tsp

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1 Overview

In this notebook we tried to find a sufficent enough solution for the **TSP** problem using genetic or memtic algorithems. Here we describe shortly the following concepts in a genetic algorithems that we used in this notebook

1.0.1 1. Gene

We used a permutation as gene in this problem due to the fact that each hamiltonian path (or cycle) should contain each vertex in the graph exactly once, mimicing a permutation.

1.0.2 2. Initial population

Instead of using all random shuffled permutations we used a greedy approach as we call it NeaigherstNeighbor, in this approach, an starting vertex is randomly selected, and from then, we start greedily pick the next vertex in the path that is closest to the current vertex and not yet been selected in the path. In order to bring diversity, we used 50% of the greedy algorithem and 50% of a random shuffled permutation.

1.0.3 3. Fitness function

The obvious fitness function for this problem is the some of weights of edges in the path.

 $fitness(gene) = _{edge path}^{\ } W(edge)$

1.0.4 4. Mutation

Out mutation is as a matter of facts a simple process in graph called **switch**. Figure we have two edges $a \to b$ and $c \to d$, we switch the edges to be like $a \to d$ and $b \to c$, this does not make any abrupt changes in the fitness function that the mutated version is not going to be a candidate for a good solution anymore, but also it changes so slightly that it may be able to escape simple local minumum implemented as **mutation**.

1.0.5 5. crossover

I tried various simple crossovers, implemented as crossover, crossover2 and cycle_crossover which are two-cut crossover, one-cut crossover and cycle decomposition crossover which are common functions for a permutation gene. however they did not bring good enough results. my own function named as my_crossover is a bit different. The idea originates from the fact that there are some small subsegments of each path, that are almost in every good solution, but the way

these subsegments are put toghether, makes the differences. so I find these mutual subsegments in both parents and reconnect them greedily to each other.

1.0.6 6. Other

The other parts that are of less importance are shown using comments in the code like the selection method or recombination.

2 Setup

```
[189]: import random
import numpy as np
import pandas as pd
```

3 Import Data

```
[148]: def testcase(id) :
    tstcase = pd.read_csv("TSP-Tests/" + id + ".tsp")
    n = int(tstcase.iloc[2, 0].split()[1])
    pos = []
    for i in range(n) :
        x, y = map(float, tstcase.iloc[6 + i, 0].split()[1:])
        pos.append([x, y])

    return n, pos
```

```
[5]: import math
```

```
[6]: def dist(p1, p2):
    return math.sqrt((p1[0] - p2[0])**2 + (p1[1] - p2[1])**2)
```

```
[192]: n, pos = testcase("gr229")
W = []
global W
for i in range(n) :
          W.append([])
          for j in range(n) :
                W[i].append(dist(pos[i], pos[j]))
```

4 Gene

```
[197]: class Gene() :
    def __init__(self, n) :
        self.n = n
```

```
self.path = list(range(self.n))
      random.shuffle(self.path)
      self.fitness = self.cal_fitness()
  def cal_fitness(self) :
      fit = 0
      for i in range(self.n) :
          fit += W[self.path[(i) % self.n]][self.path[(i + 1) % self.n]]
      self.fitness = fit
      return self.fitness
  def mutation(self, alpha = 0.15) :
      if random.random() < alpha:</pre>
          edge_a = random.randint(0, self.n - 2)
          edge_b = random.randint(0, self.n - 2)
          if(edge_a > edge_b) :
               edge_a, edge_b = edge_b, edge_a
          self.path = self.path[:edge_a + 1] + self.path[edge_b + 1:] + self.
→path[edge_a + 1: edge_b + 1]
      self.cal_fitness()
  def local_search(self, iter = 20) :
      for _ in range(iter) :
          temp = Gene(self.n)
          temp.path = self.path.copy()
          for i in range(self.n // 20) :
              a = random.randint(0, self.n - 1)
              b = random.randint(0, self.n - 1)
              self.path[a], self.path[b] = self.path[b], self.path[a]
          temp.cal_fitness()
          if(temp.fitness > self.fitness) :
              self.path = temp.path
              self.fitness = temp.fitness
```

5 Crossover

```
[9]: def crossover(par1 : Gene, par2 : Gene) -> Gene :
         child = Gene(par1.n)
         start = random.randint(0, par1.n - 2)
         end = random.randint(start, par1.n - 1)
         center = par2.path[start : end + 1]
         left = []
         right = []
         counter = 0
         for i in range(len(par1.path)):
             if (par1.path[i] not in center):
                 if (counter < start):</pre>
                     left.append(par1.path[i])
                 else:
                     right.append(par1.path[i])
                 counter += 1
         child.path = left + center + right
         child.cal_fitness()
         return child
```

```
child.path = left + center + right
child.cal_fitness()
return child
```

```
[11]: def cycle_crossover(par1 : Gene, par2 : Gene) -> Gene :
          child = Gene(par1.n)
          cycles = []
          mark = []
          for i in range(par1.n) :
              if(par1.path[i] in mark) :
                  continue
              cycle = []
              node = par1.path[i]
              while(node not in cycle) :
                  cycle.append(node)
                  mark.append(node)
                  node = par1.path[par2.path.index(node)]
              cycles.append(cycle)
          for i in range(par1.n) :
              x = par1.path[i]
              idx = 0
              for j in range(len(cycles)) :
                  if(x in cycles[j]) :
                      idx = j
                      break
              if(idx \% 2 == 0) :
                  child.path[i] = par1.path[i]
              else :
                  child.path[i] = par2.path[i]
          child.cal_fitness()
          return child
```

```
for i in range(1, par1.n) :
      \hookrightarrow 1])) == 1):
          seg.append(child.path[i])
      else :
          segments.append(seg)
          seg = [child.path[i]]
  segments.append(seg)
  mark = [0] * len(segments)
  mark[0] = 1
  par = [i for i in range(len(segments))]
  pth = segments[0]
  i = 0
  for _ in range(len(segments) - 1) :
      bst_seg = 0
      bst_val = 1000000
      for j in range(len(segments)) :
         en = segments[i][-1]
          st = segments[j][0]
          if(mark[j] == 0 and W[en][st] < bst_val) :</pre>
             bst_val = W[en][st]
             bst_seg = j
      mark[bst\_seg] = 1
      par[bst_seg] = par[i]
      i = bst_seg
      pth.extend(segments[bst_seg])
  child.path = pth
  child.cal_fitness()
  if(len(set(child.path)) != par1.n) :
      print(segments)
      print(mark)
      print(par)
      print(child.path)
  return child
```

```
[125]: def NearstNeighborGreedy(st, n) :
    res = Gene(n)
    res.path = [st]

mark = [0] * n
    mark[st] = 1
```

```
while(len(res.path) != n) :
    v = res.path[-1]
    bst_value = 10000000
    bst_node = 0
    for i in range(n) :
        if(W[v][i] < bst_value and mark[i] == 0) :
            bst_node = i
            bst_value = W[v][i]
    res.path.append(bst_node)
    mark[bst_node] = 1

return res</pre>
```

6 Genetic Algorithem

```
[204]: def genetic_algorithem(iterations, pop_size, n, alpha = 0.2, is_memtic = False,__
        ⇔elite_rate = 0.05, prep_p = 0.2) :
           hist = []
           # first population
           # -----
           population = []
           for i in range(pop_size // 2) :
               st = random.randint(0, n - 1)
               population.append(NearstNeighborGreedy(st, n))
           for i in range(pop_size // 2) :
               population.append(Gene(n))
           # random.shuffle(population)
           population.sort(key = lambda x : x.fitness, reverse = False)
           hist.append(population[0].fitness)
           for _ in range(iterations) :
               elite = population[:int(n * elite_rate)]
               children = []
               # selection
               for __ in range(pop_size) :
                    # parents = random.choices(population, k = 2, weights = \lfloor (n - i)/\rfloor
        \hookrightarrow (n*(n + 1)/2) for i in range(len(population))])
                    # tournament
```

```
parents = random.choices(population, k = 3, weights = [1 for i inu
→range(len(population))])
         parents.sort(key = lambda x : x.fitness, reverse = False)
         parents = parents[:2]
         # crossover
         # -----
         child = my_crossover(*parents)
         # -----
         # mutation
         # -----
         child.mutation(alpha)
         children.append(child)
     # local search (Memtic Algorithem)
      # -----
     if is_memtic :
         for i in range(len(children) // 2) :
            children[i].local_search()
     # replacement
      # -----
     npop = elite
     children.sort(key = lambda x : x.fitness, reverse = False)
     for gene in population[len(elite):] :
         q = random.random()
         if(q < prep_p) :</pre>
            npop.append(gene)
     rem = pop_size - len(npop)
     for i in range(int(rem * 0.05)) :
         npop.append(children[i])
     while(len(npop) != pop_size) :
         x = random.randint(int(rem * 0.05), len(children) - 1)
         npop.append(children[x])
     population = npop
     population.sort(key = lambda x : x.fitness, reverse = False)
```

```
if(_ % 50 == 0) :
    print('best_fitness of iter ' ,_, " : ", population[0].fitness)

# exit strategy
# ------

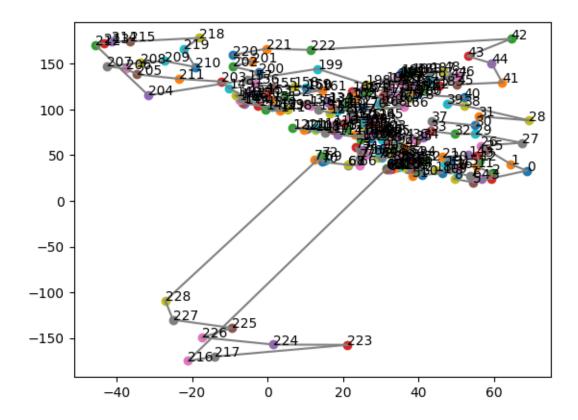
hist.append(population[0].fitness)

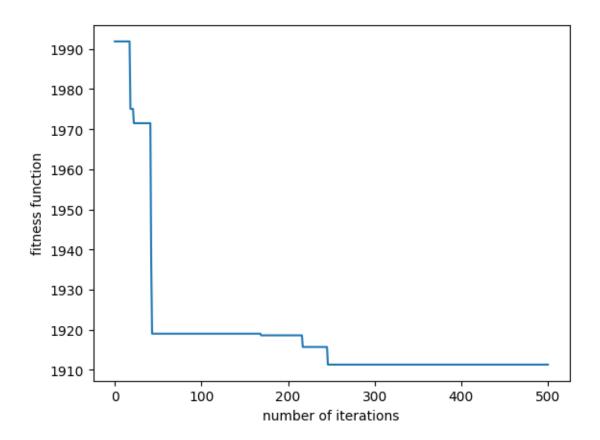
return [population[0], hist]
```

7 Plot solution

8 Testcase #1

```
[212]: res = genetic_algorithem(501, 100, n)
sol = res[0]
hist = res[1]
draw_solution(sol, pos)
draw_plot(hist[1:])
```





9 Testcase #2

```
[213]: n, pos = testcase("pr1002")
       W = []
       global W
       for i in range(n) :
           W.append([])
           for j in range(n) :
               W[i].append(dist(pos[i], pos[j]))
[216]: res2 = genetic_algorithem(301, 100, n)
       sol2 = res2[0]
       hist2 = res2[1]
       draw_solution(sol2, pos)
       draw_plot(hist2)
      best_fitness of iter 0 : 316653.2034460359
      best_fitness of iter
                                   312185.29473546124
                            50 :
      best_fitness of iter
                                    311963.9835895973
                            100
      best_fitness of iter
                                    311963.9835895973
                           150
```

best_fitness of iter 200 : 311963.9835895973
best_fitness of iter 250 : 311963.9835895973
best_fitness of iter 300 : 311963.9835895973

