Evolutionary Computation 2024/25 Master Artificial Intelligence

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two main classes:

• Monte Carlo algorithm:

for a certain number of iterations do:

- perform some randomized algorithm step towards a better solution
- (usually keep track of your best solution found so far)
- Monte Carlo algorithms always terminate and (hopefully) find a somewhat good solution.
- Las Vegas algorithm:

while a certain end condition still is not met do:

- perform some randomized algorithm step towards a better solution
- Las Vegas algorithms only terminate with a correct solution (or do not terminate at all), but their runtime is probabilistic.

classical algorithmic paradigms

- backtracking
- branch and bound
- brute-force (or exhaustive) search
- divide and conquer
- dynamic programming
- greedy algorithm
- prune and search
- online algorithms

What are heuristic algorithms?

- Just do something (you come up with)
- and be happy (with the properties of the result).

What are evolutionary algorithms?

- Evolutionary algorithms are heuristic optimization algorithms usually implemented with the Monte Carlo approach (and possibly a Las Vegas stopping condition when available)
- that exhibit, let's say, at least a tendency to approach a global minimum as solution of the optimization problem.
- Often they are inspired by some phenomenon observable in nature (or a *creative* name has been used).
- for evolutionary algorithms often much weaker properties are accepted for the output configuration, i.e., for TSP the guaranteed property is just to have at least a tour, but the tour might be arbitary far from the optimum

- Given a search space X (called as well search domain or problem space) and
- a function *f* (bounded from below) from the search space to the real numbers (or at least a totally ordered set), e.g.
 f : X → R,
- find an element $x^* \in \mathbb{X}$ such that $f(x^*) \leq f(x)$ for all $x \in \mathbb{X}$.
- i.e., we look for a global minimum.

Observe: whenever we look for a maximum, we can use just a negative sign and look for a minimum (and *f* must be bounded from above)!

local versus global minimum

- If we can determine a neighborhood around each element $x \in \mathbb{X}$, we call $\mathcal{N}(x)$ the set of neighbors of x.
- and if we have for all such neighbors $x' \in \mathcal{N}(x)$, that $f(x) \leq f(x')$,
- then we call x a local minimum (sometimes written as \hat{x}).
- Reaching a local minimum is often somewhat easier, as we can take advantage of a possibly available gradient (local search algorithms).
- It happens to be an issue in optimization not to get stuck in a local minimum while searching for a global minimum, which is the ultimate goal.
- Often relative error or *gap* is used to qualify the solution: $100 \cdot (L - L_{opt})/L_{opt}$



a closest-neighbor tour: 8.49% gap



a pair-center tour: 7.28% gap



the best tour (known for this example): 0% gap



a quick tour (with Monte Carlo): 2.32% gap



a genetic algorithm tour: 8.37% gap



the best tour (known for this example): 0% gap

Please ask yourself the question: How would you evaluate approximation algorithms aimed to provide practical solutions to complex problems, especially in order to compare different approaches? For exact algorithms this is easy:

- first prove the algorithm is correct and correcly implemented
- analyse its runtime (according to input size)
- analyse its memory requirements

- simple bound: sum of minimal distances to neighbors
- Held-Karp bound:
 - typically comes close to 1% on random instances
 - and below 2% on TSPLIB, arguments for the bound are quite complicated
 - computing the bound is an iterative process as well (but in polynomial time, or linear time for randomized approximation)
 - can be as worse as 2/3 times optimal length

- tour around minimal spanning tree yields $\leq 2 \cdot L_{opt}$ runtime $\mathcal{O}(n^2)$
- Christofides algorithm yields $\leq 3/2 \cdot L_{opt}$ runtime $\mathcal{O}(n^3)$

known solving algorithms for TSP

- brute force exhaustive search 𝒪(n!) (quite easy to implement)
- Bellman-Held-Karp dynamic programming for Euclidean TSP 𝒪(n²2ⁿ) time and 𝒪(n2ⁿ) space (not covered here, please refer to advanced algorithms in computer science)
- state-of-the-art solver Concorde

https://www.math.uwaterloo.ca/tsp/concorde.html

• state-of-the-art approximative solver LKH

http://webhotel4.ruc.dk/~keld/research/LKH-3/

start with some small tour generated by a simple heuristic, then:

- use 2-opt moves (modifing tour by changing two edges, for instance, to eliminate crossings in Euclidean TSP)
- or use 3-opt moves (modifying tour by changing three edges);
- or use Lin-Kernighan heuristic algorithm (variable mixture of 2-opt til k-opt moves), currently the best known heuristic strategy





(e)

(f)

i (g) (h)

let's take a look at a regular $m \times n$ grid (e.g. checker board)

- an optimal tour on a regular grid is easy to build
- optimal length:
 - $L_{opt} = n \cdot m$ if *n* or *m* even
 - $L_{opt} = n \cdot m 1 + \sqrt{2}$ if $n \cdot m$ odd
- there are many! optimal tours
- there are other structures of graphs (point sets) that allow for finding easily optimal tours (so it is worthwhile to analyse input data beforehand...)

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More on traveling salesperson problem

- The version of the TSP problem as shown until now is a special case of a more general problem definition:
- Let G = (V, E) be a graph. V are the nodes (or locations), E are the edges (or connections) with some weight (e.g., distance, time, cost).
- Goal: find a minimal tour through all nodes.
- Particularly we talked about the Euclidean TSP, where the nodes are points in the Euclidean plane and the distance among all pairs, hence complete graph, is just the Euclidean distance.

- One step to be more general is, just require the triangular condition to be met (then, possibly, the pair-center approach cannot be used as we have no distances for the centers), this is called the metric TSP (mTSP).
- Moreover, the distances might be asymmetric, i.e., going in one direction is different from going in the other (ATSP).
- or we have additional conditions: open loop, arrival time windows, asymmetric distances, interrupted tours, etc.

More recent results on the eTSP

- In the 90's it was shown that eTSP can be solved in $\mathcal{O}(2^{O(\sqrt{n}\log n)})$.
- In the 10's this was improved to 𝒫(2^{√n}), and with certain arguments that further improvement may be very unlikely.
- One recent result of complexity theory is that eTSP has a polynomial time approximation scheme (PTAS) of $\mathscr{O}_{\varepsilon,d}(n \log n)$ (with fixed error ε and fixed dimension d), however, an implementation is not available (to my knowledge).
- This has been improved to $\mathcal{O}_{\varepsilon,d}(n)$ with high probability (2013).



the cities distributed geographically



a best tour (trivial for this example): 0% gap



a closest-neighbor tour (with Monte Carlo): 3.09% gap



a pair-center tour: 14.46% gap



a best tour (trivial for this example): 0% gap



a quick tour (with Monte Carlo): 0.00% gap



a genetic algorithm tour: 4.14% gap



a best tour (trivial for this example): 0% gap



the locations distributed in the plane



the best tour (known for this example): 0% gap



a closest-neighbor tour (with Monte Carlo): 10.23% gap



a pair-center tour: 13.93% gap


the best tour (known for this example): 0% gap



a quick tour (with Monte Carlo): 9.66% gap



a genetic algorithm (GA) tour: 205.65% gap



the best tour (known for this example): 0% gap

gaps for the above heuristics

problem	heuristic	gap
berlin52	closest neighbor tour	8.49
	quick tour	2.32
	pair-center tour	7.28
	genetic algorithm tour	8.37
	improved pair-center tour	0.00
	Lin-Kernighan tour	0.00
rat195	closest neighbor tour	10.23
	quick tour	9.66
	pair-center tour	13.93
	genetic algorithm tour	205.65
	improved pair-center tour	1.16
	Lin-Kernighan tour	0.00
block40	closest neighbor tour	3.09
	quick tour	0.00
	pair-center tour	14.46
	genetic algorithm tour	4.14
	improved pair-center tour	0.00
	Lin-Kernighan tour	0.00

Your goal: make genetic algorithm tour consistently better than pair-center tour or quick tour

The classical closest-neighbor algorithm is a greedy algorithm with a small random component:

- select a random city
- while there are still unconnected cities
 - connect to the closest unconnected neighbor
 - use a random tie break
- connect the first with the last city
- runtime is $\mathcal{O}(n^2)$,
- can be run in Monte Carlo fashion keeping the shortest tour
- worst tour may have a length up to $0.5 \cdot \log n \cdot L_{opt}$

















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How does the quick tour algorithm work?

The quick tour algorithm (also known as random insertion approach) is a probabilistic greedy algorithm:

- select three random cities to form an initial triangular tour
- while there are still unconnected cities
 - choose a random (closest) unconnected city
 - expand the current tour by inserting the new city such that the tour increment is minimal
- runtime is in $\mathcal{O}(n^2)$,
- the random version can be run in Monte Carlo fashion keeping the shortest tour

There are more similar approaches, e.g., nearest addition or farthest addition.







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The pair-center tour algorithm is a contribution of my own for this course. It is a deterministic algorithm:

- with a bottom-up construction build a binary tree by replacing the/a closest pair of points by their center
- with a top-down construction build the tour by inserting the corresponding pairs in the best possible way
- the runtime is in 𝒪(nlog n), https://www.sciencedirect. com/science/article/pii/S1877750324002175
- implemented is 𝒪(n³) (in Python) and a 𝒪(n polylog n) version with more sophisticated data structures achieving quite low gaps




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length of tour

L _{CN}	closest-neighbor tour (can be large, 1974)
2 · L _{opt} · · · · ·	minimum spanning tree algorithm (or quick tour)
1.5 · L _{opt} · · · · ·	Christofides algorithm (best known, 1976)
L _{play} · · · · ·	playground for good heuristic algorithms
L _{opt}	optimal tour length, Bellman-Held-Karp algorithm (1962)
L _{НКВ}	Held-Karp bound (1971)
L _{MDB}	minimal distance bound (possible $L_{MDB} = L_{opt}$)