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Assignment 2

We will use a class to define the two methods (Powell's method & Steepest Descent method) because they both will solve the same problem.

Our Class Function Code:

```
import sympy as sp
import numpy as np

class opt_tech():
    """
    This is a class for the two main classes of optimization techniques for solving
    n-D unconstrained minimization problems numerically

    ...
    Attributes
    -----
    fi : sympy class obj
    the objective function you want to find its optimum point
    itr_no : int
    the number of iterations you will go through (default 1)
    epsilon : float
    used to help find a suitable search direction Si
    """

    def __init__(self, fi, itr_no=1, epsilon=0.01):
        """
        The constructor for opt_tech class.

        ...
        Parameters
        -----
        fi : sympy class obj
        the objective function you want to find its optimum point
        itr_no : int
        the number of iterations you will go through (default 1)
        epsilon : float
        used to help find a suitable search direction Si
        """
        self.fi = fi
        self.itr_no = itr_no
        self.epsilon = epsilon
        self.x = sp.Symbol("x")
        self.y = sp.Symbol("y")
        self.lamda = sp.Symbol("lamda")
```

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Initializing our Class:

```
# the objective function
x = sp.Symbol("x")
y = sp.Symbol("y")
fi = x - y + 2*x**2 + 2*x*y + y**2

# the number of iterations
itr_no = 5

# initializing our optimization techniques class
opt_tech = opt_tech(fi, itr_no)
```

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Powell's Method:

It's an iterative direct search optimization method, which requires an initial guess X_1 vector for the optimum point.

Required Input:

```
# our initial guess
X = np.array([0, 0])

# Calling our Powell's Method
opt_tech.powells_method(X)
```

Powell's method code (part 1):

```
def powells_method(self, X=np.array([0, 0])):
    """
    A direct search Optimization method for solving n-D unconstrained problem.
    ...
    Parameters
    -----
    X : np.array (vector)
        the initial guess needed to compute the optimum point (default for 2 variables [0, 0])
    """
    print()
    print()
    print("Powell's Method :")
    print("_____")

    # initializing variables for our loop
    Z = X

    # find the optimal value for the given number of iterations
    for i in range(self.itr_no):
        # for Cycle #1: S2, S1, S2;
        # we will need to manually initialize S1 & S2
        if i < 3:
            if i % 2:
                S = np.array([1, 0]) # S1
            else:
                S = np.array([0, 1]) # S2
        # otherwise, we can calculate it
        else:
            S = X - Z
        print("S{} = {}".format(i+1, S))
```

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Powell's method code (part 2):

```
# calculate fi(x, y) at point X
fi = self.fi.subs({self.x: X[0], self.y: X[1]})

# calculate fi_+ve & fi_-ve to find the suitable search direction
fi_postive = self.fi.subs(
    {self.x: X[0]+self.epsilon*S[0], self.y: X[1]+self.epsilon*S[1]})
fi_negative = self.fi.subs(
    {self.x: X[0]-self.epsilon*S[0], self.y: X[1]-self.epsilon*S[1]})

print("f{}={}".format(i+1, fi))
print("f{}_+ve={:.{prec}f}, f{}_-ve={:.{prec}f}".format(fi_postive,
                                                         fi_negative, i=i+1, prec=4))

# check if we reached our optimum point
if fi_postive > fi and fi_negative > fi:
    print("Reached Optimum Point at X{} = {}".format(i+1, X))
    break
# check which direction will make objective function decrease
elif fi_postive > fi:
    S *= -1
    print("f{} decrease along -ve S{}".format(i+1, i+1))
else:
    print("f{} decrease along +ve S{}".format(i+1, i+1))

# to find the approx step length  $\lambda^*$  along dir Si
# sub  $\lambda$  in the objective function
fi_lamda = self.fi.subs(
    {self.x: X[0]+self.lamda*S[0], self.y: X[1]+self.lamda*S[1]})
print("f{}_lamda = {}".format(i+1, fi_lamda))

# get the derivative to find the appropriate step length  $\lambda^*$ 
dfi = sp.diff(fi_lamda)
print("df/d1 = {} = 0".format(dfi))
lamda = sp.solve(dfi)
print(f" $\lambda^* = \{lamda\}$ ")
# calcualte the new approx point
X = X + lamda * S
print("X{} = X = {}".format(i+2, X))

# set our Z (X2) point
if i == 0:
    Z = X
    print(f"X{i+2} = X = Z = {X}")
print()
print()
```

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Powell's method output:

Powell's Method :

```
S1 = [0 1]
f1=0
f1_+ve=-0.0099, f1_-ve=0.0101
f1 decrease along +ve S1
f1_lambda = lambda**2 - lambda
df/d1 = 2*lambda - 1 = 0
lambda* = [1/2]
X2 = X = [0 1/2]
X2 = X = Z = [0 1/2]

S2 = [1 0]
f2=-1/4
f2_+ve=-0.2298, f2_-ve=-0.2698
f2 decrease along -ve S2
f2_lambda = 2*lambda**2 - 2*lambda - 1/4
df/d1 = 4*lambda - 2 = 0
lambda* = [1/2]
X3 = X = [-1/2 1/2]

S3 = [0 1]
f3=-3/4
f3_+ve=-0.7599, f3_-ve=-0.7399
f3 decrease along +ve S3
f3_lambda = -2*lambda + (lambda + 1/2)**2 - 1
df/d1 = 2*lambda - 1 = 0
lambda* = [1/2]
X4 = X = [-1/2 1]

S4 = [-1/2 1/2]
f4=-1
f4_+ve=-1.0050, f4_-ve=-0.9950
f4 decrease along +ve S4
f4_lambda = -lambda + 2*(-lambda/2 - 1/2)**2 + 2*(-lambda/2 - 1/2)*(lambda/2 + 1) + (lambda/2 + 1)**2 - 3/2
df/d1 = lambda/2 - 1/2 = 0
lambda* = [1]
X5 = X = [-1 3/2]
```

```
S5 = [-1 1]
f5=-5/4
f5_+ve=-1.2499, f5_-ve=-1.2499
Reached Optimum Point at X5 = [-1 3/2]
```

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Steepest Descent Method:

It's an iterative (Gradient) Descent search optimization method, which requires an initial guess X_1 vector for the optimum point.

We will use the same objective function from Powell's method and same initial guess but we will change the iteration number.

Required Input:

```
# the number of iterations
opt_tech.itr_no = 3

# Calling our Steepest Descent Method
opt_tech.steepest_descent(X)
```


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Steepest Descent method code (part 1):

```
def steepest_descent(self, X=np.array([0, 0])):
    """
    A (Gradient) Descent search Optimization method for solving n-D unconstrained problem.
    ...
    Parameters
    -----
    X : np.array (vector)
        the initial guess needed to compute the optimum point (default for 2 variables [0, 0])
    """
    print()
    print()
    print("Steepest Descent Method :")
    print("_____")
    print()

    # find the gradient (1st order partial derivative) for our objective function
    gradient_f = [sp.diff(self.fi, self.x), sp.diff(self.fi, self.y)]
    print(f"∇f = {gradient_f}")
    print()

    # find the optimal value for the given number of iterations
    for i in range(self.itr_no):
        # calculate the gradient values at point X
        dx = gradient_f[0].subs({self.x: X[0], self.y: X[1]})
        dy = gradient_f[1].subs({self.x: X[0], self.y: X[1]})
        neg_grad_fi = -1 * np.array([dx, dy])
        print(f"-∇f{i+1} = {neg_grad_fi}")

        # if -∇fi = [0, 0] then we reached out optimal point
        if (neg_grad_fi == np.zeros(2)).all():
            print("Reached Optimum Point at X{} = {}".format(i+1, X))
            break
```

```
        # to find the approx step length  $\lambda^*$  along dir  $S_i$ 
        # sub  $\lambda$  in the objective function
        fi_lambda = self.fi.subs(
            {self.x: X[0]+self.lamda*neg_grad_fi[0], self.y: X[1]+self.lamda*neg_grad_fi[1]})
        print(f"f{lambda} = {}".format(i+1, fi_lambda))

        # get the derivative to find the appropriate step length
        dfi = sp.diff(fi_lambda)
        print("df/dλ = {} = 0".format(dfi))
        lamda = sp.solve(dfi)
        print(f"λ* = {lamda}")

        # calculate the new approx point
        X = X + lamda * neg_grad_fi
        print("X{} = {}".format(i+2, X))
        print()
    print("_____")
```

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Steepest Descent method output:

Steepest Descent Method :

$\nabla f = [4x + 2y + 1, 2x + 2y - 1]$

$-\nabla f_1 = [-1 \ 1]$

$f_1_{\text{lamda}} = \text{lamda}^2 - 2\text{lamda}$

$df/d\lambda = 2\text{lamda} - 2 = 0$

$\lambda^* = [1]$

$X_2 = [-1 \ 1]$

$-\nabla f_2 = [1 \ 1]$

$f_2_{\text{lamda}} = 2(\text{lamda} - 1)^2 + 2(\text{lamda} - 1)(\text{lamda} + 1) + (\text{lamda} + 1)^2 - 2$

$df/d\lambda = 10\text{lamda} - 2 = 0$

$\lambda^* = [1/5]$

$X_3 = [-4/5 \ 6/5]$

$-\nabla f_3 = [-1/5 \ 1/5]$

$f_3_{\text{lamda}} = -2\text{lamda}/5 + 2(-\text{lamda}/5 - 4/5)^2 + 2(-\text{lamda}/5 - 4/5)(\text{lamda}/5 + 6/5) + (\text{lamda}/5 + 6/5)^2 - 2$

$df/d\lambda = 2\text{lamda}/25 - 2/25 = 0$

$\lambda^* = [1]$

$X_4 = [-1 \ 7/5]$