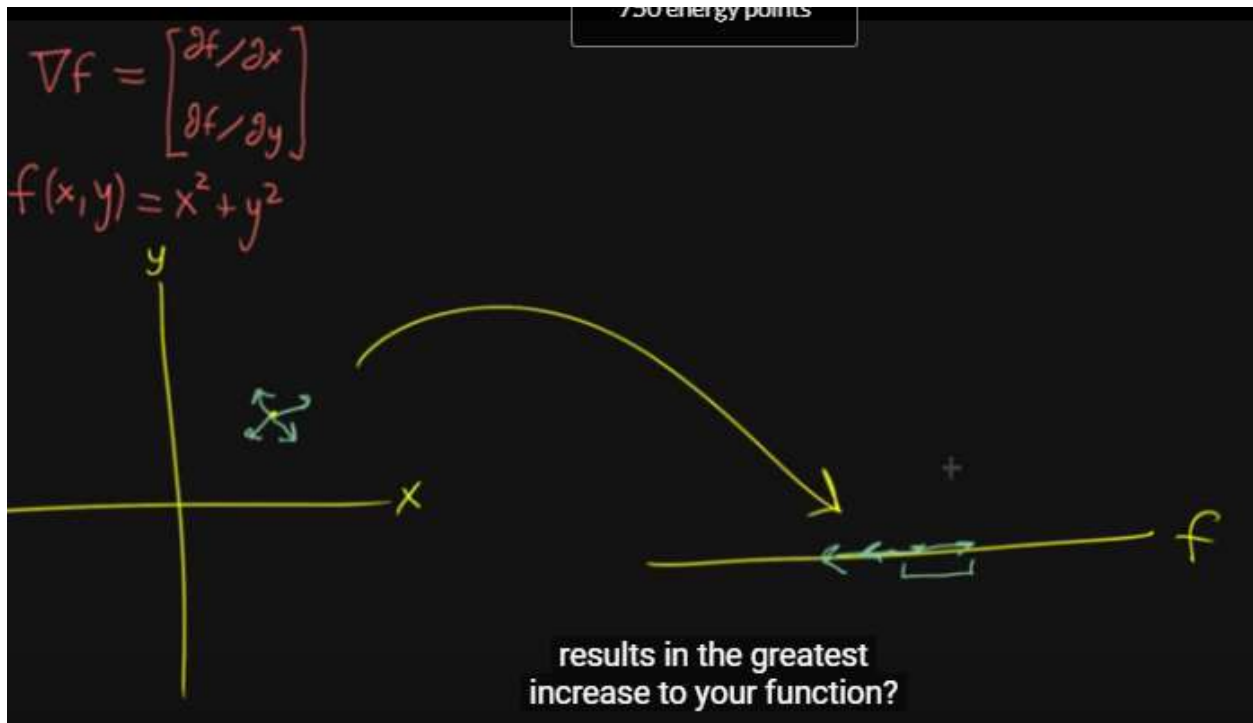
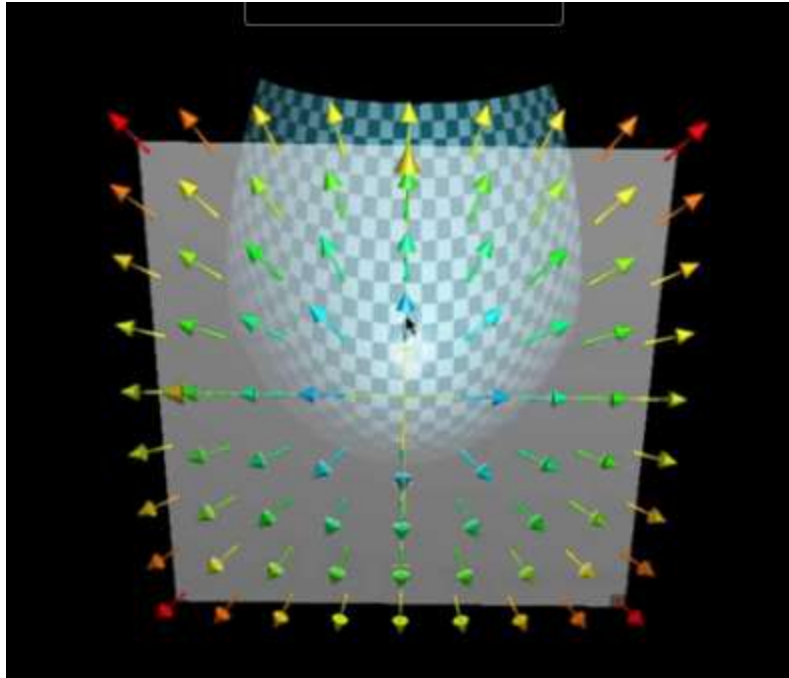


Why the gradient is the direction of steepest ascent



- In red we have the computation of the gradient for function f
 - o Which is simply a vector of partial derivatives
- Graphical interpretation: The gradient always points in direction of steepest ascent
 - o Out of all the different direction we can nudge the point above (In XY space), which one results in the greatest increase to your function f

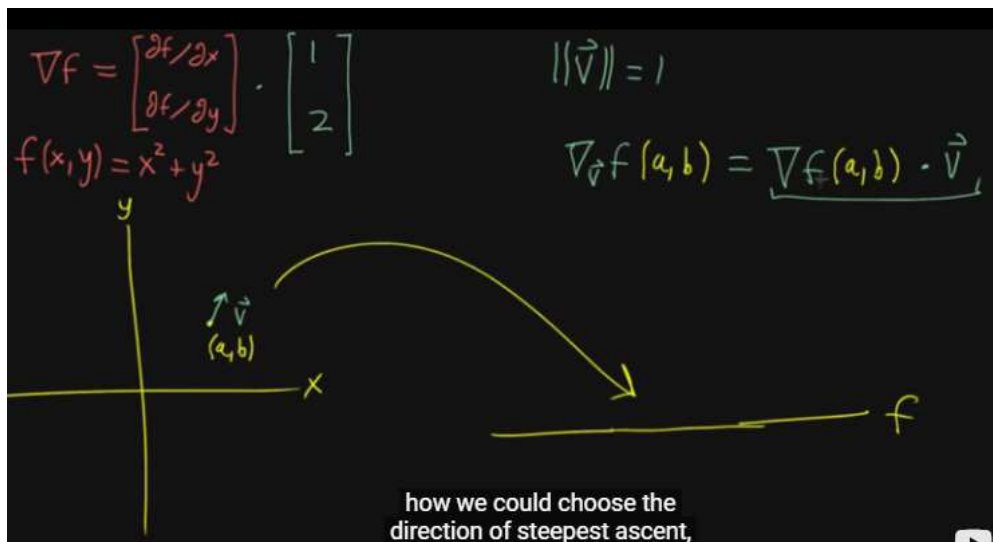


Here we have mapped out our function f and show the gradient field at the bottom

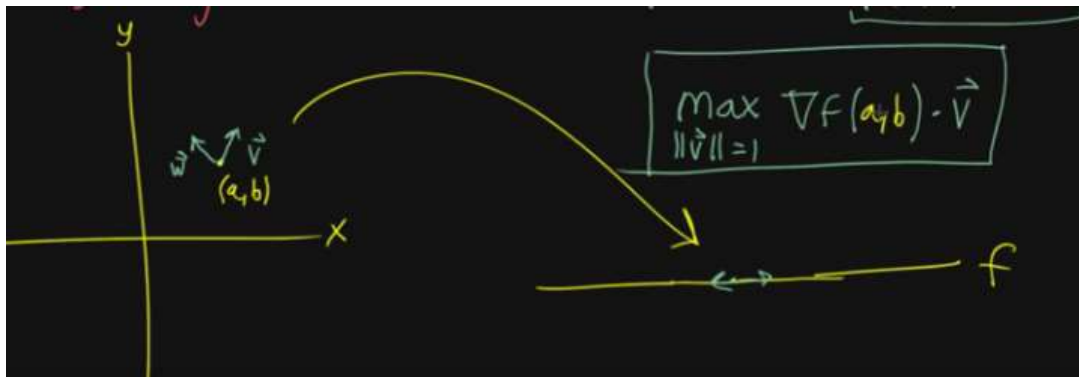
- The field shows the direction to steepest ascent based on where a point lies in the function

Comparing these two visuals, it may be difficult to initially see the connection

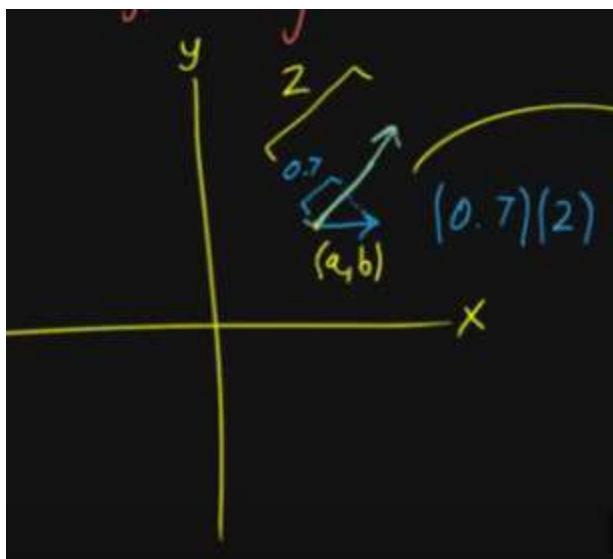
- Why does combination of partial derivatives coincide with choosing the direction of steepest ascent?
 - Intuition:



- Lets say we have single unit vector v
 - Magnitude of 1
- You can tell rate at which the function changes when it moves in direction of v by :
 - Taking the directional derivative of function with respect to vector v at some point (a, b)
 - The way we do this is dotting the gradient of f at point (a, b) together with unit vector v
 - This is how you tell the rate of change
 - Imagine you were dotting the gradient together with vector $[1 \ 2]$
 - Vector represents 1 step in x direction, 2 steps in y direction
 - The amount that the function changes should be the partial derivative with respect to x times a 1 step change in x direction plus df/dy times 2 step change in y direction
- This starts to give us the key for how we could choose the direction of steepest ascent
 - What we are really asking when we say which direction of the unit vector at point (a,b) changes function f the most:
 - Find max for all unit vectors v (magnitude = 1) of the dot product of gradient f at point (a,b) times vector v



- What does dot product represent?
 - Dot product of gradient of f at point (a,b) and vector v
 - Length of projection of vector v onto gradient vector times length of gradient vector



- Maximized when vector v is in same direction as gradient vector because then calculation would be $(1)(2) = 2$ and you return length of gradient vector



- Thus: the direction of steepest ascent is the direction of the gradient vector.
 - We have to normalize the gradient vector in case it has a magnitude larger than 1 because we are interested purely in direction here

$$\boxed{\max_{\|\vec{v}\|=1} \nabla f(a, b) \cdot \vec{v}} = \frac{\|\nabla f(a, b)\|}{\|\nabla f(a, b)\|}$$

- Fundamental fact: The gradient is a tool for computing directional derivatives
 - Gradient is vector that loves to be dotted with other things
 - (what a rascal that gradient)

- Because of this: the direction of steepest ascent is that vector itself: because the max of the dot product with the gradient vector and any other vector is a vector that points in same direction as gradient vector
- This leads into greater intuition for what we should do with the length of the gradient
 - The directional derivative in the direction of gradient itself has a value equal to the magnitude of the gradient
 - When you are moving in direction of gradient, the rate at which the function changes is given by the magnitude of the gradient (MAGIC VECTOR!)