CSC 467 2.0 Evolutionary Computing

Assignment 2

Index # AS2016525

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Code

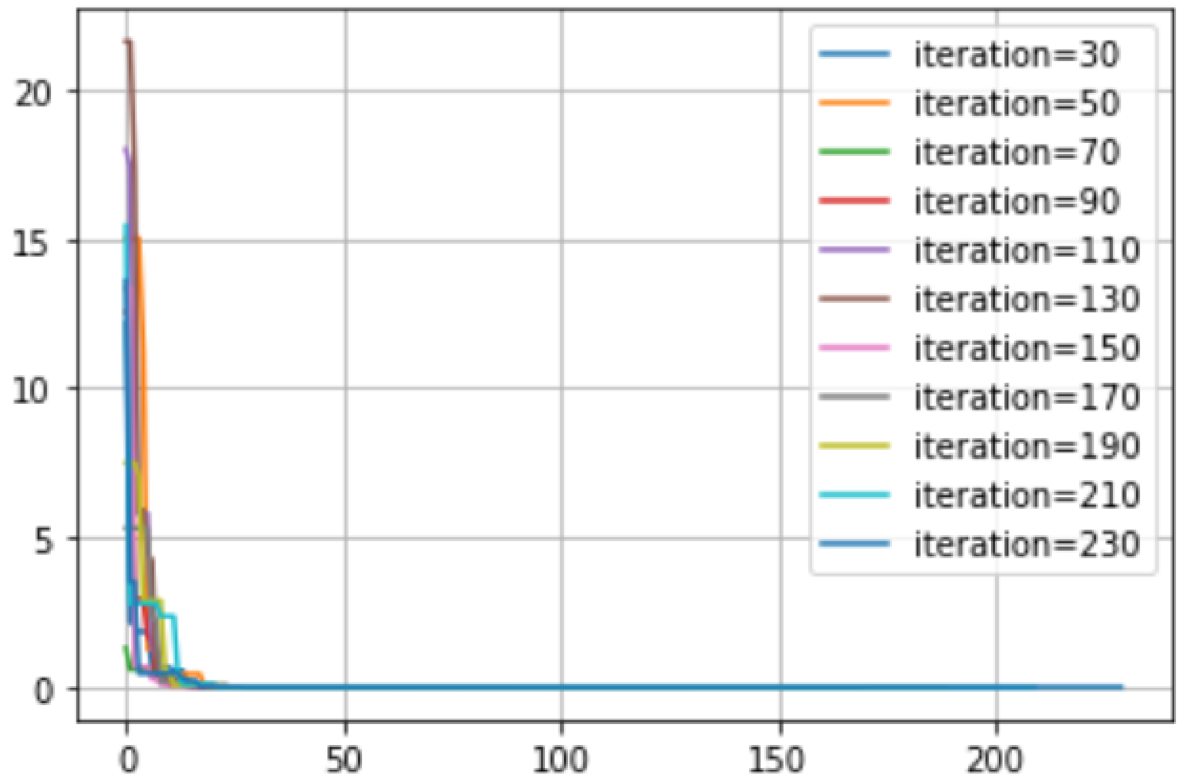
```
import numpy as np
import matplotlib.pyplot as plt


def de(fobj, bounds, mut=0.8, crossp=0.7, popsize=20, its=1000):
    dimensions = len( bounds )
    pop = np.random.rand( popsize, dimensions )
    min_b, max_b = np.asarray( bounds ).T
    diff = np.fabs( min_b - max_b )
    pop_denorm = min_b + pop * diff
    fitness = np.asarray( [fobj( ind ) for ind in pop_denorm] )
    best_idx = np.argmin( fitness )
    best = pop_denorm[best_idx]
    for i in range( its ):
        for j in range( popsize ):
            idxs = [idx for idx in range( popsize ) if idx != j]
            a, b, c = pop[np.random.choice( idxs, 3, replace=False )]
            mutant = np.clip( a + mut * (b - c), 0, 1 )
            cross_points = np.random.rand( dimensions ) < crossp
            if not np.any( cross_points ):
                cross_points[np.random.randint( 0, dimensions )] =True
            trial = np.where( cross_points, mutant, pop[j] )
            trial_denorm = min_b + trial * diff
            f = fobj( trial_denorm )
            if f < fitness[j]:
                fitness[j] = f
                pop[j] = trial
                if f < fitness[best_idx]:
                    best_idx = j
                    best = trial_denorm
        yield best, fitness[best_idx]


def f_obj(x1, x2):
    return pow( (x1 + 2 * x2 - 7), 2 ) + pow( (2 * x1 + x2 - 5), 2 )


for d in range( 30, 300, 20 ):
    result = list( de( lambda x: f_obj( x[0], x[1] ), bounds=[(-
10, 10)] * 2, its=d ) )
    x, f = zip( *result )
    plt.plot( f, label='iteration={}'.format( d ) )

    print(result[-1])

plt.grid()
plt.rcParams["figure.figsize"] = (750, 750)
plt.legend()
```

Run 1:

Results

```
(array([0.95388423, 3.02623318]), 0.004396113851650085)
(array([0.99908238, 3.00012905]), 3.3460495769480616e-06)
(array([1.00002093, 2.9999564 ]), 4.3938700822717066e-09)
(array([1.00000246, 2.99999336]), 1.2023340924545983e-10)
(array([1.00000035, 2.99999961]), 2.844034227115767e-13)
(array([1., 3.]), 7.599191752763452e-18)
(array([1., 3.]), 2.369530508132133e-17)
(array([1., 3.]), 4.917839410068993e-22)
(array([1., 3.]), 1.231552290291288e-23)
(array([1., 3.]), 1.2549199280255856e-25)
(array([1., 3.]), 0.0)
```

Plot

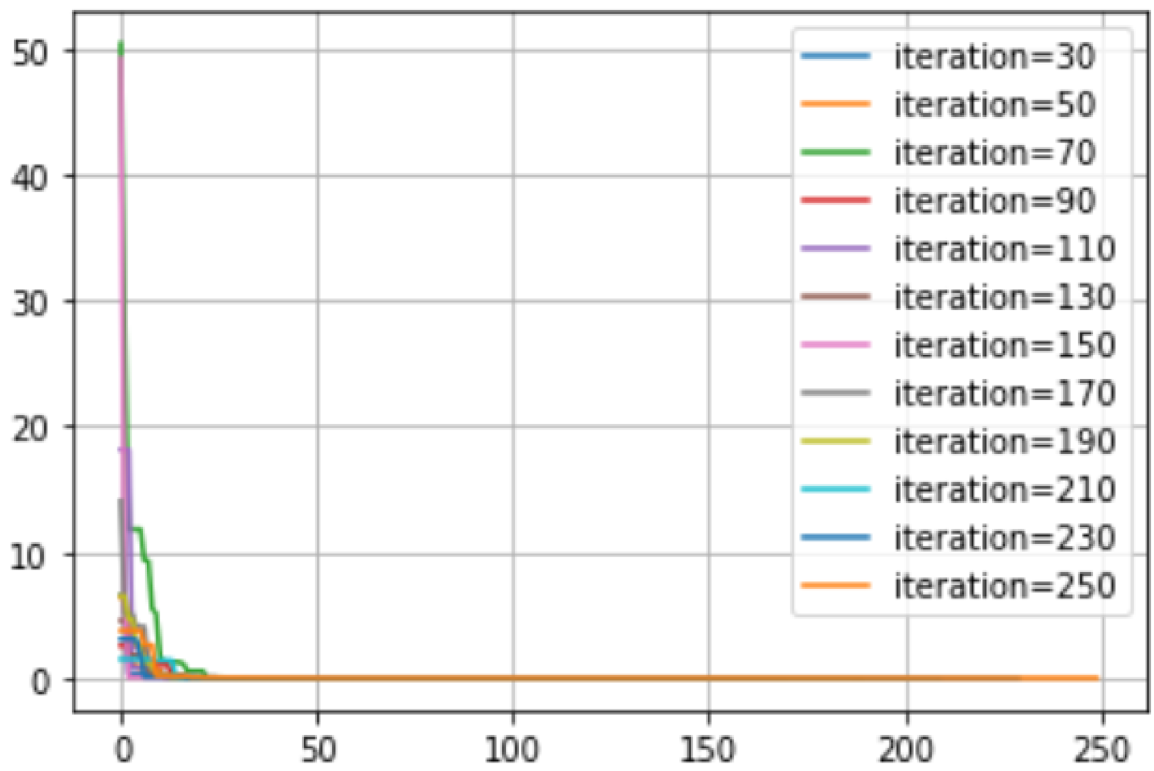


Run 2:

Results

```
(array([1.03449198, 2.95212714]), 0.004197699537059782)
(array([0.99796553, 3.00248738]), 1.1146600595691996e-05)
(array([0.99999777, 2.9999622 ]), 7.845466247206218e-09)
(array([1.00000539, 2.99999444]), 6.011816613792951e-11)
(array([1.00000004, 2.99999996]), 3.3021580991045217e-15)
(array([1.00000001, 2.99999999]), 2.02880681192957e-16)
(array([1., 3.]), 4.1929226997116175e-19)
(array([1., 3.]), 2.2358987291685123e-19)
(array([1., 3.]), 1.2910813119209168e-25)
(array([1., 3.]), 2.145701662201152e-28)
(array([1., 3.]), 2.524354896707238e-29)
(array([1., 3.]), 0.0)
```

Plot

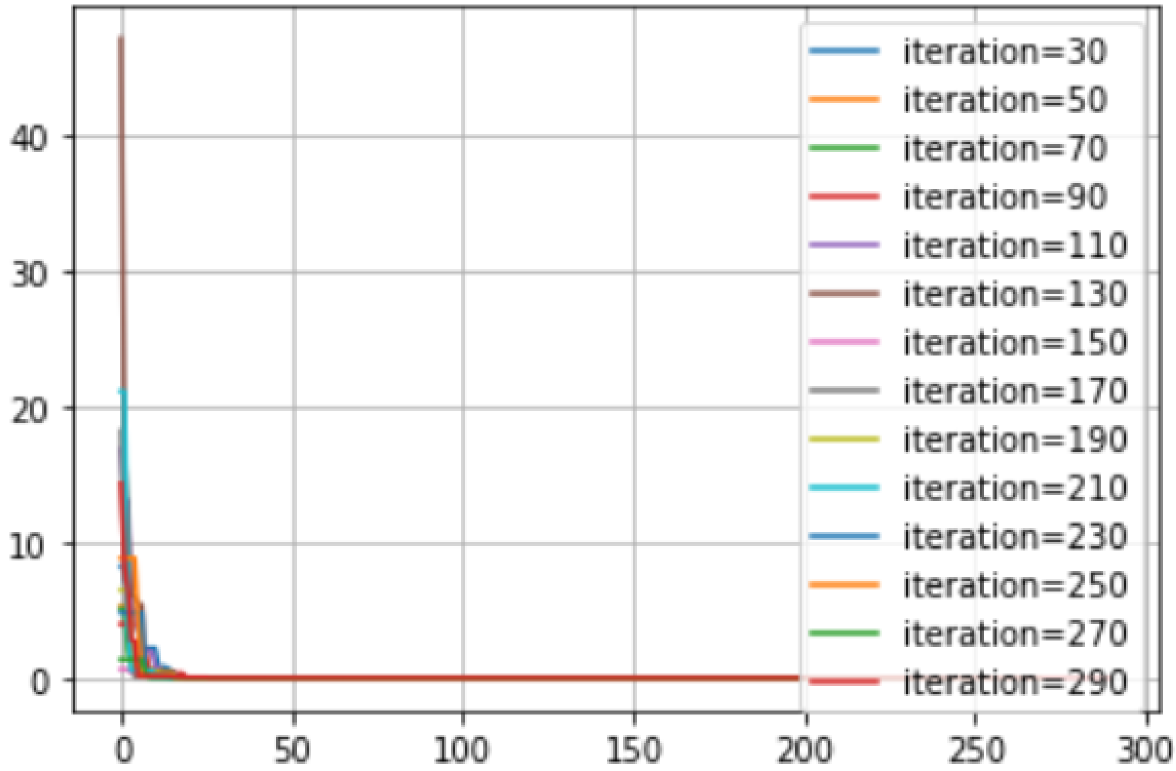


Run 3:

Results

```
(array([1.00068176, 3.00492581]), 0.00015050797765621486)
(array([0.99886079, 3.00115553]), 2.6341147923691524e-06)
(array([1.00001934, 2.99992965]), 1.5727944417040896e-08)
(array([0.99999131, 3.00000053]), 3.4232542474686633e-10)
(array([0.99999996, 3.00000001]), 5.943460138058679e-15)
(array([0.99999999, 3.00000003]), 2.615297231700319e-15)
(array([1., 3.]), 2.0281013559234127e-19)
(array([1., 3.]), 1.004208604303749e-22)
(array([1., 3.]), 1.834221511496446e-23)
(array([1., 3.]), 3.6716741972606773e-26)
(array([1., 3.]), 0.0)
(array([1., 3.]), 0.0)
(array([1., 3.]), 0.0)
(array([1., 3.]), 0.0)
```

Plot

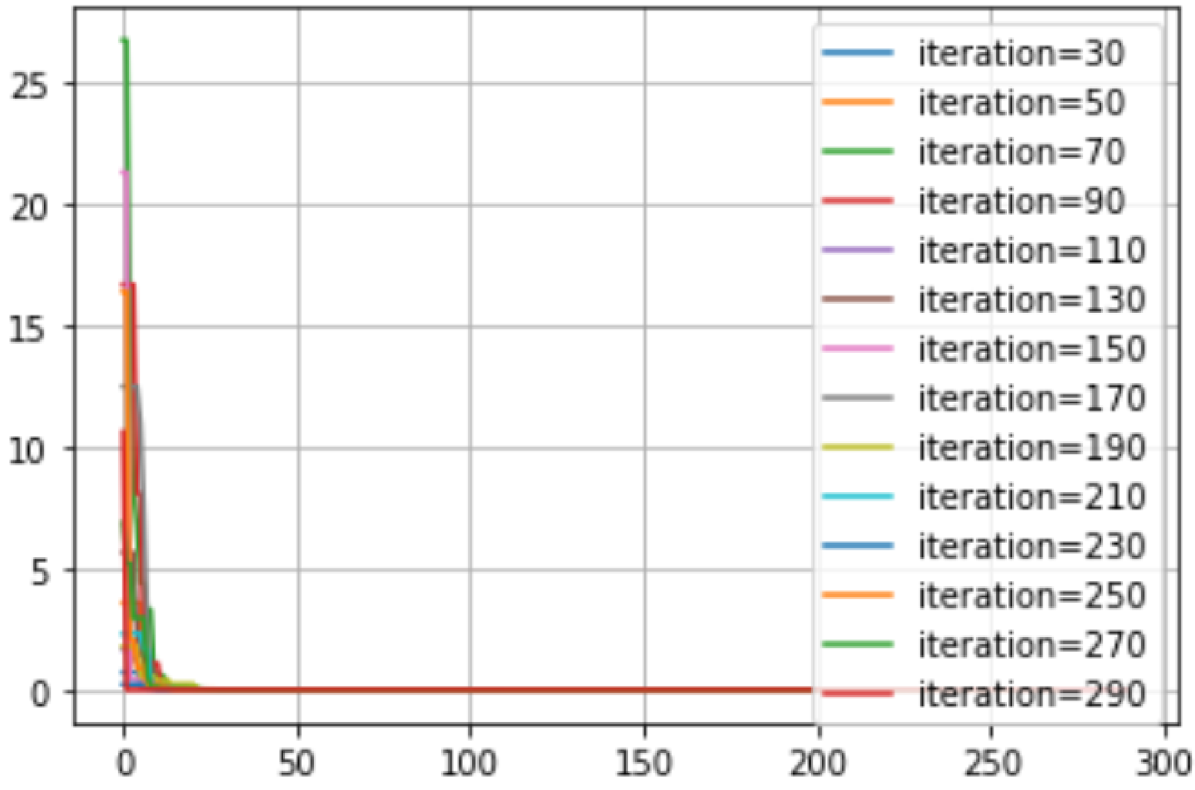


Run 4:

Results

```
(array([1.00700877, 2.99827387]), 0.00016372727278238003)
(array([0.99935719, 2.99812599]), 2.9262666278892852e-05)
(array([0.99998194, 3.00001443]), 5.86964194762511 7e-10)
(array([0.99998587, 3.00001101]), 3.5991699784350 52e-10)
(array([1.00000006, 2.99999999]), 1.3161892430613935e-14)
(array([1.00000004, 2.99999996]), 3.1798009471751253e-15)
(array([1., 3.]), 1.2099921285280378e-21)
(array([1., 3.]), 1.1383689272897364e-19)
(array([1., 3.]), 8.283713507578045e-23)
(array([1., 3.]), 6.310887241768094e-29)
(array([1., 3.]), 1.5777218104420236e-29)
(array([1., 3.]), 0.0)
(array([1., 3.]), 0.0)
(array([1., 3.]), 0.0)
```

Plot



Discussion

There are 4 sets of results mentioned above and those are taken according to the number of runs with 300 iterations. Each result output line time the number of iterations is setup to increment by 20 and the initial output iteration is 30 at each run.

From the start of the run the numbers are off and with each increment the numbers get better. After the 10^{th} & 11^{th} Results which are the 210^{th} and the 230^{th} iteration the numbers tend to be good. So above 10^{th} and 11^{th} iterations we can see a constant stable result output at each run.

Conclusion

According to the results and the graphs it is clear that when the number of iterations is getting higher the accuracy tends to be high.

From the above mentioned 4 different runs there are no any relation with the changes of number of runs according to my perspective.