

Q: Ex 1

Find the tangent plane to the unit sphere $x^2 + y^2 + z^2 = 1$ at an arbitrary point.

$$f(x, y, z) = x^2 + y^2 + z^2 - 1 = 0$$

$$\nabla f(x, y, z) = \left(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z} \right) = (2x, 2y, 2z)$$

$$\text{We take points } x_0, y_0, z_0 \Rightarrow \nabla f(x_0, y_0, z_0) = (2x_0, 2y_0, 2z_0)$$

$$\text{Equation of tangent plane: } 2x_0(x - x_0) + 2y_0(y - y_0) + 2z_0(z - z_0) = 0 \Rightarrow$$

$$\Rightarrow 2x_0x + 2y_0y + 2z_0z = 2x_0^2 + 2y_0^2 + 2z_0^2 = 2$$

$$\Rightarrow 2x_0x + 2y_0y + 2z_0z = 2 \Rightarrow x_0x + y_0y + z_0z = 1$$

Q: Ex 2

Let $x, y, f: \mathbb{R}^2 \rightarrow \mathbb{R}$ and $f(x, y) = f(x(u, v), y(u, v))$. Prove that

$$\frac{\partial f}{\partial u} = \frac{\partial f}{\partial x} \frac{\partial x}{\partial u} + \frac{\partial f}{\partial y} \frac{\partial y}{\partial u} \quad \text{and} \quad \frac{\partial f}{\partial v} = \frac{\partial f}{\partial x} \frac{\partial x}{\partial v} + \frac{\partial f}{\partial y} \frac{\partial y}{\partial v}$$

$f(x, y)$ depends on u, v indirectly through $x(u, v)$ and $y(u, v)$.

When u changes, f changes both through x and y :

$$x \Rightarrow \frac{\partial f}{\partial x} \frac{\partial x}{\partial u}, \quad y \Rightarrow \frac{\partial f}{\partial y} \frac{\partial y}{\partial u} \Rightarrow$$

$$\Rightarrow \frac{\partial f}{\partial u} = \frac{\partial f}{\partial x} \frac{\partial x}{\partial u} + \frac{\partial f}{\partial y} \frac{\partial y}{\partial u}$$

When v changes, f changes both through x and y :

$$x \Rightarrow \frac{\partial f}{\partial x} \frac{\partial x}{\partial v}, \quad y \Rightarrow \frac{\partial f}{\partial y} \frac{\partial y}{\partial v} \Rightarrow$$

$$\Rightarrow \frac{\partial f}{\partial v} = \frac{\partial f}{\partial x} \frac{\partial x}{\partial v} + \frac{\partial f}{\partial y} \frac{\partial y}{\partial v}$$

Q: Ex 3

Consider the quadratic function $f: \mathbb{R}^2 \rightarrow \mathbb{R}$, $f(x, y) = 1/2 \cdot (x^2 + by^2)$ with $b > 0$ and the following gradient descent method for finding its minimum $(x_{k+1}, y_{k+1}) = (x_k, y_k) - s_k \nabla f(x_k, y_k)$, with step size $s_k > 0$ (also called learning rate in the machine learning literature)

a) Find the step size s_k using exact line search, such that it minimizes the function $\varphi(s_k) = f(x_{k+1}, y_{k+1}) = f((x_k, y_k) - s_k \nabla f(x_k, y_k))$.

$$\nabla f(x, y) = \left(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right) = (x, by)$$

$$\text{At point } (x_k, y_k) \Rightarrow \nabla f(x_k, y_k) = (x_k, by_k)$$

$$(x_{k+1}, y_{k+1}) = (x_k, y_k) - s_k \nabla f(x_k, y_k) \Rightarrow x_{k+1} = x_k - s_k x_k, y_{k+1} = y_k - s_k by_k$$

$$\Rightarrow x_{k+1} = (1 - s_k)x_k, y_{k+1} = (1 - s_k b)y_k$$

$$\varphi(s_k) = f(x_{k+1}, y_{k+1}) = 1/2 \cdot (x_{k+1}^2 + b y_{k+1}^2) = 1/2 \cdot ((1 - s_k)^2 x_k^2 + b(1 - s_k b)^2 y_k^2)$$

$$\varphi'(s_k) = \frac{\partial}{\partial s_k} \left[\frac{1}{2} ((1 - s_k)^2 x_k^2 + b(1 - s_k b)^2 y_k^2) \right] = -(1 - s_k)x_k^2 - b^2(1 - s_k b)y_k^2$$

$$\varphi'(s_k) = 0$$

$$(1 - s_k)x_k^2 + b^2(1 - s_k b)y_k^2 = 0 \Rightarrow x_k^2 - s_k x_k^2 + b^2 y_k^2 - b^3 s_k y_k^2 = 0 \Rightarrow$$

$$\Rightarrow s_k(x_k^2 + b^3 y_k^2) = x_k^2 + b^2 y_k^2 \Rightarrow s_k = \frac{x_k^2 + b^2 y_k^2}{x_k^2 + b^3 y_k^2}$$

b) What do you notice as b gets smaller? $x_k^2 + b^3 y_k^2$

For $b=1 \Rightarrow$ The contours are circular, and the gradient descent path is straight toward the minimum.

As b decreases \Rightarrow The contours become elongated ellipses. Gradient descent steps "zig-zag" more and take longer to converge. This behaviour occurs because the function has a condition number that worsen as $b \rightarrow 0$.


```
import numpy as np
import matplotlib.pyplot as plt

# Function definition and gradient
def f(x, y, b):
    return 0.5 * (x ** 2 + b * y ** 2)

def grad_f(x, y, b):
    return np.array([x, b * y])

# Gradient descent function
def gradient_descent(x0, y0, b, num_steps=50):
    x, y = x0, y0
    trajectory = [(x, y)] # To store the path of descent
    step_size = 1 / (1 + b ** 2) # Optimal step size derived earlier

    for _ in range(num_steps):
        grad = grad_f(x, y, b)
        x -= step_size * grad[0]
        y -= step_size * grad[1]
        trajectory.append((x, y))
    return np.array(trajectory)
```

Plotting function

```
def plot_contours_and_descent(b_values, num_steps=50):
```

```
    x = np.linspace(-2, stop=2, num=100)
```

```
    y = np.linspace(-2, stop=2, num=100)
```

```
    X, Y = np.meshgrid(*xi: x, y)
```

```
    for b in b_values:
```

```
        Z = f(X, Y, b) # Compute contours
```

```
        # Initial point
```

```
        x0, y0 = 1.5, 1.5
```

```
        # Perform gradient descent
```

```
        trajectory = gradient_descent(x0, y0, b, num_steps)
```

```
        # Plotting
```

```
        plt.figure(figsize=(8, 6))
```

```
        plt.contour(*args: X, Y, Z, levels=20, cmap='jet')
```

```
        plt.plot(*args: trajectory[:, 0], trajectory[:, 1], 'o-', color='red', label='Gradient Descent Path')
```

```
        plt.title(f"Gradient Descent for b = {b}")
```

```
        plt.xlabel('x')
```

```
        plt.ylabel('y')
```

```
        plt.legend()
```

```
        plt.grid()
```

```
        plt.show()
```

```
# Main function
```

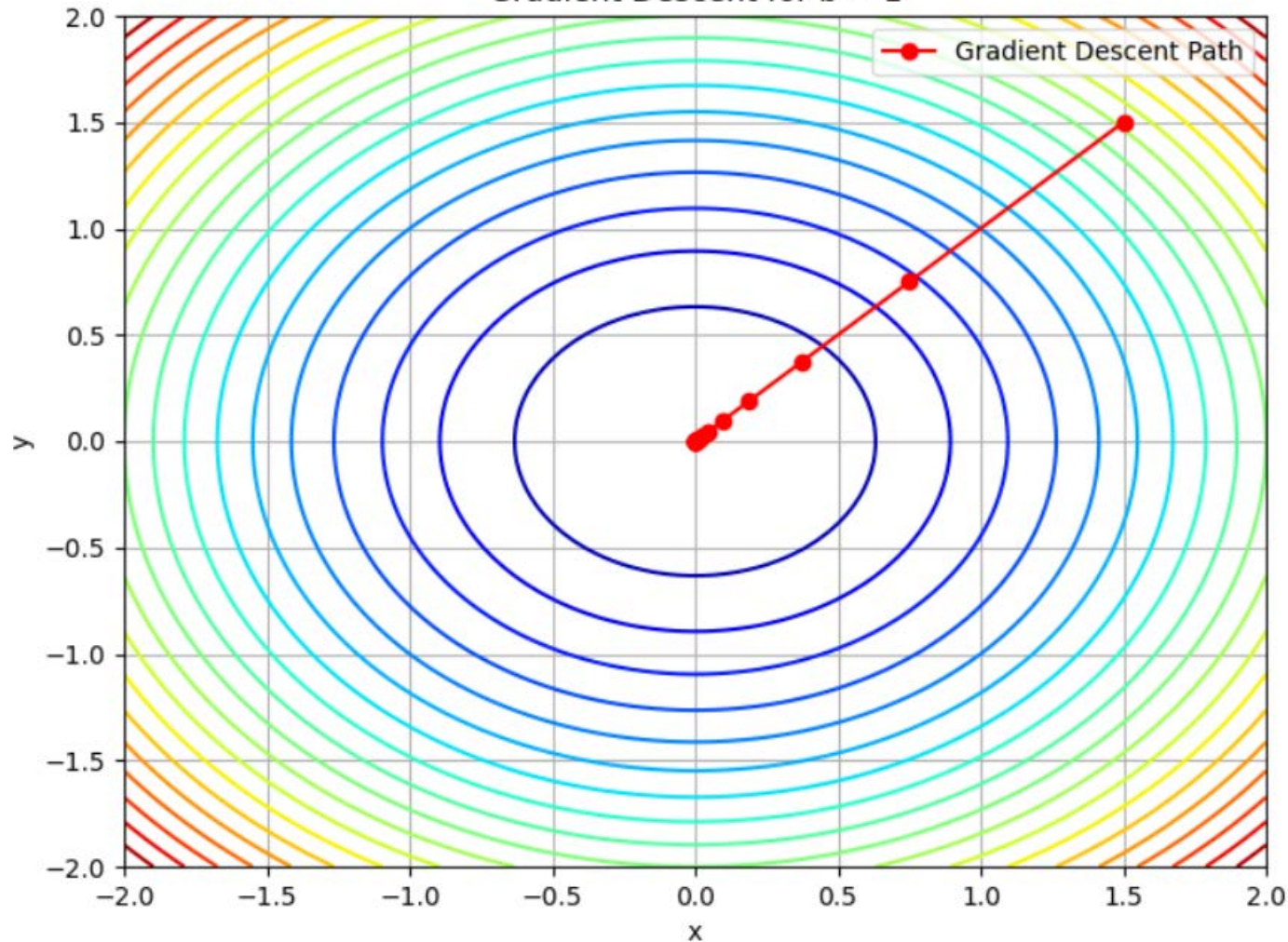
```
if __name__ == "__main__":
```

```
    b_values = [1, 0.5, 0.2, 0.1] # b = 1, 1/2, 1/5, 1/10
```

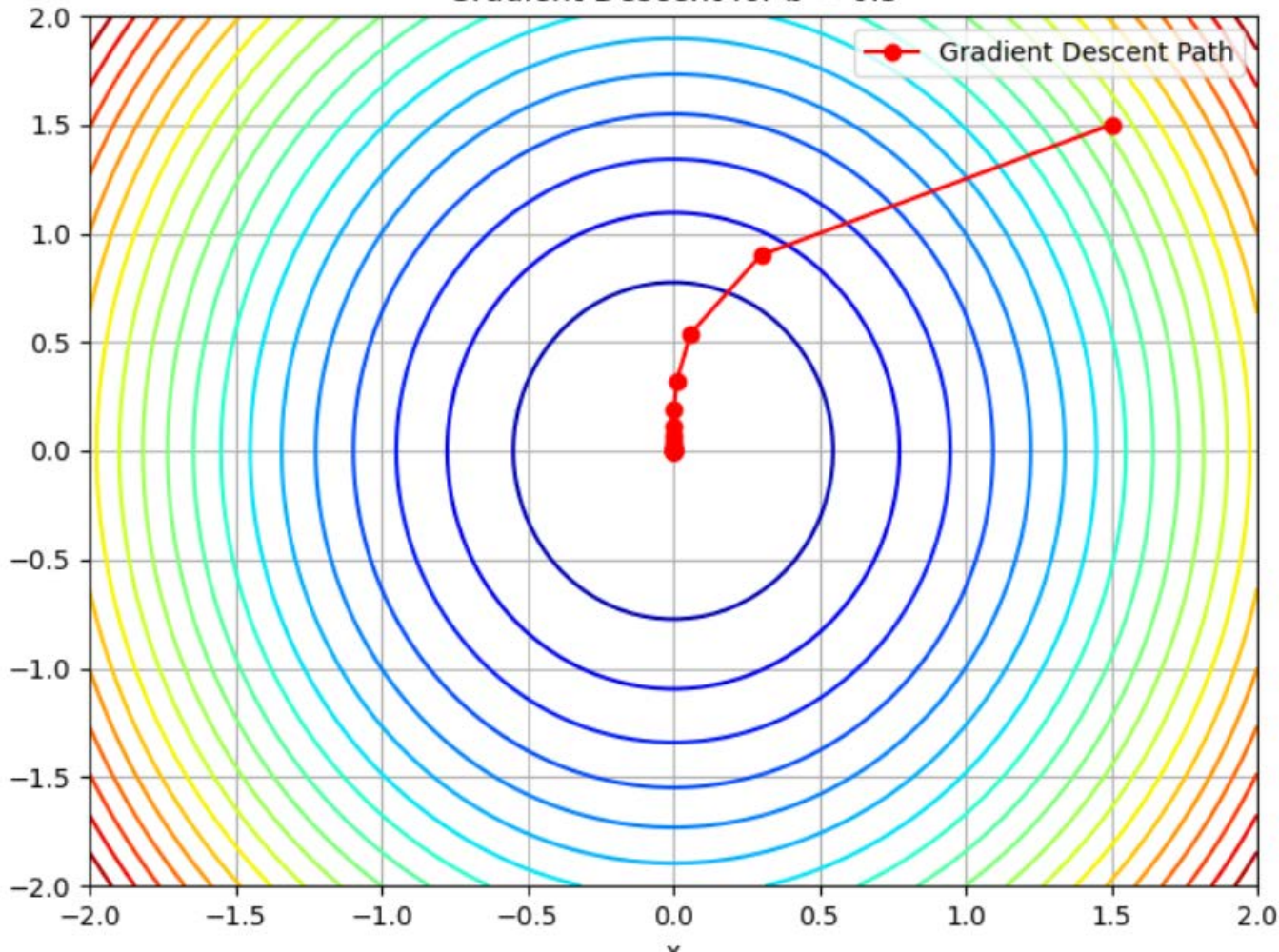
```
    plot_contours_and_descent(b_values)
```

Clo

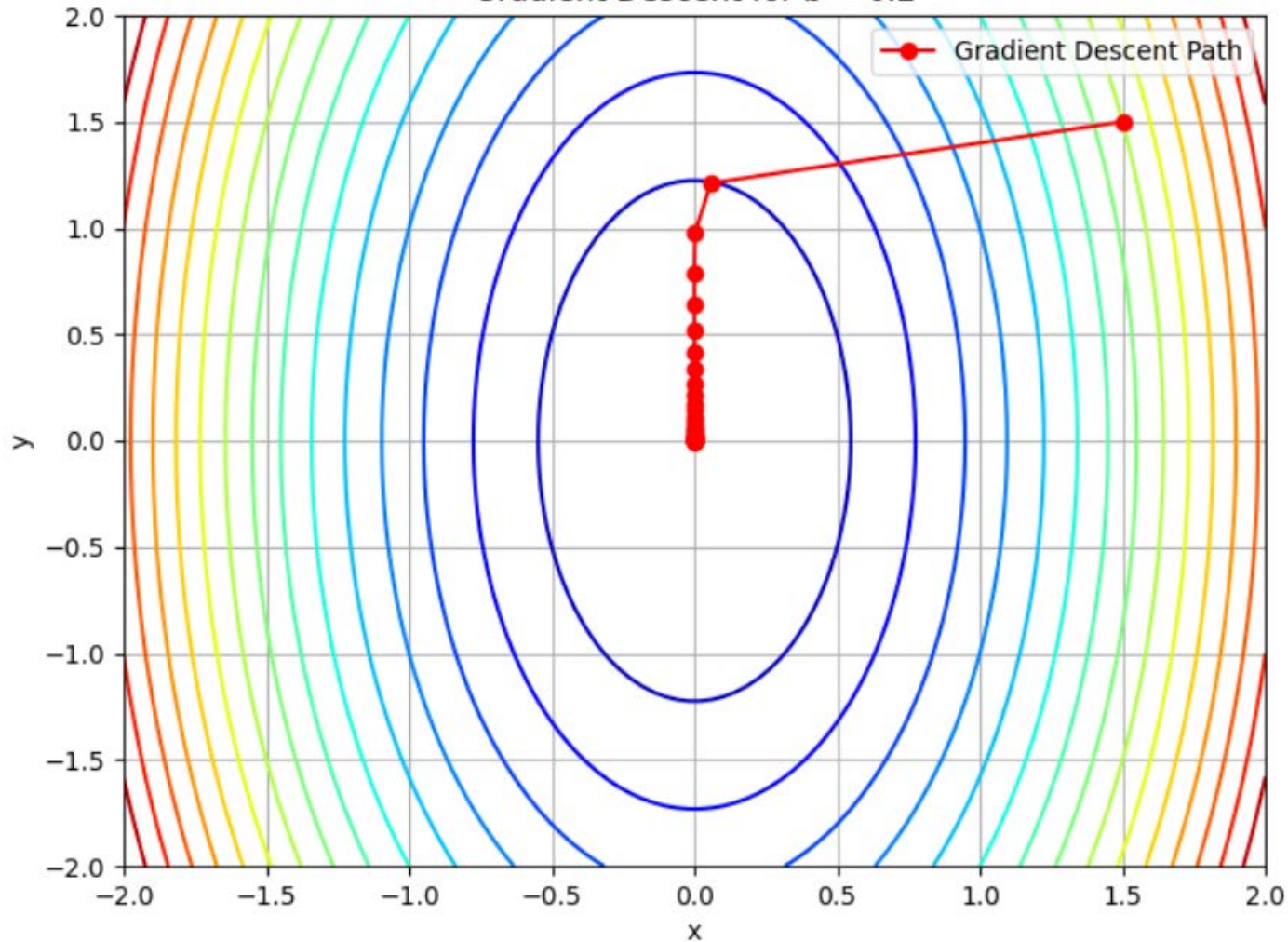
Gradient Descent for $b = 1$



Gradient Descent for $b = 0.5$



Gradient Descent for $b = 0.2$



Gradient Descent for $b = 0.1$

