



Optimization

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Optimization and Protein Folding

- Theoretically, the structure with the minimum total energy is the structure of interest
- Total energy is defined by the force-field

$$E_{Total} = \sum \left[w_{BOND}^p E_{BOND} + w_{ANGL}^p E_{ANGL} + w_{DIHE}^p E_{DIHE} + w_{IMPR}^p E_{IMPR} + w_{VDW}^p E_{VDW} + w_{ELEC}^p E_{ELEC} \right]$$

- The core of Ab Initio protein folding is optimization
- A robust optimization method is crucial for successful protein folding algorithms



Optimization Problem

- Given an objective (cost) function $f(x)$ find the optimal point X^* such that:

$$\begin{cases} X, X^* \in R_n \\ f(X): R_n \rightarrow R \\ f(X^*) \leq f(X) \forall X \end{cases}$$

- Optimization is the root of most computational problems
- Many different approaches with their unique set of advantages and disadvantages



Monte Carlo

- Easiest to implement
- Very effective for low dimensional problems
- Very ineffective for large dimensional problems
- Algorithm consists of randomly sampling space and accepting the point X^* with the smallest value of objective function

```
for i=1 to 10000 {  
    X = random(range)  
    If  $f(X) \leq f(X^*)$  then  $X^*=X$   
}
```



Gradient Descent

(Conjugate Gradient, Hill Climbing)

- Start with some initial point X_0
- Calculate X_{k+1} from X_k in the following way:

$$X_{k+1} = X_k \pm \rho \cdot \nabla f(X_k)$$

- Here ρ is the descent step size parameter
 - ρ needs to be selected carefully. Too small or too large can have severe consequences.
- Calculate $f(X_{k+1})$
- Go to step 2.



Gradient of A Function

- A multi-dimensional derivative
- For an n-dimensional function produces an n-dimensional vector pointing at the direction of highest increase
- Following the direction of the gradient will increase $f(x)$ optimally
- Following in the opposite direction of the gradient will decrease $f(x)$ optimally
- Example:

$$f(x, y, z) = x^2 y + xyz + y^3 + 3xy\sqrt{z}$$

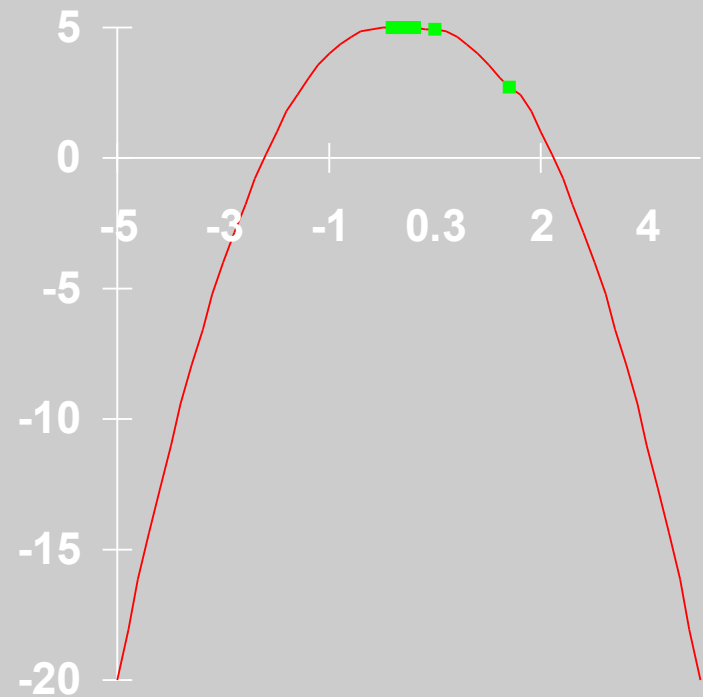
$$\nabla \vec{f}(x, y, z) = \begin{pmatrix} 2xy + yz + 3y\sqrt{z} \\ x^2 + xz + 3y^2 + 3x\sqrt{z} \\ xy - \frac{3xy}{2\sqrt{z}} \end{pmatrix}$$



Example of Gradient ascend

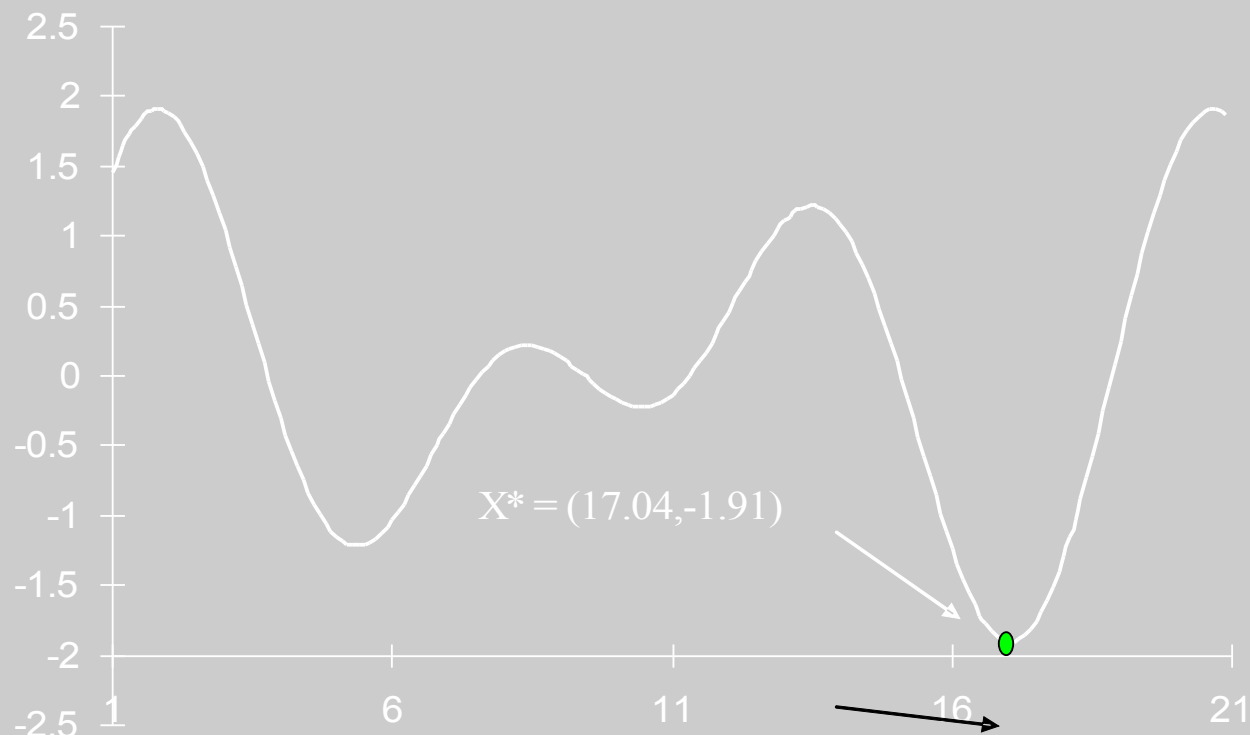
$$f(x) = -x^2 - 5;$$
$$x_{\max} = 0, f_{\max} = 5$$

x_k	$\nabla f(x_k) = -2x$	$x_{k+1} = x_k + 0.4 * \nabla f(x_k)$
1.5	-3	0.3
0.3	-0.6	0.06
0.06	-0.12	0.012
0.012	-0.024	0.0024



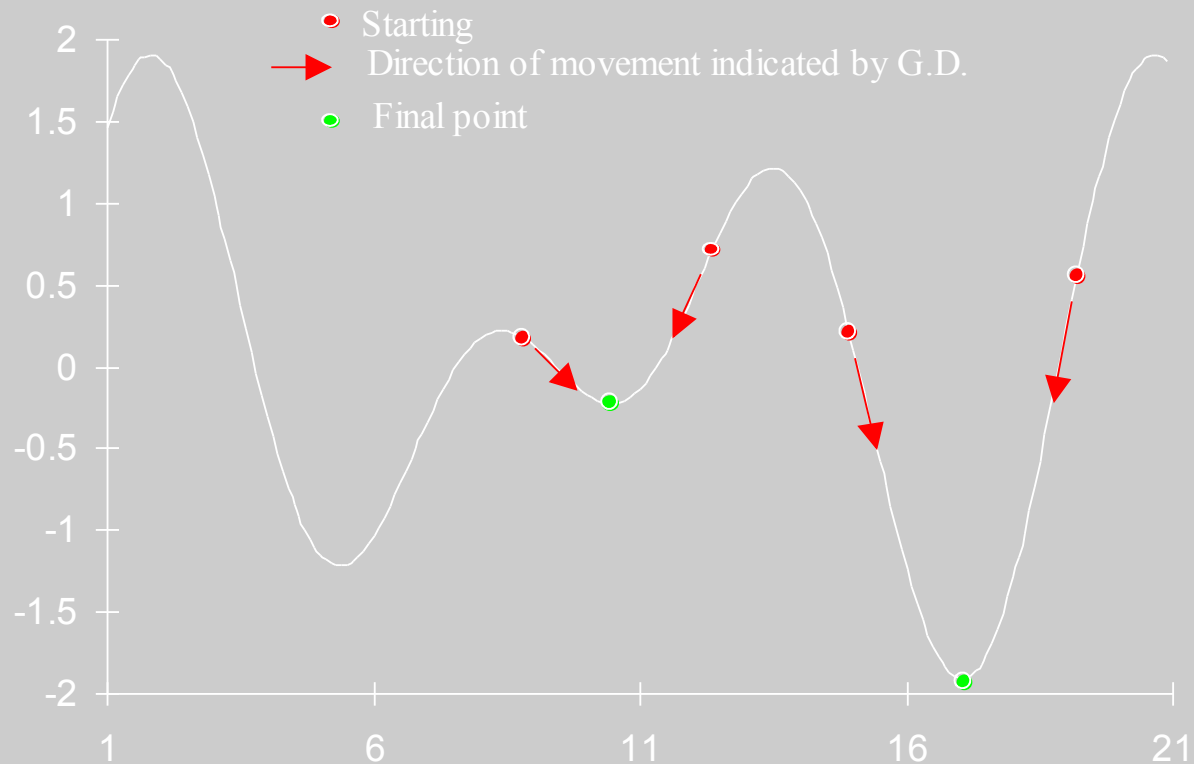


Example of an Objective (Cost) Function



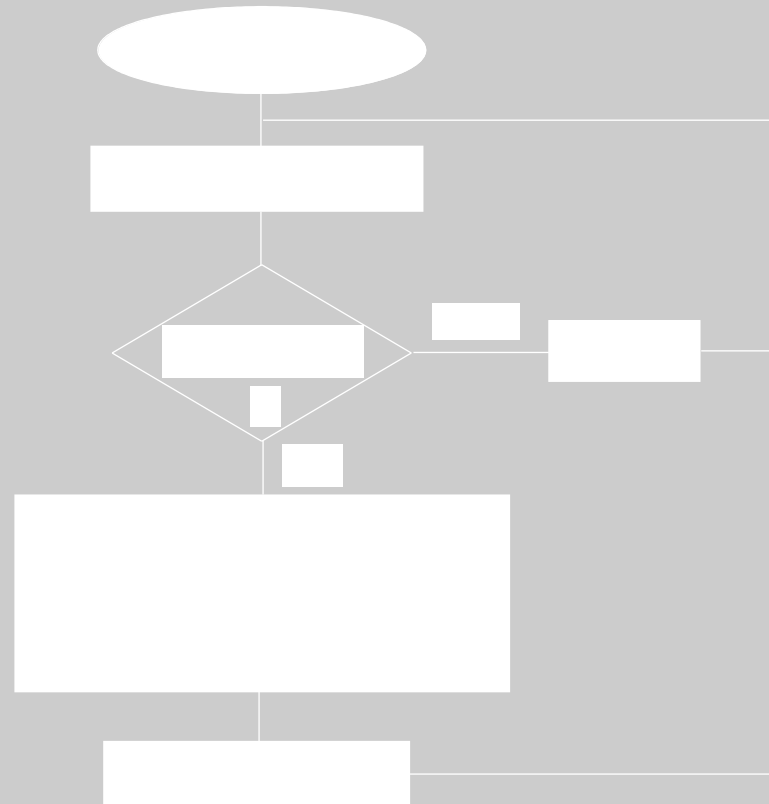


Gradient Descent





Simulated Annealing Metropolis Algorithm





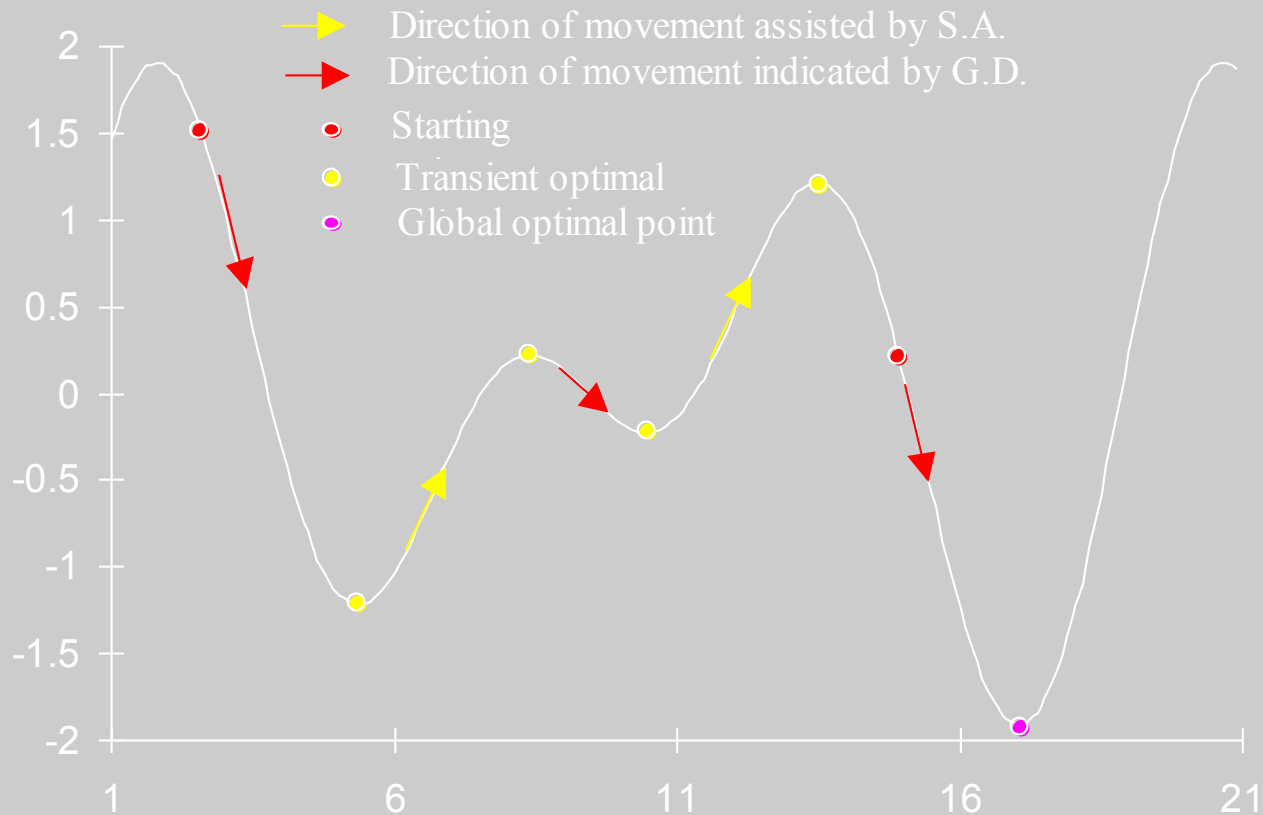
Pseudo PASCAL code

```
Initialize( $i_{\text{stat}}$ ,  $T_0$ ,  $L_0$ );  
 $k := 0$ ;  $i := i_{\text{stat}}$  ;  
repeat  
  for  $i := 1$  to  $L_k$  do  
    begin  
      Generate( $X_j$  from  $X_i$ );  
      if  $f(j) < f(i)$  then  $i := j$ ;  
      else  
        if  $(\exp(f(i) - f(j))/T_k) > \text{random}[0,1)$  then  $i := j$   
      end;  
       $k := k+1$ ;  
      Calculate_Control( $T_K$ );  
    end;  
  Calculate_Length( $L_k$ );  
until stop criterion
```



Contribution of Simulated Annealing

Simulated annealing helps to escape from the local minima.





Limited Success with GD

