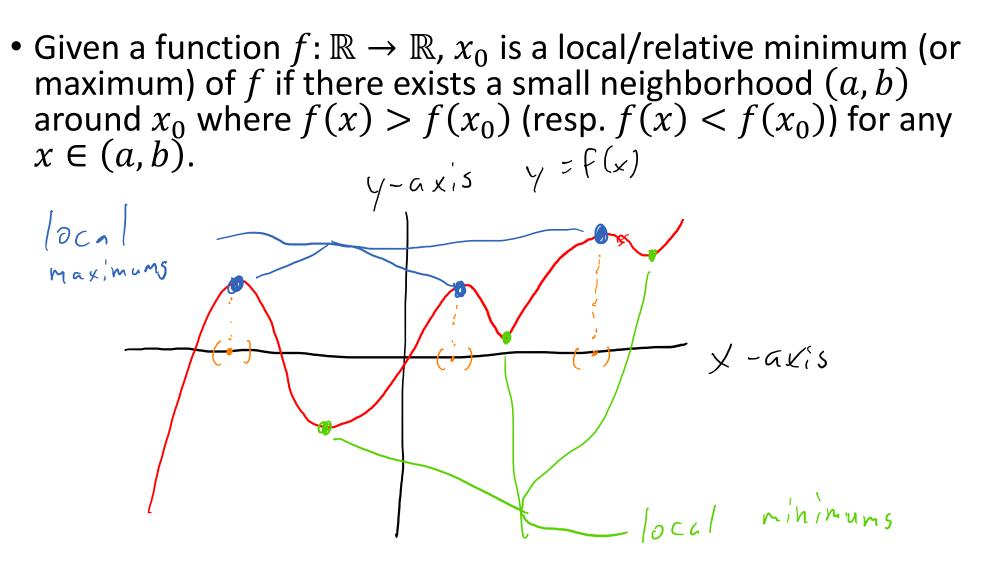
# Critical points, maximums, and minimums Lecture 5d – 2021-06-11

MAT A35 – Summer 2021 – UTSC

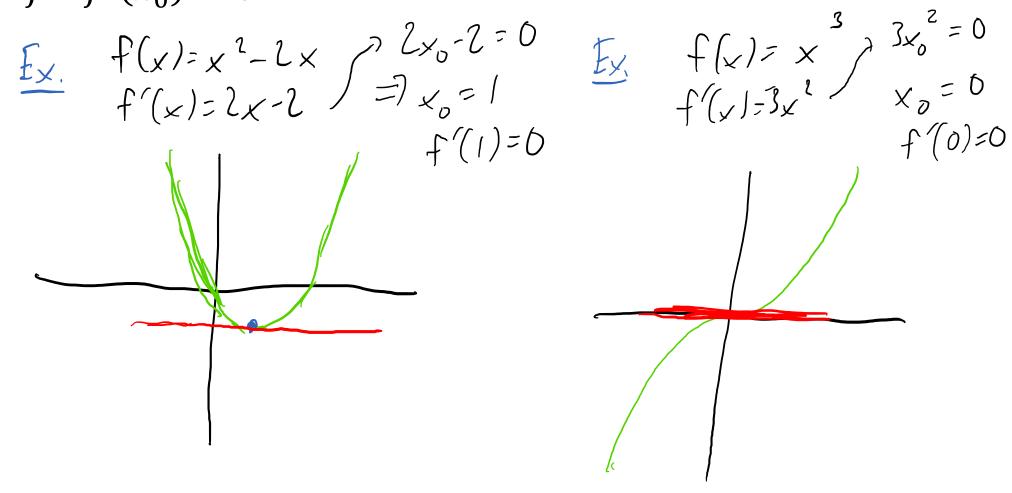
Prof. Yun William Yu

#### Local extrema of $f: \mathbb{R} \to \mathbb{R}$



#### Critical points of $f: \mathbb{R} \to \mathbb{R}$

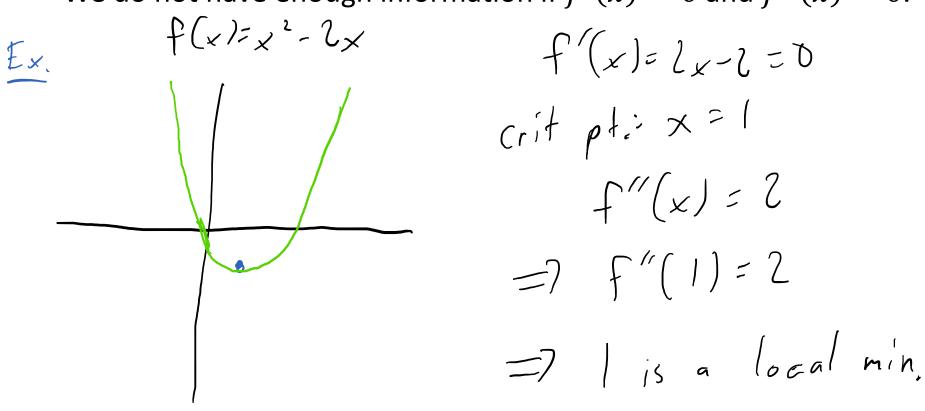
• Given a differentiable function  $f: \mathbb{R} \to \mathbb{R}, x_0$  is a critical point of f if  $f'(x_0) = 0$ .



#### 2<sup>nd</sup> derivative test

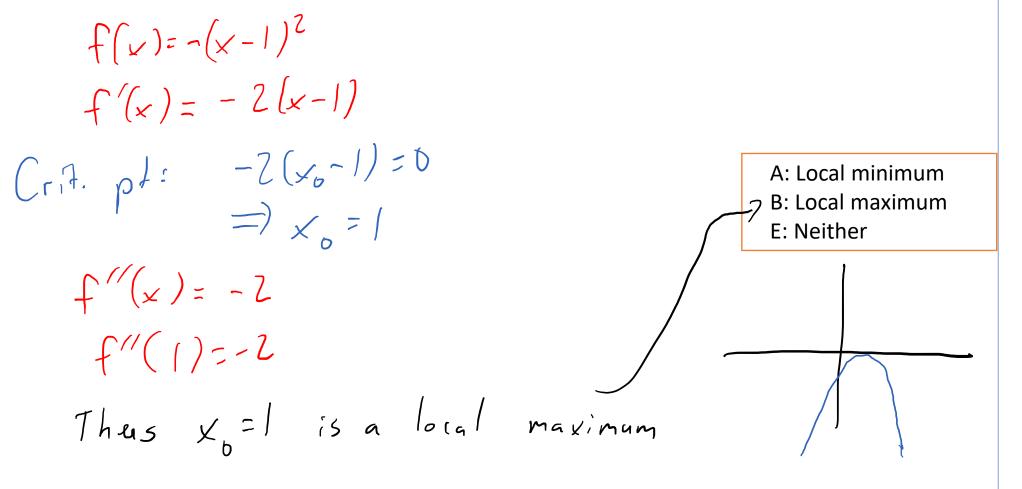
• Consider a twice-differentiable function  $f: \mathbb{R} \to \mathbb{R}$  given by f(x).

- For any  $x \in \mathbb{R}$  where f'(x) = 0 and f''(x) > 0, x is a local minimum.
- For any  $x \in \mathbb{R}$  where f'(x) = 0 and f''(x) < 0, x is a local maximum.
- We do not have enough information if f'(x) = 0 and f''(x) = 0.



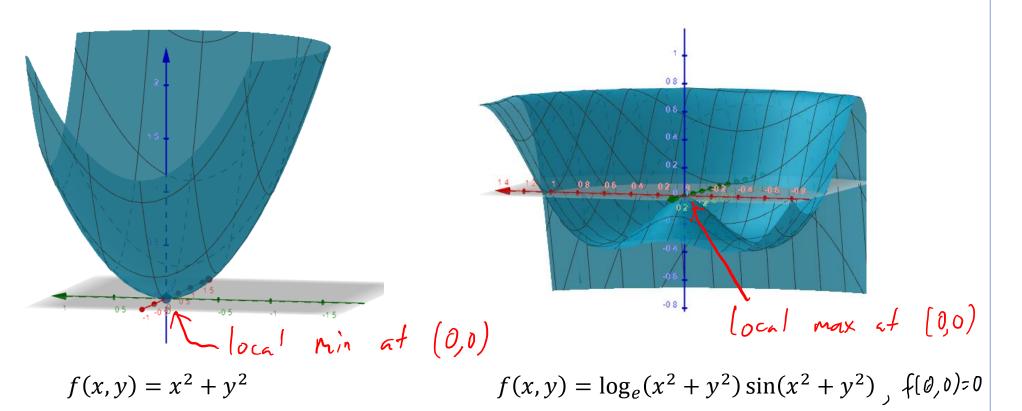
#### Try it out

• Find the only critical point of  $f(x) = -(x - 1)^2$ . Determine if it is a local minimum, a local maximum, or neither?



### Local extrema of $f: \mathbb{R}^2 \to \mathbb{R}$

• Given a function  $f: \mathbb{R}^2 \to \mathbb{R}$ ,  $(x_0, y_0)$  is a local/relative minimum (or maximum) of f if there exists a small rectangular neighborhood N around  $(x_0, y_0)$  where  $f(x, y) > f(x_0, y_0)$ (resp.  $f(x, y) < f(x_0, y_0)$ ) for any  $(x, y) \in N$ .



#### Derivatives in higher dimensions

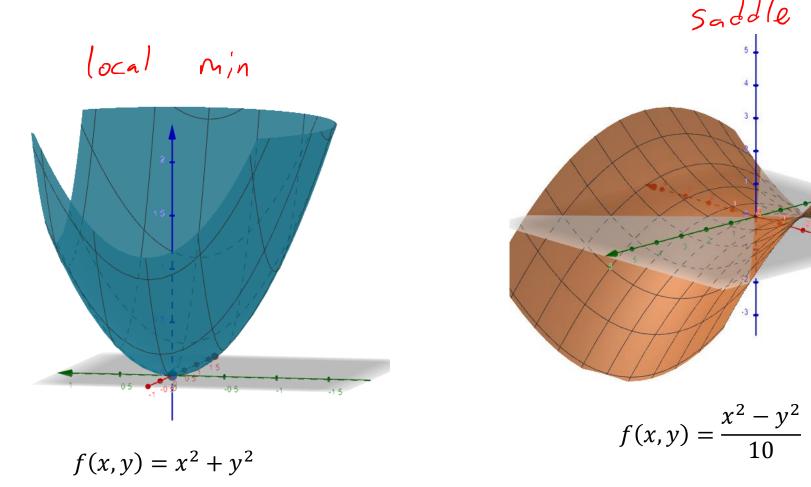
- We had an entire tangent plane.
- $f_x = \frac{\partial f}{\partial x}$  says how fast f grows in the x-direction.
- $f_y = \frac{\partial f}{\partial y}$  says how fast f grows in the y-direction.
- Given a direction vector  $u = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$  where  $u_1^2 + u_2^2 = 1$ , we can compute how quickly f grows in the u-direction by computing the matrix product

$$\begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \frac{\partial f}{\partial x} \cdot u_1 + \frac{\partial f}{\partial y} \cdot u_2$$

where 
$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \end{bmatrix}$$
 is the gradient of  $f$ 

# Critical points of $f: \mathbb{R}^2 \to \mathbb{R}$

• Consider a differentiable function  $f: \mathbb{R}^2 \to \mathbb{R}$  given by f(x, y).  $(x_0, y_0)$  is a critical point of f if  $f_x = 0$  and  $f_y = 0$ . Saddle pt

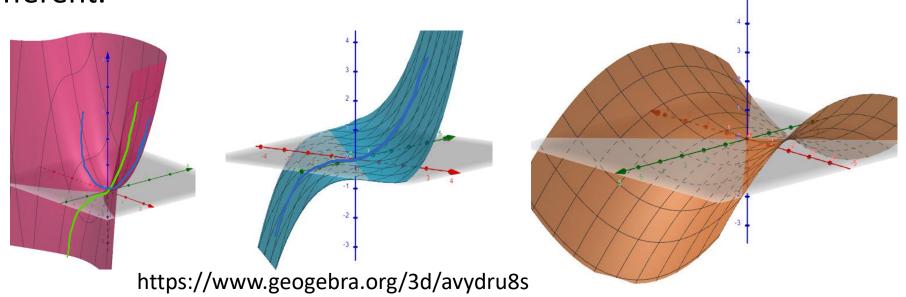


# Saddle points

- Saddle points are critical points which are not local extrema.
- Prototypical example looks like a horse riding saddle because along one axis it goes down in both directions, and along the other axis, it goes up in both directions.
- Other examples may look quite different.



https://catscustomsaddlepads.com/wp-content/uploads/2017/10/TexInGlitterGold\_HS2-1024x768.jpg



#### Higher-dimensional 2<sup>nd</sup> derivative test??

- For a single variable function, if  $x_0$  is a critical point, we just need to check if  $f''(x_0)$  is positive or negative to determine if minimum or maximum.
- Is there an analogous test for a critical point  $(x_0, y_0)$  of a multivariable function f(x, y)?

#### Attempt 1: all partial derivatives

- Consider a function  $f: \mathbb{R}^2 \to \mathbb{R}$  given by f(x, y). We have four second-order partial derivatives  $f_{xx}, f_{xy}, f_{yx}, f_{yy}$ .
- What if all four 2<sup>nd</sup>-order partial derivatives are positive?
- Try it out. The below functions have critical points at (0,0). Use Geogebra to classify the critical point.
  - $f(x,y) = x^2 + xy + y^2$   $f_x = 2x + y$   $f_y = x + 2y$  $f_{xx} = 2$   $f_{xy} = 1$   $f_{yx} = 1$   $f_{yy} = 2$

A: Minimum B: Maximum C: Saddle Point

- $f(x,y) = x^2 + 2xy + y^2$   $f_x = 2 + 2y$   $f_y = 2x + 2y$  $f_{xx} = 2$   $f_{xy} = 2$   $f_{yx} = 2$   $f_{yy} = 2$
- $f(x,y) = x^2 + 4xy + y^2$  $f_{xx} = i \quad f_{xy} = 4 \quad f_{yx} = 4 \quad f_{yy} = i$

#### What about the Hessian matrix?

• Analogous to 2<sup>nd</sup>-order total derivative.

• 
$$H = \begin{bmatrix} f_{xx} & f_{xy} \\ f_{yx} & f_{yy} \end{bmatrix} = \begin{bmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial y dx} \\ \frac{\partial^2 f}{\partial x dy} & \frac{\partial^2 f}{\partial y^2} \end{bmatrix}$$

- What does it mean for a matrix to be "positive"?
- What does it mean for a matrix to be "negative"?
- Answer depends on whether we are talking about matrix addition or matrix multiplication.

#### Eigenpairs show what happens to the axes

• If we have *n* distinct eigenpairs of an *n* × *n* matrix *A*, we can interpret the "action" of *A* by what it does to the eigenvectors.

$$A = \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix} \quad \text{has eigenpairs} \qquad \begin{pmatrix} 3 & -1 \\ 1 & 2 \end{pmatrix} \\ \begin{pmatrix} 1 & 1 & 2 \\ 1 & 2 \end{pmatrix} \\ \begin{pmatrix} 1 & 1 & 2 \\ 1 & 2 \end{pmatrix} \\ \begin{pmatrix} 1 & 1 & 2 \\ 1 & 2 \end{pmatrix} \\ \begin{pmatrix} 1 & 1 & 2 \\ 1 & 2 \end{pmatrix} \\ \begin{pmatrix} 1 & 1 & 2 \\ 1 & 2 \end{pmatrix} \\ \text{Note } \begin{bmatrix} 2 \\ 4 \\ 7 \end{bmatrix} = 1 \cdot A \cdot \begin{bmatrix} -1 \\ 1 \\ 7 \end{bmatrix} + 3 \cdot A \begin{bmatrix} 1 \\ 1 \\ 7 \end{bmatrix} \\ = 3 \cdot \begin{bmatrix} -1 \\ 7 \\ 1 \end{bmatrix} + 3 \cdot A \begin{bmatrix} 1 \\ 1 \\ 7 \\ 1 \end{bmatrix} \\ = \begin{bmatrix} 0 \\ 6 \end{bmatrix}$$

#### Hessian test: eigenvalue signs

• Given a twice-differentiable function  $f: \mathbb{R}^2 \to \mathbb{R}$ , let the Hessian

$$H = \begin{bmatrix} J_{xx} & J_{xy} \\ f & f \end{bmatrix}$$
. If  $(x_0, y_0)$  is a critical point of  $f$  (i.e.

 $[J_{yx} \quad J_{yy}]$  $f_x(x_0, y_0) = f_y(x_0, y_0) = 0)$ , then f is a local minimum if all eigenvalues of H are positive.

- f is a local maximum if all eigenvalues of H are negative.
- *f* is a saddle point if one eigenvalue is positive and one eigenvalue is negative.
- We do not have enough information if any eigenvalue is zero.

 $f_{x} = 2x + y = 0$ Example  $f_{Y} = x + 2y = 0$ •  $f(x,y) = x^2 + xy + y^2 \quad \neq \stackrel{>}{\rightarrow} \stackrel{\bigcirc}{}$ V=0  $f_{xx} = 2$ Crif. pt.  $f_{xy} = f_{yx} = 1$ at  $(\partial_1 b)$  $f_{yy} = 2$  $f_{2}(0,0) = l$ f xy (0,0) = 1  $H = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$  $\begin{vmatrix} 2-\lambda & 1 \\ 1 & 2-\lambda \end{vmatrix} = 4 - 4\lambda + \lambda^2 - 1 = 0$  $\lambda^2 - 4\lambda + 3 = 0$  $H(0,0) = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$ (1 - 1)(1 - 3) = 01=1,3 tuo pos eigenvals, so local minimum

Example

•  $f(x, y) = x^2 + 2xy + y^2$ crit pt at (0,0)  $f_{xx} = 2 \quad f_{xy} = f_{yx} = 2 \quad f_{yy} = 2$  $||(0,0) = \int_{7}^{2} \frac{2}{2}$ -0.4 -0.6  $\begin{vmatrix} 2 - 1 & 2 \\ - 2 & -4 \\ - 4 &$ > Cannot say using Hessian test ハ(ノ-4)こひ became one eigenvalue a = 0, 4 \_

Example

- $f(x, y) = x^2 + 4xy + y^2$  $f_{y} = 2x + 4y = 0$  $f_{y} = 4_{x} + 2_{y} = 0$  $=) \times z 0, \quad \gamma z b \quad is \quad cri^{4}. \quad p^{\perp}.$  $f_{XX} = 2$ ,  $f_{XY} = F_{YX} = 4$ ,  $f_{YY} = 2$  $H(0,0) = \begin{bmatrix} 2 & 4 \\ 4 & 2 \end{bmatrix}$  $\begin{vmatrix} 2-1 & 4 \\ 4 & 2-1 \end{vmatrix} = 4 - 4 + 1 + 1 - 16 = 0$  $\begin{vmatrix} 2-1 & 4 \\ -12 = 0 \end{vmatrix}$ (1-6)(1+2)= other direction neg  $\lambda = 6, -2$
- 7 saddle pt e cause direction por and

#### Example with nonconstant Hessian

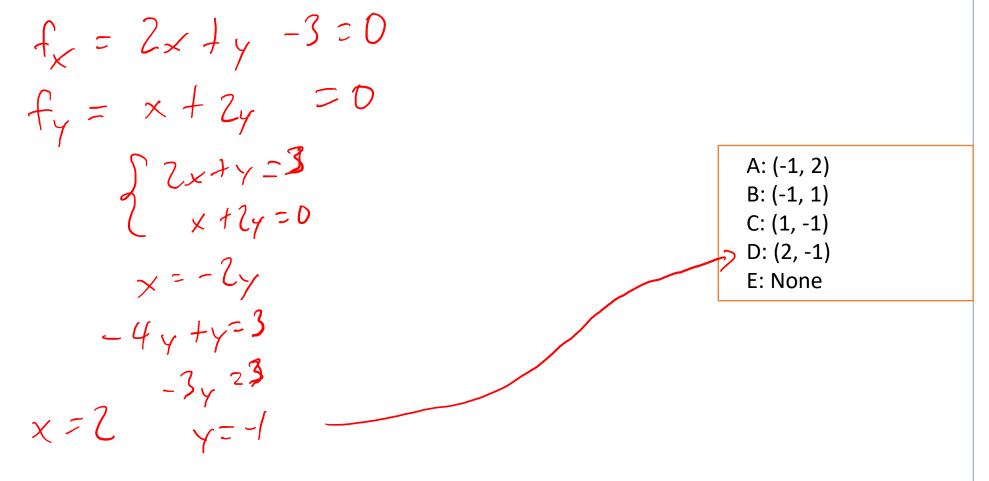
• 
$$f(x, y) = \sin(x^2 + y^2) + 1.1(x^2 + y^2)$$
  
 $f_x = 2 \times \cos(x^2 + y^2) + 1.1(x^2 + y^2)$   
 $f_x = 2 \times \cos(x^2 + y^2) + 1.1 \cdot 2 \times$   
 $= 2 \times \left[ 1.1 + \cos(x^2 + y^2) \right]$   
 $f_y = 2 \times \cos(x^2 + y^2) + 1.1 \cdot 2 \times$   
 $= 2 \times \left[ 1.1 + \cos(x^2 + y^2) \right] = 0$   
Solve  $\begin{cases} 2 \times \left[ 1.1 + \cos(x^2 + y^2) \right] = 0 \\ 2 \times \left[ 1.1 + \cos(x^2 + y^2) \right] = 0 \\ 2 \times \left[ 1.1 + \cos(x^2 + y^2) \right] = 0 \\ 2 \times \left[ 1.1 + \cos(x^2 + y^2) \right] = 0 \end{cases}$   
 $= 2 \times \left[ \frac{2 \times \left[ 1.1 + \cos(x^2 + y^2) \right] = 0}{2 \times \left[ 1.1 + \cos(x^2 + y^2) \right] = 0} \right]$ 

Example continued (2<sup>nd</sup> order partials) •  $f(x, y) = \sin(x^2 + y^2) + 1.1(x^2 + y^2)$ •  $f_x = 2x[1.1 + \cos(x^2 + y^2)]$ •  $f_y = 2y[1.1 + \cos(x^2 + y^2)]$  $f_{XX} = 2x \cdot 2x \cdot (-\sin(x^2 + y^2)) + 2 [1.1 + \cos(x^2 + y^2)]$  $= -4x^{2} \sin(x^{2} + y^{2}) + 2 \left[ 1.1 + \cos(x^{2} + y^{2}) \right]$  $f_{r}(0,0) = 4.2$  $f_{XY} = f_{YX} = -4xy \sin(x^2 t_Y^2) \qquad f_{XY}(0,0) = f_{YX}(0,0) = 0$  $f_{yy} = -4\gamma \sin(x^2 + \gamma^2) + 2\left[1.1 + \cos(x^2 + \gamma^2)\right]$  $f_{yy}(0,0) = 4.2$ 

# Example continued (Hessian) 4.2 4.2 • $f_{xx}(0,0) = 2.2, f_{xy}(0,0) = f_{yx}(0,0) = 0, f_{yy}(0,0) = 2.2$ $H(0,0) = \begin{bmatrix} 4.2 & 0 \\ 0 & 4.2 \end{bmatrix}$ Eigenvalues are 4.2 (two times), all positive This (0,0) is a local minimum

#### Try it out

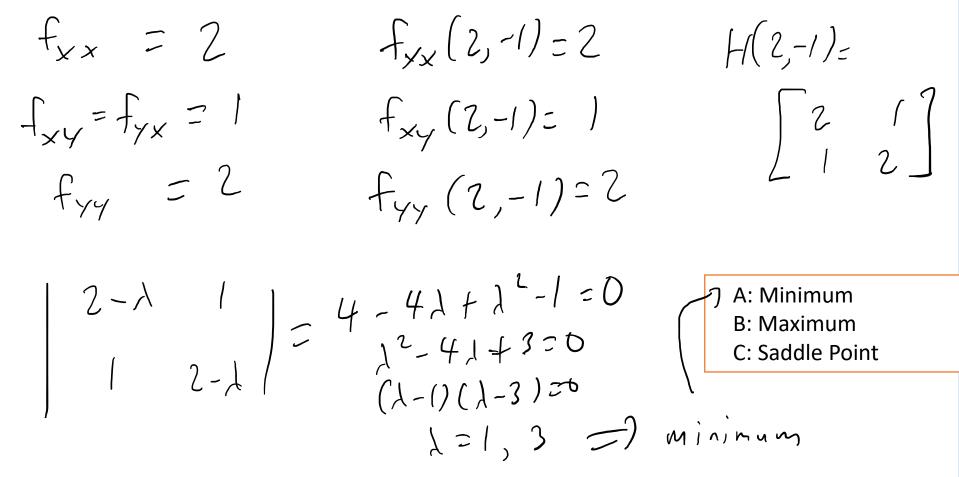
- $f(x, y) = x^2 + xy + y^2 3x$
- What is the only critical point of *f*?



Try it out

$$f(x,y) = x^2 + xy + y^2 - 3x$$
 Crit pt (2, -1)

• Is the critical point a min, max, or saddle point?



#### Shortcut strategy: D-test

- Given a function f(x, y), find the crucal point. and  $f_y = 0$  simultaneously. Let (a, b) be a critical point.  $f_{xx} f_{xy} = f_{yx}(a, b) f_{yx}(a, b) \cdot f_{yx}(a, b)$ . • Given a function f(x, y), find the critical points by setting  $f_{y} = 0$
- Let  $D = f_{xx}(a, b) \cdot f_{yy}(a, b) f_{xy}(a, b) \cdot f_{yx}(a, b)$ .
  - Note that D is the determinant of the Hessian at the critical point.
  - f has a maximum at (a, b) if D > 0 and  $f_{\chi\chi}(a, b) < 0$ .
  - f has a minimum at (a, b) if D > 0 and  $f_{\chi\chi}(a, b) > 0$ .
  - f has a saddle point at (a, b) if D < 0.
  - We don't have enough information if D = 0.
- Advanced: This works because it turns out that the determinant is the product of the eigenvalues (counting repeats) and the sum of the diagonal elements (the "trace") equals the sum of the eigenvalues (counting repeats).

Example (from above)  $\begin{bmatrix} -1z \\ 1 \\ 2 \end{bmatrix}$  $\begin{vmatrix} 2 & 1 \\ 1 & 2 \end{vmatrix} = 4 - 1 = 3$   $\begin{cases} local \\ minimum \\ m$ 

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