# Numerical Methods Implementation Report

# December 6, 2024

# Introduction

This report covers the implementation of three numerical methods:

- 1. Bisection Method for root-finding,
- 2. Golden Section Method for optimizing a unimodal function,
- 3. Gradient Ascent for finding a maximum of a differentiable function.

Each method's logic, observations about convergence, and implementation challenges are discussed.

# 1 Task 1: Bisection Method

# 1.1 Logic

The Bisection Method narrows down a root by repeatedly halving an interval that contains a root. We ensure  $f(a) \cdot f(b) < 0$ , guaranteeing at least one root. On each iteration, we evaluate f(m) at the midpoint  $m = \frac{a+b}{2}$ . If f(m) = 0, we stop; otherwise, we pick the subinterval where the sign change persists.

#### 1.2 Observations

For the function f(x), we tested the method with intervals  $[a_1, b_1]$  and  $[a_2, b_2]$ . The root at x = c was found very quickly. The choice of the interval affects how fast we converge. A smaller initial bracket or one closer to the actual root reduces the number of steps.

# 2 Task 2: Golden Section Method

#### 2.1 Logic

The Golden Section Method finds the minimum of a unimodal function by evaluating two interior points determined by the golden ratio. Based on comparing  $f(x_1)$  and  $f(x_2)$ , we discard a portion of the interval and repeat. This process continues until the interval length is below a tolerance  $\epsilon$ .

#### 2.2 Observations

For the function f(x), we started with points  $x_1$  and  $x_2$ . The method quickly converged to a value near  $x^*$ . Since the function is strictly unimodal, the method reliably found the global minimum.

# 3 Task 3: Gradient Ascent Method

# 3.1 Logic

Gradient Ascent updates the solution by moving in the direction of the gradient. For f(x), we have  $\nabla f(x)$ . Starting from  $x_0$  and using a learning rate  $\alpha$  for 100 iterations, the estimate converged near  $x_{\text{max}}$ , where the true maximum occurs.

#### 3.2 Observations

The choice of  $\alpha$  (learning rate) influences convergence: too large and the method overshoots; too small and it converges slowly.

# 4 Challenges

- Ensuring that the stopping criteria were met accurately (handling floating-point precision issues).
- Choosing intervals and parameters appropriately to ensure smooth convergence.
- Avoiding infinite loops if a sign change or convergence criterion is not met.

# 5 Conclusion

All methods worked as expected:

- Bisection Method correctly identified the root at x = c.
- Golden Section Method approximated the minimum near  $x^*$ .
- Gradient Ascent converged to the maximum near  $x_{\text{max}}$ .

Parameter choice and interval selection are crucial for efficient convergence and accuracy.