In [1]:
```python
import math
import random
import matplotlib.pyplot as plt
import numpy as np
import matplotlib.image as mpimg

from deap import base, creator, tools, gp, algorithms
import math, operator, random, numpy
import seaborn
import pandas as pd
```

Assignment 1

We have the formula

$$S_m(H) = (1 - p_m)^{o(H)}$$

For H = A1 we have:

S_m(#1#100###) = (1 - 0.01)^{4} = 0.96059601

For H = A2 we have:

S_m(##010#011) = (1 - 0.01)^{6} = 0.9414801494

A1 has the highest chance of survival because Sm(A1) > Sm(A2)

Assignment 2

This would be the Needle in a haystack problem.

The fitness function of a EA, when modelling this problem, will for example either have a value of 0 or 1 and nothing in between. This means that there is no way to stepwise improve the fitness that will lead us from 0 to the global optimum of 1.

In other words, with the building block hypothesis we assume that a GA can create stepwise better solutions by mutating, selecting and crossing short good partial solutions(low order, high fitness, short defining lenght) but with this problem there are no partial solutions to combine.

Assignment 3

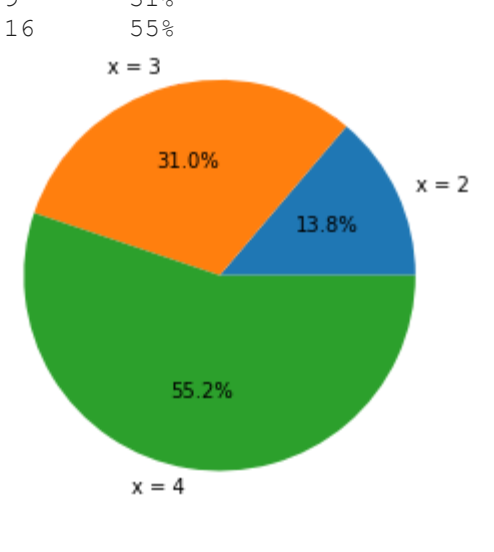
a)

In [2]:
```python
values = [2, 3, 4]
labels = ['x = 2', 'x = 3', 'x = 4']
out = list(map(lambda x: x**2, values)), list(map(lambda x: x**2 + 20, values))
outnorm = [float(i)/sum(out[0]) for i in out[0]], [[float(i)/sum(out[1]) for i in out[1]]]

fig1, ax1 = plt.subplots()
ax1.pie(out[0], labels=labels, autopct='%1.1f%%')
ax1.axis('equal')


print('\tf(x)\tselection probability')
[print(f'x={values[i]}\t{out[0][i]}\t{"{:.0%}".format(outnorm[0][i])}') for i in range(len(values))]
plt.show()
```

```
     f(x)    selection probability
x=2  4       14%
x=3  9       31%
x=4  16      55%
```



b)

The selection pressure is high when some indivuduals have a higher chance of being chosen due to their fitness.

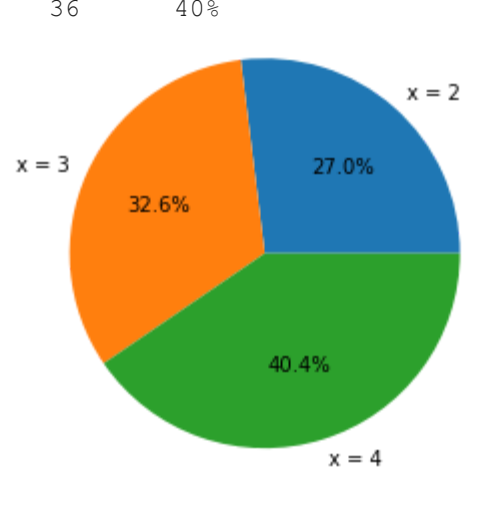
Here, function f_1 yields a lower selection pressure than $f(x)$ because the fitnesses values of the individuals are much closer to each other when using fitness function f_1.

Thus, in f_1 the chance of being selected for the individuals are more closer to each other compared to the chance of being selected in f.

In [3]:
```python
fig1, ax1 = plt.subplots()
ax1.pie(out[1], labels=labels, autopct='%1.1f%%')
ax1.axis('equal')


print('\tf(x)+20\tselection probability')
[print(f'x={values[i]}\t{out[1][i]}\t{"{:.0%}".format(outnorm[1][0][i])}') for i in range(len(values))]
plt.show()
```

```
     f(x)+20 selection probability
x=2  24      27%
x=3  29      33%
x=4  36      40%
```



c)

Fitness scaling decreases selection pressure (if the scaling constant is large enough) because it adds the same constant value to the selection probability of each individual making sure one very fit individual does not outcompete all others.

Assignment 4.1

In [4]:
```python
def compute_score(goal, x_m):
    counter = 0
    print(goal, x_m)
    for i in range(len(goal)):
        if goal[i] == x_m[i]:
            counter += 1

    return counter

def binary_GA(goal, x, p_m):
    digit_x = [int(a) for a in str(x)]
    digit_x_m = [int(a) for a in str(x)]
    while True:
        for index in range(len(digit_x_m)):
            rand = random.uniform(0, 1)
            if rand <= p:
                if digit_x_m[index] == 1:

                    digit_x_m[index] = 0
                else:
                    digit_x_m[index] = 1
        digit_goal = [int(a) for a in str(goal)]
        digit_x = [int(a) for a in str(x)]


        mutate_score = compute_score(str(goal), (''.join(map(str,digit_x_m))))
        origin_score = compute_score(str(goal), (''.join(map(str,digit_x))))

        print(goal,x, digit_x_m, mutate_score, origin_score)
        if mutate_score > origin_score:
            return (''.join(map(str,digit_x_m)))
```

In [5]:
```python
goal = '11100010'
x = '01111001'
p = 0.05

counter = 0
while not (x == goal):
    x = binary_GA(goal, x, p)
    print('iteration {0:2d} complete.\n'.format(counter))
    print(x)
    counter += 1
```

Assignment 4.2

Name: Student_Age_Data.csv

```
In [6]:
def genbin(n):
    number = ''
    for i in range(n):
        number += str(random.randint(0, 1))

    return number

def counting_ones(l, p, fitness, iterations, x, goal_runs):
    runs_lst = []

    runs = 0
    while runs < goal_runs:
        iteration = 0
        iteration_lst = []
        x = [random.randint(0, 1) for _ in range(l)]
        while len(iteration_lst) < iterations:
            x_m = x.copy()
            for index in range(len(x_m)):
                rand = random.uniform(0, 1)
                if rand <= p:
                    if x_m[index] == 1:
                        x_m[index] = 0
                    else:
                        x_m[index] = 1

            mutate_score = fitness(x_m)
            origin_score = fitness(x)

            if mutate_score > origin_score:
                x = x_m
            iteration_lst.append(origin_score)
        runs_lst.append(iteration_lst)
        runs += 1
    return runs_lst

def dumb_counting_ones(l, p, fitness, iterations, x, goal_runs):
    runs_lst = []

    runs = 0
    while runs < goal_runs:
        iteration = 0
        best_score = 0
        iteration_lst = []
        x = [random.randint(0, 1) for _ in range(l)]
        while len(iteration_lst) < iterations:
            x_m = x.copy()
            for index in range(len(x_m)):
                rand = random.uniform(0, 1)
                if rand <= p:
                    if x_m[index] == 1:
                        x_m[index] = 0
                    else:
                        x_m[index] = 1

            mutate_score = fitness(x_m)

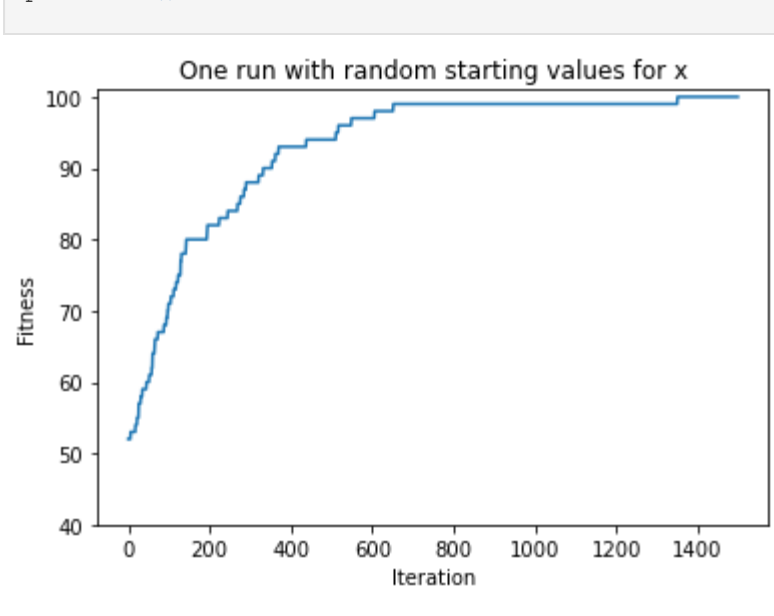
            if mutate_score > best_score:
                best_score = mutate_score
            iteration_lst.append(best_score)
        runs_lst.append(iteration_lst)
        runs += 1

    return runs_lst
```

```
In [7]:
l = 100
p = 1/l
fitness = lambda x: sum(x)
iterations = 1500
x = [random.randint(0, 1) for _ in range(l)]
goal_runs = 1


runs_lst = counting_ones(l,p,fitness, iterations, x, goal_runs)


plt.title('One run with random starting values for x')
for index, run in enumerate(runs_lst):
    plt.plot(run, label = 'Run {0:2d}'.format(index))
plt.ylim([40,101])
plt.xlabel('Iteration')
plt.ylabel('Fitness')
plt.show()
```

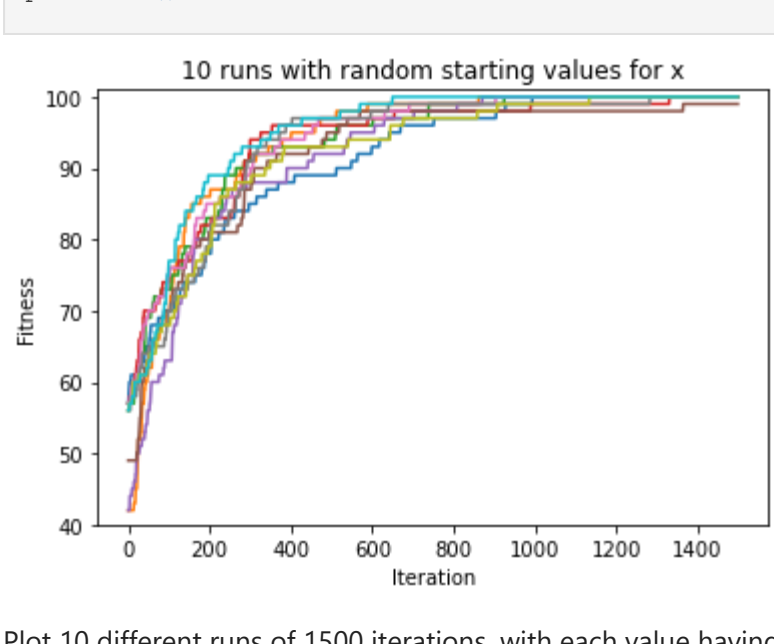


b)

```
In [8]:
l = 100
p = 1/l
fitness = lambda x: sum(x)
x = [random.randint(0, 1) for _ in range(l)]
iterations = 1500
goal_runs = 10


runs_lst = counting_ones(l,p,fitness, iterations, x, goal_runs)

plt.title('10 runs with random starting values for x')
for index, run in enumerate(runs_lst):
    plt.plot(run, label = 'Run {0:2d}'.format(index))
plt.ylim([40,101])
plt.xlabel('Iteration')
plt.ylabel('Fitness')
plt.show()
```



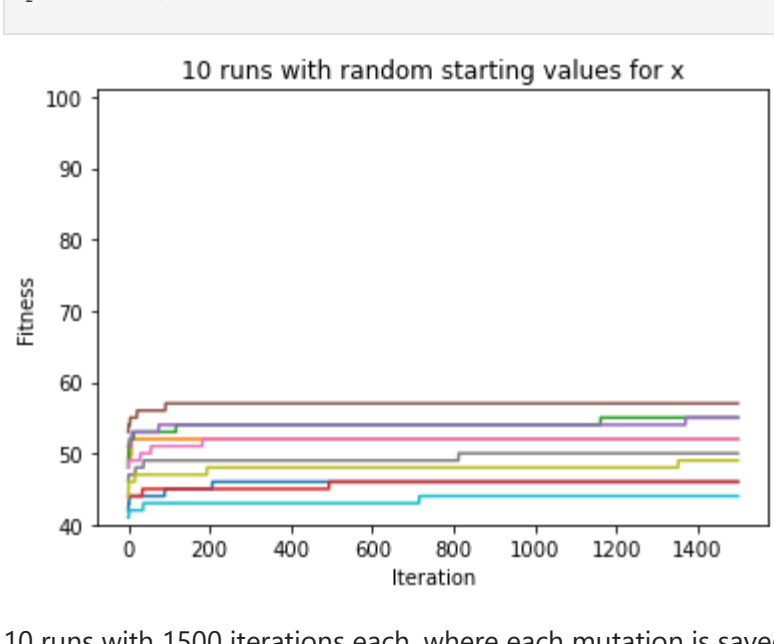
Plot 10 different runs of 1500 iterations, with each value having a different starting x. Pretty much all of the runs will converge, however rarely one run will be just below the optimal fitness at the 1500th iteration.

c)

```
In [9]:
l = 100
p = 1/l
fitness = lambda x: sum(x)
x = [random.randint(0, 1) for _ in range(l)]
iterations = 1500
goal_runs = 10


runs_lst = dumb_counting_ones(l,p,fitness, iterations, x, goal_runs)

plt.title('10 runs with random starting values for x')
for index, run in enumerate(runs_lst):
    plt.plot(run, label = 'Run {0:2d}'.format(index))
plt.ylim([40,101])
plt.xlabel('Iteration')
plt.ylabel('Fitness')
plt.show()
```



10 runs with 1500 iterations each, where each mutation is saved and used as the basis for the next iteration. This means the best mutation is not saved, therefore the algorithm will probably (very likely) never converge to 100 fitness. The plot depitcts the best achieved scores per run.

Assignment 5

a)

A 1+1 evolutionary algorithm has each parent generate one offspring. A 1+5 evolutionary algorithm, to our understanding at least, would then have each parent generate 5 offspring. The offspring are then compared to its/their parent and the fittest will proceed. In essence creating a subpool of parent(s) + offspring, from which the individual with the greatest fitness leaves. A larger pool of offspring results in more possible mutations, which might result in more/better mutations over the parent. So 1+5 would probably converge to a local optimum sooner at the cost of a larger computational complexity.

b)

We understand 1+λ EA to a mutarionrate self-regulating EA. Where one parent who creates a set of offspring in which one half of the offspring will mutate at double the set mutation rate, and the other half at half the set mutation rate. The best offspring is chosen and the set mutation rate is chosen to be the mutation rate of which this individual originates (either double or half the previous rate). Comparing this (still) stochastical process to the local search we would think that the local search would perform better, since we know that that 1+λ remains a stochastical algorithm, and therefore does not guarrantee immediate optima in the local search, whereas the local search (is assumed) to always make a locally optimal step. Furthermore both algorithms seem to be greedy in nature due to them prioritising direct (within one or a few steps) gains in fitness over long term benefit, which puts them on equal footing. Therefore we maintain that we think the local search would perform better (albeit probably less efficient).

Assignment 6

a)

b)

```
In [10]:
distance = lambda pos1, pos2: math.sqrt((pos2[0] - pos1[0])**2 + (pos2[1] - pos1[1])**2)


def load_file(name):
    tsp = []
    with open(name) as f:
        lines = f.readlines()

    for line in lines:
        tsp_single = []
        coordinates = line.split()
        tsp_single.append(float(coordinates[0]))
        tsp_single.append(float(coordinates[1]))
        tsp.append(tsp_single)

    return tsp

def total_distance(city_coords, cities):
    total_dist = 0
    for i in range(len(cities)-1):
        total_dist += distance(city_coords[cities[i]], city_coords[cities[i+1]])
    return total_dist


def two_opt(route):
    get_slice = lambda x: x if x is not None else []
    best_route = route
    best_distance = total_distance(city_coords, route)
    for i in range(len(route)):
        for k in range(i+2, len(route)+1):
            mid = get_slice(route[i:k])
            mid.reverse()
            new_route = get_slice(route[:i]) + mid + get_slice(route[k:])
            new_distance = total_distance(city_coords, new_route)
            if new_distance < best_distance:
                best_route = new_route
                best_distance = new_distance
    return best_route

def crossover(pool):
    m, d = random.sample(range(len(pool)), 2)
    mom = pool[m]
    dad = pool[d]
    c1 = random.randint(0, len(mom)-1)
    c2 = random.randint(c1+1, len(mom))
    dadw = dad[c2:] + dad[:c2]
    momw = mom[c2:] + mom[:c2]
    rest_one = [x for x in dadw if x not in mom[c1:c2]]
    rest_two = [x for x in momw if x not in dad[c1:c2]]
    child_one = rest_one[len(mom)-c2:] + mom[c1:c2] + rest_one[:len(mom)-c2]
    child_two = rest_two[len(mom)-c2:] + dad[c1:c2] + rest_two[:len(mom)-c2]
    return child_one, child_two

def mutate(list, mutate_chance):
    if random.uniform(0, 1) > mutate_chance:
        return list
    i, j = np.random.choice(range(len(list)), 2, replace = False)
    list[i], list[j] = list[j], list[i]
    return list

def create_next_generation(pool, prop_fitnesses, num_start_instances, mutate_chance, use_local, num_elites):
    parents = random.choices(pool, prop_fitnesses, k=num_start_instances)
    elites = [pool[x] for x in np.argpartition(prop_fitnesses, num_elites)[:num_elites]]
    new_generation = elites
    loop_max = int(np.ceil(len(parents)/2))
    for i in range(loop_max-num_elites):
        o1, o2 = crossover(parents)
        o1 = mutate(o1, mutate_chance)
        o2 = mutate(o2, mutate_chance)
        if use_local:
            o1 = two_opt(o1)
            o2 = two_opt(o2)
        new_generation.append(o1)
        new_generation.append(o2)

    return new_generation

def show_map(route):
    for i in range(len(route)-1):
        path_x = [city_coords[route[i]][0], city_coords[route[i+1]][0]]
        path_y = [city_coords[route[i]][1], city_coords[route[i+1]][1]]
        plt.plot(path_x, path_y, 'ro-')
    plt.show()

def mem_tsp(num_iterations, num_start_instances, mutate_chance, num_elites):
    avg_fitnesses = []
    best_fitnesses = []
    use_local = True
    pool = [np.random.permutation(len(city_coords)).tolist() for x in range(num_start_instances)]
    pool = [two_opt(r) for r in pool]
    fitnesses = [total_distance(city_coords, r) for r in pool]
    prop_fitnesses = [f/sum(fitnesses) for f in fitnesses]
    print('Memetic')
    for it in range(num_iterations):
        pool = create_next_generation(pool, prop_fitnesses, num_start_instances, mutate_chance, use_local, num_
        fitnesses = [total_distance(city_coords, r) for r in pool]
        prop_fitnesses = [f/sum(fitnesses) for f in fitnesses]
        avg_fitnesses.append(sum(fitnesses)/len(fitnesses))
        best_fitnesses.append(min(fitnesses))
        print(it)
    return avg_fitnesses, best_fitnesses

def ea_tsp(num_iterations, num_start_instances, mutate_chance, num_elites):
    avg_fitnesses = []
    best_fitnesses = []
    use_local = False
    pool = [np.random.permutation(len(city_coords)).tolist() for x in range(num_start_instances)]
    fitnesses = [total_distance(city_coords, r) for r in pool]
    prop_fitnesses = [f/sum(fitnesses) for f in fitnesses]
    print('EA')
    for it in range(num_iterations):
        pool = create_next_generation(pool, prop_fitnesses, num_start_instances, mutate_chance, use_local, num_
        fitnesses = [total_distance(city_coords, r) for r in pool]
        prop_fitnesses = [f/sum(fitnesses) for f in fitnesses]
        avg_fitnesses.append(sum(fitnesses)/len(fitnesses))
        best_fitnesses.append(min(fitnesses))
        print(it)
    return avg_fitnesses, best_fitnesses


city_coords = load_file('file-tsp.txt')

iterations = 1500
instances = 26
elites = 10
avg_mem, best_mem = mem_tsp(iterations, instances, 0.05, elites)
avg_ea, best_ea = ea_tsp(iterations, instances, 0.1, elites)
```

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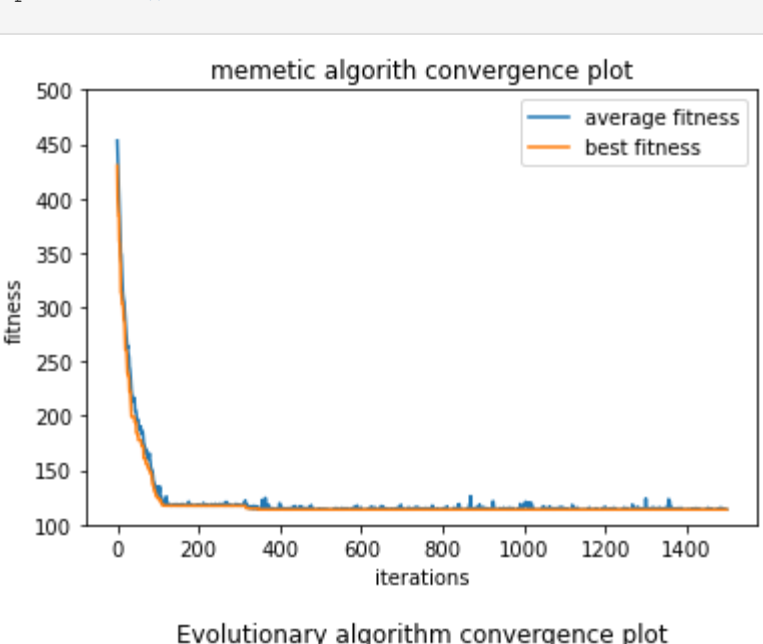
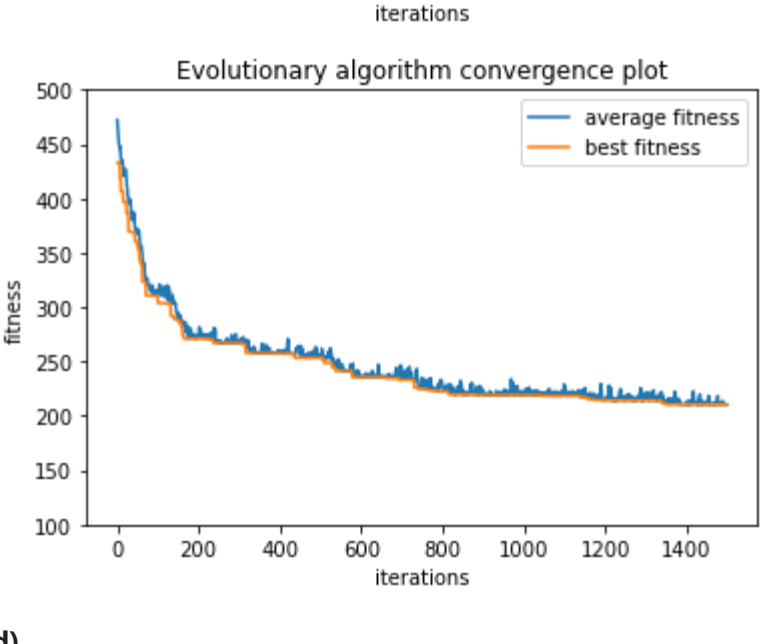
```

c)

In [11]:
```
plt.plot(range(iterations), avg_mem, label = 'average fitness')
plt.plot(range(iterations), best_mem, label = 'best fitness')
plt.title('memetic algorith convergence plot')
plt.ylim([100,500])
plt.legend()
plt.ylabel('fitness')
plt.xlabel('iterations')
plt.show()

plt.plot(range(iterations), avg_ea, label = 'average fitness')
plt.plot(range(iterations), best_ea, label = 'best fitness')
plt.title('Evolutionary algorithm convergence plot')
plt.ylim([100,500])
plt.legend()
plt.ylabel('fitness')
plt.xlabel('iterations')
plt.show()
```





d)

The memetic algorithm works a lot better

e)

It is not fair, because the memetic algorithm uses local search which is an additional method to improve the pool. The regular evolution algorithm doesn't have this and merely relies on the number of iterations. I think it would be more fair if we increased the number of iterations for the evolution algorithm. The evolution algorithm would otherwise be exactly the same as the memetic approach minus the local search function, and the local search function only improves the instances and never makes them worse.

f) In https://arxiv.org/ftp/arxiv/papers/1004/1004.0574.pdf it is found that memetic algorithms work better than genetic algorithms, it was tested on many NP-hard problems.

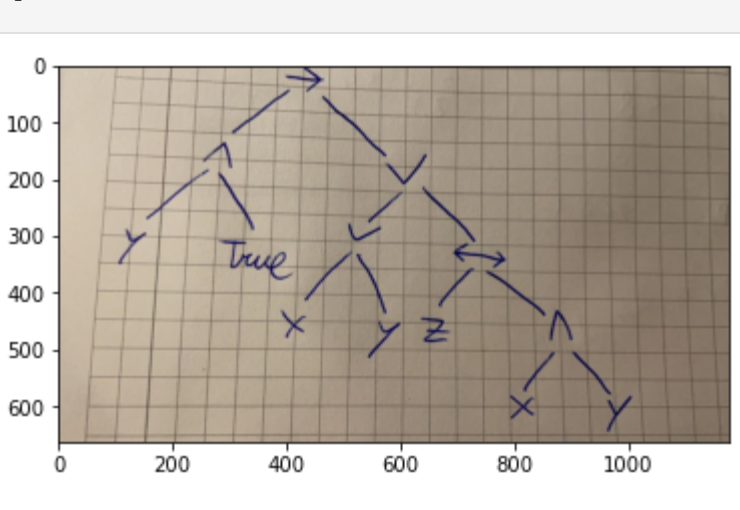
Assignment 7

a)

T1 = {y, True, x, z}

F1 = {f(→, x1, x2), f(∧, x1, x2), f(∨, x1, x2), f(↔, x1, x2)}

In [12]:
```
plt.imshow(mpimg.imread('7a.jpeg'))
plt.show()
```

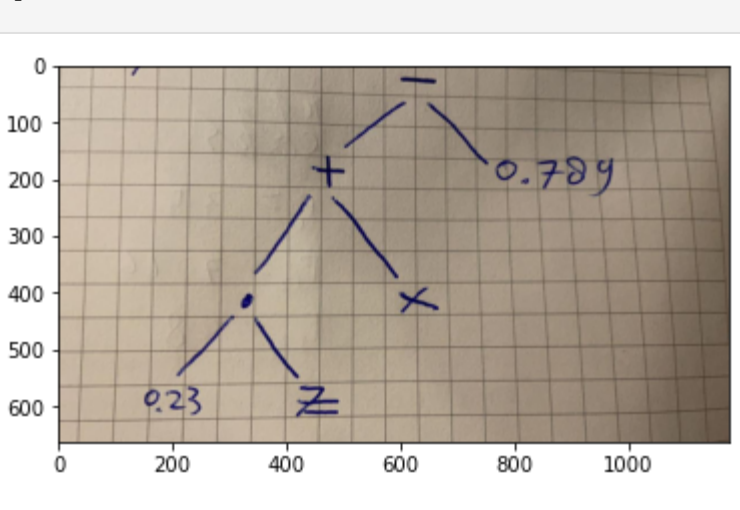


b)

T2 = {0.23, Z, X, 0.789}

F2 = {f(*, x1, x2), f(+, x1, x2), f(-, x1, x2)}

In [13]:
```
plt.imshow(mpimg.imread('7b.jpeg'))
plt.show()
```



Assignment 8

In [14]:
```
# all initialisation code:
# IMPORTANT this code can only be run once (so empty kernel if you need to run it again), this is a limitation
data = [
  (-1.0, 0.0000),
  (-0.9, -0.1629),
  (-0.8, -0.2624),
  (-0.7, -0.3129),
  (-0.6, -0.3264),
  (-0.5, -0.3125),
  (-0.4, -0.2784),
  (-0.3, -0.2289),
  (-0.2, -0.1664),
  (-0.1, -0.0909),
  (0, 0.0),
  (0.1, 0.1111),
  (0.2, 0.2496),
  (0.3, 0.4251),
  (0.4, 0.6496),
  (0.5, 0.9375),
  (0.6, 1.3056),
  (0.7, 1.7731),
  (0.8, 2.3616),
  (0.9, 3.0951),
  (1.0, 4.0000)
]
# creating function set f
def protectedDiv(left, right):
    try:
        return left / right
    except ZeroDivisionError:
        return 1
def protectedLog(left, right):
    try:
        left = abs(left)
        right = abs(right)
        return math.log(left,right)
    except ValueError:
        return 0
    except ZeroDivisionError:
        return 0

primitives = gp.PrimitiveSet("MathematicalOperators", 1)
primitives.addPrimitive(operator.add, 2)
primitives.addPrimitive(operator.sub, 2)
primitives.addPrimitive(operator.mul, 2)
primitives.addPrimitive(protectedDiv, 2)
primitives.addPrimitive(protectedLog, 2)
primitives.addPrimitive(math.exp, 1)
primitives.addPrimitive(math.cos, 1)
primitives.addPrimitive(math.sin, 1)
primitives.addEphemeralConstant("x", lambda: random.uniform(-1.000000000,1.000000000))

# create fitness and individual, which are building blocls for deap library
creator.create("FitnessMax", base.Fitness, weights=(1.0,))
creator.create("Individual", gp.PrimitiveTree, fitness=creator.FitnessMax)

INITIAL_POPULATION_SIZE = 1000

#creating initialisation
toolbox = base.Toolbox()
toolbox = base.Toolbox()
toolbox.register("expr", gp.genHalfAndHalf, pset=primitives, min_=1, max_=2)
toolbox.register("individual", tools.initIterate, creator.Individual, toolbox.expr)
toolbox.register("population", tools.initRepeat, list, toolbox.individual)
toolbox.register("compile", gp.compile, pset=primitives)

# self made fitnessfunction for -sum of absolute value
def fitnessfunc(individual):
    func = toolbox.compile(expr=individual)
    sum = 0
    for x in data:
        sum += abs(func(x[0]) - x[1])
    return (-1*sum,)

# self made func to calculate number of nodes of best individual during iteration
def best_func(ind):
    poplist =[]
    for x in pop:
        poplist.append(x.fitness.values)
    bestfit = max(poplist)
    if ind.fitness.values == bestfit:
        return len(ind)
    else: return 0

# instantiate evaluation, selection, mate and mutate , also set max_value =17 as standart to avoid bloat (from
toolbox.register("evaluate", fitnessfunc)
toolbox.register("select", tools.selTournament, tournsize=3)
toolbox.register("mate", gp.cxOnePoint)
toolbox.register("expr_mut", gp.genFull, min_=0, max_=2)
toolbox.register("mutate", gp.mutUniform, expr=toolbox.expr_mut, pset=primitives)
toolbox.decorate("mate", gp.staticLimit(key=operator.attrgetter("height"), max_value=17))
toolbox.decorate("mutate", gp.staticLimit(key=operator.attrgetter("height"), max_value=17))

# Stats for logbook
stats_fit = tools.Statistics(lambda ind: ind.fitness.values)
stats_size = tools.Statistics(len)
stat_f = tools.Statistics(best_func)
mstats = tools.MultiStatistics(fitness=stats_fit, size=stats_size, bestf= stat_f)
mstats.register("avg", numpy.mean)
#mstats.register("std", numpy.std)
#mstats.register("min", numpy.min)
mstats.register("max", numpy.max)
```

In [15]:
```
# running model

# running model with 50 generations, cross prob = 0.7 , mutation prob = 0
pop = toolbox.population(n=INITIAL_POPULATION_SIZE)
hof = tools.HallOfFame(1)
pop, log = algorithms.eaSimple(pop, toolbox, 0.7, 0, 50, stats=mstats, halloffame=hof, verbose=True)

# creating dataframe for plot from logbook
gen = log.select("gen")
fit_max = log.chapters["fitness"].select("max")
size_avg = log.chapters["size"].select("avg")
best_f = log.chapters["bestf"].select("max")

df = pd.DataFrame(list(zip(gen,fit_max,size_avg, best_f)), columns=['gen','max_fitness','avg_nodes', 'nodes bes
df
```

```
                        bestf                                    fitness                                      si
ze
               ------------------------------   ---------------------------------------------   ---------------
---------------
gen     nevals  avg     gen     max     nevals  avg             gen     max             nevals  avg     gen
max     nevals
0       1000    0.005   0       5       1000    -57.1708        0       -5.45326        1000    3.843   0
7       1000
1       686     0.004   1       4       686     -3.37794e+13    1       -4.24698        686     3.6     1
9       686
2       720     0.004   2       4       720     -15.851         2       -4.24698        720     3.489   2
9       720
3       690     0.024   3       4       690     -14.5393        3       -4.24698        690     3.519   3
8       690
4       670     0.006   4       6       670     -13.9522        4       -3.9279         670     3.763   4
9       670
5       716     0.006   5       6       716     -12.7336        5       -3.79774        716     4.156   5
10      716
6       710     0.006   6       6       710     -11.9869        6       -3.04161        710     4.558   6
11      710
7       680     0.012   7       6       680     -11.3773        7       -3.04161        680     4.898   7
11      680
8       692     0.007   8       7       692     -9.99117        8       -3.04161        692     5.011   8
12      692
9       690     0.006   9       6       690     -10.7524        9       -2.9756         690     4.902   9
13      690
10      666     0.042   10      7       666     -10.0431        10      -3.04161        666     4.789   10
11      666
11      706     0.008   11      8       706     -13.5909        11      -2.92102        706     4.983   11
13      706
12      686     0.008   12      8       686     -11.0791        12      -2.3637         686     5.251   12
14      686
13      688     0.008   13      8       688     -10.972         13      -2.3637         688     5.654   13
18      688
14      684     0.015   14      15      684     -11.4923        14      -2.63569        684     5.918   14
15      684
15      714     0.016   15      8       714     -12.9963        15      -2.79064        714     6.327   15
15      714
16      668     0.008   16      8       668     -17.2702        16      -2.47565        668     6.493   16
20      668
17      700     0.01    17      10      700     -16.0377        17      -2.1332         700     6.666   17
16      700
18      716     0.01    18      10      716     -39.279         18      -2.1332         716     6.909   18
18      716
19      690     0.01    19      10      690     -15.6606        19      -0.990774       690     6.987   19
18      690
20      686     0.01    20      10      686     -15.6042        20      -0.990774       686     7.178   20
16      686
21      736     0.024   21      12      736     -25.5163        21      -0.993626       736     7.356   21
19      736
22      744     0.012   22      12      744     -24.5789        22      -0.993626       744     7.432   22
16      744
23      728     0.012   23      12      728     -23.1577        23      -0.993626       728     7.562   23
18      728
24      704     0.02    24      10      704     -27.4585        24      -1.11998        704     7.756   24
17      704
25      690     0.014   25      14      690     -58.6232        25      -1.02515        690     7.989   25
22      690
26      702     0.016   26      16      702     -18.9581        26      -1.08905        702     8.163   26
21      702
27      676     0.028   27      14      676     -15.3748        27      -1.05924        676     8.578   27
20      676
28      718     0.012   28      12      718     -35.2589        28      -0.990774       718     9.251   28
24      718
29      666     0.048   29      12      666     -536193         29      -0.990774       666     10.285  29
27      666
30      698     0.068   30      12      698     -13.3794        30      -0.990774       698     11.305  30
28      698
31      704     0.096   31      12      704     -18.3658        31      -0.990774       704     12.233  31
35      704
32      706     0.024   32      24      706     -21.9859        32      -0.990621       706     13.571  32
39      706
33      712     0.026   33      26      712     -30.2666        33      -0.933577       712     14.503  33
43      712
34      672     0.026   34      26      672     -34.3981        34      -0.933577       672     15.267  34
48      672
35      678     0.026   35      26      678     -29.1704        35      -0.94498        678     15.398  35
49      678
36      708     0.078   36      26      708     -41.1126        36      -0.94498        708     15.269  36
56      708
37      704     0.031   37      31      704     -1.07454e+08    37      -0.948561       704     16.262  37
57      704
38      700     0.03    38      30      700     -106.522        38      -0.920451       700     16.724  38
55      700
39      690     0.018   39      18      690     -38.08          39      -0.849018       690     17.715  39
58      690
40      682     0.026   40      26      682     -94.7421        40      -0.835036       682     19.109  40
65      682
41      730     0.052   41      26      730     -31.4626        41      -0.835036       730     21.087  41
65      730
42      694     0.052   42      26      694     -20.595         42      -0.835036       694     24.342  42
72      694
43      710     0.028   43      28      710     -48.3482        43      -0.831504       710     26.995  43
80      710
44      696     0.068   44      68      696     -23.8761        44      -0.800457       696     29.136  44
71      696
45      710     0.068   45      68      710     -26.2635        45      -0.800457       710     32.143  45
78      710
46      664     0.272   46      68      664     -19.2334        46      -0.800457       664     33.582  46
87      664
47      722     0.028   47      28      722     -4.96966        47      -0.785629       722     34.769  47
89      722
48      708     0.078   48      78      708     -1317.61        48      -0.770763       708     35.22   48
89      708
49      674     0.234   49      78      674     -4.33184        49      -0.770763       674     38.018  49
91      674
50      706     0.072   50      72      706     -4.31858        50      -0.761353       706     42.007  50
120     706
```

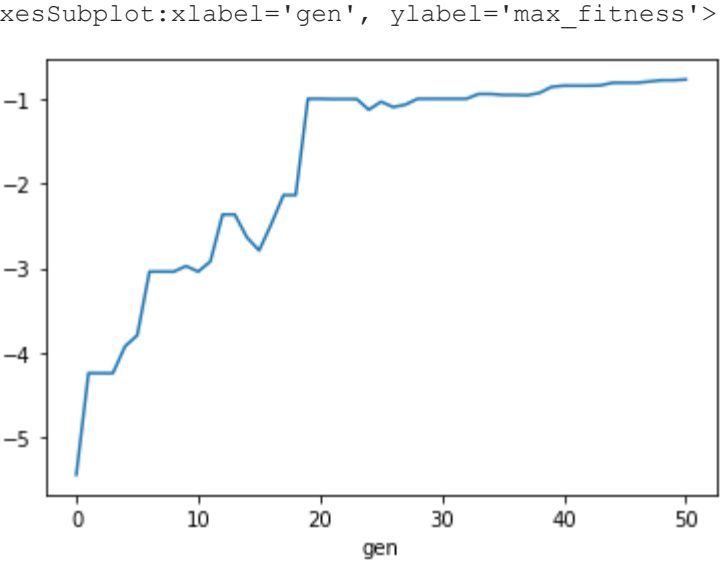
Out[15]:

	gen	max_fitness	avg_nodes	nodes best individual
0	0	-5.453263	3.843	5
1	1	-4.246982	3.600	4
2	2	-4.246982	3.489	4
3	3	-4.246982	3.519	4
4	4	-3.927896	3.763	6
5	5	-3.797742	4.156	6
6	6	-3.041613	4.558	6
7	7	-3.041613	4.898	6
8	8	-3.041613	5.011	7
9	9	-2.975597	4.902	6
10	10	-3.041613	4.789	7
11	11	-2.921019	4.983	8
12	12	-2.363699	5.251	8
13	13	-2.363699	5.654	8
14	14	-2.635686	5.918	15
15	15	-2.790636	6.327	8
16	16	-2.475647	6.493	8
17	17	-2.133204	6.666	10
18	18	-2.133204	6.909	10
19	19	-0.990774	6.987	10
20	20	-0.990774	7.178	10
21	21	-0.993626	7.356	12
22	22	-0.993626	7.432	12
23	23	-0.993626	7.562	12
24	24	-1.119979	7.756	10
25	25	-1.025145	7.989	14
26	26	-1.089045	8.163	16
27	27	-1.059242	8.578	14
28	28	-0.990774	9.251	12
29	29	-0.990774	10.285	12
30	30	-0.990774	11.305	12
31	31	-0.990774	12.233	12
32	32	-0.990621	13.571	24
33	33	-0.933577	14.503	26
34	34	-0.933577	15.267	26
35	35	-0.944980	15.398	26
36	36	-0.944980	15.269	26
37	37	-0.948561	16.262	31
38	38	-0.920451	16.724	30
39	39	-0.849018	17.715	18
40	40	-0.835036	19.109	26
41	41	-0.835036	21.087	26
42	42	-0.835036	24.342	26
43	43	-0.831504	26.995	28
44	44	-0.800457	29.136	68
45	45	-0.800457	32.143	68
46	46	-0.800457	33.582	68
47	47	-0.785629	34.769	28
48	48	-0.770763	35.220	78
49	49	-0.770763	38.018	78
50	50	-0.761353	42.007	72

8.a

In [16]:
```
# question a
seaborn.lineplot(data=df,x='gen',y='max_fitness')
```

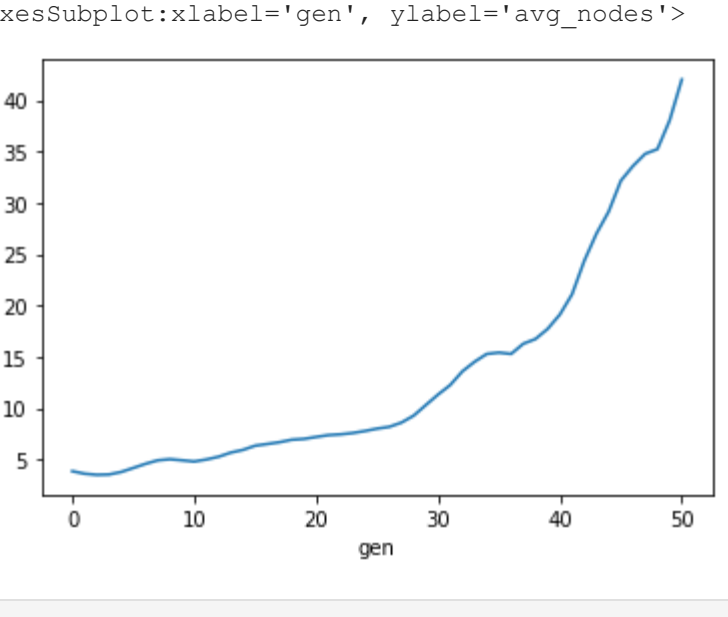
Out[16]: `<AxesSubplot:xlabel='gen', ylabel='max_fitness'>`



8.b

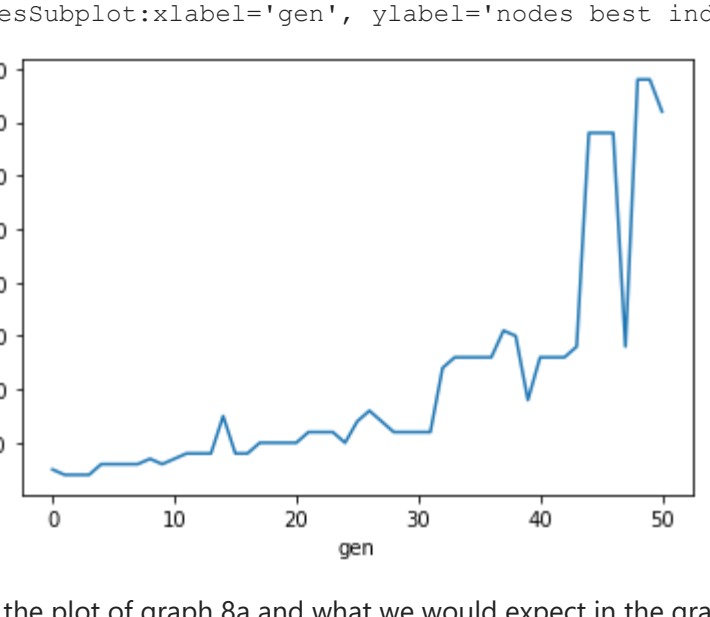
In [17]:
```
# question b (BONUS plot with averagenodes best individual nodes)
# gebruik ipv y= avg_nodes de size van de beste individual (gebruik HallOffame) ,
seaborn.lineplot(data=df,x='gen',y='avg_nodes')
```

Out[17]: `<AxesSubplot:xlabel='gen', ylabel='avg_nodes'>`



In [18]:
```
# question b
# gebruik ipv y= avg_nodes de size van de beste individual (gebruik HallOffame) ,
seaborn.lineplot(data=df,x='gen',y='nodes best individual')
```

Out[18]: `<AxesSubplot:xlabel='gen', ylabel='nodes best individual'>`



b) In the plot of graph 8a and what we would expect in the graph of 8b we see observe that running the model somethimes converges quicker than other times with visable plateaus in the search space. We also see a steady increase in the avg number of nodes in graph 8b (and expect to see this in 8b if we plotted the number nodes of the best individual per iteration). The problem this will cause is bloat. That the search algorithm is baised towards bigger trees. Note that now 8b is also plotted and we see that indeed the size of the trees increases over time, also for the best individual.

We can try to overcome this issue by adjusting the max lenght of a tree, pruning or giving a penality for big trees. Or reducing the size of the trees by applying simplification[1], creating several childsubtrees from the parent tree. This ofcourse causes the childtrees to be less bloated than the parent tree as they are per defenition smaller.

[1] Javed, Noman, and Fernand Gobet. "On-the-fly simplification of genetic programming models." Proceedings of the 36th Annual ACM Symposium on Applied Computing. 2021.