

## Exercise 1 - Taylor Series

Compute the Taylor series expansion up to the second order term for the following multivariate functions around a given point:

- (a)  $f(x) = 5x^3$  around  $x_0 = 1$ .
- (b)  $f(x, y) = x^2 \cdot y^3 + x^2$  around  $x_0 = 3, y_0 = 2$ .
- (c)  $f(\mathbf{x}) = x_1^3 \cdot x_2 \cdot \log(x_2)$  around  $\mathbf{x}_0 = (2, 1)^\top$ .
- (d)  $f(\mathbf{x}) = \sin(x_1) + \cos(x_2)$  around  $\mathbf{x}_0 = (-\pi, \pi)^\top$ .

### Solution

There are different ways to write the second order Taylor series expansion at a point  $\mathbf{a}$  for multivariate functions  $f$ . We will use the following form

$$T(x) = f(\mathbf{a}) + \nabla f(\mathbf{a})^\top (\mathbf{x} - \mathbf{a}) + \frac{1}{2} (\mathbf{x} - \mathbf{a})^\top \mathbf{H}(\mathbf{x} - \mathbf{a})$$

where  $\nabla f(\mathbf{a})$  is the gradient of  $f$  at  $\mathbf{a}$  and  $\mathbf{H}$  is the Hessian of  $f$  at  $\mathbf{a}$ . As a reminder, the Hessian is the matrix of second order partial derivatives. So, all we need to do for all of the exercises is evaluate  $f(\mathbf{a})$  and compute its gradient and Hessian.

- (a)  $T(x) = 5 + 15(x - 1) + 15(x - 1)^2$
- (b) First, we simplify  $f(x, y) = x^2(y^3 + 1)$  and compute  $f(3, 2) = 81$  and then we compute the gradient and Hessian of  $f$  resulting in

$$\nabla f(x, y) = \begin{pmatrix} 2x(y^3 - 1) \\ x^2(3y^2 - 1) \end{pmatrix}, \quad \mathbf{H} = \begin{pmatrix} 2(y^3 - 1) & 6xy^2 \\ 6xy^2 & 6x^2y \end{pmatrix}.$$

- (c) This one is similar to (b) but we have to be careful with the logarithm. First, we have  $f(\mathbf{x}_0) = 0$  because  $\log(1) = 0$ . Then, we compute the gradient and Hessian of  $f$  resulting in

$$\nabla f(\mathbf{x}) = \begin{pmatrix} 3x_1^2 x_2 \log(x_2) \\ x_1^3 (1 + \log(x_2)) \end{pmatrix}, \quad \mathbf{H} = \begin{pmatrix} 6x_1 x_2 \log(x_2) & 3x_1^2 (1 + \log(x_2)) \\ 3x_1^2 (1 + \log(x_2)) & x_1^3 x_2^{-1} \end{pmatrix}$$

- (d) Evaluating the trigonometric functions here is simpler than it seems because they are evaluated at  $\pi$  and  $-\pi$ . We get  $f(\mathbf{x}_0) = \sin(-\pi) + \cos(\pi) = 0 - 1 = -1$  and

$$\nabla f(\mathbf{x}) = \begin{pmatrix} \cos(x_1) \\ -\sin(x_2) \end{pmatrix}, \quad \mathbf{H} = \begin{pmatrix} -\sin(x_1) & 0 \\ 0 & -\cos(x_2) \end{pmatrix}.$$

## Exercise 2 - Eigenvalues, Eigenvectors

You are given the sets of eigenvalues and eigenvectors. Compute the corresponding matrix.

- (a)  $\lambda_1 = 2, \lambda_2 = 3, \mathbf{v}_1 = (1, 0)^\top, \mathbf{v}_2 = (0, 1)^\top$ .
- (b)  $\lambda_1 = 2, \lambda_2 = 3, \mathbf{v}_1 = (1, 1)^\top, \mathbf{v}_2 = (1, -1)^\top$ .

**Solution**

First, remember that the normalized eigenvectors of a symmetric matrix are orthogonal. Thus, we have

$$\mathbf{e}_i^\top \mathbf{e}_j = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases}.$$

Second, for symmetric  $\mathbf{A}$ , its spectral decomposition is given by  $\mathbf{A} = \mathbf{Q} \mathbf{Q}^\top$ , where  $\mathbf{Q}$  is a matrix where each column is an (orthogonal) eigenvector of unit length.

- (a) Here, the eigenvectors are already normalized and orthogonal, so we can simply write  $\mathbf{Q} = (\mathbf{e}_1, \mathbf{e}_2)$  and  $\Lambda = \text{diag}(\lambda_1, \lambda_2)$ . Then, we have

$$\mathbf{A} = \begin{pmatrix} 2 & 0 \\ 0 & 3 \end{pmatrix}$$

- (b) Here, we have to normalize the eigenvectors first. Each has length  $\sqrt{2}$ , so we have to divide each of them by  $\sqrt{2}$ , i.e. we set  $\tilde{\mathbf{e}}_i := \mathbf{e}_i / \sqrt{2}$ . With this, we can construct an orthogonal matrix of eigenvectors as  $\mathbf{Q} = (\tilde{\mathbf{e}}_1, \tilde{\mathbf{e}}_2)$ . The resulting matrix  $\mathbf{A}$  is

$$\mathbf{A} = \begin{pmatrix} 2.5 & -0.5 \\ -0.5 & 2.5 \end{pmatrix}$$

**Exercise 3 - SGD with Momentum**

Implement stochastic gradient descent with momentum and apply it to optimize some elementary functions in 1d and 2d.

**Solution**

An example implementation could look like this. First we define the objective function and its gradient:

```
def objective(x):
    return x**2

def obj_grad(x):
    return 2*x
```

Then, we implement the momentum optimizer itself:

```
def sgd_with_momentum(obj, grad, x_init, learning_rate, momentum, max_iter):
    x = x_init
    update = 0
    for i in range(max_iter):
        update = momentum * update - learning_rate * grad(x)
        x = x + update

        print('>%d f(%s) = %.5f' % (i, x, obj(x)))
    return x
```

It can now be invoked directly via:

```
sgd_with_momentum(  
    objective, obj_grad, x_init=3.0, learning_rate=0.1, momentum=0.5,  
    max_iter=20  
)
```