# Tabu Search\*

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### Abstract

The Clever Algorithms project aims to describe a large number of Artificial Intelligence algorithms in a complete, consistent, and centralized manner, to improve their general accessibility. The project makes use of a standardized algorithm description template that uses well-defined topics that motivate the collection of specific and useful information about each algorithm described. This report describes the Tabu Search algorithm using the standardized template.

Keywords: Clever, Algorithms, Description, Optimization, Tabu, Search

### 1 Introduction

The Clever Algorithms project aims to describe a large number of algorithms from the fields of Computational Intelligence, Biologically Inspired Computation, and Metaheuristics in a complete, consistent and centralized manner [1]. The project requires all algorithms to be described using a standardized template that includes a fixed number of sections, each of which is motivated by the presentation of specific information about the technique [2]. This report describes the Tabu Search algorithm using the standardized template.

### 2 Name

Tabu Search, TS, Taboo Search

# 3 Taxonomy

Tabu Search is a Global Optimization algorithm and a Metaheuristic or Meta-strategy for controlling an embedded heuristic technique. Tabu Search is a parent for a large family of derivative approaches that introduce memory structures in Metaheuristics, such as Reactive Tabu Search and Parallel Tabu Search.

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## 4 Strategy

The objective for the Tabu Search algorithm is to constrain an embedded heuristic from returning to recently visited areas of the search space, referred to as cycling. The strategy of the approach is to maintain a short term memory of the specific changes of recent moves within the search space and preventing future moves from undoing those changes. Additional intermediate-term memory structures may be introduced to bias moves toward promising areas of the search space, as well as longer-term memory structures that promote a general diversity in the search across the search space.

### 5 Procedure

Algorithm 1 provides a pseudo-code listing of the Tabu Search algorithm for minimizing a cost function. The listing shows the simple Tabu Search algorithm with short term memory, without intermediate and long term memory management.

**Algorithm 1**: Pseudo Code for the Tabu Search algorithm.

```
Input: TabuList_{size}
    Output: S_{best}
 1 S_{best} \leftarrow \texttt{ConstructInitialSolution()};
    TabuList \leftarrow 0;
 3 while ¬ StopCondition() do
        CandidateList \leftarrow 0:
 4
        for S_{candidate} \in Sbest_{neighborhood} do
 5
             \mathbf{if} \ \neg \ \mathsf{ContainsAnyFeatures} (S_{candidate}, \ \mathsf{TabuList}) \ \mathbf{then}
 6
                 CandidateList \leftarrow S_{candidate};
             end
 8
        end
        S_{candidate} \leftarrow \texttt{LocateBestCandidate(CandidateList)};
10
        if Cost(S_{candidate}) \leq Cost(S_{best}) then
11
             S_{best} \leftarrow S_{candidate};
12
             TabuList \leftarrow FeatureDifferences(S_{candidate}, S_{best});
13
             while TabuList > TabuList_{size} do
14
              DeleteFeature(TabuList);
15
             end
16
        end
17
18 end
19 return S_{best};
```

#### 6 Heuristics

- Tabu search was designed to manage an embedded hill climbing heuristic, although may be adapted to manage any neighborhood exploration heuristic.
- Tabu search was designed for, and has predominately been applied to discrete domains such as combinatorial optimization problems.
- Candidates for neighboring moves can be generated deterministically for the entire neighborhood or the neighborhood can be stochastically sampled to a fixed size, trading off efficiency for accuracy.

- Intermediate-term memory structures can be introduced (complementing the short-term memory) to focus the search on promising areas of the search space (intensification), called aspiration criteria.
- Long-term memory structures can be introduced (complementing the short-term memory) to encourage useful exploration of the broader search space, called diversification. Strategies may include generating solutions with rarely used components and biasing generation away from the most commonly used solution components.

# 7 Code Listing

Listing 1 provides an example of the Tabu Search algorithm implemented in the Ruby Programming Language. The algorithm is applied to the Berlin52 instance of the Traveling Salesman Problem (TSP), taken from the TSPLIB. The problem seeks a permutation of the order to visit cities (called a tour) that minimized the total distance traveled. The optimal tour distance for Berlin52 instance is 7542 units.

The algorithm is an implementation of the simple Tabu Search with a short term memory structure that executes for a fixed number of iterations. The starting point for the search is prepared using a random permutation that is refined using a stochastic 2-opt Local Search procedure. The stochastic 2-opt procedure is used as the embedded hill climbing heuristic with a fixed sized candidate list. The two edges that are deleted in each 2-opt move are stored on the tabu list. This general approach is similar to that used by Knox in his work on Tabu Search for symmetrical TSP [14] and Fiechter for the Parallel Tabu Search for the TSP [4].

```
MAX_ITERATIONS = 100
   MAX_NO_IMPROVEMENTS = 50
   TABU_LIST_SIZE = 15
   MAX\_CANDIDATES = 50
4
   BERLIN52 = [[565,575],[25,185],[345,750],[945,685],[845,655],[880,660],[25,230],[525,1000],
5
    [580,1175], [650,1130], [1605,620], [1220,580], [1465,200], [1530,5], [845,680], [725,370], [145,665],
6
    [415,635], [510,875], [560,365], [300,465], [520,585], [480,415], [835,625], [975,580], [1215,245],
7
     [1320,315], [1250,400], [660,180], [410,250], [420,555], [575,665], [1150,1160], [700,580], [685,595],
8
     [685,610], [770,610], [795,645], [720,635], [760,650], [475,960], [95,260], [875,920], [700,500],
9
     [555,815],[830,485],[1170,65],[830,610],[605,625],[595,360],[1340,725],[1740,245]]
10
11
12
   def euc_2d(c1, c2)
     Math::sqrt((c1[0] - c2[0])**2.0 + (c1[1] - c2[1])**2.0).round
13
14
15
   def cost(permutation, cities)
16
     distance =0
17
     permutation.each_with_index do |c1, i|
18
       c2 = (i==permutation.length-1) ? permutation[0] : permutation[i+1]
19
       distance += euc_2d(cities[c1], cities[c2])
20
21
     return distance
22
   end
23
24
25
   def random_permutation(cities)
     all = Array.new(cities.length) {|i| i}
26
     return Array.new(all.length) {|i| all.delete_at(rand(all.length))}
27
   end
28
29
   def stochastic_two_opt(permutation)
30
     perm = Array.new(permutation)
31
     c1, c2 = rand(perm.length), rand(perm.length)
32
     c2 = rand(perm.length) while c1 == c2
33
     c1, c2 = c2, c1 if c2 < c1
34
     perm[c1...c2] = perm[c1...c2].reverse
35
```

```
return perm, [[permutation[c1-1], permutation[c1]], [permutation[c2-1], permutation[c2]]]
36
37
38
   def generate_initial_solution(cities, maxNoImprovements)
39
     best = {}
40
     best[:vector] = random_permutation(cities)
41
42
     best[:cost] = cost(best[:vector], cities)
43
     noImprovements = 0
     begin
44
       candidate = {}
45
       candidate[:vector] = stochastic_two_opt(best[:vector])[0]
46
       candidate[:cost] = cost(candidate[:vector], cities)
47
       if candidate[:cost] <= best[:cost]</pre>
48
         noImprovements, best = 0, candidate
49
       else
50
51
         noImprovements += 1
52
       end
     end until noImprovements >= maxNoImprovements
53
54
     return best
55
   end
56
   def is_tabu?(permutation, tabuList)
57
     permutation.each_with_index do |c1, i|
58
       c2 = (i==permutation.length-1) ? permutation[0] : permutation[i+1]
59
       tabuList.each do |forbidden_edge|
60
61
         return true if forbidden_edge == [c1, c2]
62
       end
63
     end
64
     return false
65
   end
66
   def generate_candidate(best, tabuList, cities)
67
     permutation, edges = nil, nil
68
69
70
       permutation, edges = stochastic_two_opt(best[:vector])
71
     end while is_tabu?(permutation, tabuList)
72
     candidate = {}
     candidate[:vector] = permutation
73
74
     candidate[:cost] = cost(candidate[:vector], cities)
     return candidate, edges
75
   end
76
77
   def search(cities, tabuListSize, candidateListSize, maxIterations, maxNoImprovementsLS)
78
79
     best = generate_initial_solution(cities, maxNoImprovementsLS)
     tabuList = Array.new(tabuListSize)
80
81
     maxIterations.times do |iter|
       candidates = Array.new(candidateListSize) {|i| generate_candidate(best, tabuList, cities)}
82
       candidates.sort! {|x,y| x.first[:cost] <=> y.first[:cost]}
83
       bestCandidate = candidates.first[0]
       bestCandidateEdges = candidates.first[1]
85
       if(bestCandidate[:cost] < best[:cost])</pre>
86
         best = bestCandidate
87
         bestCandidateEdges.each do |edge|
88
           tabuList.pop
89
           tabuList.push(edge)
90
91
92
93
       puts " > iteration #{(iter+1)}, best: c=#{best[:cost]}"
94
     end
95
     return best
96
   end
97
   best = search(BERLIN52, TABU_LIST_SIZE, MAX_CANDIDATES, MAX_ITERATIONS, MAX_NO_IMPROVEMENTS)
```

Listing 1: Tabu Search algorithm in the Ruby Programming Language

## 8 References

## 8.1 Primary Sources

Tabu Search was introduced by Glover applied to scheduling employees to duty rosters [11] and a more general overview in the context of the TSP [7], based on his previous work on surrogate constraints on integer programming problems [6]. Glover provided a seminal overview of the algorithm in a two-part journal article, the first part of which introduced the algorithm, and reviewed then-recent applications [8], and the second which focused on advanced topics and open areas of research [9].

#### 8.2 Learn More

Glover provides a high-level introduction to Tabu Search in the form of a practical tutorial [10], as does Glover and Taillard in a user guide format [12]. The best source of information for Tabu Search is the book dedicated to the approach by Glover and Laguna that covers the principles of the technique in detail as well as an in-depth review of applications [13]. The approach appeared in Science, that considered a modification for its application to continuous function optimization problems [3]. Finally, Gendreau provides an excellent contemporary review of the algorithm, highlighting best practices and application heuristics collected from across the field of study [5].

### 9 Conclusions

This report described the Tabu Search algorithm as an approach that adds a memory structure to an existing hill climbing heuristic to prohibit cycling-like behavior while navigating the search space.

Some research discovered during the preparation of this report that may prove useful to the Clever Algorithms project was a list of heuristics for applying a previously unknown technique to a given problem by Gendreau [5]. These heuristics may be generalized and provided and elaborated as an advanced topic to accompany with algorithm descriptions prepared for the project.

#### 10 Contribute

Found a typo in the content or a bug in the source code? Are you an expert in this technique and know some facts that could improve the algorithm description for all? Do you want to get that warm feeling from contributing to an open source project? Do you want to see your name as an acknowledgment in print?

Two pillars of this effort are i) that the best domain experts are people outside of the project, and ii) that this work is wrong by default. Please help to make this work less wrong by emailing the author 'Jason Brownlee' at jasonb@CleverAlgorithms.com or visit the project website at http://www.CleverAlgorithms.com.

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