Convergence of Simulated Annealing

View the search space X with neighbourhood structure N as a *graph* (X,N). Assume that this graph is undirected, connected, and of degree r. (Each node=solution has exactly r neighbours.)

Denote by $X^* \subseteq X$ the set of globally optimal solutions. The following result was proved by Geman & Geman (1984) and Mitra, Romeo & Sangiovanni-Vincentelli (1986):

Theorem. Consider a simulated annealing computation on structure (X,N,c). Assume the neighbourhood graph (X,N) is connected and regular of degree r. Denote:

$$\Delta = \max\{c(x') - c(x) \mid x \in X, x' \in N(x)\}.$$

Choose

$$L \geq \min_{x \in X \setminus X^*} \max_{x^* \in X^*} \text{dist}(x,x^*),$$

where dist(x,x^*) is the shortest-path distance in graph (X,N) from node x to node x^*. Suppose the cooling schedule used is of the form $\langle T_0,L\rangle, \langle T_1,L\rangle, \langle T_2,L\rangle, \ldots$, where for each cooling stage $\ell \geq 2$:

$$T_\ell \geq \frac{L\Delta}{\ln \ell} \quad (\text{but } T_\ell \xrightarrow[\ell\to\infty]{} 0).$$

Then the distribution of states visited by the computation converges in the limit to π^*, where

$$\pi^*_x = \begin{cases} 0, & \text{if } x \in X \setminus X^*, \\ 1/|X^*|, & \text{if } x \in X^*. \end{cases}$$

3.5 The A* Algorithm

Note: A* is actually a complete algorithm, so should have been presented earlier.

A* is basically a reformulation of the branch-and-bound search technique in terms of path search in graphs.

Given:

- search graph [neighbourhood structure] (X,N)
- *start node* $x_0 \in X$
- set of *goal nodes* $X^* \subseteq X$
- *edge costs* $c(x,x') \geq 0$ for $x \in X$, $x' \in N(x)$

Task: find a (minimum-cost) path from x_0 to some $x \in X^*$.

A*: Path Length Estimation

An important characteristic of A* is that the remaining distance from a node x to a goal node is estimated by some *heuristic* $h(x) \geq 0$.

As the algorithm visits a new node, it is placed in a set OPEN. Nodes in OPEN are selected for further exploration in increasing order of the *evaluation function*

$$f(x) = g(x) + h(x),$$

where $g(x) = \mathrm{dist}(x_0, x)$ is the shortest presently known distance from the start node.

A heuristic $h(x)$ is *admissible*, if it underestimates the true remaining minimal distance $h^*(x)$, i.e. if for all $x \in X$:

$$h(x) \leq h^*(x) := \min_{x^* \in X^*} \mathrm{dist}(x, x^*).$$


```
function A*(X, N, x_0, c, h):
    place x_0 in OPEN; set g(x_0) = 0;
    while OPEN ≠ ∅ do
        choose some x ∈ OPEN for which f(x) is minimum;
        if x ∈ X* then return {found path to x};
        move x from OPEN to CLOSED;
        for all x' ∈ N(x) do
            if x' is not yet in OPEN or CLOSED then
                estimate h(x');
                compute f(x') = g(x') + h(x'),
                    where g(x') = g(x) + c(x, x');
                place x' in OPEN
            else {x' is already in OPEN or CLOSED}
                recompute f(x') = g(x') + h(x');
                if x' was in CLOSED and its f-value decreased then
                    move x' from CLOSED to OPEN
    end while;
    return fail {no path to goal found}.
```


A*: Convergence

A basic property of the A* algorithm is the following:

Theorem. Assume that the heuristic h is admissible. If the graph (X, N) is finite, and some path from x_0 to X^* exists, then A* returns one with a minimum cost.

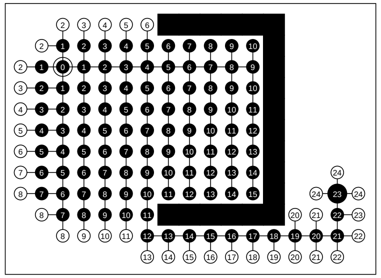
Note 1: This result holds even for infinite search graphs satisfying some structural conditions. (Every node has only finitely many neighbours and all infinite paths have infinite cost.)

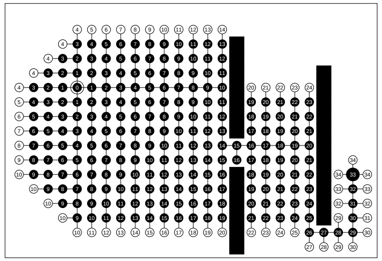
Note 2: Convergence of the algorithm can be guaranteed also for nonadmissible heuristics, but very little can be said about the cost of the paths returned in that case.

Note 3: The special case $h(x) \equiv 0$ reduces to the well-known Dijkstra's algorithm for shortest paths in graphs.

A*: Examples

In these two examples of A* search in graphs with obstacles, the heuristic $h(x)$ is taken to be the Manhattan (square-block) distance from a node x to the goal node x^* when the obstacles are ignored. The white nodes are in OPEN and the black nodes in CLOSED when the algorithm terminates.





3.6 Tabu Search (Glover 1986)

Note: Now we return to local search algorithms.

Idea: Prevent a local search algorithm from getting stuck at a local minimum, or cycling at a set of solutions with the same objective function value, by maintaining a limited history of recent solutions (*tabu list*) and excluding those solutions from the move selection process.

function TABU(c, tt):
    $x \leftarrow$ initial feasible solution;
    initialise TL to $\{x\}$;
    while moves $<$ max_moves **do**
        remove from TL solutions entered there
            more than tt moves ago;
        choose an $x' \in N(x) \setminus TL$ of minimum cost;
        add x to TL;
        $x \leftarrow x'$
    end while;
    return best x seen so far.

Tabu Search: Practical Considerations

To save tabu list memory and access time, it may be worthwhile not to store complete solutions in the list, but just the recent *moves* (local transformations). This, however, introduces the problem that a move may be superfluously tabu at time t from the context of some earlier solution $x_{t'}$, $t' < t$, whereas it would lead to an interesting new solution in the context of solution x_t.

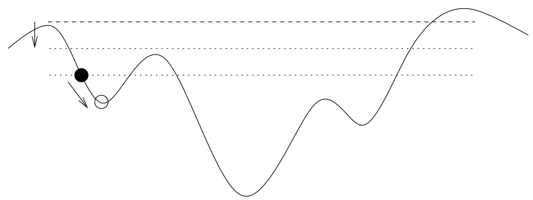
To resolve this issue, heuristics for overriding the tabu rule have been introduced, such as "always accept objective-improving moves" (i.e. such that $c(x') < c(x)$).

3.7 Record-to-Record Travel (Dueck 1993)

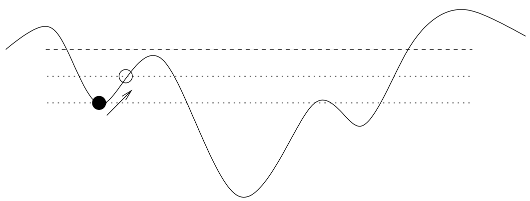
Idea: Candidate solution can move freely within a tolerance δ of the best ("record") solution value found so far. When a new record solution is found, the tolerance level falls correspondingly.

function RRT(c, δ):
  $x \leftarrow$ initial feasible solution;
  $x^* \leftarrow x$; $c^* \leftarrow c(x)$;
  while moves $<$ max_moves **do**
    choose some $x' \in N(x)$;
    if $c(x') \leq c^* + \delta$ **then** $x \leftarrow x'$;
    if $c(x') < c^*$ **then**
      $x^* \leftarrow x'$; $c^* \leftarrow c(x')$
  end while;
  return x^*.

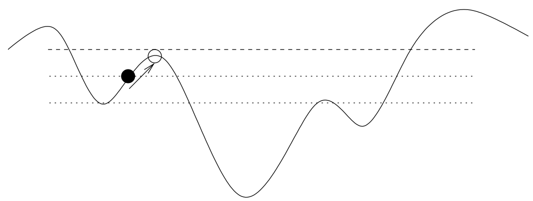
RRT in Action ($\delta = 2$)



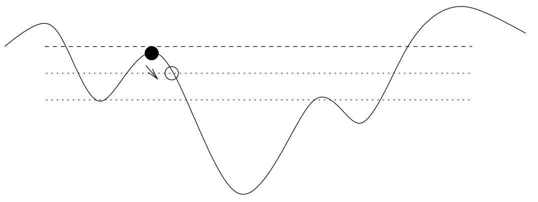
RRT in Action ($\delta = 2$)



RRT in Action ($\delta = 2$)



RRT in Action ($\delta = 2$)



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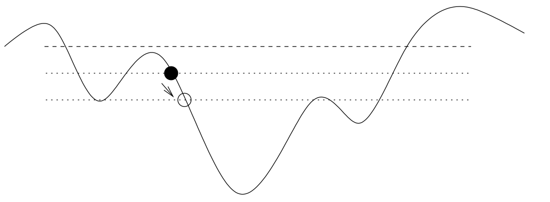
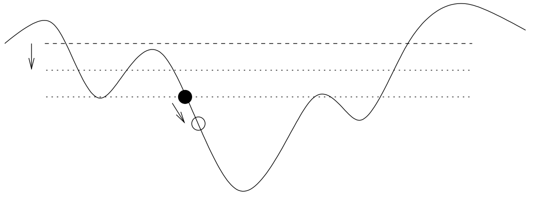
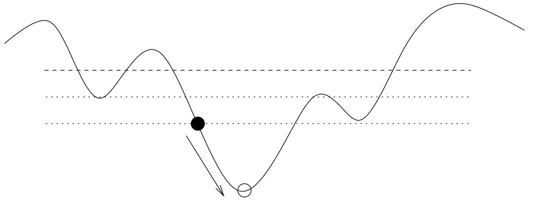


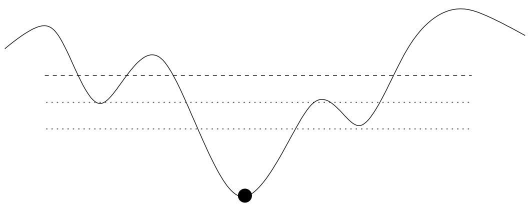
RRT in Action ($\delta = 2$)



RRT in Action ($\delta = 2$)



RRT in Action ($\delta = 2$)



3.8 Local Search for Satisfiability: GSAT (Gu, Selman et al. 1992)

Idea: View propositional satisfiability as an optimisation problem, where $c = c_F(t)$ is the number of unsatisfied clauses in formula F under truth assignment t. Apply a greedy (deterministic) local search strategy to minimise $c(t)$.

function GSAT(F):
  $t \leftarrow$ initial truth assignment;
  while flips $<$ max_flips **do**
    if t satisfies F **then return** t
    else
      find a variable x whose flipping in t causes
        largest decrease in $c(t)$ (if no decrease is
        possible, then smallest increase);
      $t \leftarrow$ (t with variable x flipped)
  end while;
  return t.

NoisyGSAT (Selman et al. $\sim$ 1996)

Idea: Augment GSAT by a fraction p of random walk moves.

function NoisyGSAT(F,p):
  $t \leftarrow$ initial truth assignment;
  while flips $<$ max_flips **do**
    if t satisfies F **then return** t
    else
      with probability p, pick a variable x
        uniformly at random;
      with probability $(1-p)$, do basic GSAT move:
        find a variable x whose flipping causes
        largest decrease in $c(t)$ (if no decrease is
        possible, then smallest increase);
      $t \leftarrow$ (t with variable x flipped)
  end while;
  return t.

3.9 The WalkSAT Algorithm (Selman et al. 1996)

Idea: NoisyGSAT *focused* on the unsatisfied clauses.

```
function WalkSAT(F,p):
    t ← initial truth assignment;
    while flips < max_flips do
        if t satisfies F then return t else
            choose a random unsatisfied clause C in F;
            if some variables in C can be flipped without
                breaking any presently satisfied clauses,
                then pick one such variable x at random; else:
            with probability p, pick a variable x in C unif. at random;
            with probability (1 − p), do basic GSAT move:
                find a variable x in C whose flipping causes
                largest decrease in c(t);
            t ← (t with variable x flipped)
    end while;
    return t.
```


WalkSAT vs. NoisyGSAT

The focusing seems to be important: in the (unsystematic) experiments in Selman et al. (1996), WalkSAT outperforms NoisyGSAT by several orders of magnitude. Later experimental evidence by other authors corroborates this.

Good values for the “noise” parameter p seem to be about $p \approx 0.5$. For instance, for large randomly generated 3-SAT formulas with clauses-to-variables ratio α near the “satisfiability threshold” $\alpha = 4.267$, the optimal value of p seems to be about $p = 0.57$.