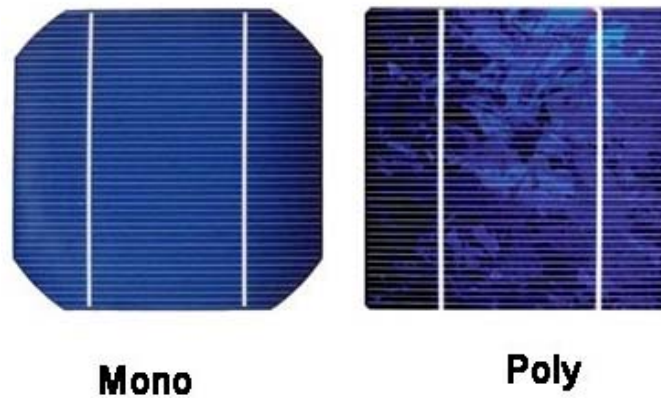


# Iterative Improvement Simulated Annealing

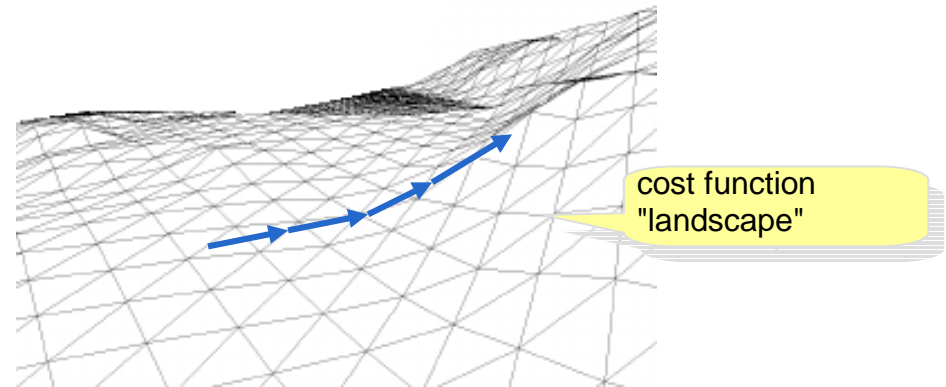


Slides based on lecture by Van Larhoven

# Iterative Improvement

# Iterative Improvement

- General method to combinatorial optimization problems



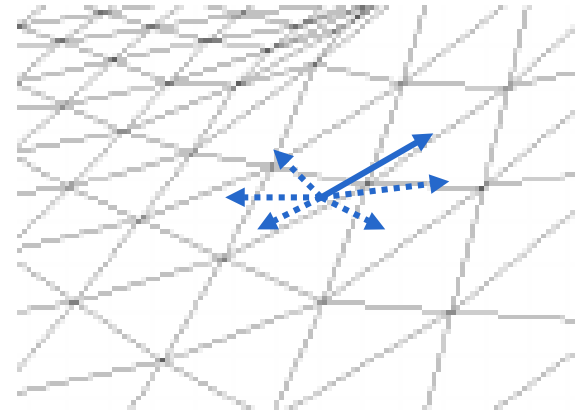
## Principle:

- Start with initial configuration
- Evaluate Gradient of some cost function (or fitness function)
- Go to direction of Gradient
- Stop if quality is sufficiently high, if no improvement can be found or after some fixed time

$$\nabla f(p) = \begin{bmatrix} \frac{\partial f}{\partial x_1}(p) \\ \vdots \\ \frac{\partial f}{\partial x_n}(p) \end{bmatrix}.$$

# Iterative Improvement - without Gradient

- General method to solve combinatorial optimization problems



## Principle:

- Start with initial configuration
- Randomly or systematically search neighborhood and select a most promising neighbor as candidate
- Evaluate some cost function (or fitness function) and accept candidate if "better"; if not, select another neighbor
- Stop if quality is sufficiently high, if no improvement can be found or after some fixed time

# Iterative Improvement Prerequisites

Needed are:

- A method to generate initial configuration
- A transition or generation function to find a neighbor as next candidate
- A cost function
- An Evaluation Criterion
- A Stop Criterion

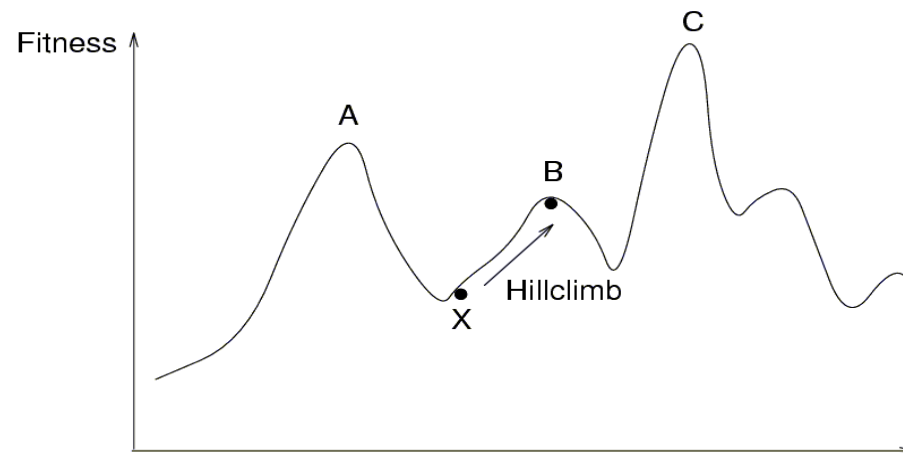
# Iterative Improvement Pros- and Cons

## Simple Iterative Improvement or Hill Climbing:

- Candidate is always and only accepted if cost is lower (or fitness is higher) than current configuration
- Stop when no neighbor with lower cost (higher fitness) can be found

## Disadvantages:

- Local optimum as best result
- Local optimum depends on initial configuration
- Generally no upper bound on iteration length



# How to cope with disadvantages

- Repeat algorithm many times with different initial configurations
- Use information gathered in previous runs
- Use a more complex Generation Function to jump out of local optimum
  
- Use a more complex Evaluation Function:
  - Do sometimes accept candidates with higher cost to escape from local optimum
  - Adapt the parameters of this Evaluation Function during execution
  - Based upon the analogy with the simulation of the annealing of solids

# Simulated Annealing



# Simulated Annealing

Use a more complex Evaluation Function:

- Do sometimes accept candidates with higher cost to escape from local optimum
- Adapt the parameters of this Evaluation Function during execution
- Based upon the analogy with the simulation of the annealing of solids

## ■ Other Names

- Monte Carlo Annealing
- Statistical Cooling
- Probabilistic Hill Climbing
- Stochastic Relaxation
- Probabilistic Exchange Algorithm

# Analogy

- Slowly cool down a heated solid, so that all particles arrange in the ground energy state -> e.g. crystal
- At each temperature wait until the solid reaches its thermal equilibrium
- Probability of being in a state with energy  $E$  :

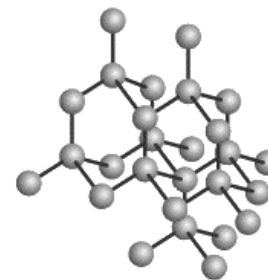
$$P(E = E_i) = \exp(-E / k_B * T * Z_{T0})$$

$E$  Energy/Cost

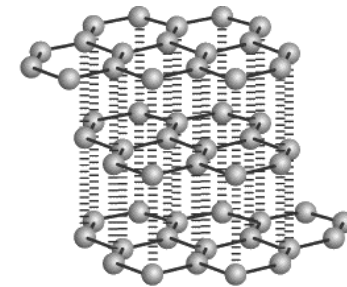
$T$  Temperature

$k_B$  Boltzmann constant

$Z_{T0}$  Normalization factor (ev. temperature dependant)



Diamant



Graphite

# Simulation of cooling (Metropolis 1953)

- At temperature  $T$ :
- Perturb (randomly) the current state to a new state
- $\Delta E$  is the difference in energy between current and new state
- If  $\Delta E < 0$  (new state is lower), accept new state as current state
- If  $\Delta E > 0$ , accept new state with probability

$$P(\text{accept}) = \exp(-\Delta E / k_B T)$$

- Eventually the system evolves into thermal equilibrium at temperature  $T$ ; then the formula mentioned before holds
- When equilibrium is reached, temperature  $T$  can be lowered and the process can be repeated

# Simulated Annealing

- Same algorithm can be used for combinatorial optimization problems:
- Energy  $E$  corresponds to the Cost function  $C$
- Temperature  $T$  corresponds to control parameter  $t$

$$P(\text{config} = \text{config}_i) = \exp(-\Delta C(i) * K_{c0} / c)$$

$C$  Cost

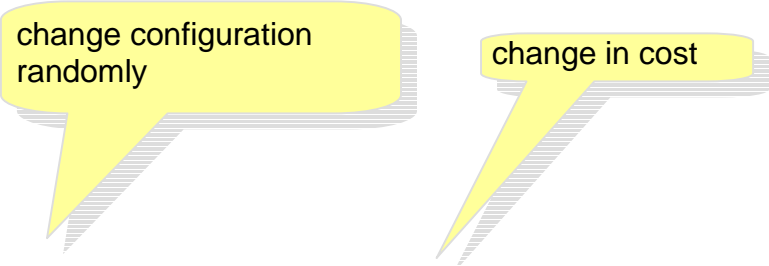
$c$  Temperature of Control parameter (slowly decreasing  $\rightarrow 0$ )

$K_{c0}$  Normalization factor

chose so that there is a 50% initial chance

# Algorithm

```
initialize;  
count = 0;  
bolzCount = 0;  
acceptCount = 0;  
LOOP  
    count++;  
    perturb ( config.i  $\rightarrow$  config.j,  $\Delta C_{ij}$ );  
    IF  $\Delta C_{ij} < 0$  THEN accept  
    ELSE IF  $\Delta C_{ij} > 0$  AND  $\exp(-\Delta C_{ij}/c) > \text{random}[0,1]$  THEN  
        accept; bolzCount++;  
    IF accept THEN update(config.j); acceptCount++;  
    measureProgress  
    next_lower (c)  
END
```



# Algorithm Termination/Acceptance

- For termination condition measure progress
- e.g. count accepted transitions in 1000 iterations

**measureProgress:**

```
IF count % 1000 == 0 THEN
    IF acceptCount == 0 BREAK
    ELSE bolzCount = 0; acceptCount = 0;
END
```

- Choose the start value of  $c$  so that in the beginning nearly all perturbations are accepted (*exploration*), but not too big to avoid long run times
- The function *next\_lower* in the homogeneous variant is generally a simple function to decrease  $c$ , e.g. a fixed part (80%) of current  $c$
- At the end  $c$  is so small that only a very small number of the perturbations is accepted (*exploitation*)
- If possible, always try to remember explicitly the best solution found so far; the algorithm itself can leave its best solution and not find it again

- SA is a **general solution** method that is **easily applicable** to a large number of problems
- "**Tuning**" of the parameters (initial **c**, decrement of **c**, stop criterion) is relatively easy
- Generally the **quality** of the results of SA is **good**, although it can take **a lot of time**
- Results are generally **not reproducible**: another run can give a different result
- SA can leave an optimal solution and not find it again (so try to remember the **best solution found so far**)
- Proven to find the **optimum** under certain conditions; one of these conditions is that you must **run forever**



## All the other Algorithms

# All the other Algorithms

- There are Thousands of other interesting algorithms:

<https://en.wikipedia.org/wiki/Category:Algorithms>

- This was only an introduction

