

Assignment - 1

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Question : 1

$$f: \mathbb{R}^2 \rightarrow \mathbb{R}$$

$$(x_1, x_2) \mapsto x_1^2 + 0.5 x_2^2 + x_1 x_2$$

(i) find the direction of greatest increase of f at $x = (1, 1)$

$$D_{\hat{v}} f(x_1, x_2) = (\nabla f(x_1, x_2)) \cdot \hat{v} = |\nabla f(x_1, x_2)| |\hat{v}| \cos \theta$$

$$\nabla f(x_1, x_2) = \left[\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2} \right]$$

Max
when
 $\cos \theta = 1$
 $\theta = 0^\circ$
 $\hat{v} \parallel \hat{\nabla} f(x_1, x_2)$

$$\frac{\partial f}{\partial x_1} = \frac{\partial}{\partial x_1} (x_1^2 + 0.5 x_2^2 + x_1 x_2)$$

$$= 2x_1 + 0 + x_2$$

$$= 2x_1 + x_2$$

\therefore in dirⁿ of
gradient
 \downarrow
greatest
increase

$$\frac{\partial f}{\partial x_2} = \frac{\partial}{\partial x_2} (x_1^2 + 0.5 x_2^2 + x_1 x_2)$$

$$= 0.5 (2x_2) + x_1$$

$$= x_1 + x_2$$

$$\nabla f(x_1, x_2) = \begin{bmatrix} 2x_1 + x_2 & x_1 + x_2 \end{bmatrix}$$

$$\text{at } (x_1, x_2) = (1, 1)$$

dirⁿ of greatest
increase.

$$\nabla f(1, 1) = [3, 2] = 3 \hat{x}_1 + 2 \hat{x}_2$$

unit vector: $\hat{\nabla} f(1, 1) = \left[\frac{3}{\sqrt{13}}, \frac{2}{\sqrt{13}} \right] = \frac{3}{\sqrt{13}} \hat{x}_1 + \frac{2}{\sqrt{13}} \hat{x}_2$
(\therefore direction) (\hat{v})

(ii) Find the direction of greatest decrease of f at $x(1,1)$.

$$D_{\hat{v}} f(x_1, x_2) = \hat{v} \cdot \nabla f(x_1, x_2)$$

$$= \|\hat{v}\| \|\nabla f(x_1, x_2)\| \cos \theta$$

$$\text{min when } \hat{v} \neq \hat{\nabla} f(x_1, x_2)$$

$$\vec{v} = -\vec{\nabla} f(x_1, x_2) \text{ @ } (1,1)$$

$$\vec{v} = -[3, 2] = [-3, -2]$$

$$= -3\hat{n}_1 - 2\hat{n}_2$$

$$\text{unit vector } (\hat{v}) \quad \because \text{dir}^n = \left[-\frac{3}{\sqrt{13}}, -\frac{2}{\sqrt{13}} \right] = -\frac{3}{\sqrt{13}}\hat{n}_1 - \frac{2}{\sqrt{13}}\hat{n}_2$$

→ dirⁿ of greatest decrease.

(iii) Find the dirⁿ in which f does not instantly change at $x = (1,1)$.

A f^{th} f has no change in any dirⁿ that is orthogonal to $\nabla f(x_1, x_2)$.

$$\text{i.e. } D_{\vec{v}} \nabla f(x_1, x_2) = \|\vec{v}\| \|\nabla f(x_1, x_2)\| \cos \theta = 0$$

$\theta = 90^\circ$

$$\text{let dir}^n \text{ vector : } \vec{u} = \langle u_x, u_y \rangle$$

$$\nabla f = \langle 2x_1 + x_2, x_1 + x_2 \rangle$$

$$\nabla f|_{x=(1,1)} = \langle 3, 2 \rangle$$

$$3u_x + 2u_y = 0$$

also \vec{u} is dirⁿ vector:

$$\|\vec{u}\| = 1$$

$$u_x^2 + u_y^2 = 1$$

$$u_x = -\frac{2}{3} u_y$$

$$\frac{4}{9} u_y^2 + u_y^2 = 1$$

$$\frac{13}{9} u_y^2 = 1$$

$$u_y = \pm \frac{3}{\sqrt{13}}$$

$$u_x = \mp \frac{2}{\sqrt{13}}$$

$$\vec{u} = \pm \left\langle -\frac{2}{\sqrt{13}}, \frac{3}{\sqrt{13}} \right\rangle$$

$$\begin{array}{cc} \swarrow + & \searrow - \\ -\frac{2}{\sqrt{13}} \hat{n}_1 + \frac{3}{\sqrt{13}} \hat{n}_2 & +\frac{2}{\sqrt{13}} \hat{n}_1 - \frac{3}{\sqrt{13}} \hat{n}_2 \end{array}$$

cin1

$$\tilde{\gamma} : \mathbb{R} \rightarrow \mathbb{R}^2$$

$$t \mapsto \tilde{\gamma}(t)$$

st. $\forall t \in \mathbb{R}$

$$f(\tilde{\gamma}(t)) = f(1, 1)$$

$$\frac{\partial f(\tilde{n}(t))}{\partial t} = \frac{\partial f(\tilde{n}(t))}{\partial \tilde{n}} \frac{\partial \tilde{n}}{\partial t} = 0$$

$$\Rightarrow \nabla f(\tilde{n}) \frac{\partial \tilde{n}}{\partial t} = 0$$

$$\therefore \nabla f(\tilde{n}) \perp^r \text{ to } \frac{\partial \tilde{n}}{\partial t}$$

let say $\tilde{n}(t) = \langle n_1(t), n_2(t) \rangle$
 $\hookrightarrow \mathbb{R} \rightarrow \mathbb{R}^2$

$$f(\tilde{n}(t)) = f(1,1) = c$$

derivation
wrt t $\left\{ \begin{array}{l} f(n_1(t), n_2(t)) = f(1,1) = c \\ f'(n_1(t), n_2(t)) = 0 \end{array} \right.$

dot
Product $\left\{ \begin{array}{l} \frac{\partial f}{\partial n_1} \cdot \frac{dn_1}{dt} + \frac{\partial f}{\partial n_2} \frac{dn_2}{dt} = 0 \\ \left(\frac{\partial f}{\partial n_1}, \frac{\partial f}{\partial n_2} \right) \cdot \left(\frac{dn_1}{dt}, \frac{dn_2}{dt} \right) = 0 \end{array} \right.$

$$\nabla f(n_1, n_2) \cdot \frac{\partial \tilde{n}}{\partial t} = 0$$

$$\nabla f(\tilde{n}) \cdot \frac{\partial \tilde{n}}{\partial t} = 0$$

$$\boxed{\nabla f(\tilde{n}) \perp^r \text{ to } \frac{\partial \tilde{n}}{\partial t}}$$

\therefore tangent line $\frac{\partial \tilde{n}}{\partial t}$ is \perp^r to the gradient $\nabla f(\tilde{n})$.

(c) Visualisation :

$$\begin{aligned} f(\tilde{n}(t)) &= f(1, 1) \\ &= 1^2 + 0.5 * 1^2 + 1 \\ &= 2.5 \end{aligned}$$

$$f(\tilde{n}(t)) = 2.5$$

$$\tilde{n}(t) \rightarrow t, n_2(t)$$

$$t^2 + 0.5 n_2^2(t) + t n_2(t) = 2.5$$

$$0.5 n^2 + t n + t^2 - 2.5 = 0$$

$$D = t^2 - 4 \times 0.5 (t^2 - 2.5)$$

$$\begin{aligned} &= t^2 - 2t^2 + 5 \\ &= -t^2 + 5 = 5 - t^2 \end{aligned}$$

$$\frac{-b \pm \sqrt{5 - t^2}}{1}$$

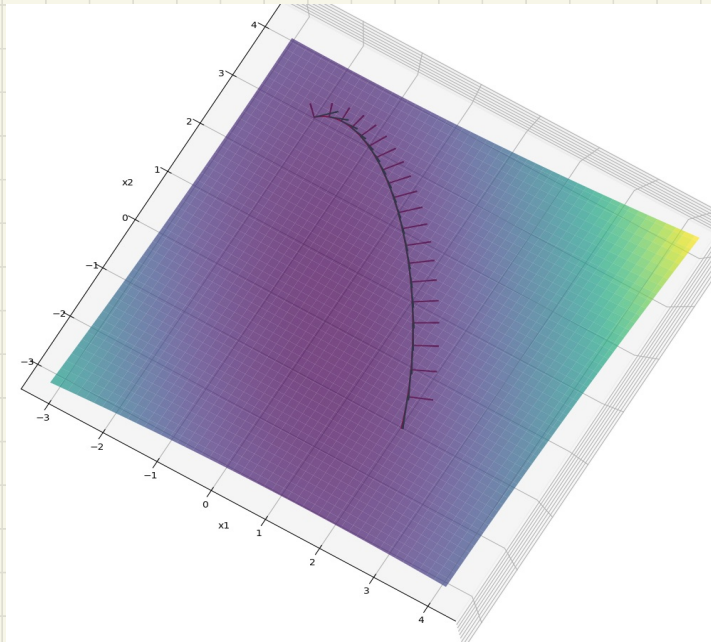
$$= -t \pm \sqrt{5 - t^2}$$

$$\therefore n_2(t) = -t \pm \sqrt{5 - t^2}$$

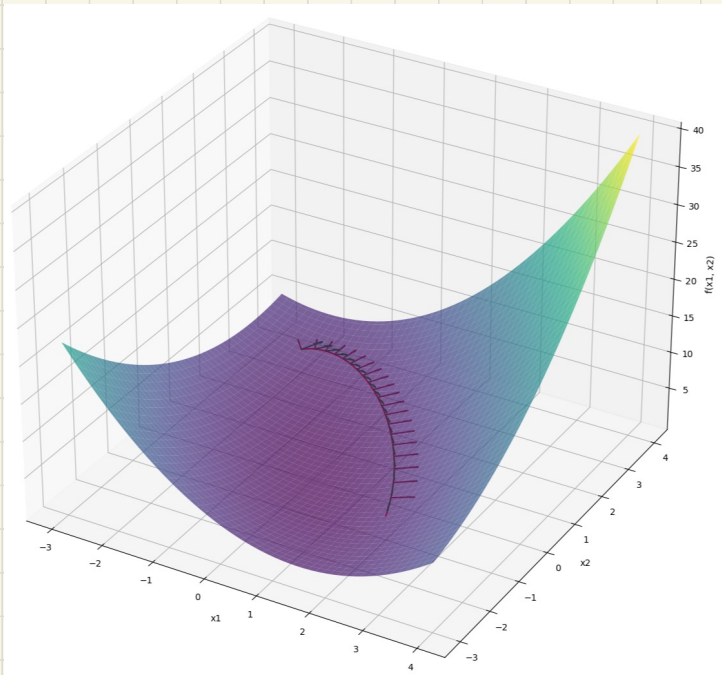
$$\text{Parametric eq.}^n (t, -t \pm \sqrt{5 - t^2})$$

$$\frac{\partial \tilde{n}}{\partial t} = \left(1, -1 + \frac{1(-2t)}{2\sqrt{5-t^2}} \right) = \left(1, -1 - \frac{t}{\sqrt{5-t^2}} \right)$$

Top View :



Side View :



Question : 2

Case $f, g : \mathbb{R} \rightarrow \mathbb{R}$ (convex functions)

To show: $f+g : \mathbb{R} \rightarrow \mathbb{R}$
 $x \mapsto f(x) + g(x)$ is convex.

$\because f$ & g are convex functions

let $x, y \in \mathbb{R}$

$$f(tx + (1-t)y) \leq tf(x) + (1-t)f(y) \quad \text{--- (i)}$$

$$g(tx + (1-t)y) \leq tg(x) + (1-t)g(y) \quad \text{--- (ii)}$$

$$\forall t \in [0, 1]$$

add (i) & (ii)

$$f(tx + (1-t)y) + g(tx + (1-t)y) \leq t(f(x) + g(x)) + (1-t)(f(y) + g(y))$$

$$\text{let } h = f + g$$

$$h(tx + (1-t)y) = f(tx + (1-t)y) + g(tx + (1-t)y)$$

$$h(x) = f(x) + g(x)$$

$$h(y) = f(y) + g(y)$$

$$h(tx + (1-t)y) \leq th(x) + (1-t)h(y)$$

∴ h is a convex f^n
 $\therefore f+g$ is a convex f^n .

(b) given: g is additionally non decreasing function

i.e. $g(y) \geq g(x)$ if $y > x$

let $h = g \circ f$

To prove h is convex:

$$h(tx + (1-t)y) \leq th(x) + (1-t)h(y) \\ \forall x, y \in \mathbb{R} \text{ \& } t \in [0, 1] \\ g(f(tx + (1-t)y)) \leq tg(f(x)) + (1-t)g(f(y))$$

∵ f is a convex function:

$$f(tx + (1-t)y) \leq tf(x) + (1-t)f(y) \\ \forall t \in [0, 1]$$

∵ g is non decreasing function:

$$g(f(tx + (1-t)y)) \leq g(tf(x) + (1-t)f(y)) \quad \text{--- (A)}$$

∵ g is also a convex function:

$$g(tf(x) + (1-t)f(y)) \\ \leq tg(f(x)) + (1-t)g(f(y)) \\ \text{--- (B)} \\ \forall t \in [0, 1]$$

from (A) & (B) :

$$g\left(f(tx + (1-t)y)\right) \leq t g(f(x)) + (1-t) g(f(y))$$

$$h(tx + (1-t)y) \leq t h(x) + (1-t) h(y) \quad \forall t \in [0,1]$$

$\therefore h$ is a convex function $\forall x, y \in \mathbb{R}$

$\therefore g \circ f$ is a convex function

Question : 3

$$f: \mathbb{R}^2 \rightarrow \mathbb{R} \\ (x_1, x_2) \mapsto e^{\pi x_1} - \sin(\pi x_2) + \pi x_1 x_2$$

(a) gradient of f (∇f) :

$$\nabla f = \left[\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2} \right]$$

$$\frac{\partial f}{\partial x_1} = e^{\pi x_1} (\pi) - 0 + \pi x_2$$

$$\frac{\partial f}{\partial x_2} = 0 - \pi \cos(\pi x_2) + \pi x_1$$

$$\nabla f(\bar{x}) = \nabla f(x_1, x_2) = \begin{bmatrix} \pi e^{\pi x_1} + \pi x_2, & -\pi \cos(\pi x_2) + \pi x_1 \end{bmatrix}$$

$$\bar{x} = (x_1, x_2)$$

$$\nabla f(\bar{x}) = \nabla f(x_1, x_2) = \begin{bmatrix} \pi e^{\pi x_1} + \pi x_2, & -\pi \cos(\pi x_2) + \pi x_1 \end{bmatrix}$$

(b) Hessian of f for an arbitrary x :

$$H = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} \\ \frac{\partial^2 f}{\partial x_1 \partial x_2} & \frac{\partial^2 f}{\partial x_2^2} \end{bmatrix}$$

$$f = e^{\pi x_1} - \sin(\pi x_2) + \pi x_1 x_2$$

$$\frac{\partial f}{\partial x_1} = \pi e^{\pi x_1} - 0 + \pi x_2$$

$$\frac{\partial^2 f}{\partial x_1 \partial x_2} = \pi$$

$$\frac{\partial^2 f}{\partial x_1^2} = \pi^2 e^{\pi x_1}$$

$$\frac{\partial f}{\partial x_2} = 0 - \pi \cos(\pi x_2) + \pi x_1$$

$$\frac{\partial^2 f}{\partial x_2^2} = +\pi^2 \sin(\pi x_2) + 0$$

$$\Rightarrow \pi^2 \sin(\pi x_2)$$

$$H = \begin{bmatrix} \pi^2 e^{\pi x_1} & \pi \\ \pi & \pi^2 \sin(\pi x_2) \end{bmatrix}$$

for $x = (x_1, x_2)$ (arbitrary)

(c) State the first order polynomial $T_{1,a}(x)$ expanded around point $a = (0, 1)$.

$$f \in C^1$$

$$f(x) = \underbrace{f(a) + \nabla f(a)^T (x-a)}_{T_1(x, a) \text{ or } T_{1,a}(x)} + R_1(x, a)$$

$$\begin{aligned} f(a) = f(x_1, x_2) \Big|_{a=(0,1)} &= e^{\pi x_1} - \sin(\pi x_2) + \pi x_1 x_2 \Big|_{a=(0,1)} \\ &= 1 - \sin(\pi) \\ &= 1 \end{aligned}$$

$$\nabla f(x) = \begin{bmatrix} \pi e^{\pi x_1} + \pi x_2 \\ -\pi \cos(\pi x_2) + \pi x_1 \end{bmatrix}$$

$$\nabla f(a) = \nabla f(0,1) = \begin{bmatrix} 2\pi \\ \pi \end{bmatrix}$$

$$(x-a) = \begin{bmatrix} x_1 \\ x_2-1 \end{bmatrix}$$

$$\nabla f(a)^T = [2\pi \quad \pi]$$

$$\begin{aligned} \nabla f(a)^T (x-a) &= [2\pi \quad \pi] \begin{bmatrix} x_1 \\ x_2-1 \end{bmatrix} \\ &= 2\pi x_1 + \pi (x_2-1) \end{aligned}$$

$$T_{1,a}(x) = f(a) + \nabla f(a)^T (x-a)$$

$$= 1 + 2\pi x_1 + \pi(x_2 - 1)$$

$$T_{1,a}(x) = 1 + 2\pi x_1 + \pi(x_2 - 1)$$

(d) Determine second order Taylor polynomial $T_{2,a}(x)$ expanded around point $a = (0, 1)$

$$f(x) = \underbrace{f(a) + \nabla f(a)^T (x-a) + \frac{1}{2} (x-a)^T H(a) (x-a)}_{T_{2,a}(x)} + R_2(x, a)$$

$$H(x) = \begin{bmatrix} \pi^2 e^{\pi x_1} & \pi \\ \pi & \pi^2 \sin(\pi x_2) \end{bmatrix}$$

$$H(a) = H(0, 1) = \begin{bmatrix} \pi^2 & \pi \\ \pi & 0 \end{bmatrix}$$

$$f(a) = 1 \quad (\text{calculated in Part d})$$

$$\nabla f(a)^T \cdot (x-a) = 2\pi x_1 + \pi(x_2 - 1) \quad (\text{calculated in Part d})$$

$$(x-a)^T H(a) = \begin{bmatrix} x_1 & x_2 - 1 \end{bmatrix} \begin{bmatrix} \pi^2 & \pi \\ \pi & 0 \end{bmatrix}$$

$$T_{2,a}(x) = 1 + (2n - n) \begin{pmatrix} x_1 \\ x_2 - 1 \end{pmatrix} + \frac{1}{2} (x_1 \ x_2 - 1) \begin{pmatrix} n^2 & n \\ n & 0 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 - 1 \end{pmatrix}$$

(c) Determine if $T_{2,a}$ is a convex function?

$T_{2,a}(x)$ is a multivariate quadratic function

to check where $T_{2,a}$ is a convex f^n or not we need to do the eigen analysis of its Hessian Matrix

$$q(x) = x^T A x + b^T x + c$$

$$\hookrightarrow H = 2A$$

$$\frac{1}{2} (n^2 x + n(y-1)nx)$$

$$\begin{pmatrix} x \\ y-1 \end{pmatrix}$$

Comparing $T_{2,a}(x)$ & $q(x)$

$$A = \frac{1}{2} \begin{bmatrix} n^2 & n \\ n & 0 \end{bmatrix}$$

$$\frac{1}{2} (n^2 x + n(y-1)nx) + \frac{1}{2} nx(y-1)$$

$$\therefore H = 2A = \begin{bmatrix} n^2 & n \\ n & 0 \end{bmatrix}$$

$$|H - \lambda I| = 0$$

$$\begin{vmatrix} n^2 - \lambda & n \\ n & -\lambda \end{vmatrix} = 0$$

$$(n^2 - 1)(-1) - n^2 = 0$$

$$(n^2 - 1)1 + n^2 = 0$$

$$n^2 \cdot 1 - 1^2 + n^2 = 0$$

$$1^2 - n^2 \cdot 1 - n^2 = 0$$

$$\frac{1 = n^2 \pm \sqrt{n^4 + 4n^2}}{2}$$

$$= \frac{n^2 \pm n\sqrt{n^2 + 4}}{2}$$

$$\lambda_1 = 10.7847$$

$$\lambda_2 = -0.9151$$

\therefore not +ve semi definite

$\therefore T_{2,a}(x)$ is not convex

Question: 4

$$f: [-1, 2] \rightarrow \mathbb{R}$$

$$x \mapsto e^{x^3 - 2x^2}$$

(a) compute f'

$$f' = \frac{d}{dx} (e^{x^3 - 2x^2})$$

$$= e^{x^3 - 2x^2} (3x^2 - 4x)$$

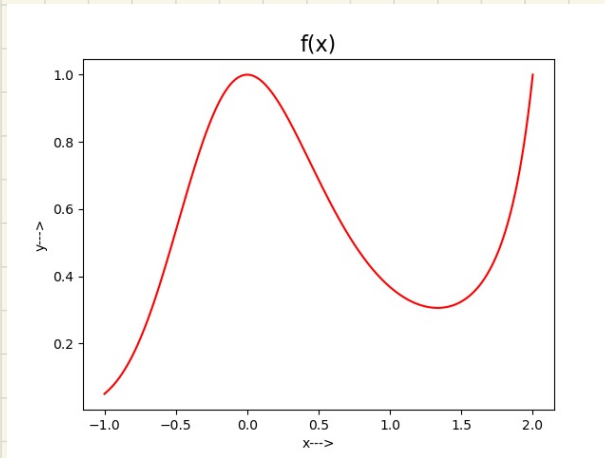
$$f' = (3x^2 - 4x) e^{x^3 - 2x^2}$$

c) Plot f and f' with Python?

Code for f :

```
f=lambda x: np.exp(x**3-2*x**2)
x=np.linspace(-1,2,1000)
y=f(x)
pt.plot(x,y,color="red")
pt.xlabel("x--->")
pt.ylabel("y--->")
pt.title("f(x)",fontsize=16)
pt.savefig('f(x).png')
```

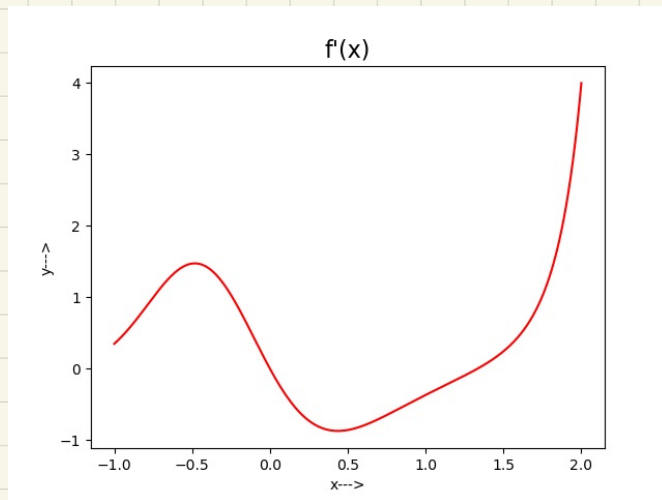
Plot :



Code for f' :

```
f_dash=lambda x: (3*x**2-4*x)*np.exp(x**3-2*x**2)
x=np.linspace(-1,2,1000)
y=f_dash(x)
pt.plot(x,y,color="red")
pt.xlabel("x--->")
pt.ylabel("y--->")
pt.title("f'(x)",fontsize=16)
pt.savefig('f\'(x).png')
```

Plot for f' :



c) Find all possible candidates x^* for maxima & minima.

possible candidates are
end points i.e. $x = -1, 2$ and

where $f'(x) = 0$

$$(3x^2 - 4x) \underbrace{e^{x^3 - 2x^2}}_{\neq 0} = 0$$

$$3x^2 - 4x = 0$$

$$x = 0$$

$$x = \frac{4}{3}$$

∴ Possible candidates are $-1, 2, 0, \frac{4}{3}$.

(d) Compute f''

$$f' = (3x^2 - 4x) e^{x^3 - 2x^2}$$

$$f'' = \frac{d}{dx} \left((3x^2 - 4x) e^{x^3 - 2x^2} \right)$$

$$= (6x - 4) e^{x^3 - 2x^2} + (3x^2 - 4x)^2 e^{x^3 - 2x^2}$$

(e) Determine if the candidates are local maxima, minima or neither.

@ $x = -1$

$$f(x) = e^{(x^3 - 2x^2)} = e^{(-1 - 2)} = e^{-3} = 0.0498$$

$$f'(x) \Big|_{x=-1} = (3 + 4) e^{-3} > 0$$

ie. f' is increasing to right of $x = -1$
 \therefore local minima

@ $x = 0$

$$f'(x) = 0$$

$$f''(x) \Big|_{x=0} = (-4) e^0 + (0)$$
$$= -4$$

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

\therefore local maxima.

$$f(x) \Big|_{x=0} = e^0 = 1$$

a) $x = \frac{4}{3}$

$$f'(x) = 0$$

$$f''(x) \Big|_{x=\frac{4}{3}} = \left(6 \cdot \frac{4}{3} - 4 \right) e^{\left(\frac{4}{3}\right)^3 - 2\left(\frac{4}{3}\right)^2} + \left(3 \cdot \left(\frac{4}{3}\right)^2 - 4 \cdot \frac{4}{3} \right) e^{\left(\frac{4}{3}\right)^3 - 2\left(\frac{4}{3}\right)^2}$$

$$= 4 e^{\left(\frac{4}{3}\right)^3 - 2\left(\frac{4}{3}\right)^2} + \left(\frac{16}{3} - \frac{16}{3} \right) e^{\left(\frac{4}{3}\right)^3 - 2\left(\frac{4}{3}\right)^2}$$

$$> 0$$

\therefore local minimum

$$\begin{aligned} f(x) &= e^{x^3 - 2x^2} \\ &= e^{\left(\frac{4}{3}\right)^3 - 2\left(\frac{4}{3}\right)^2} \\ &= e^{\frac{64}{27} - 2 \cdot \frac{16}{9}} \\ &= e^{\frac{64}{27} - \frac{32}{9}} \\ &= e^{\frac{64-96}{27}} = e^{-\frac{32}{27}} \\ &= 0.306 \end{aligned}$$

a) $x = 2$

$$f(x) = e^{(x^3 - 2x^2)} = e^0 = 1$$

$$f'(x)|_{x=2} > 0$$

$\therefore f'$ is \uparrow as $x=2$ is approached from Left
 $\therefore b$ is a local maxima

(f) global maxima and global minima of f :

$$\text{global maxima} \Rightarrow \max \{ f(-1), f(0), f(\frac{1}{3}), f(2) \}$$

$$\Rightarrow 1$$

$$\text{at } x = 0 \text{ \& } 2$$

$$\text{global minima} = \min \{ f(-1), f(0), f(\frac{1}{3}), f(2) \}$$

$$= e^{-3} = 0.0498$$

$$@ x = -1$$

