

Lagrange Multipliers

Wiki { - is a strategy for finding the local maxima & minima of a function subject to Equality constraints.
The great advantage of this method is

Vector field \rightarrow of a function say $f(x, y) = \begin{bmatrix} x^2 + y^2 \\ 2x - y^2 \end{bmatrix}$
Gradient

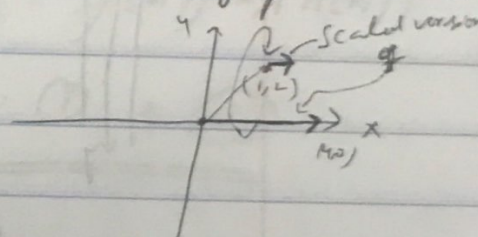
f has 2D input
 f has 2 dimensional vector

\rightarrow Take up points on the xy coordinate system & add the $f(x, y)$ value at to x, y points

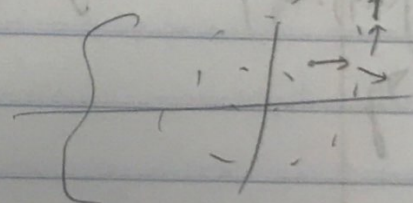
Ex: $(x, y) = 1, 2$

$$f(1, 2) = \begin{bmatrix} 3 \\ -2 \end{bmatrix}$$

$$1, 2 + \begin{bmatrix} 3 \\ -2 \end{bmatrix} = 4, 0$$



(Chain Rule) Is called vector field.



Gradient

$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \quad (\text{Ex: } f(x, y))$$

\rightarrow The vector field of points in the direction of steepest ascent.

\rightarrow Why gradient is the direction of steepest ascent?

P.T.O

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

$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} = \begin{bmatrix} 2x \\ 2y \end{bmatrix}$$

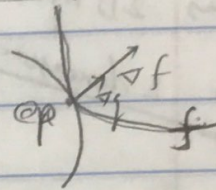
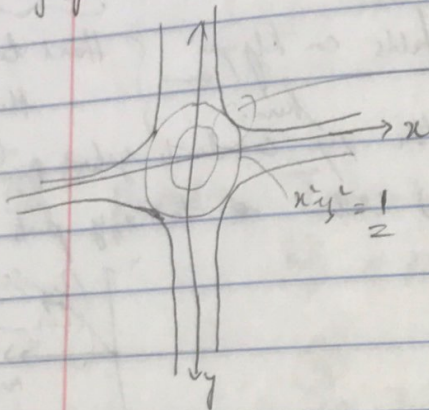
Gradient continued later (not to study)

Lagrange continued

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

on the set

$$x^2 + y^2 = 1 \rightarrow (1)$$



∇f is perpendicular to contour f

∇g is " to " g

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

by observation $f(x, y)$ on the $x^2 + y^2 = 1$ is maximum @ p , so

Here they are tangent.

$$\nabla f(x_p, y_p) = \lambda \nabla g(x_p, y_p) \rightarrow (2)$$

Gradients are parallel but not necessarily same magnitude

is called Lagrange Multiplier

$$\Rightarrow 2xy = \lambda 2x; \quad x^2 = \lambda 2y; \quad x^2 + y^2 = 1$$

→ $\mathcal{L}(x, y, \lambda) = f(x, y) - \lambda (g(x, y) - 1)$

! solve $\nabla_{x, y, \lambda} \mathcal{L}(x, y, \lambda) = 0$

$\mathcal{L}(x, y, \lambda)$ Solve =

→ 3 Equations 3 unknowns p. 7.0

~~min~~ $L(x, y, \lambda)$

$$\nabla_{\lambda} L(x, y, \lambda) = 0 - (g(x, y) - 1) = 0$$

$$\Rightarrow g(x, y) = 1$$

is a constant.

$$\nabla_{x, y} L(x, y, \lambda) = \nabla_{x, y} f(x, y) - \lambda \nabla_{x, y} g(x, y) = 0$$

$$\Rightarrow \nabla f(x, y) = 2 \nabla g(x, y)$$

Solving 3 equations
w.r.t. x, y might have
more than one
solⁿ, So we
are maximizing
the w.r.t that
maximizes $f(x, y)$

So the auxiliary function we assumed

$$L = f(x, y) - \lambda g(x, y) \quad L = f(x, y) - \lambda h(x, y)$$

Satisfies condition (1) + (2)

→

$$W_{\text{LS}} = \arg \min_w w^T w$$

subject to $Xw = y$

$$L =$$