0 \quad \text{Inconclusive.}$$



So the second derivative tells us,
take a look at the first one.

Curvature

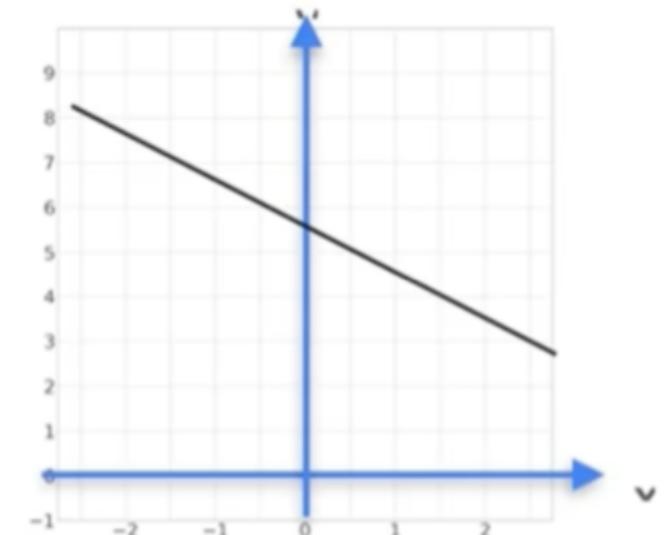
First derivative



Increasing

$$f'(0) > 0$$

↳ Maxima

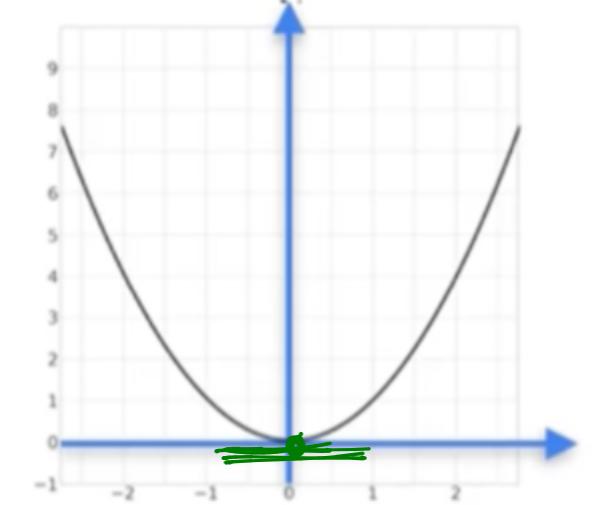


Decreasing

$$f'(0) < 0$$

↳ Minima

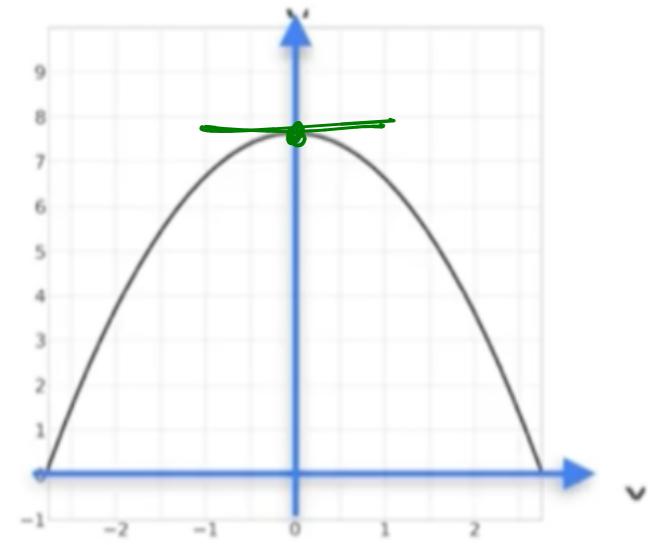
Second derivative



Concave up

$$f''(0) > 0$$

↳ Minima



Concave down

$$f''(0) < 0$$

↳ Maxima

Hessian:

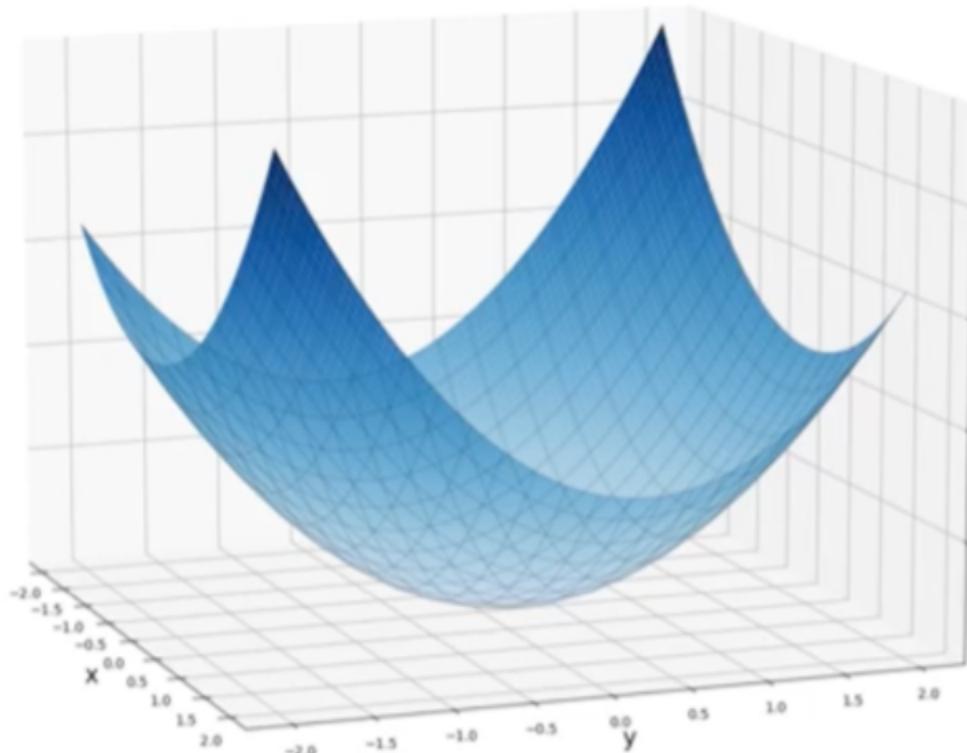
For multiple variables, the second derivative is actually a matrix full of second derivatives called the Hessian.

Second Derivative

	1 variable	2 variables
Function	$f(x)$	$f(x, y)$
First derivative	$f'(x)$ Rate of change of $f(x)$	$f_x(x, y)$ Rate of change w.r.t x $f_y(x, y)$ Rate of change w.r.t y $\nabla f = \begin{bmatrix} f_x(x, y) \\ f_y(x, y) \end{bmatrix}$
Second derivative	$f''(x)$ Rate of change of the rate of change of $f(x)$???

That's the rate of change of the rate

Second Derivative



$$f(x, y) = 2x^2 + 3y^2 - xy$$

Diagram illustrating the second derivatives of $f(x, y)$:

$$\begin{aligned} & \text{f}_x'(x_1, y) \text{ w.r.t } x \\ & \text{f}_x'(x_1, y) \text{ w.r.t } y \\ & \text{f}_y'(x_1, y) \text{ w.r.t } x \\ & \text{f}_y'(x_1, y) \text{ w.r.t } y \end{aligned}$$

Arrows point from the terms in the function to their respective second derivatives:

- $4x - y$ points to $f'_x(x_1, y)$ w.r.t. x
- $6y - x$ points to $f'_x(x_1, y)$ w.r.t. y
- -1 points to $f'_y(x_1, y)$ w.r.t. x
- 6 points to $f'_y(x_1, y)$ w.r.t. y

y) equals 2x squared plus
3y squared minus xy.

What Do These Mean?

Rate of change of
 $f_x(x, y)$ w.r.t x

Rate of change of
 $f_y(x, y)$ w.r.t y

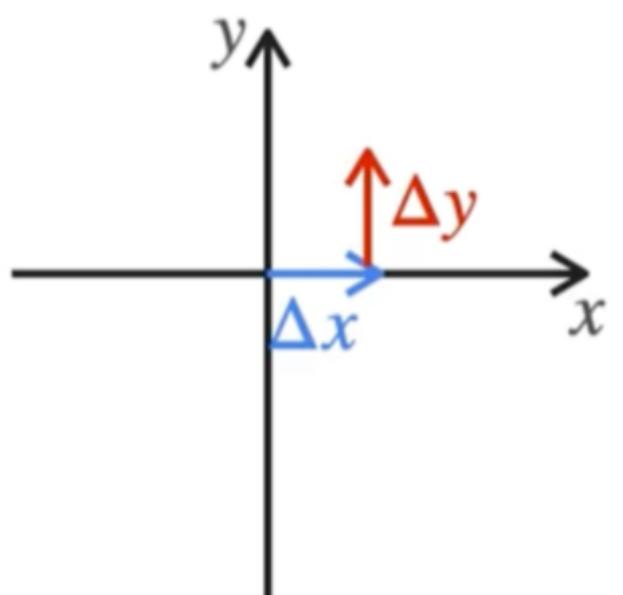
Rate of change of
 $f_x(x, y)$ w.r.t y

Rate of change of
 $f_y(x, y)$ w.r.t x

Change in the change in the function
w.r.t tiny changes in x and y

Same idea as
with one
variable!

1. Change in the slope along one coordinate axis w.r.t tiny changes along an orthogonal coordinate axis
2. They are the same!
(In most cases)



x of the derivative respect to y

Notation

Rate of change of
 $f'_x(x, y)$ w.r.t x

Rate of change of
 $f'_y(x, y)$ w.r.t y

Rate of change of
 $f'_x(x, y)$ w.r.t y

Rate of change of
 $f'_y(x, y)$ w.r.t x

Leibniz's notation

$$\frac{\partial^2 f}{\partial x^2}$$

$$\frac{\partial^2 f}{\partial y^2}$$

$$\frac{\partial^2 f}{\partial x \partial y}$$

$$\frac{\partial^2 f}{\partial y \partial x}$$

Lagrange's Notation

$f_{xx}(x, y)$

$f_{yy}(x, y)$

$f_{xy}(x, y)$

$f_{yx}(x, y)$

as d squared f over dx squared,

Hessian Matrix

$$f(x, y) = 2x^2 + 3y^2 - xy$$

When we put these four together in a matrix,

$$\begin{bmatrix} 4 & -1 \\ -1 & 6 \end{bmatrix} = \begin{bmatrix} f_{xx} & f_{xy} \\ f_{yx} & f_{yy} \end{bmatrix}$$

$$f(x, y) = x^2 + y^2$$

$$f'(x, y) = 2x + 2y$$

$$x^2 + y^2 \rightarrow \begin{array}{ccc} x & \rightarrow & 2x \\ y & \rightarrow & 2y \end{array}$$

$$x^2 + y^2 \rightarrow \begin{array}{ccc} x & \rightarrow & 0 \\ y & \rightarrow & 0 \end{array}$$

$$\begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}$$

Hessian Matrix keeps the f'' information

which is

Jacobian Matrix

f''

Second Derivative

	1 variable	2 variables
Function	$f(x)$	$f(x, y)$
First derivative	$f'(x)$ Rate of change of $f(x)$	$f_x(x, y)$ $f_y(x, y)$ $\nabla f = \begin{bmatrix} f_x(x, y) \\ f_y(x, y) \end{bmatrix}$
Second derivative	$f''(x)$ Rate of change of the rate of change of $f(x)$	$H(x, y) = \begin{bmatrix} f_{xx}(x, y) & f_{xy}(x, y) \\ f_{yx}(x, y) & f_{yy}(x, y) \end{bmatrix}$

Hessian Matrix

of all the second
partial derivatives.

Concave Up:

$$f(x,y) = 2x^2 + 3y^2 - xy$$

$$H(0,0) = \begin{bmatrix} 4 & -1 \\ -1 & 6 \end{bmatrix}$$

Check if min'x f'v or -vp?

use → Eigen Value.

$$\det(H(0,0) - \lambda I) = \det \left(\begin{bmatrix} 4-\lambda & -1 \\ -1 & 6-\lambda \end{bmatrix} \right)$$

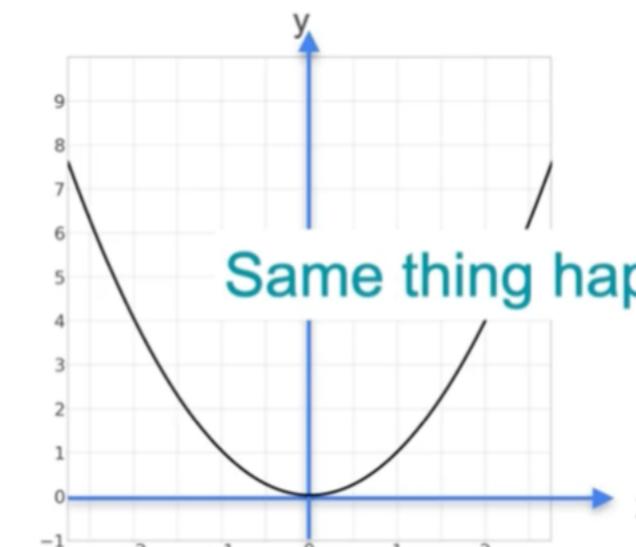
$$\Rightarrow (4-\lambda)(6-\lambda) - (-1)(-1)$$

$$\Rightarrow \lambda^2 - 10\lambda + 23$$

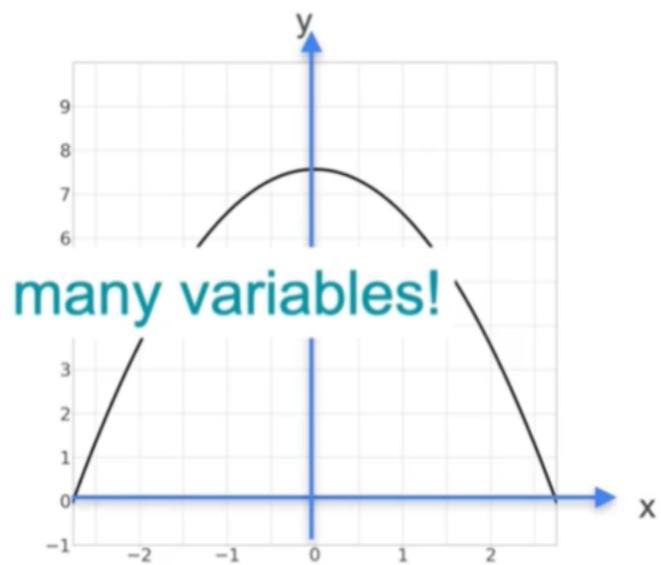
$$\rightarrow \lambda_1 = 8.41 \text{ (+ve)}$$

$$\rightarrow \lambda_2 = 3.59 \text{ (+ve)}$$

Remember...



Concave up or convex



Concave down

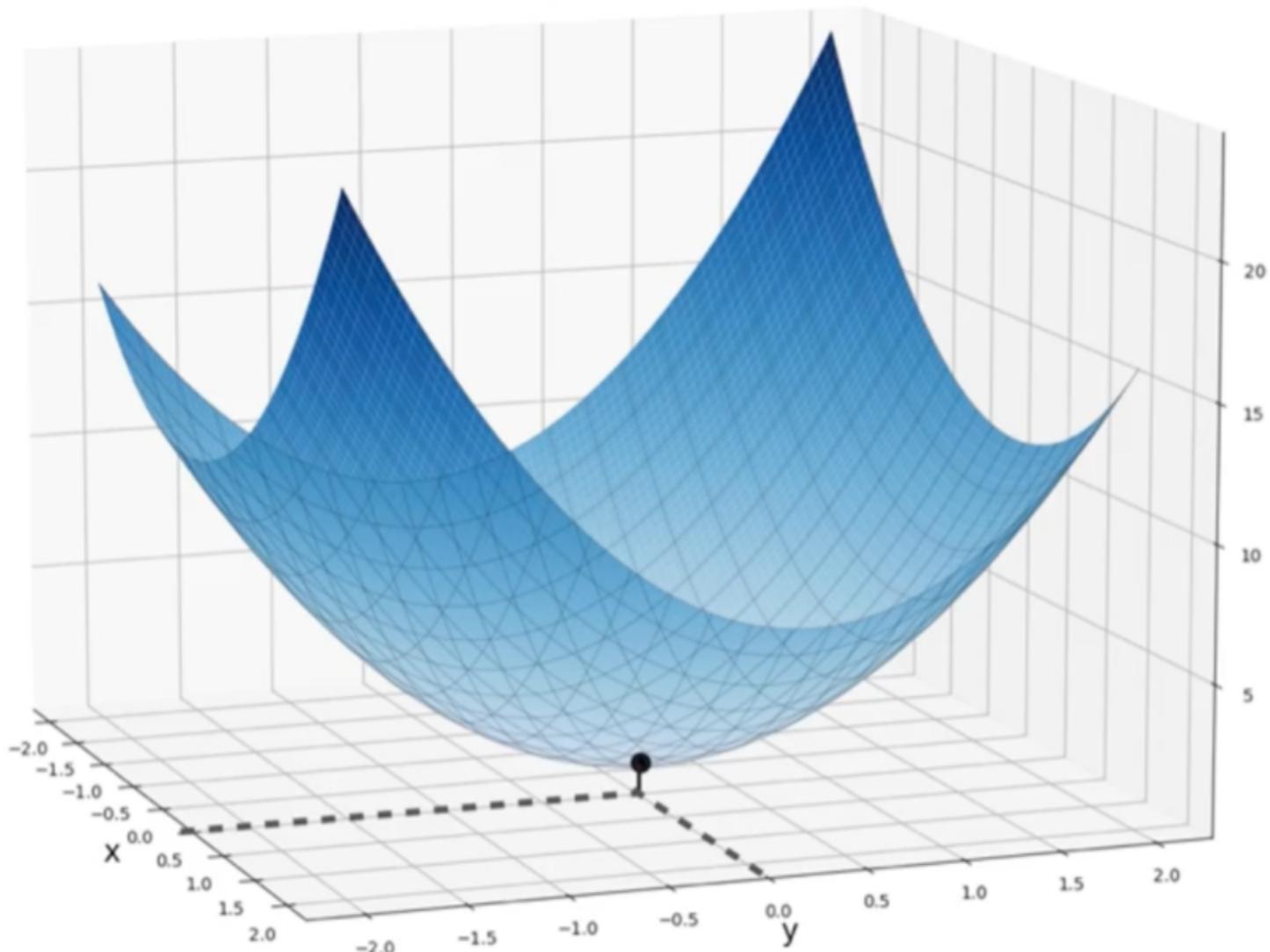
$f''(0) < 0$ except you have to keep track of a couple more things.

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→ $(0,0)$ is minimum.

Eigen Values +ve
so it is
Concave Up

Concave Up



$$f(x, y) = 2x^2 + 3y^2 - xy$$

$$H(0,0) = \begin{bmatrix} 4 & -1 \\ -1 & 6 \end{bmatrix}$$

$$\det(H(0,0) - \lambda I) = \det \left(\begin{bmatrix} 4 - \lambda & -1 \\ -1 & 6 - \lambda \end{bmatrix} \right)$$

$$= (4 - \lambda)(6 - \lambda) - (-1)(-1)$$

$$= \lambda^2 - 10\lambda + 23$$

$$\lambda_1 = 6.41$$
$$\lambda_2 = 3.59$$

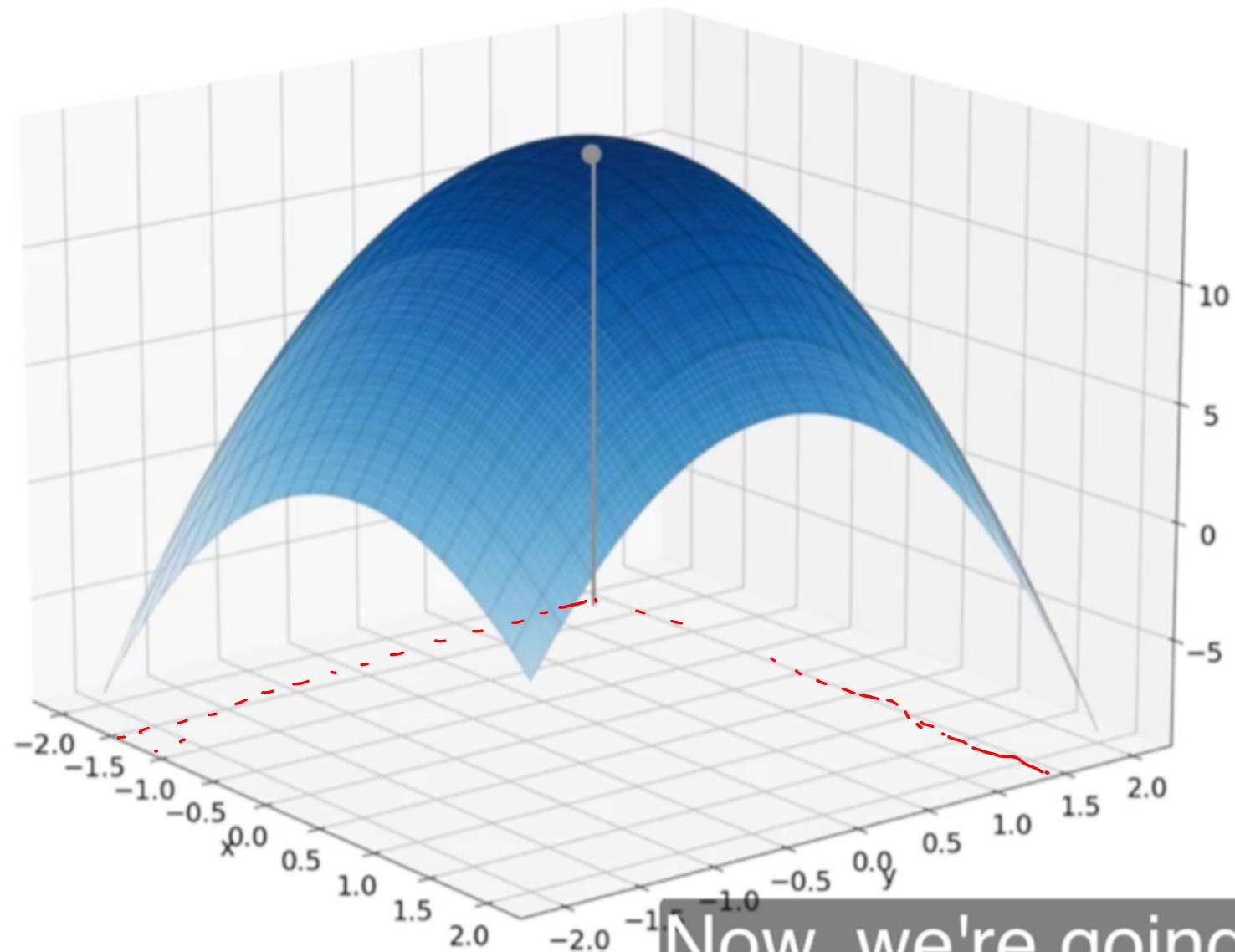
(0,0) is a minimum!

> 0

up and the 0.00 is a minimum.

Maximum point at $(0,0) = ?$

Concave Down



$$f(x, y) = -2x^2 - 3y^2 - xy + 15$$

$$\nabla f(x, y) = \begin{bmatrix} -4x - y \\ -x - 6y \end{bmatrix}$$

$$H(0, 0) = \begin{bmatrix} -4 & -1 \\ -1 & -6 \end{bmatrix}$$

$$\text{det}(H(0, 0) - \lambda I) =$$
$$\begin{pmatrix} -4 - \lambda & -1 \\ -1 & -6 - \lambda \end{pmatrix} = (-6 - \lambda) - (-1)(-1)$$

$$\Rightarrow \lambda_1 + 10\lambda + 23$$

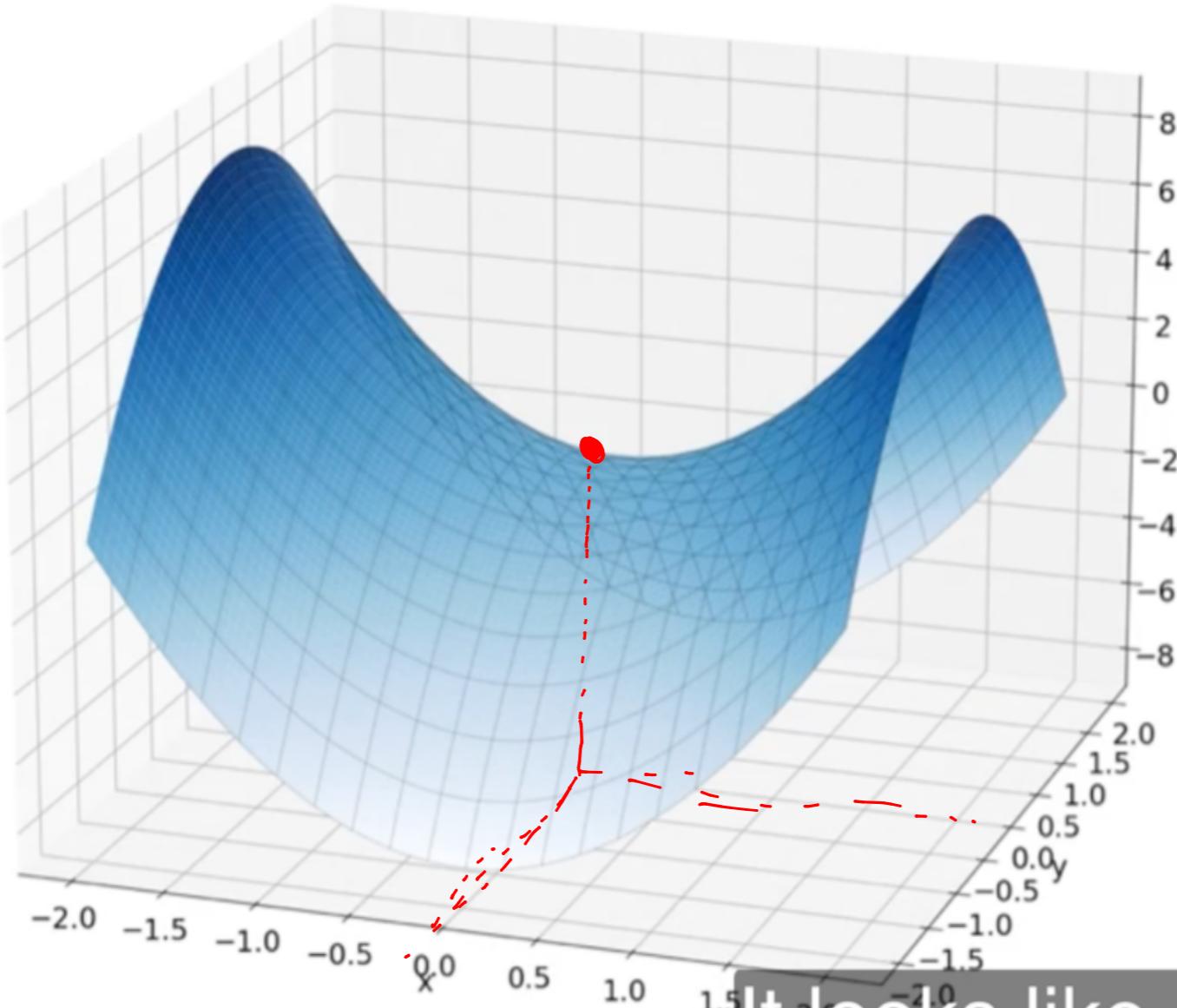
$$\lambda_1 \Rightarrow -3.59$$

$$\lambda_2 \Rightarrow -6.41$$

$(0, 0)$ is a maximum < 0

Now, we're going to look
at the Hessian matrix.

Saddle Point



It looks like a saddle
or a potato chip.

$$f(x, y) = 2x^2 - 2y^2$$

$$\nabla f(x, y) = \begin{bmatrix} 4x \\ -4y \end{bmatrix}$$

$$H(0, 0) = \begin{bmatrix} 4 & 0 \\ 0 & -4 \end{bmatrix}$$

$$\det(H(0, 0)) - \lambda^2 = (4 - \lambda)(-4 - \lambda) - 0$$

$$\boxed{\begin{aligned} \lambda_1 &= -4 \\ \lambda_2 &= 4 \end{aligned}}$$

$(0, 0)$ is the Saddle point

Summary

	1 variable $f(x)$	2 variables $f(x, y)$	More variables $f(x_1, x_2, \dots, x_n)$
(Local) minima	Happy face $f''(x) > 0$	Upper paraboloid $\lambda_1 > 0 \& \lambda_2 > 0$	All $\lambda_i > 0$
(Local) maxima	Sad face $f''(x) < 0$	Down paraboloid $\lambda_1 < 0 \& \lambda_2 < 0$	All $\lambda_i < 0$
Need more information	$f''(x) = 0$	Saddle point $\lambda_1 > 0 \& \lambda_2 < 0$ $\lambda_1 < 0 \& \lambda_2 > 0$ Or some $\lambda_i = 0$	Some $\lambda_i > 0$ and some $\lambda_j < 0$ OR At least one $\lambda_i = 0$

you have a local minimum.

Newton's Method

1 variable

$$x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)}$$

2 variables

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \end{bmatrix} = \begin{bmatrix} x_k \\ y_k \end{bmatrix} - H^{-1}(x_k, y_k) \nabla f(x_k, y_k)$$

2x2 2x1

Gradient:

$$\nabla f(x, y) = \begin{bmatrix} 4x^3 + 8x - y - 0.4xy \\ 3.2y^3 + 4y - x - 0.2x^2 \end{bmatrix}$$

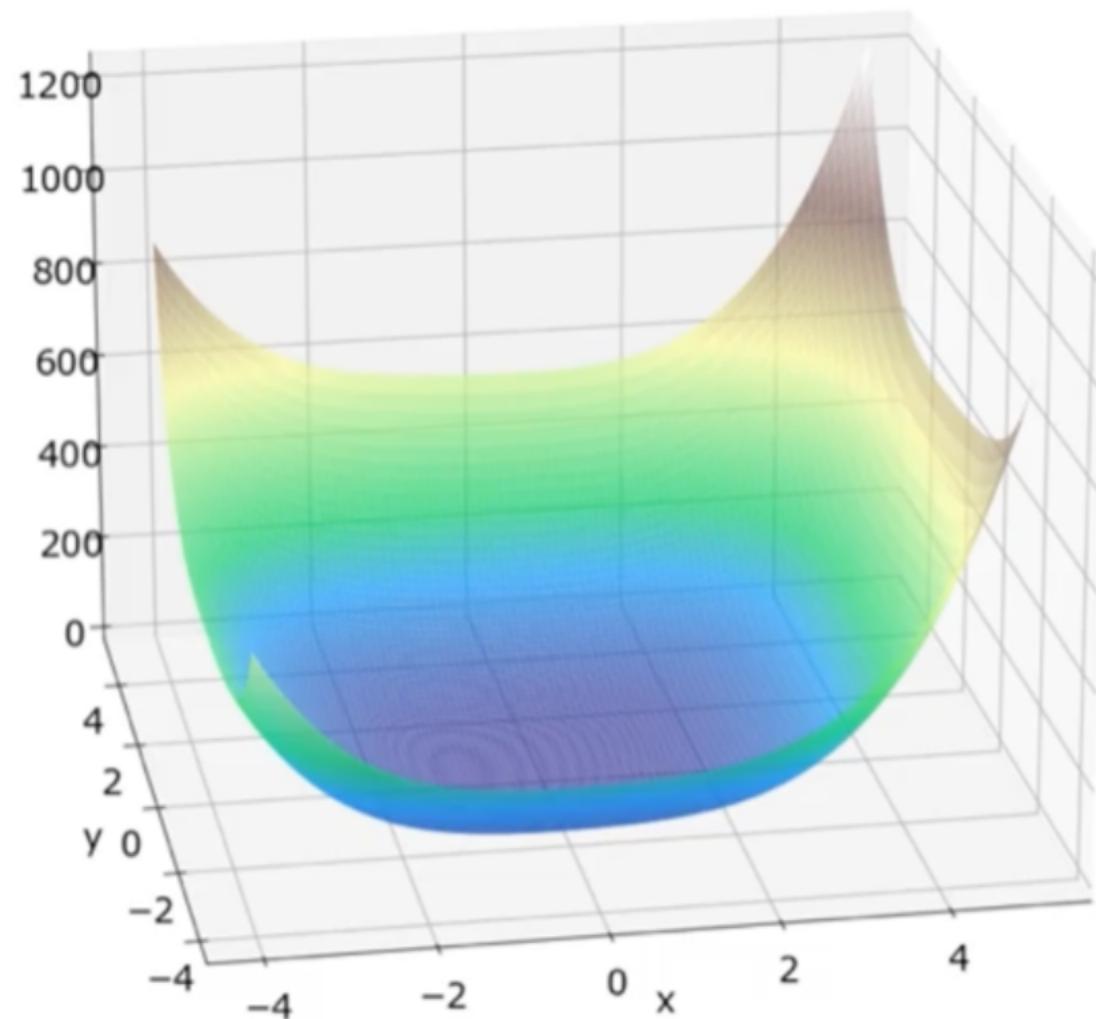
Hessian

$$H(x, y) =$$

$$\begin{bmatrix} 12x^2 + 8 - 0.4 & -1 - 0.4x \\ -1 - 0.4x & 9.6y^2 + 4 \end{bmatrix}$$

When working with 2 variables the order matters.

An Example



$$f(x, y) = x^4 + 0.8y^4 + 4x^2 + 2y^2 - xy - 0.2x^2y$$

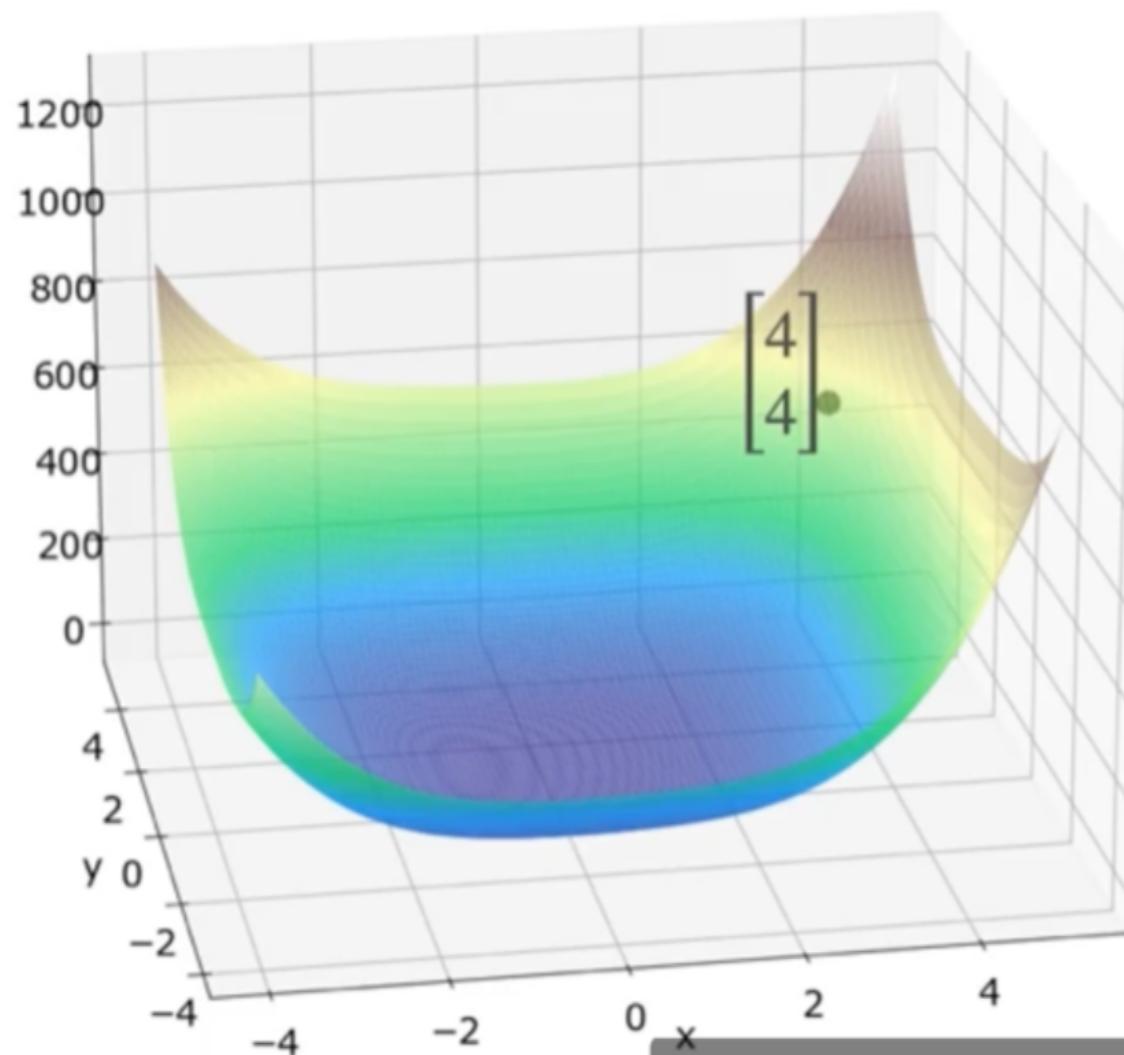
Handwritten notes:

$$\begin{aligned} f(x, y) &\rightarrow \begin{aligned} x &\rightarrow 4x^3 + 8x - y - 0.4xy \\ y &\rightarrow 3.2y^3 + 4y - x - 0.2x^2 \end{aligned} \\ &\rightarrow \begin{aligned} x &\rightarrow 12x^2 + 8 - 0.4y \\ y &\rightarrow -1 - 0.4x \\ &\rightarrow -1 - 0.4x \\ &\rightarrow 9.6y^2 + 4 \end{aligned} \end{aligned}$$

So first,

let's take a look at the two partial

An Example



Start at some point

$$\begin{bmatrix} x_0 \\ y_0 \end{bmatrix} = \begin{bmatrix} 4 \\ 4 \end{bmatrix}$$

$$\nabla f(4,4) = \begin{bmatrix} 277.6 \\ 213.6 \end{bmatrix}$$

$$H(u,u) =$$

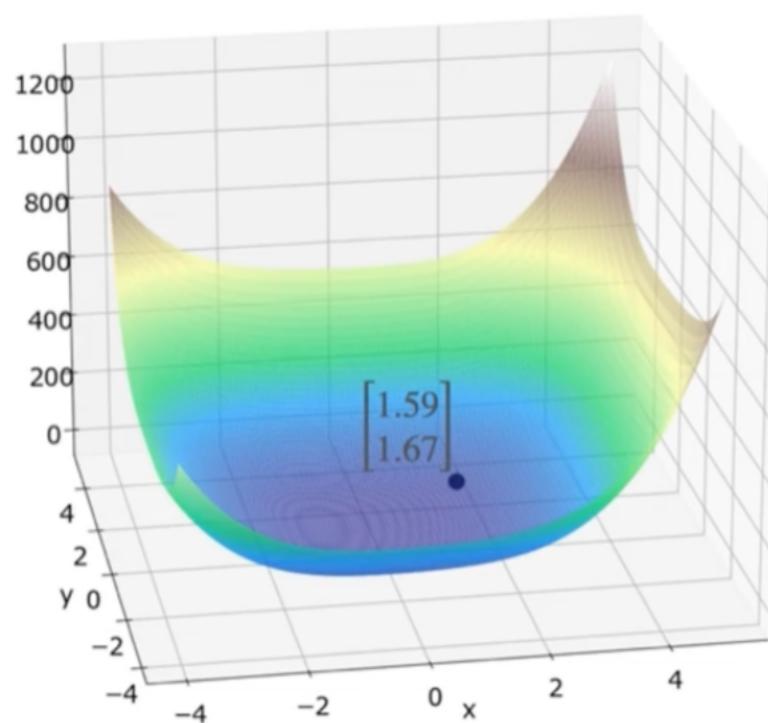
$$\begin{bmatrix} 198.4 & -2.6 \\ -2.6 & 157.6 \end{bmatrix}^{-1} = \begin{bmatrix} 277.6 \\ 213.6 \end{bmatrix}$$

$$\begin{bmatrix} x_1 \\ y_1 \end{bmatrix} = \begin{bmatrix} 4 \\ 4 \end{bmatrix} - \begin{bmatrix} 198.4 & -2.6 \\ -2.6 & 157.6 \end{bmatrix}^{-1}$$

$$\begin{bmatrix} x_1 \\ y_1 \end{bmatrix} \Rightarrow \begin{bmatrix} 2.58 \\ 2.62 \end{bmatrix}$$

we simply put the numbers 4 and 4,
and now let's find the Hessian.

An Example



$$\begin{bmatrix} x_1 \\ y_1 \end{bmatrix} = \begin{bmatrix} 2.58 \\ 2.61 \end{bmatrix}$$

$$\nabla f(2.58, 2.61) = \begin{bmatrix} 84.25 \\ 63.4 \end{bmatrix} \quad H(2.58, 2.61) = \begin{bmatrix} 86.83 & -2.032 \\ -2.032 & 69.39 \end{bmatrix}$$

$$\begin{bmatrix} x_2 \\ y_2 \end{bmatrix} = \begin{bmatrix} 2.58 \\ 2.61 \end{bmatrix} - \begin{bmatrix} 86.83 & -2.032 \\ -2.032 & 69.39 \end{bmatrix}^{-1} \begin{bmatrix} 84.25 \\ 63.4 \end{bmatrix}$$
$$= \begin{bmatrix} 1.59 \\ 1.67 \end{bmatrix}$$

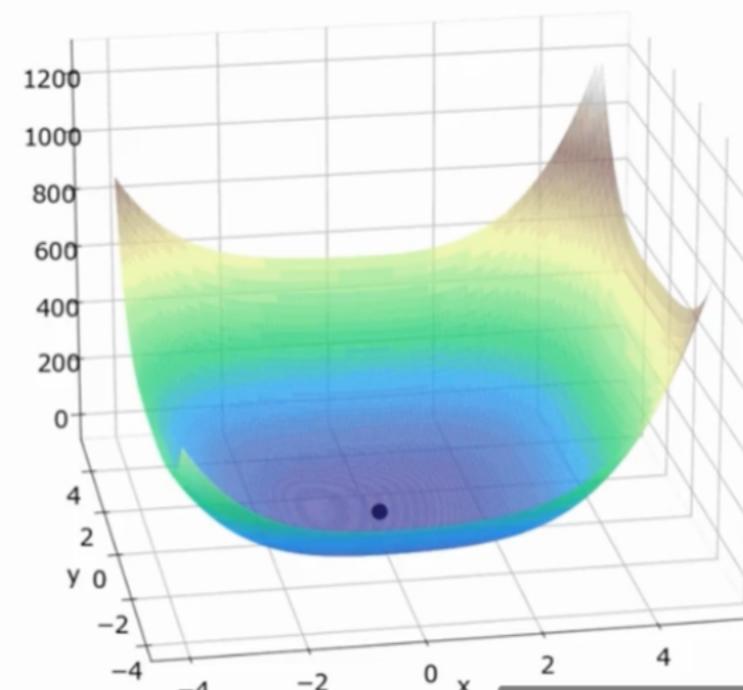
Newton's Method to
optimise functions of
many variables.

An Example

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So we get the 1.59, 1.6

Newton's Method for
two variables is able
to approximate closely
the 0 of f .



Repeat until you are close enough to the actual zero!

Needed $k = 8$ steps

$$\begin{bmatrix} x_8 \\ y_8 \end{bmatrix} = \begin{bmatrix} 4.15 \cdot 10^{-17} \\ -2.05 \cdot 10^{-17} \end{bmatrix}$$

$$\begin{bmatrix} x^* \\ y^* \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

Is really, really, really close to 0, 0, and 0, 0 is actually optimal