

# Apply Metropolis - Hastings Algo to

Optimization of a function and we will

review "simulated annealing".

function  $f : S \rightarrow \mathbb{R} ; i \in S \mapsto f(i).$

$\uparrow$

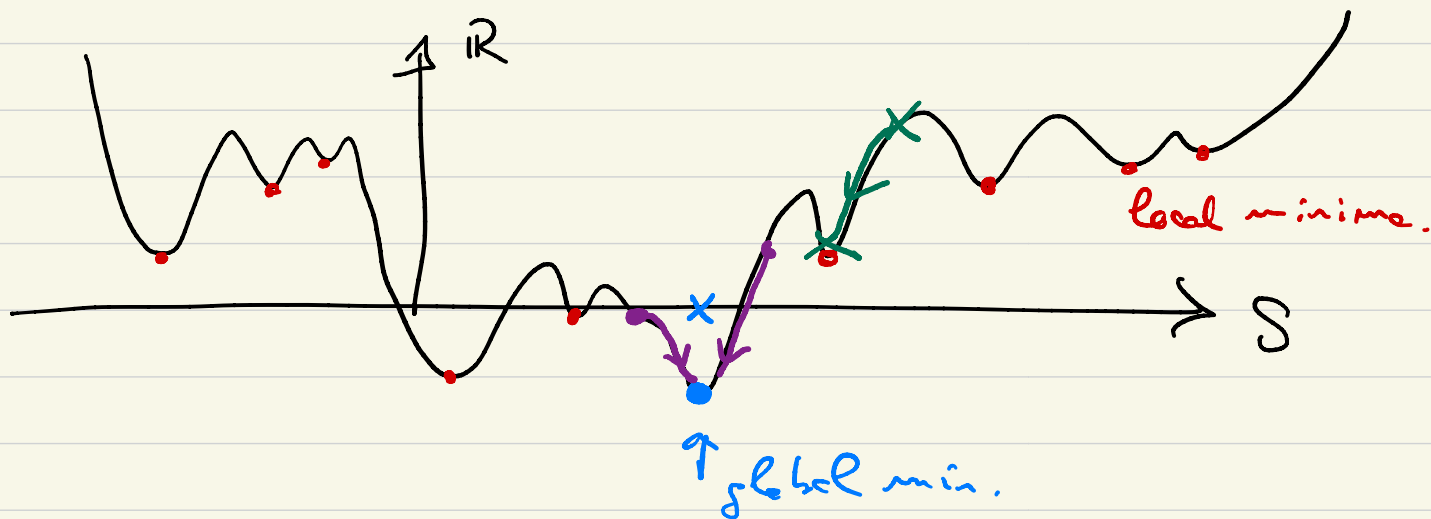
discrete space

$\mathbb{Z}$ ; colorings of graphs;

assignment of binary variables  
in Ising model

Goal: find a global minimum of  $f$ .

(content to find some "good minimum of  $f$ ")



## Examples of functions of interest:

- optimization probl is hard generally for high dimensional sets.

Coloring  $G = (V, E)$ , Proper coloring is

an assignment of colors  $x \in \{1, \dots, q\}$  to  
( $q$  colors)

$$k \in V \text{ s.t. } (k, l) \in E \quad x_k \neq x_l.$$

State space  $i \leftrightarrow \underline{x} = (x_1, \dots, x_{|V|})$ .

Minimize the "cost fct":

$$f \mapsto C(\underline{x}) = \sum_{(k, l) \in E} \mathbb{1}(x_k = x_l) \geq 0$$

= Number of edges whose two vertices have the same color.

$$C : S = \{1, \dots, q\}^V \rightarrow \mathbb{R},$$
$$\underline{x} \mapsto C(\underline{x}).$$

Using Hamiltonian or energy fct or cost fct:

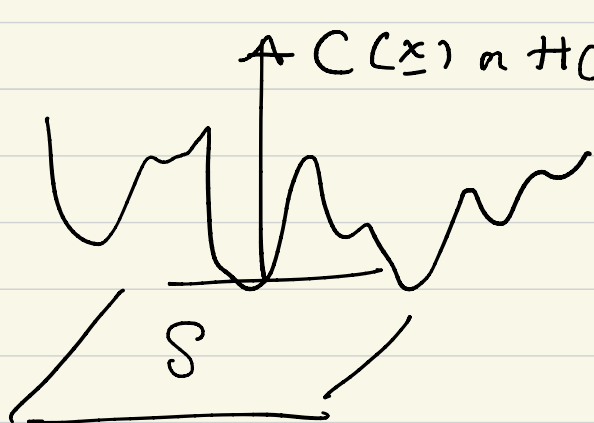
$G = (V, E)$ . assign  $S_k = \pm 1$  to vertex  $k \in V$

assignment  $\underline{S} = (s_1, \dots, s_{|V|})$ .

Cost  $H(\underline{S}) = - \sum_{(k,l) \in E} \underbrace{J_{kl}}_{\in \mathbb{R}} s_k s_l$ .

Goal find  $\underline{S}^*$  s.t.  $H(\underline{S}^*) = \min_{\underline{S} \in \{\pm 1\}^V} H(\underline{S})$

$H: S = \{\pm 1\}^V \rightarrow \mathbb{R}$ .



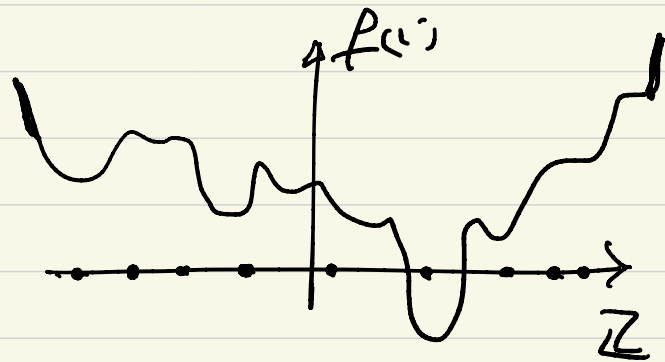
$C(x)$  or  $H(S) \mapsto$  very complicated fcts in general with many many local minima & can have many global minima.

$\mapsto$  Algor (greedy) will typically be stuck in local minima.

- To illustrate the concept of how to apply the Metropolis-Hastings algo I use an easy fct (one dimensional). But conceptually what comes next is general.

$$f: \mathbb{Z} \rightarrow \mathbb{R}.$$

$$i \mapsto f(i)$$



Assume  $\lim_{i \rightarrow +\infty} f(i) = +\infty$ .

"First Idea": use sampling of the uniform distr over global minima  $\rightarrow$  By using some form of MCMC.

$$\pi_{\infty}(i) = \frac{\mathbb{1}\{i \text{ is a global min of } f\}}{\mathbb{Z}_{\infty}}$$

$$\mathbb{Z}_{\infty} = \sum_{\substack{i \in \mathbb{Z} \\ \uparrow S}} \mathbb{1}\{i \text{ is a global min of } f\}.$$

Better Idea consider sampling by MCMC of

the following distribution

$$\pi_{\beta}(i) = \frac{e^{-\beta f(i)}}{Z_{\beta}} \quad ; \quad \beta > 0.$$

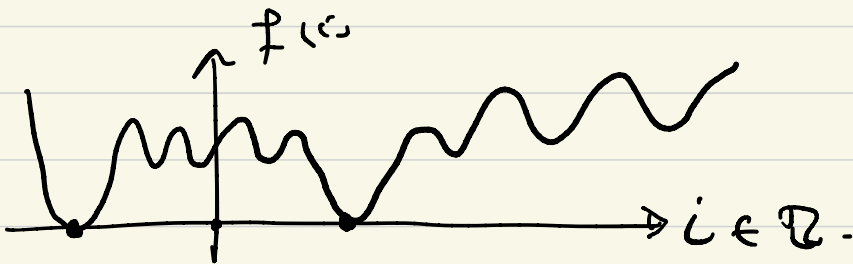
↓  
interpret this later!

and  $Z_{\beta} = \sum_{i \in \mathcal{Z}} e^{-\beta f(i)}$ .

↑  
S

Remark: for  $\beta \rightarrow +\infty$

$$\pi_{\beta}(i) \rightarrow \pi_{\infty}(i).$$



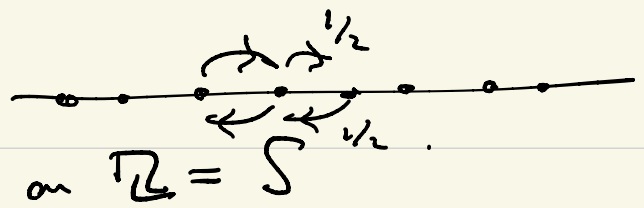
Not a ton of generality to set the problem s.t

$$\min_{i \in \mathcal{Z}} f(i) = 0.$$

Remark: in fact if you think of Ising Model then

clearly you can interpret  $\beta$  as "inverse temperature" and  $f(i)$  as the "energy of state  $i$ " or "cost of state  $i$ ".

# Metropolis algorithm:



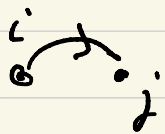
1. Choose a base chain  $\psi$ . Here I propose to choose

s.t  $\psi_{i, i \pm 1} = \frac{1}{2}$  and zero otherwise.

(sym random walk on  $\mathbb{Z}$ ).

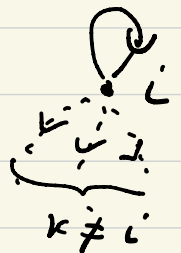
2. Accept moves with acceptance probabilities

$$a_{ij} = \min\left(1, \frac{\pi_j}{\pi_i}\right) = \begin{cases} \min(1, e^{-\beta(f_j - f_i)}) & \text{if } j = i \pm 1 \\ 0 & \text{otherwise.} \end{cases}$$

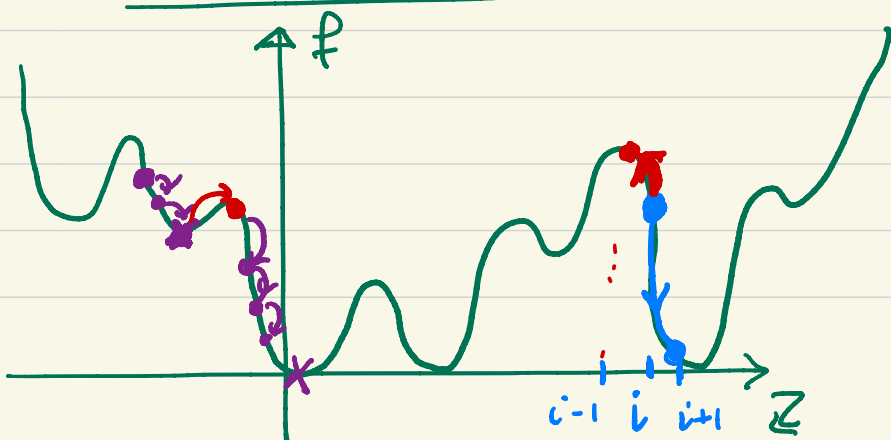


3. The following is the <sup>New</sup> Markov Chain constructed

$$P_{ij} = \begin{cases} \psi_{ij} a_{ij} & i \neq j \\ 1 - \sum_{k \neq i} \psi_{ik} a_{ik} & i = j \end{cases}$$



## PICTURE OF WHAT HAPPENS:



- $f(i+1) - f(i) < 0 \Rightarrow a_{i, i+1} = 1$  certainly accept this move.
- $f(i-1) - f(i) > 0 \Rightarrow a_{i, i-1} < 1$  accept with prob  $< 1$  or you stay at  $i$  (self loop) with  $1 - \text{prob} < 1$ .

Remarks: mm • if a <sup>proposed</sup> move lowers the cost then you certainly accept it.

- if a proposed move increases the cost, well you should sometimes accept it! That is the only way to get out of local minima and "un-stuck" yourself!

• What effect of  $\beta$ ? "The inverse temperature"

✓ \* If  $\beta$  is large then  $a_{ij} = \min(1, e^{-\beta(f(j) - f(i))})$

very low probability to accept a move that increases the cost.  $\uparrow$  is very small if  $f(j) > f(i)$   
is equal to 1 if  $f(j) < f(i)$

you don't have too many self-loops  $\rightarrow$  ~~chain is not~~  
you have tendency of being stuck in local mins.

✓ \* If  $\beta$  is small then  $a_{ij} \approx 1$ . so you tend to always accept a move and chain will explore the whole state space and will tend  $\pi_{\beta}$  but for  $\beta$  small and this very different than  $\pi_{\infty}$ .

⇒ One must be careful how you choose  $\beta$ .

This is a kind of art. In the notes find  
bell park estimate how to choose it ✓

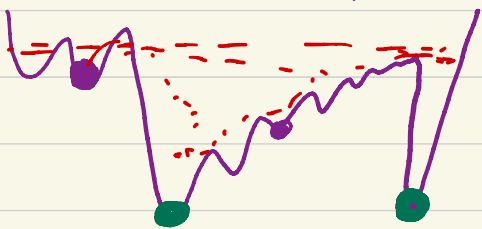
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Simulated Annealing: combine both  $\beta$  small  
and  $\beta$  large.

- Start with  $\beta_0$  small (appropriate) you explore well

$$\pi_{\beta_0} = \frac{e^{-\beta_0 f(x)}}{Z_{\beta_0}} \approx \text{unif distr over whole state space if } \beta = 0.$$

the whole state space and after a reasonable amount of time you have almost converged to  $\pi_{\beta_0}$ .



$$\beta_0 \rightarrow \beta_1.$$

- Then you increase  $\beta$  by a little. And run the new chain for some time. Converge approx  $\pi_{\beta_1}$ .
- Repeat.  $\beta_1 \rightarrow \beta_2$ . Run the chain and approx conv to  $\pi_{\beta_2}$ .
- Repeat ...

|| Eventually you reach samples distributed as almost  $\pi_{\infty}$  or  $\pi_{\beta \text{ very large}}$  ⇒ These samples are low lying Minima  
Maybe you can reach global Min.



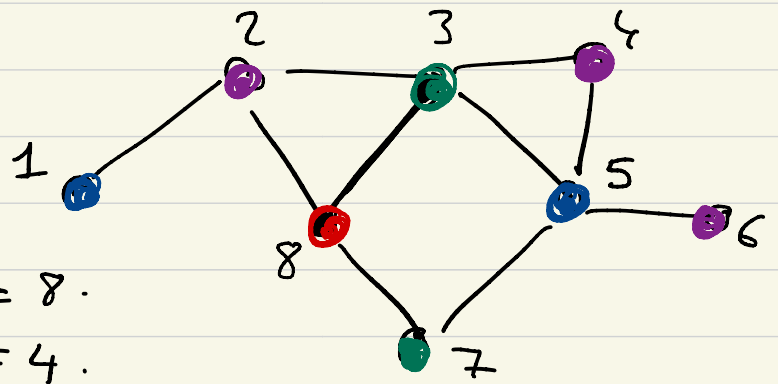
# Introduction to graph coloring and MCMC.

Today: introduction & statement of a theorem.

Next time: Proof and analysis.

Recall the problem:

$$G = (V, E)$$



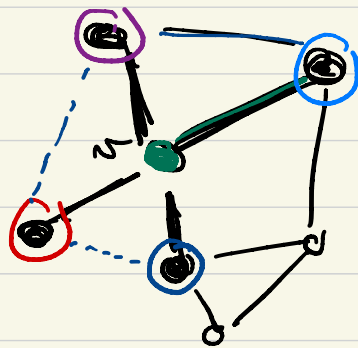
$$\begin{cases} |V| = 8. \\ q = 4. \end{cases}$$

- assignment of colors  $\{1, 2, 3, \dots, q\}$  is a vector  $(x_1, x_2, \dots, x_{|V|}) = \underline{x}$  where and  $x_k \in \{1, 2, 3, \dots, q\}$ .
- Proper coloring or proper assignment is s.t any  $(k, l) \in E$  are s.t  $x_k \neq x_l$ .
- Aim is to sample from:

$$\pi(\underline{x}) = \frac{\mathbb{1}(\underline{x} \text{ is a proper } q\text{-coloring})}{|\mathcal{Z}|} \quad \checkmark$$

Remark: arbitrary  $G = (V, E)$  and arbitrary  $q$   
 it is not always the case that a proper col exists.

But at least if  $q \geq \max_{v \in V} \deg(v) + 1$  then  
 a proper coloring exists.



$$\deg(v) = 4.$$

Notation:  $\max_{v \in V} \deg(v) \equiv \Delta.$

For now on  $q \geq \Delta + 1.$

Remark: Space of proper  $q$ -colorings is called

$$S = \{ \underline{x} = (x_1, \dots, x_{|V|}) \mid \forall e, l \in E \quad x_k \neq x_l \}.$$

$\uparrow$   
 will play the role of the state-space of the MC.

[  $S \subset$  space of all assignments. ]

- We want to sample uniformly from  $S$ .
- The following Algorithm is used and we will prove that indeed this works at least for  $q$  large enough.

• Algorithm.

1. Start from a proper  $q$ -col  $\underline{x} \in S$ . (\*)
2. Select a vertex  $v \in V$  uniformly at random.
3. Select a color  $c \in \{1, \dots, q\}$  unif at random.
4. If  $c$  is allowed at  $v$  then recolor vertex  $v$   
 (that is  $x_v \rightarrow c$ ). If  $c$  is not allowed then you do nothing.  
                   ↑                  ↑  
                   old color      New color.

- We will convince ourselves later that this is an instance of a Metropolis Algo.

- First step is not really a problem because one can always start from any assignment  $\underline{x}$  and proceed as the algo tells you; apply steps 2-4.
- Nb of edges that have a wrong color can only decrease, or stay equal.
- Eventually you will converge to  $\mathcal{S}$ .

#.

Theorem. If  $q > 3\Delta$ , then for all proper

(initial) colorings  $\underline{x}$ :

$$\| \mathbb{P}_{\underline{x}}^m - \pi \|_{TV} \leq |V| e^{-\frac{m}{|V|} \left(1 - \frac{3\Delta}{q}\right)}$$

$$\| \mathbb{P}_{\underline{x}}^m - \pi \|_{TV} \leq |V| e^{-\frac{m}{|V|} \left(1 - \frac{3\Delta}{q}\right)}$$

$$- \frac{m}{|V|} \left(1 - \frac{3\Delta}{q}\right)$$

↑  
prob distr of  
chain starting at  
 $\underline{x}$  running for  
 $m$ -steps

↑  
unif prob distr  
over proper sol.

Furthermore  $T_\epsilon \leq \frac{1}{1 - \frac{3\Delta}{q}} |V| \left( \log |V| + \log \frac{1}{\epsilon} \right).$

Remarks: optimal  $q_c$  s.t algo works given  $\Delta$ .

is it  $\Delta+1$ ? . In general this question is difficult and depends on  $G$ .

. This works for all  $G$ 's.

. Interesting classes of graphs

e.g., Erdős-Rényi graph,  $q_c(\Delta)$

can be determined.

\* We limit ourselves to arbitrary graphs.

$$q > 3\Delta$$

\* Book Levin, Peres you find a better condition and

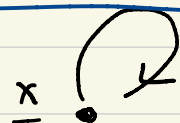
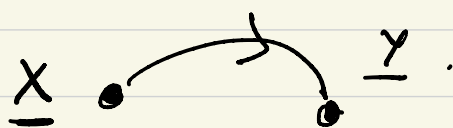
a better than, however analysis is more difficult.

Remark: We prove the thm (next time) with no reference to general theory of ergodic MC's.

Last thing for today: recognize Me also as  
as Metropolis's algo.

1. Start from  $\underline{x}$  proper  $q$ -col.
  2. Select  $N \in V$  at random.
  3. Select  $c \in \{1, \dots, q\}$  at random.
  4. If  $c$  is allowed you recolor  $N$ . Otherwise do nothing.
- Repeat.

Base chain?



$$\psi_{\underline{x}\underline{y}} = \left( \frac{1}{|V|} \frac{1}{q} \right)$$

←  $j$

if  $\underline{y}$  is such  
that  $\underline{x}$  and  $\underline{y}$   
differ at only one  
vertex,  $N$ ,

Neighboring cols  
in  $S$ .

if  $\underline{x} = \underline{y}$   
self loop.

$$\begin{aligned} \psi_{\underline{x}\underline{x}} &= 1 - \sum_{\underline{y} \neq \underline{x}} \psi_{\underline{x}\underline{y}} \\ &= 1 - \frac{1}{q|V|} \sum_{\underline{y} \neq \underline{x}} \psi_{\underline{x}\underline{y}} \\ &\quad |V|(q-1) \end{aligned}$$

$$= 1 - \frac{|V|(q-1)}{q|V|} = 1 - \left(1 - \frac{1}{q}\right) = \frac{1}{q}$$

$$\psi_{\underline{x}\underline{y}} = 0 \quad \text{if } \underline{y} \text{ \& } \underline{x} \text{ are not Neighbored or equal.}$$

acceptance prob:  $(\psi_{\underline{x}\underline{y}} = \psi_{\underline{y}\underline{x}})$

$$a_{\underline{x}\underline{y}} = \min \left( 1; \frac{\pi_{\underline{y}}}{\pi_{\underline{x}}} \right)$$
$$= \min \left( 1; \frac{\cancel{1}(\underline{y} \text{ is a proper col})}{\cancel{1}} \cdot \frac{1}{\cancel{1}(\underline{x} \text{ is proper})} \right)$$

= 1  
at each step of  
chain

$$\Rightarrow a_{\underline{x}\underline{y}} = \min \left( 1; \cancel{1}(\underline{y} \text{ is a proper col}) \right)$$
$$= \cancel{1}(\underline{y} \text{ is a proper col}).$$

↓

This means that if the receiver of  $\omega$  is allowed

$$a_{\underline{x}\underline{y}} = 1$$

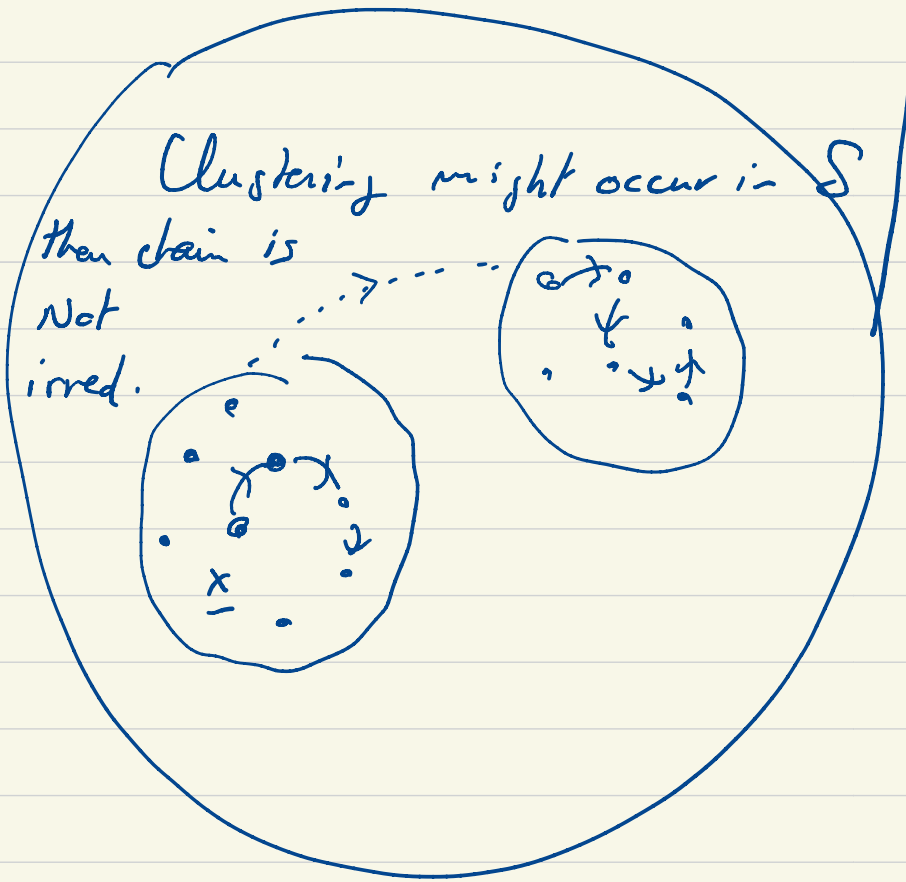
and if the receiver of  $\omega$  is not allowed

$$a_{\underline{x}\underline{y}} = 0 \text{ and do nothing.}$$

Remark: Not easy to see if the chain is irreducible. ■

Indeed we will not have to prove this because we prove the theorem by "bare hands".

But if  $q > 3 \Rightarrow \rightarrow$  irred.



$S$  space  
of all  
proper col.

