```
In [ ]: import autograd.numpy as anp
   from autograd import grad
   import matplotlib.pyplot as plt
```

Question 3.5

```
In []: def gradient_descent(alpha, max_its, w_init):
    # Define the cost and its gradient functions
    def g(w):
        return 1/50 * (w**4 + w**2 + 10*w)

    def grad_g(w):
        return 1/50 * (4*w**3 + 2*w + 10)

# Initialize variables
    w = w_init
    cost_history = [g(w)]

for _ in range(max_its):
    w -= alpha * grad_g(w) # Update step
    cost_history.append(g(w)) # Store the cost

return cost_history
```

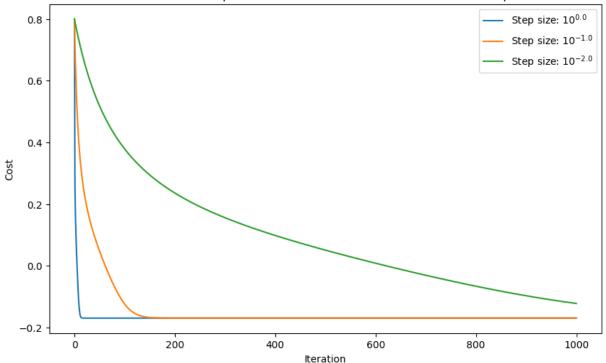
```
In []: initial_weight = 2.0
    iterations = 1000
    step_sizes = [10**0, 10**(-1), 10**(-2)]
    histories = []

for step_size in step_sizes:
        histories.append(gradient_descent(step_size, iterations, initial_weight)

plt.figure(figsize=(10, 6))
    for index, history in enumerate(histories):
        plt.plot(history, label=f'Step size: $10^{{np.log10(step_sizes[index])}})

plt.xlabel('Iteration')
    plt.ylabel('Cost')
    plt.title('Gradient Descent Optimization: Cost vs. Iterations for Different plt.legend()
    plt.show()
```





Question 3.8

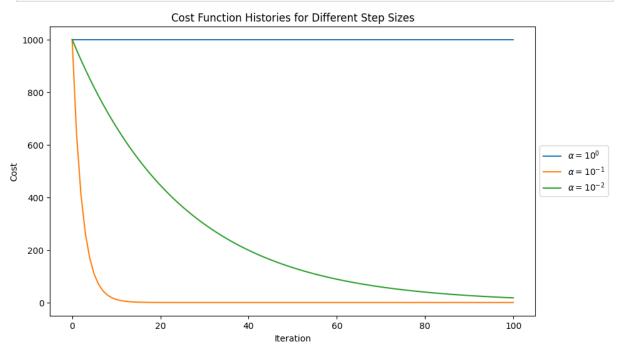
```
In [ ]: def gradient_descent(function_to_optimize, step_size, max_iterations, initia
            compute_gradient = grad(function_to_optimize)
            weights_history = [initial_weight]
            costs_history = [function_to_optimize(initial_weight)]
            for in range(max iterations):
                current_gradient = compute_gradient(weights_history[-1])
                updated_weight = weights_history[-1] - step_size * current_gradient
                weights_history.append(updated_weight)
                costs_history.append(function_to_optimize(updated_weight))
            return weights_history, costs_history
In [ ]: def squared_norm(w):
            return anp.dot(w.T, w)[0, 0]
In [ ]: def g(w):
            return squared_norm(w)
        N = 10
        initial_weight = 10 * anp.ones((N, 1))
        max iterations = 100
        step_sizes = [10**0, 10**(-1), 10**(-2)]
```

```
results = []
for alpha in step_sizes:
    weights_history, costs_history = gradient_descent(g, alpha, max_iteratic
    results.append(costs_history)

def plot_cost_histories(cost_histories, labels):
    plt.figure(figsize=(10, 6))
    for history, label in zip(cost_histories, labels):
        plt.plot(history, label=label)
    plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
    plt.xlabel('Iteration')
    plt.ylabel('Cost')
    plt.title('Cost Function Histories for Different Step Sizes')
    plt.show()

labels = [r'$\alpha = 10^{0}$', r'$\alpha = 10^{-1}$', r'$\alpha = 10^{-2}$'

plot_cost_histories(results, labels)
```



4.

(9) For any vector Z, the arrvature function of a matrix (with non-negative eigenvalues dn is $\psi(z) = z^T Cz = z^T \left(\sum_{n=1}^{N} e_n e_n^T d_n \right) z = \sum_{n=1}^{N} (e_n^T z)^2 d_n$ This expression is non-negative due to the non-negativity of lenz) and dn, confirming that C is positive semidefinite.

(b) Conversely, if Cis positive semidefinite, its curvature function (tz) must satisfy;

(Pe)=ZTCZZO

This regularement is inherently fulfilled by sum of squares form in its eigen decomposition, which implies that all eigenvalues du ave non-regative. Any regative eigenvalue would violate the Positive semidefiniteness by Producing a negative curvature function for zaligned with its corresponding eigenvector

C, The matrix C=[1], Possessing eigenvalues $d_1=0$, $d_2=2$, is thus Positive semidefinite,

in dicatins the convexity of the associated function g.

(d) Enhancing matrix C with IInxn, where

I is a scalar, modifies the curvature function

to:

(CZ)= N (en 2) (dn+)

To ensure semipositivity, A must be chosen to offset the Smallest resortive eigenvalue of C.

This augmentation guarantees that yez, Yemains non-negative for any z, solidifying the positive semide finite status of C+A Inxn

4,5

On set
$$G(w) = lg((te^{w^{T}w}))$$
 to zero

 $\nabla_{S}(w) = \frac{2e^{w^{T}w}}{1+e^{w^{T}w}} = O_{Nx}$

As $\frac{2e^{w^{T}w}}{1+e^{w^{T}w}} \ge 1$ only when $w = O_{Nx}$

(b) The Hessian of g,
$$\nabla^2 gw) = \frac{4e^{w^*w}}{1+e^{w^*w}} 2WW^{T} + \frac{2e^{w^*w}}{1+e^{w^*w}} IN^{N}.$$

Fixing w

$$Z^{T}Z^{2}g(w)z = z^{T}\left(\frac{4e^{w^{T}w}}{(1+e^{w^{T}w})^{2}}w^{W}T + \frac{2e^{w^{T}w}}{1+e^{w^{T}w}}I^{NXN}\right)Z$$

$$= Z^{T}Z^{2}g(w)z = z^{T}\frac{4e^{w^{T}w}}{(1+e^{w^{T}w})^{2}}w^{W}Z + z^{T}\frac{2e^{w^{T}w}}{1+e^{w^{T}w}}I^{NXN}Z$$

$$= \frac{4e^{w^{T}w}}{(1+e^{w^{T}w})^{2}}z^{T}w^{W}Z + \frac{2e^{w^{T}w}}{1+e^{w^{T}w}}z^{T}Z$$

$$= \frac{4e^{w^{T}w}}{(1+e^{w^{T}w})^{2}}(z^{T}w)^{2} + \frac{2e^{w^{T}w}}{1+e^{w^{T}w}}|1|z|^{2}$$

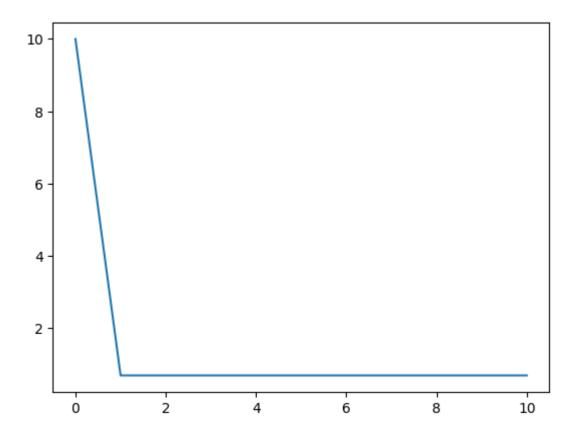
all component is nonnescrive wherever z is

so zTP scw) 2>0

for all ward 2, g is indeed convex

Question4.5

```
In []: from autograd import grad
        from autograd import hessian
        import matplotlib.pyplot as plt
        from autograd import numpy as np
        def g(w):
            return np.log(1+np.exp(np.dot(w.T, w)))
        def newton_method(g, max_its, w, **kwargs):
            gradient = grad(g)
            hess = hessian(q)
            epsilon = 10**(-7)
            if 'epsilon' in kwarqs:
                 epsilon = kwargs['epsilon']
            weight_history = [w]
            cost_history = [g(w)]
            for k in range(max its):
                 grad_eval = gradient(w)
                 hess_eval = hess(w)
                hess eval.shape = (int((np.size(hess eval))**(0.5)), int((np.size(hess eval))**(0.5))
                A = hess_eval + epsilon*np.eye(w.size)
                b = grad_eval
                w = np.linalg.solve(A, np.dot(A, w) - b)
                weight_history.append(w)
                 cost history.append(q(w))
            cost_history = [np.squeeze(val) for val in cost_history]
            return weight_history, cost_history
        N = 10
        w0 = np.ones((N, 1))
        weights, cost_history = newton_method(g, 10, w0)
        plt.plot(cost_history)
        plt.show()
```

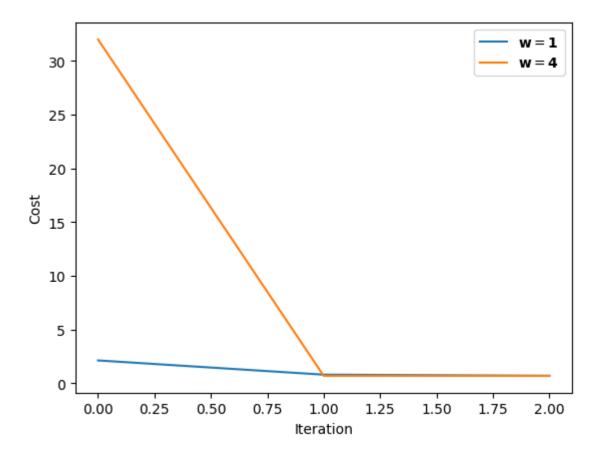


```
In []: import matplotlib.pyplot as plt

def plot_cost_histories(cost_histories, labels, start=0, points=False):
    for cost_history, label in zip(cost_histories, labels):
        if points:
            plt.scatter(range(start, len(cost_history)), cost_history[start:else:
            plt.plot(range(start, len(cost_history)), cost_history[start:],

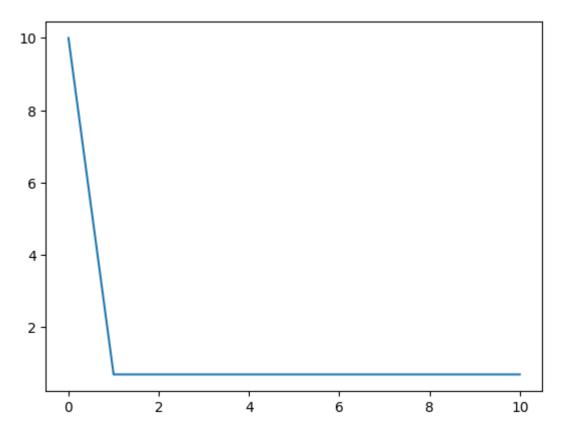
    plt.xlabel('Iteration')
    plt.ylabel('Cost')
    plt.legend()
    plt.show()

plot_cost_histories([cost_history, cost_history_2], labels=[r'$\mathbf{w}=\n
```



Question4.5

```
In []: from autograd import grad
        from autograd import hessian
        import matplotlib.pyplot as plt
        from autograd import numpy as np
        def g(w):
            return np.log(1+np.exp(np.dot(w.T, w)))
        def newton_method(g, max_its, w, **kwargs):
            gradient = grad(g)
            hess = hessian(q)
            epsilon = 10**(-7)
            if 'epsilon' in kwarqs:
                 epsilon = kwargs['epsilon']
            weight_history = [w]
            cost_history = [g(w)]
            for k in range(max its):
                 grad_eval = gradient(w)
                 hess_eval = hess(w)
                hess eval.shape = (int((np.size(hess eval))**(0.5)), int((np.size(hess eval))**(0.5))
                A = hess_eval + epsilon*np.eye(w.size)
                b = grad_eval
                w = np.linalg.solve(A, np.dot(A, w) - b)
                weight_history.append(w)
                 cost history.append(q(w))
            cost_history = [np.squeeze(val) for val in cost_history]
            return weight_history, cost_history
        N = 10
        w0 = np.ones((N, 1))
        weights, cost_history = newton_method(g, 10, w0)
        plt.plot(cost_history)
        plt.show()
```



```
In [ ]: import matplotlib.pyplot as plt
        def plot_cost_histories(cost_histories, labels, start=0, points=False):
            for cost_history, label in zip(cost_histories, labels):
                if points:
                     plt.scatter(range(start, len(cost_history)), cost_history[start:
                else:
                     plt.plot(range(start, len(cost_history)), cost_history[start:],
            plt.xlabel('Iteration')
            plt.ylabel('Cost')
            plt.legend()
            plt.show()
        w = np.ones((2,)); max_its = 2;
        weight_history,cost_history = newtons_method(g,max_its,w)
        w = 4*np.ones((2,)); max_its = 2;
        weight_history_2,cost_history_2 = newtons_method(g,max_its,w)
        plot_cost_histories([cost_history, cost_history_2], labels=[r'$\mathbf{w}=\mathbf{w}=\mathbf{w}
```

