Informe Tarea 3

November 13, 2017

1 Informe Tarea 3

1.1 Introducción

El objetivo de este trabajo es experimentar con algoritmos genéticos para la selección de pesos (weights) y bias en redes neuronales aplicadas a diferentes problemas.

Los experimentos realizados corresponden a: * Algoritmos genéticos para encontrar una secuencia de números (tanto en ints como floats). * Algoritmos genéticos para encontrar una operación lógica con redes neuronales XOR. * Algoritmos genéticos para clasificar un dataset real con redes neuronales.

1.2 Experimentos

Se describirá los experimentos realizados y el código utilizado.

1.2.1 Secuencia de números

En este experimeto se intentará encontrar una secuencia de números oculta utilizando redes neuronales (el código que se utilizará a continuación tambien se encuentra en el archivo bit_sequence.py).

En primer lugar se intentara encontrar una secuencia de solo unos y ceros.

```
In [3]: import random
        import numpy as np
        import matplotlib.pyplot as plt
        from genetic import Genetic
        from genetic import Fit
        from genetic import FitFloat
```

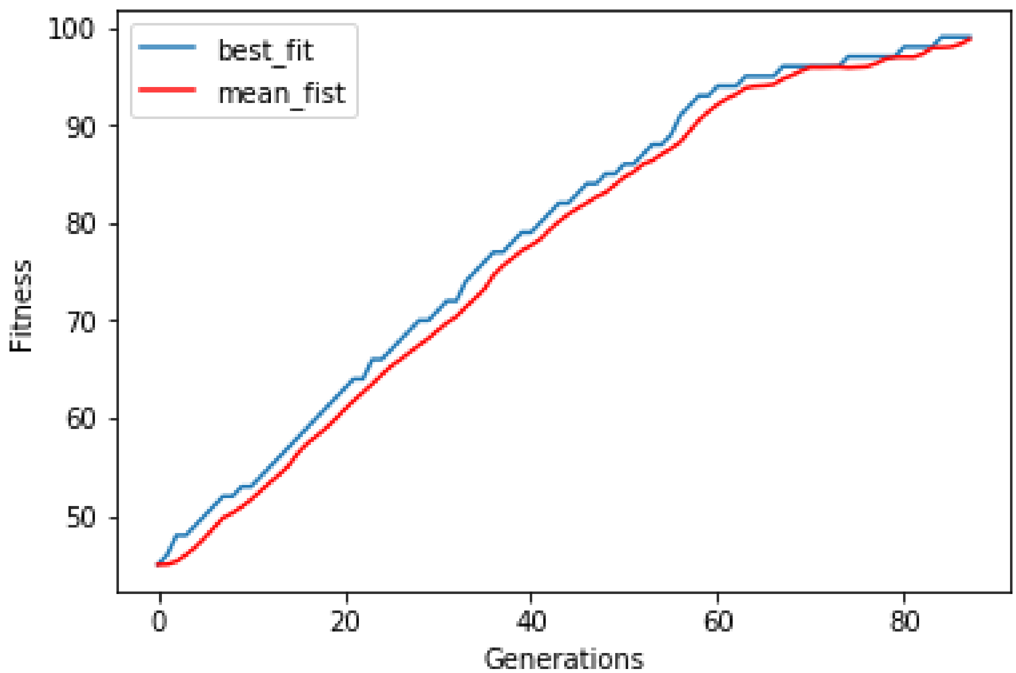
```
In [6]: vec_size = 100
        pop_size = 100
        max_generation = 3000
        answer = np.array([random.randint(0, 1) for i in range(vec_size)])

        fit_class = Fit(answer)

        bit_seq = Genetic(fitness_class=fit_class, gene_size=vec_size, population_size=pop_size
        fitest, best_vector, mean_vector = bit_seq.evolve(max_generation)
```

```
        max_generation = best_vector.size

        print('vector found at iteration', max_generation)
        print('anwser: ', answer, ' found: ',fitest)
        line_up, =  plt.plot(np.array([i for i in range(max_generation)]), best_vector, label=
        line_down, = plt.plot(np.array([i for i in range(max_generation)]), mean_vector, '-r',

        plt.xlabel('Generations')
        plt.ylabel('Fitness')

        plt.legend(handles=[line_up, line_down])
        plt.show()
```

```
iteration:  0  max fit:  45  mean fit:  45.0
iteration:  1  max fit:  46  mean fit:  45.03
iteration:  2  max fit:  48  mean fit:  45.34
iteration:  3  max fit:  48  mean fit:  45.99
iteration:  4  max fit:  49  mean fit:  46.77
iteration:  5  max fit:  50  mean fit:  47.72
iteration:  6  max fit:  51  mean fit:  48.77
iteration:  7  max fit:  52  mean fit:  49.79
iteration:  8  max fit:  52  mean fit:  50.29
iteration:  9  max fit:  53  mean fit:  50.92
iteration:  10  max fit:  53  mean fit:  51.66
iteration:  11  max fit:  54  mean fit:  52.52
iteration:  12  max fit:  55  mean fit:  53.4
iteration:  13  max fit:  56  mean fit:  54.2
iteration:  14  max fit:  57  mean fit:  55.1
iteration:  15  max fit:  58  mean fit:  56.4
iteration:  16  max fit:  59  mean fit:  57.39
iteration:  17  max fit:  60  mean fit:  58.16
iteration:  18  max fit:  61  mean fit:  58.95
iteration:  19  max fit:  62  mean fit:  59.85
iteration:  20  max fit:  63  mean fit:  60.85
iteration:  21  max fit:  64  mean fit:  61.77
iteration:  22  max fit:  64  mean fit:  62.64
iteration:  23  max fit:  66  mean fit:  63.49
iteration:  24  max fit:  66  mean fit:  64.42
iteration:  25  max fit:  67  mean fit:  65.32
iteration:  26  max fit:  68  mean fit:  65.99
iteration:  27  max fit:  69  mean fit:  66.74
iteration:  28  max fit:  70  mean fit:  67.47
iteration:  29  max fit:  70  mean fit:  68.15
iteration:  30  max fit:  71  mean fit:  68.99
iteration:  31  max fit:  72  mean fit:  69.76
iteration:  32  max fit:  72  mean fit:  70.39
iteration:  33  max fit:  74  mean fit:  71.36
iteration:  34  max fit:  75  mean fit:  72.26
```

```
iteration:  35  max fit:  76  mean fit:  73.21
iteration:  36  max fit:  77  mean fit:  74.66
iteration:  37  max fit:  77  mean fit:  75.61
iteration:  38  max fit:  78  mean fit:  76.36
iteration:  39  max fit:  79  mean fit:  77.13
iteration:  40  max fit:  79  mean fit:  77.66
iteration:  41  max fit:  80  mean fit:  78.3
iteration:  42  max fit:  81  mean fit:  79.27
iteration:  43  max fit:  82  mean fit:  80.11
iteration:  44  max fit:  82  mean fit:  80.86
iteration:  45  max fit:  83  mean fit:  81.47
iteration:  46  max fit:  84  mean fit:  82.02
iteration:  47  max fit:  84  mean fit:  82.64
iteration:  48  max fit:  85  mean fit:  83.09
iteration:  49  max fit:  85  mean fit:  83.87
iteration:  50  max fit:  86  mean fit:  84.67
iteration:  51  max fit:  86  mean fit:  85.19
iteration:  52  max fit:  87  mean fit:  85.98
iteration:  53  max fit:  88  mean fit:  86.36
iteration:  54  max fit:  88  mean fit:  87.02
iteration:  55  max fit:  89  mean fit:  87.58
iteration:  56  max fit:  91  mean fit:  88.26
iteration:  57  max fit:  92  mean fit:  89.38
iteration:  58  max fit:  93  mean fit:  90.51
iteration:  59  max fit:  93  mean fit:  91.36
iteration:  60  max fit:  94  mean fit:  92.12
iteration:  61  max fit:  94  mean fit:  92.71
iteration:  62  max fit:  94  mean fit:  93.15
iteration:  63  max fit:  95  mean fit:  93.8
iteration:  64  max fit:  95  mean fit:  93.97
iteration:  65  max fit:  95  mean fit:  94.03
iteration:  66  max fit:  95  mean fit:  94.16
iteration:  67  max fit:  96  mean fit:  94.73
iteration:  68  max fit:  96  mean fit:  95.1
iteration:  69  max fit:  96  mean fit:  95.57
iteration:  70  max fit:  96  mean fit:  95.91
iteration:  71  max fit:  96  mean fit:  95.9
iteration:  72  max fit:  96  mean fit:  95.92
iteration:  73  max fit:  96  mean fit:  95.95
iteration:  74  max fit:  97  mean fit:  95.87
iteration:  75  max fit:  97  mean fit:  95.92
iteration:  76  max fit:  97  mean fit:  95.97
iteration:  77  max fit:  97  mean fit:  96.29
iteration:  78  max fit:  97  mean fit:  96.76
iteration:  79  max fit:  97  mean fit:  96.93
iteration:  80  max fit:  98  mean fit:  96.95
iteration:  81  max fit:  98  mean fit:  96.94
iteration:  82  max fit:  98  mean fit:  97.28
```

```
iteration:  83  max fit:  98  mean fit:  97.9
iteration:  84  max fit:  99  mean fit:  97.93
iteration:  85  max fit:  99  mean fit:  97.98
iteration:  86  max fit:  99  mean fit:  98.28
iteration:  87  max fit:  99  mean fit:  98.76
vector found at iteration 88
anwser:  [1 1 0 1 1 0 0 1 0 0 1 0 1 1 1 1 1 1 0 1 0 0 1 1 0 1 1 1 1 1 1 1 1 1 1 0
 0 0 0 1 1 1 0 1 0 0 1 1 0 0 1 1 0 0 0 1 1 1 1 1 1 0 1 0 0 0 1 1 0 0 0 1 0
 1 1 0 0 1 0 1 0 0 1 0 0 1 0 0 0 1 1 1 0 0 0 1 0 0 1]  found:  [1 1 0 1 1 0 0 1 0 0 1 0 1 1 1 1
 0 0 0 1 1 1 0 1 0 0 1 1 0 0 1 1 0 0 0 1 1 1 1 1 1 0 1 0 0 0 1 1 0 0 0 1 0
 1 1 0 0 1 0 1 0 0 1 0 0 1 0 0 0 1 1 1 0 0 0 1 0 0 1]
```



El código anterior encuentra una secuencia de 100 numeros unos o zeros utilizando un algoritmo genetico.

La clase "Genetic" ubicada en el archivo "genetic.py" describe las fases de un algoritmo genetico genérico, mientras que la clase "Fit" contiene las funciones que se deben reescribir para cada caso particular.

Se decidio mantener las clases "Fit*" en el mismo archivo (genetic.py) para poder utilizarlas en conjunto con la biblioteca multiprocessing y hacer de esta forma el calculo del fitness multiproceso.

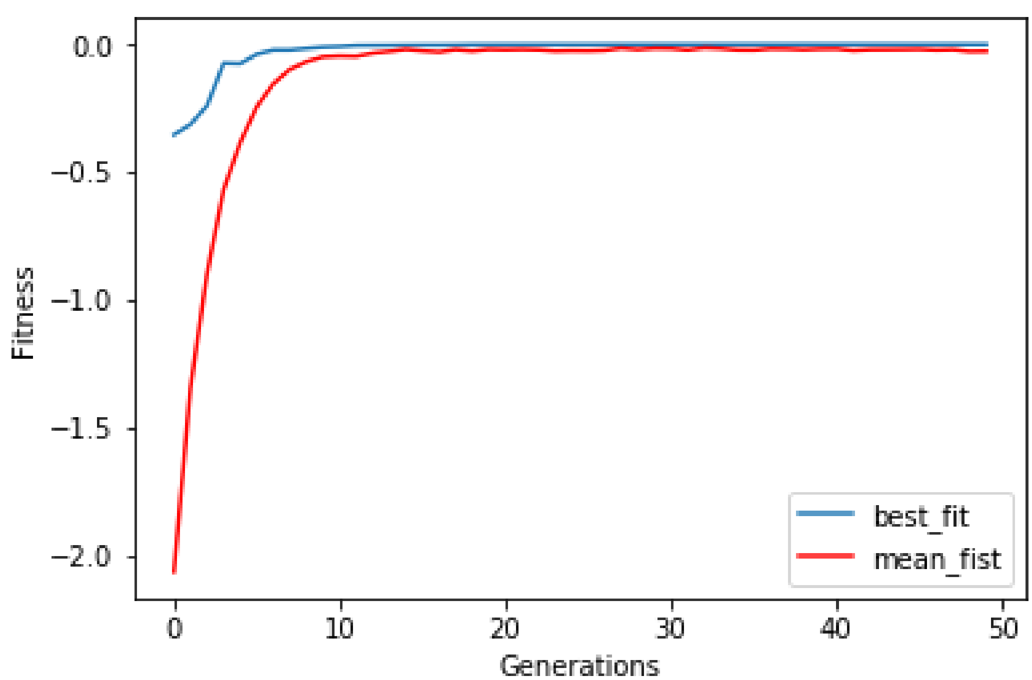
A continuación se realiza un experimento para encontrar una secuencia de números de tipo float entre 0 y 1.

```
In [10]: vec_size = 10
         pop_size = 750
         max_generation = 50
```

```
answer = np.array([random.uniform(0, 1) for i in range(vec_size)])

fit_class = FitFloat(answer)
vec_seq = Genetic(fitness_class=fit_class, gene_size=vec_size, population_size=pop_si
fitest, best_vector, mean_vector = vec_seq.evolve(max_generation)
max_generation = best_vector.size

print('vector found at iteration', max_generation)
print('anwser: ', answer, ' found: ',fitest)

line_up, =  plt.plot(np.array([i for i in range(max_generation)]), best_vector, label=
line_down, = plt.plot(np.array([i for i in range(max_generation)]), mean_vector, '-r'

plt.xlabel('Generations')
plt.ylabel('Fitness')

plt.legend(handles=[line_up, line_down])
plt.show()
```

```
iteration:  0  max fit:  -0.353600760927  mean fit:  -2.06559351999
iteration:  1  max fit:  -0.312877304847  mean fit:  -1.34406468168
iteration:  2  max fit:  -0.239425031782  mean fit:  -0.897481949541
iteration:  3  max fit:  -0.0735413425776  mean fit:  -0.56917816558
iteration:  4  max fit:  -0.075612226605  mean fit:  -0.384461208238
iteration:  5  max fit:  -0.0382119034372  mean fit:  -0.243724343489
iteration:  6  max fit:  -0.0217200136499  mean fit:  -0.153549806287
iteration:  7  max fit:  -0.0217200136499  mean fit:  -0.09780250579
iteration:  8  max fit:  -0.0154932444091  mean fit:  -0.067606169217
iteration:  9  max fit:  -0.00995043740612  mean fit:  -0.0483493846048
iteration:  10  max fit:  -0.00796868379384  mean fit:  -0.0453013563459
iteration:  11  max fit:  -0.00390442876512  mean fit:  -0.0466197013759
iteration:  12  max fit:  -0.00356443100621  mean fit:  -0.0339364316077
iteration:  13  max fit:  -0.00327195421475  mean fit:  -0.0272624735053
iteration:  14  max fit:  -0.00270216817324  mean fit:  -0.0188150841471
iteration:  15  max fit:  -0.00230500705244  mean fit:  -0.025239148587
iteration:  16  max fit:  -0.0022579935678  mean fit:  -0.0296798299118
iteration:  17  max fit:  -0.00190500083151  mean fit:  -0.0198286888971
iteration:  18  max fit:  -0.000991564923582  mean fit:  -0.0257859758915
iteration:  19  max fit:  -0.000933084805379  mean fit:  -0.0191594147178
iteration:  20  max fit:  -0.000692139237093  mean fit:  -0.0205102611843
iteration:  21  max fit:  -0.00065638833735  mean fit:  -0.0193639050923
iteration:  22  max fit:  -0.000645048269218  mean fit:  -0.0209668862451
iteration:  23  max fit:  -0.000645048269218  mean fit:  -0.0257694698724
iteration:  24  max fit:  -0.000645048269218  mean fit:  -0.0245014495444
iteration:  25  max fit:  -0.000645048269218  mean fit:  -0.025058199236
iteration:  26  max fit:  -0.000553751849255  mean fit:  -0.0231071715237
iteration:  27  max fit:  -0.000401951168984  mean fit:  -0.0142554396196
iteration:  28  max fit:  -0.000401951168984  mean fit:  -0.0194569736824
```

```
iteration:  29  max fit:  -0.000389246405989  mean fit:  -0.0147902786687
iteration:  30  max fit:  -0.000376332475437  mean fit:  -0.0157438032567
iteration:  31  max fit:  -0.000374132024089  mean fit:  -0.0215651533603
iteration:  32  max fit:  -0.000374132024089  mean fit:  -0.0131984058554
iteration:  33  max fit:  -0.000348513330542  mean fit:  -0.0158714260859
iteration:  34  max fit:  -0.000348513330542  mean fit:  -0.0217038143542
iteration:  35  max fit:  -0.00033575208349  mean fit:  -0.0220879733967
iteration:  36  max fit:  -0.000310133389943  mean fit:  -0.0166462773287
iteration:  37  max fit:  -0.000291783161671  mean fit:  -0.017398799433
iteration:  38  max fit:  -0.000183085446437  mean fit:  -0.0200125561838
iteration:  39  max fit:  -0.000273643359166  mean fit:  -0.0175720947898
iteration:  40  max fit:  -0.000273643359166  mean fit:  -0.0170610486115
iteration:  41  max fit:  -0.000272698865951  mean fit:  -0.0237786670346
iteration:  42  max fit:  -0.000272698865951  mean fit:  -0.0202634028599
iteration:  43  max fit:  -0.000272698865951  mean fit:  -0.0199349026332
iteration:  44  max fit:  -0.000272698865951  mean fit:  -0.0194946692146
iteration:  45  max fit:  -0.000272698865951  mean fit:  -0.018699951321
iteration:  46  max fit:  -0.000272698865951  mean fit:  -0.0219772259776
iteration:  47  max fit:  -0.000113057533214  mean fit:  -0.0201921653106
iteration:  48  max fit:  -0.000272698865951  mean fit:  -0.0274907878644
iteration:  49  max fit:  -0.000272698865951  mean fit:  -0.0267472501881
vector found at iteration 50
anwser:  [ 0.60799485  0.99382102  0.72754455  0.87066124  0.04591024  0.04845555
  0.22176449  0.33486527  0.99873785  0.53912602]  found:  [ 0.60784335  0.99565535  0.7264470
  0.21844721  0.34120687  0.99988532  0.5448143 ]
```



El código intenta encontrar un vector aleatorio de 10 digítos.

Debido a la naturaleza discreta del alforitmo genético, no es posible encontrar exactamente el mismo vector. Sin embargo se llega a un error mínimo de 0.000272698865951 de diferencia total entre los vectores y si se comparan visualmente son muy similares.

En el segmento siguiente se deja comentado las clases Fit que se utilizaron para estos dos experimentos, ubicadas en "genetic.py".

In [11]:
```
#class Fit(object):
#     def __init__(self, ref=np.array([])):
#         self.ref = ref
#
#     def random_individual(self, gene_num):
#         return np.array([self.random_gene_func(0, 1) for i in range(gene_num)])
#
#     # Overwrite this function for especific problem
#     def random_gene_func(self, min, max):
#         return np.random.randint(min, max)
#
#     # Overwrite this function for especific problem
#     def evaluate(self, vec):
#         return np.sum(np.logical_not(np.logical_xor(vec, self.ref)))
#
#     # Overwrite this function for especific problem
#     def reproduce_parents(self, p1, p2):
#         n = p1.shape[0]
#         div = random.randint(1, n - 1)
#         return np.concatenate((p1[0:div], p2[div:n]))
#
#     # Overwrite this function for especific problem
#     def mut_func(self, individual, mut_rate):
#         # Change one gene if mutation is activated
#         if (random.uniform(0, 1) <= mut_rate):
#             index = random.randint(0, individual.size-1)
#             individual[index] = int(not(individual[index]))
#         return individual
#
# class FitFloat(Fit):
#
#     def random_gene_func(self, min, max):
#         return np.random.uniform(min, max)
#
#     def mut_func(self, individual, mut_rate):
#         # Change one gene if mutation is activated
#         if (random.uniform(0, 1) <= mut_rate):
#             index = random.randint(0, individual.size-1)
#             individual[index] = random.uniform(0,1)
#         return individual
```

```
#
#     def evaluate(self, vec):
#         return -np.sum(np.power(vec - self.ref, 2))
```

1.2.2 Simular XOR utilizando una red neuronal

Para esta ocasión se utilizaa la biblioteca de Redes Neuronales escrita para las tareas anteriores. Admás se debe definir una función Fit que describa el caso particular de un fitness para XOR.

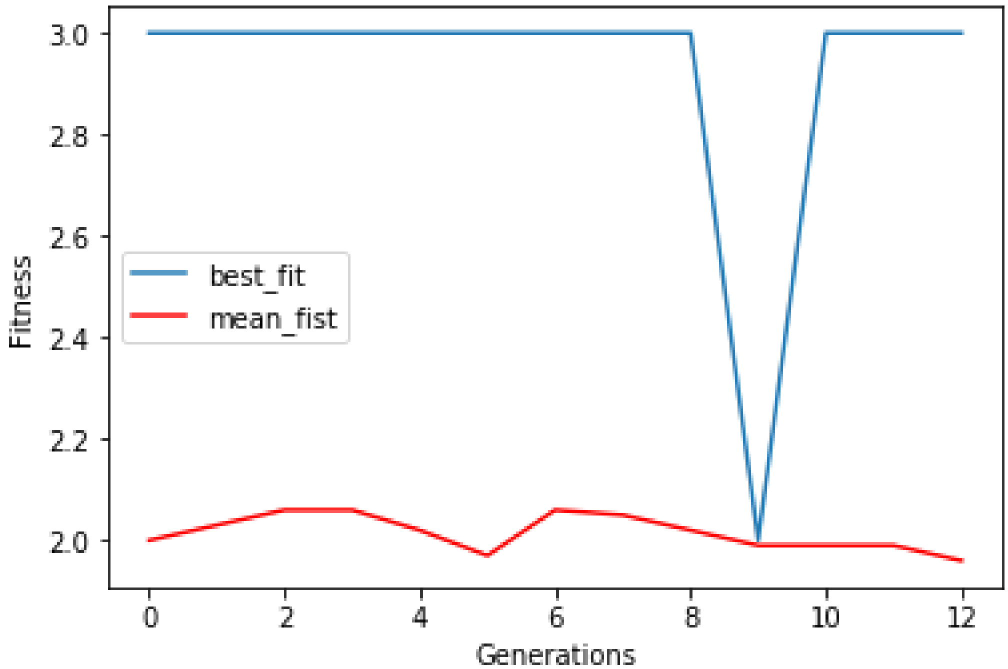
La arquitectura elegida es [2,6,4,2,1] en donde el primer número son las entradas y desde el segundo en adelante la cantidad de neuronas por capa. Lo cual quiere decur una red neuronal de 2 entradas, 1 salida, 4 capas y con 6, 4, 2, 1 neuronas en cada una.

```
In [23]: from genetic import FitXor
         from neuron_network import NeuronNetwork
```

```
In [35]: pop_size = 100
         max_generation = 100

         ar = np.array([2,4,2,1])
         fit_clas = FitXor(ar)
         vec_seq = Genetic(fitness_class=fit_class, population_size=pop_size, mut_rate=0.2, ma
         fitest, best_vector, mean_vector = vec_seq.evolve(max_generation)
         max_generation = best_vector.size

         def create_network(arqu):
             network = NeuronNetwork(arqu[0], 0.5)
             for i in range(1, arqu.size):
                 network.add_layer(arqu[i])
             return network

         network = create_network(ar)
         network.from_list(fitest)

         inp  = np.array([0, 0])
         output = 1.0 if network.feed(inp)[0] > 0.5 else 0.0
         print('for input: ', inp, " got output: ", output)

         inp  = np.array([1, 0])
         output = 1.0 if network.feed(inp)[0] > 0.5 else 0.0
         print('for input: ', inp, " got output: ", output)


         inp = np.array([0, 1])
         output = 1.0 if network.feed(inp)[0] > 0.5 else 0.0
         print('for input: ', inp, " got output: ", output)


         inp = np.array([1, 1])
```

```
        output = 1.0 if network.feed(inp)[0] > 0.5 else 0.0
        print('for input: ', inp, " got output: ", output)

        print('vector found at iteration', max_generation)
        print(' found: ',fitest)

        line_up, =  plt.plot(np.array([i for i in range(max_generation)]), best_vector, label=
        line_down, = plt.plot(np.array([i for i in range(max_generation)]), mean_vector, '-r'

        plt.xlabel('Generations')
        plt.ylabel('Fitness')

        plt.legend(handles=[line_up, line_down])
        plt.show()
```

```
iteration:  0  max fit:  3  mean fit:  2.0
iteration:  1  max fit:  3  mean fit:  2.03
iteration:  2  max fit:  3  mean fit:  2.06
iteration:  3  max fit:  3  mean fit:  2.06
iteration:  4  max fit:  3  mean fit:  2.02
iteration:  5  max fit:  3  mean fit:  1.97
iteration:  6  max fit:  3  mean fit:  2.06
iteration:  7  max fit:  3  mean fit:  2.05
iteration:  8  max fit:  3  mean fit:  2.02
iteration:  9  max fit:  2  mean fit:  1.99
iteration:  10  max fit:  3  mean fit:  1.99
iteration:  11  max fit:  3  mean fit:  1.99
iteration:  12  max fit:  3  mean fit:  1.96
for input:  [0 0]  got output:  0.0
for input:  [1 0]  got output:  1.0
for input:  [0 1]  got output:  1.0
for input:  [1 1]  got output:  0.0
vector found at iteration 13
 found:  [array([ 5.69362871,  4.34846488,  6.46600893])
 array([ 9.63743775, -0.8875876 ,  4.02099072])
 array([ 5.92790356,  7.48777496, -4.43516555])
 array([ 9.51201896, -4.01938974,  4.05825117])
 array([ 9.75876488, -0.48786106, -5.21935185, -7.17209464,  3.45709527])
 array([ 8.10577875, -1.68160728, -7.35851316,  0.78011984, -1.5828538 ])
 array([ 4.45126325, -2.72783617, -2.20975119])]
```



Los pesos necesarios para simular un XOR con redes neuronales, son encontrados de esta forma.

En el segmento siguiente se adjunta comentado la clase FitXor (ubicada en "genetic.py") utilizada por el algoritmo.

```
In [15]: #class FitXor(Fit):
         #
         #     def __init__(self, arqu):
         #         super().__init__()
         #         self.arq = arqu
         #
         #     def random_gene_func(self, min, max, n_weight):
         #         return np.array([random.uniform(-10.0, 10.0) for i in range(n_weight+1)])
         #
         #     def random_individual(self, gene_num):
         #         indv = []
         #         for j, val in enumerate(self.arq[0:self.arq.size-1]):
         #             for i in range(self.arq[j+1]):
         #                 indv.append(self.random_gene_func(0, 1, val))
         #         return indv
         #
         #     def evaluate(self, vec):
         #         network = create_network(np.array(self.arq))
         #         network.from_list(vec)
         #         fit = 0
```

```
#
#           input  = np.array([0, 0])
#           output = 1.0 if network.feed(input)[0] > 0.5 else 0.0
#           if output == xor_function(input[0], input[1]):
#               fit +=1
#
#           input  = np.array([1, 0])
#           output = 1.0 if network.feed(input)[0] > 0.5 else 0.0
#           if output == xor_function(input[0], input[1]):
#               fit +=1
#
#           input = np.array([0, 1])
#           output = 1.0 if network.feed(input)[0] > 0.5 else 0.0
#           if output == xor_function(input[0], input[1]):
#               fit += 1
#
#           input = np.array([1, 1])
#           output = 1.0 if network.feed(input)[0] > 0.5 else 0.0
#           if output == xor_function(input[0], input[1]):
#               fit += 1
#
#           return fit
#
#       def mut_func(self, individual, mut_rate):
#           if (random.uniform(0, 1) <= mut_rate):
#               index = random.randint(0, len(individual) - 1)
#               index2 = random.randint(0, len(individual[index]) - 1)
#
#               # Choose a random weight and negated
#               individual[index] [index2] = -individual[index] [index2]
#
#               # Choose a random weight and change it for random
#               # individual[index][index2] = random.uniform(-2.0, 2.0)
#
#           return individual
#
#       def reproduce_parents(self, p1, p2):
#           child = np.copy(p1)
#           for i, gene in enumerate(p1):
#               if random.randint(0,1) == 1:
#                   child[i] = p2[i]
#           return child
```

1.2.3 Dataset de Trigo (Wheat)

En una Tarea anterior se utilizo un dataset que contiene tres clasificaciones de trigo segun 7 parametros de la semilla. Utilizando backpropagation se llego a obtener alrededor de 0.75 de precisión en la clasificación.

Se utilizará el algoritmo genético para intentar encontrar una red adecuada, utilizando como fitness el número de aciertos en el dataset. Los resultados se adjuntn de foma separada, ya que el código toma mas tiempo cuando es ejecutado desde jupyter.

```
In [36]: import pandas as pd
         from sklearn import preprocessing
         from genetic import FitWheat

         seeds= pd.read_csv('./data/seeds_dataset.txt', sep='\t')
         seeds['t2'] = seeds['t1']
         seeds['t3'] = seeds['t1']
         seeds['t1'] = seeds['t1'].apply(lambda x: 1 if x==1 else 0)
         seeds['t2'] = seeds['t2'].apply(lambda x: 1 if x==2 else 0)
         seeds['t3'] = seeds['t3'].apply(lambda x: 1 if x==3 else 0)

         min_max_scaler = preprocessing.MinMaxScaler()
         seeds_scaled = min_max_scaler.fit_transform(np.array(seeds))
```

```
In [ ]: pop_size = 150
        max_generation = 2

        ar = np.array([7, 10, 20, 10, 5, 3])
        fit_class = FitWheat(arqu=ar, data=seeds_scaled)
        vec_seq = Genetic(fitness_class=fit_class, population_size=pop_size, mut_rate=0.30, ma
        fitest, best_vector, mean_vector = vec_seq.evolve(max_generation)
        max_generation = best_vector.size

        def create_network(arqu):
            network = NeuronNetwork(arqu[0], 0.5)
            for i in range(1, arqu.size):
                network.add_layer(arqu[i])
            return network

        network = create_network(ar)
        network.from_list(fitest)

        sumTrue = 0
        errors = np.array([])
        count = 0
        for i in range(0, 200):
            count += 1
            inputs = np.array(seeds_scaled[i][0:7])
            raw_output = network.feed(inputs)
            output = [(1.0 if x > 0.5 else 0.0) for x in raw_output.tolist()]
            expected = np.array(seeds_scaled[i][7:10])

            errors = np.append(errors, np.sum(np.abs(expected - raw_output)))
            if output[0] == expected[0] and output[1] == expected[1] and output[2] == expected
```

```python
            sumTrue += 1

    precision = float(sumTrue) / float(count)
    promError = np.mean(np.abs(errors))
    print('prec: ', str(precision), 'error: ', str(promError))

    print('vector found at iteration', max_generation)
    print('fitest one: \n', fitest)
    plt.plot(np.array([i for i in range(max_generation)]), best_vector)
    plt.plot(np.array([i for i in range(max_generation)]), mean_vector, '-r')
    plt.show()
```

iteration: 0 max fit: 71 mean fit: 27.2666666667 iteration: 1 max fit: 128 mean fit: 37.7 iteration: 2 max fit: 70 mean fit: 40.4333333333 iteration: 3 max fit: 77 mean fit: 41.74 iteration: 4 max fit: 118 mean fit: 43.76 iteration: 5 max fit: 70 mean fit: 42.4066666667 iteration: 6 max fit: 70 mean fit: 53.3866666667 iteration: 7 max fit: 104 mean fit: 35.0866666667 iteration: 8 max fit: 92 mean fit: 43.1866666667 iteration: 9 max fit: 70 mean fit: 37.4533333333 iteration: 10 max fit: 70 mean fit: 40.54 iteration: 11 max fit: 70 mean fit: 49.8466666667 iteration: 12 max fit: 70 mean fit: 64.0666666667 iteration: 13 max fit: 70 mean fit: 62.0933333333 iteration: 14 max fit: 70 mean fit: 52.9266666667 iteration: 15 max fit: 70 mean fit: 56.9466666667 iteration: 16 max fit: 122 mean fit: 36.6066666667 iteration: 17 max fit: 70 mean fit: 20.2466666667 iteration: 18 max fit: 102 mean fit: 28.9933333333 iteration: 19 max fit: 124 mean fit: 38.8133333333 iteration: 20 max fit: 72 mean fit: 46.76 iteration: 21 max fit: 108 mean fit: 63.04 iteration: 22 max fit: 75 mean fit: 64.58 iteration: 23 max fit: 70 mean fit: 24.7333333333 iteration: 24 max fit: 70 mean fit: 20.4666666667 iteration: 25 max fit: 70 mean fit: 30.52 iteration: 26 max fit: 70 mean fit: 3.78666666667 iteration: 27 max fit: 78 mean fit: 60.62 iteration: 28 max fit: 127 mean fit: 47.9066666667 iteration: 29 max fit: 80 mean fit: 52.5 iteration: 30 max fit: 121 mean fit: 54.8733333333 iteration: 31 max fit: 71 mean fit: 57.3 iteration: 32 max fit: 70 mean fit: 65.3466666667 iteration: 33 max fit: 70 mean fit: 67.3266666667 iteration: 34 max fit: 70 mean fit: 66.1133333333 iteration: 35 max fit: 70 mean fit: 61.4466666667 iteration: 36 max fit: 0 mean fit: 0.0 iteration: 37 max fit: 70 mean fit: 70.0 iteration: 38 max fit: 0 mean fit: 0.0 iteration: 39 max fit: 70 mean fit: 10.62 iteration: 40 max fit: 70 mean fit: 70.0 iteration: 41 max fit: 70 mean fit: 67.7533333333 iteration: 42 max fit: 70 mean fit: 62.56 iteration: 43 max fit: 70 mean fit: 70.0 iteration: 44 max fit: 70 mean fit: 68.8466666667 iteration: 45 max fit: 70 mean fit: 4.42666666667 iteration: 46 max fit: 88 mean fit: 15.12 iteration: 47 max fit: 0 mean fit: 0.0 iteration: 48 max fit: 3 mean fit: 0.04 iteration: 49 max fit: 0 mean fit: 0.0 prec: 0.35 error: 1.15510249649

Se llegan a resultados de 0.35 de precisión con estos parámetros.

En primera instancia backpropagation pareciera ser mejor forma de clasificar este dataset teniendo una red de arquitectura fija y cambiando solo los pesos, sin embargo durante la realización del experimento se ha constatado que la arquitectura misma de la red influye mucho en la forma que se comporta el algoritmo, probablemente por la forma discreta en que se utiliza el crossover entre individuos termina desembocando en que los individuos que se cruzan cada vez se parecen y más y por esto se estanca el crecimiento.

Como trabajo futuro se espera utilizar el algoritmo para cambiar otras propiedades de la red neuronal, como el número de layers o la forma que se conecta la misma red.

In [38]:
```
#class FitWheat(FitXor):
#
#     def __init__(self, arqu, data):
#         super().__init__(arqu=arqu)
#         self.data = data
#
#     def evaluate(self, vec):
#         network = create_network(np.array(self.arq))
#         network.from_list(vec)
#
#         error = 0
#         sumTrue = 0
#         for i in range(210):
#             inputs = np.array(self.data[i][0:7])
#             raw_output = network.feed(inputs)
#             output = [(1.0 if x > 0.5 else 0.0) for x in raw_output.tolist()]
#             expected = np.array(self.data[i][7:10])
#
#             error += np.sum(np.abs(expected - raw_output))
#             # if output[0] == expected[0]:
#             #     sumTrue += 1
#             # else:
#             #     sumTrue -= 1
#             # if output[1] == expected[1]:
#             #     sumTrue +=1
#             # else:
#             #     sumTrue -= 1
#             # if output[2] == expected[2]:
#             #     sumTrue +=1
#             # else:
#             #     sumTrue -= 1
#
#             if output[0] == expected[0] and output[1] == expected[1] and output[2]
#                 sumTrue += 1
#
#         return sumTrue
#
#     def random_gene_func(self, min, max, n_weight):
#         return np.array([random.uniform(-10.0, 10.0) for i in range(n_weight+1)])
#
#     def mut_func(self, individual, mut_rate):
```

```
#           if (random.uniform(0, 1) <= mut_rate):
#           # for i in range(random.randint(0, len(individual) - 1)):
#               index = random.randint(0, len(individual) - 1)
#               index2 = random.randint(0, len(individual[index]) - 1)
#
#               # Choose a random weight and negated
#               individual[index] [index2] = -individual[index] [index2]
#
#               # Scale weight
#               # individual[index][index2] = individual[index][index2] * random.unifor
#
#                   # Choose a random weight and change it for random
#                   # individual[index][index2] = random.uniform(-2.0, 2.0)
#
#           return individual
```