#### Local Search Algorithms for Random Satisfiability

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#### **Outline**

- Background
- WalkSAT and related algorithms
- Results and conjectures on WalkSAT
- Experiments on WalkSAT
- Record-to-Record Travel and variants
- Experiments on RRT
- Focused Metropolis Search
- Experiments on FMS
- Dynamics of FMS
- Analysis?



## Background

Denote N = number of variables, M = number of clauses,  $\alpha = M/N.$ 

Satisfiability transition at  $\alpha_c \approx 4.267$  (Mitchell et al. 1992, ..., Braunstein et al. 2002).

Good experiences with local search methods in the satisfiable region  $\alpha < \alpha_c$ : e.g. GSAT (Selman et al. 1992), WalkSAT (Selman et al. 1996). Experiments 1996:  $N \leq 2000$  at  $\alpha \approx \alpha_c$ .



Selman et al. 1992 ... 1996.

Denote by  $E = E_F(s)$  the number of unsatisfied clauses in formula F under truth assignment s.

```
GSAT(F):
    s = initial truth assignment;
    while flips < max_flips do
    if s satisfies F then output s & halt, else:
        - find a variable x whose flipping causes
        largest decrease in E (if no decrease is
        possible, then smallest increase);
        - flip x.</pre>
```



# **NoisyGSAT**

GSAT augmented by a fraction p of random walk moves.

```
NoisyGSAT(F,p):
s = initial truth assignment;
while flips < max_flips do
    if s satisfies F then output s & halt, else:
    - with probability p, pick a variable x
    uniformly at random and flip it;
    - with probability (1-p), do basic GSAT move:
        - find a variable x whose flipping causes
        largest decrease in E (if no decrease is
        possible, then smallest increase);
        flip u
```

- flip x.



#### WalkSAT

NoisyGSAT *focused* on the unsatisfied clauses.

WalkSAT(F,p): s = initial truth assignment; while flips < max\_flips do if s satisfies F then output s & halt, else: - pick 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 at random; - with probability (1-p), pick an x in C

that breaks a minimal number of presently satisfied clauses;



- flip x.

## 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.



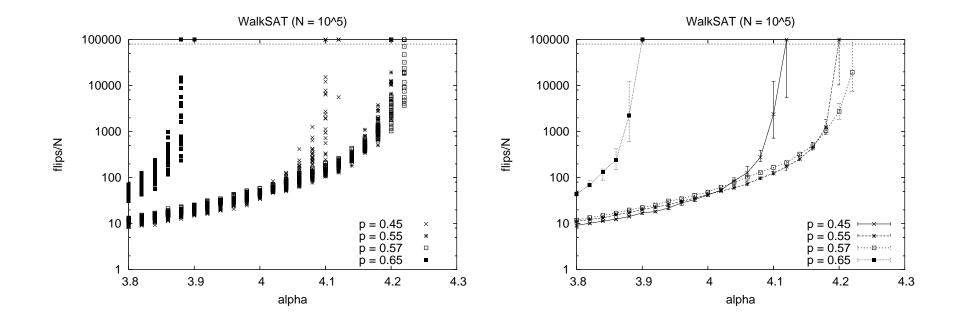
## **Recent results and conjectures**

- Barthel et al. (2003): numerical experiments with WalkSAT (mainly with p = 1, some also with p < 1) at N = 50,000,  $\alpha = 2.0 \dots 4.0$ . Observed transition in the dynamics at  $\alpha_{dyn} \approx 2.7 2.8$ . When  $\alpha < \alpha_{dyn}$ , satisfying assignments are found in linear time per variable (i.e. in a total of cN "flips"), when  $\alpha > \alpha_{dyn}$  exponential time is required.
- Similar results obtained by Semerjian & Monasson (2003), though with smaller experiments (N = 500).
- Explanation: for  $\alpha > \alpha_{dyn}$  the search equilibrates at a nonzero energy level, and can only escape to a ground state through a large enough random fluctuation.



Conjecture: no local search algorithm works in linear time beyond the clustering transition at  $\alpha_s \approx 3.92 - 3.93$  (Mézard, Monasson, Weigt et al.)

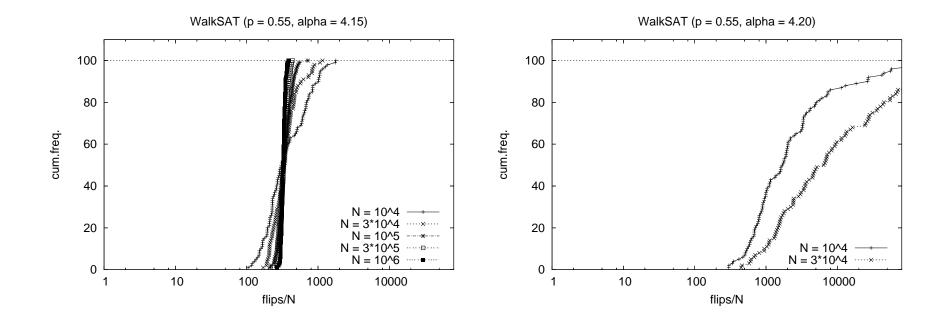
# WalkSAT experiments (3-SAT)



Normalised solution times for WalkSAT,  $\alpha = 3.8 \dots 4.3$ . Left: complete data; right: medians and quartiles.



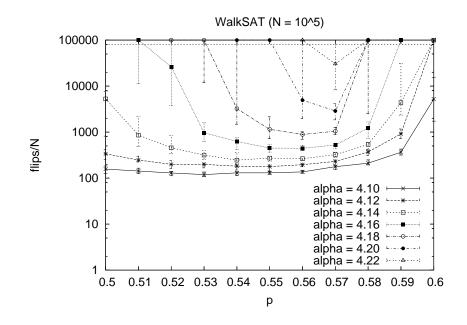
# WalkSAT linear scaling



Cumulative solution time distributions for WalkSAT with p = 0.55.



## WalkSAT optimal noise level?

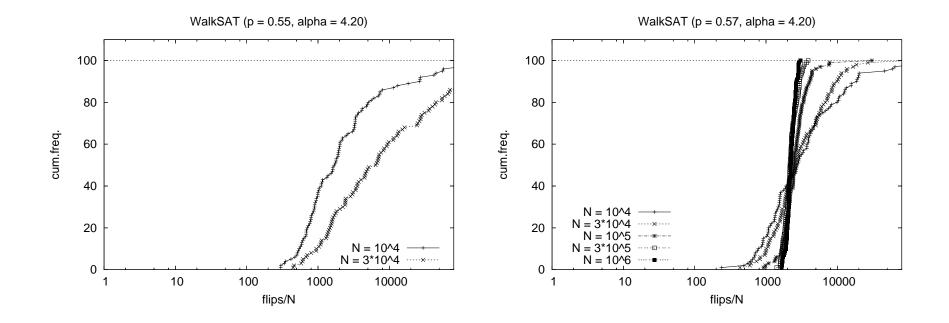


Normalised solution times for WalkSAT with  $p = 0.50 \dots 0.60$ ,  $\alpha = 4.10 \dots 4.22$ .



Local Search Algorithms for Random Satisfiability – 11/30

## WalkSAT sensitivity to noise



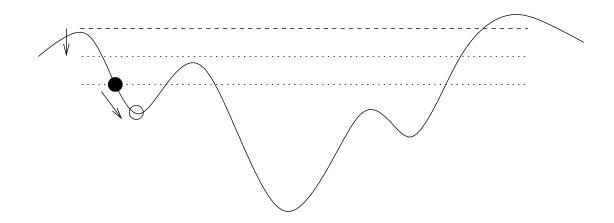
Cumulative solution time distributions for WalkSAT at  $\alpha = 4.20$  with p = 0.55 and p = 0.57.



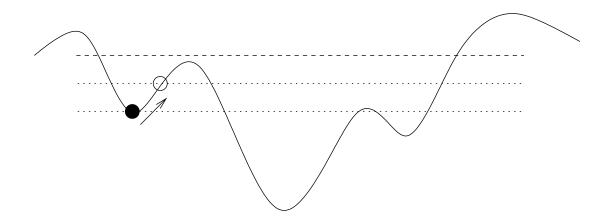
Very simple stochastic local optimisation algorithm introduced by Dueck (1993). Dueck claimed good results on solving 442-city and 532-city TSP's; after that little used.

```
RRT(E,d):
    s = initial feasible solution;
    s* = s; E* = E(s);
    while moves < max_moves do
    if s is a global min. of E then output s & halt,
    else:
        pick a random neighbour s' of s;
        if E(s') <= E* + d then let s = s';
        if E(s') < E* then:
            s* = s'; E* = E(s').</pre>
```

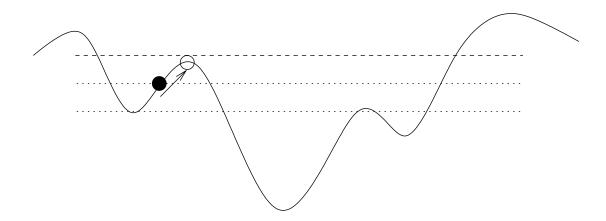




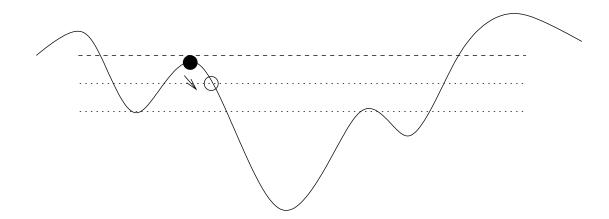




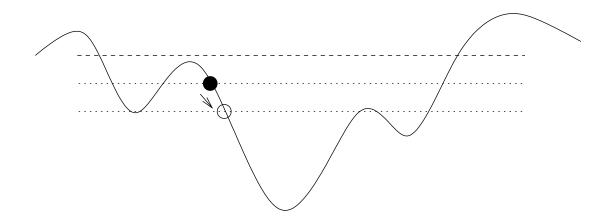




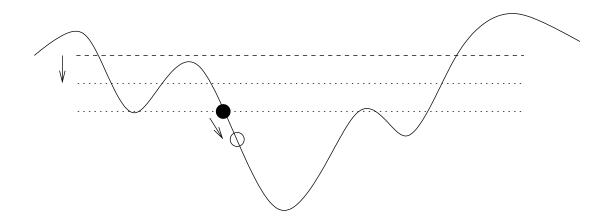




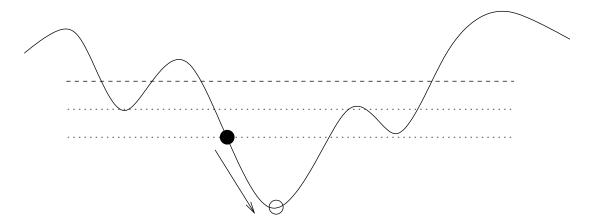




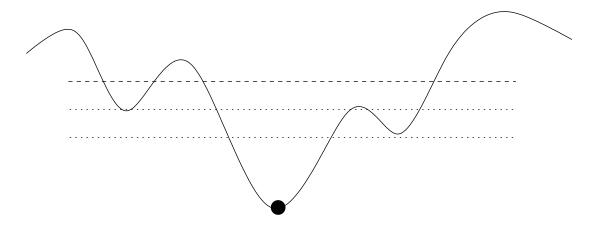














#### **Focused RRT**

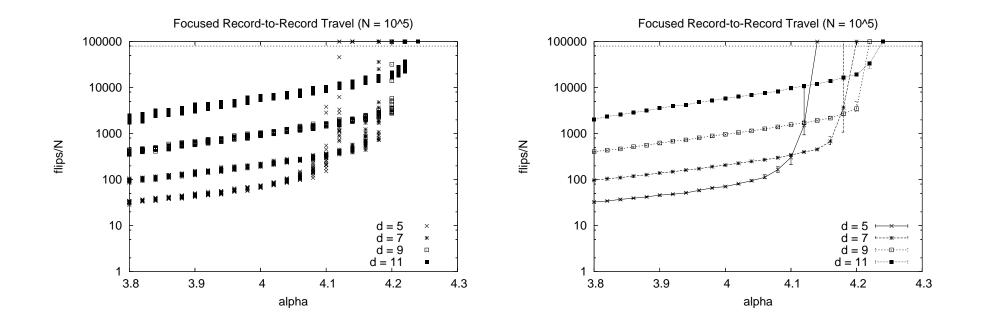
In applying RRT to SAT, E(s) = number of clauses unsatisfied by truth assignment s. Single-variable flip neighbourhoods.

*Focusing:* flipped variables chosen from unsatisfied clauses. (Precisely: one unsatisfied clause is chosen at random, and from there a variable at random.)

 $\Rightarrow$  FRRT = focused RRT.



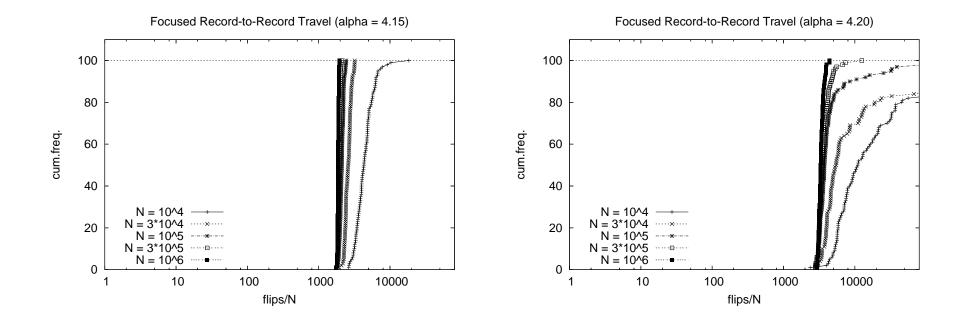
# **FRRT experiments (3-SAT)**



Normalised solution times for FRRT,  $\alpha = 3.8 \dots 4.3$ . Left: complete data; right: medians and quartiles.



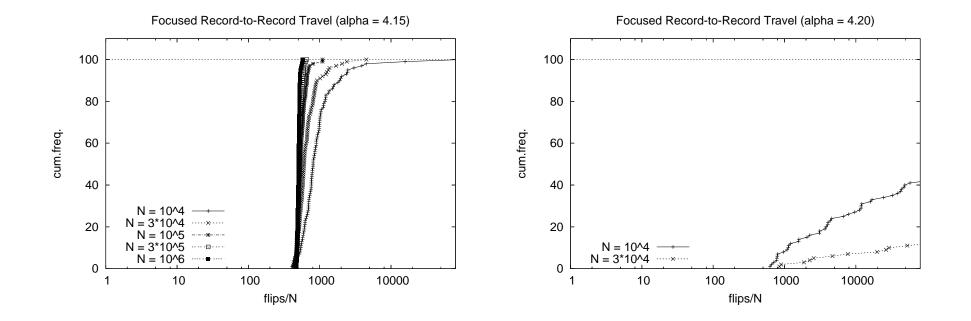
# **FRRT linear scaling**



#### Cumulative solution time distributions for FRRT with d = 9.



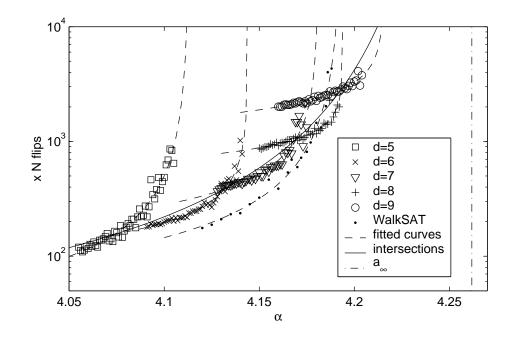
# FRRT linear scaling (cont'd)



#### Cumulative solution time distributions for FRRT with d = 7.



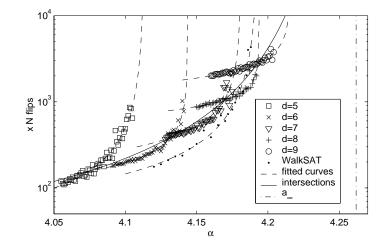
## **FRRT qualitative observations**



For each fixed *d* there seems to be a transition value  $\alpha_d$  s.th. for  $\alpha < \alpha_d$  the algorithm runs in linear time per variable, and for  $\alpha > \alpha_d$  requires exponential time per variable. (Empirical estimates:  $\alpha_5 \approx 4.11$ ,  $\alpha_6 \approx 4.14$ ,  $\alpha_7 \approx 4.18$ ,  $\alpha_8 \approx 4.19$ ,  $\alpha_9 \approx 4.21$ .)



## FRRT qualitative observations cont'd



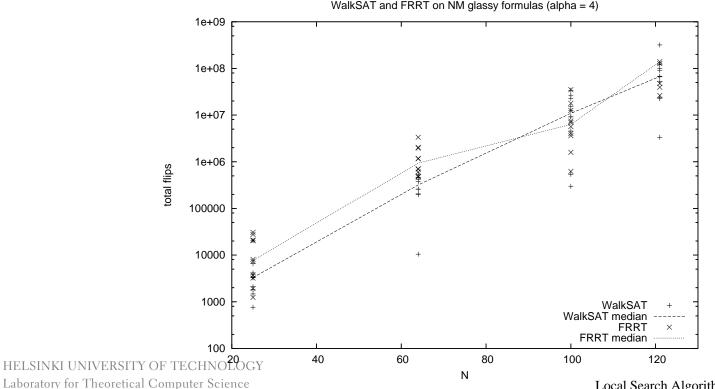
An empirical fit of the transition points  $\alpha_d$  suggests that for large d they converge towards  $\alpha_{\infty} \approx 4.26$ .

Comparative experiments using WalkSAT with near optimal parameter settings (p = 0.55) yield estimate  $\alpha_{dyn} \approx 4.19$  for WalkSAT's transition point.



#### WalkSAT & FRRT on structured problems

Jia, Moore & Selman (2004) tested WalkSAT and FRRT on highly structured "glassy" 3-SAT formulas. Here the number of variables is always of the form  $N = L \times L$ ; values of L = 5, 8, 10, 11, 16 were tried out. At L = 16 WalkSAT no longer converged; FRRT did, but only for d = 5.





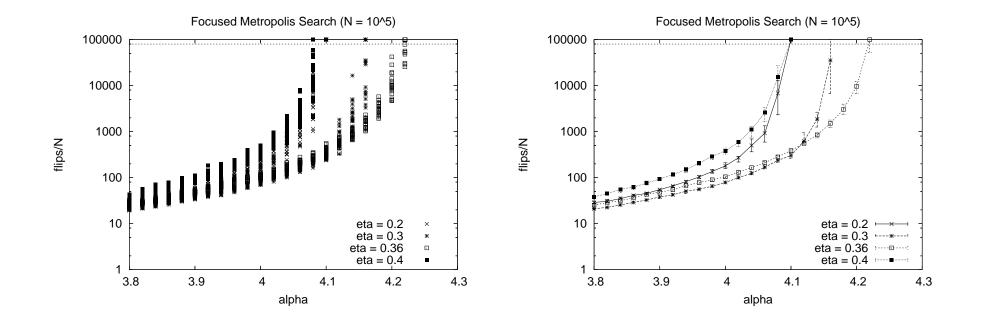
Local Search Algorithms for Random Satisfiability - 21/30

Arguably the most natural focused local search algorithm. Variable flip acceptance probabilities determined by a parameter  $\eta$ ,  $0 \le \eta \le 1$ .

```
FMS(F,eta):
    s = initial truth assignment;
    while flips < max_flips do
    if s satisfies F then output s & halt, else:
        pick a random unsatisfied clause C in F;
        pick a variable x in C at random;
        let x' = flip(x), s' = s[x'/x];
        if E(s') <= E(s) then flip x, else:
            flip x with prob. eta^(E(s')-E(s)).</pre>
```



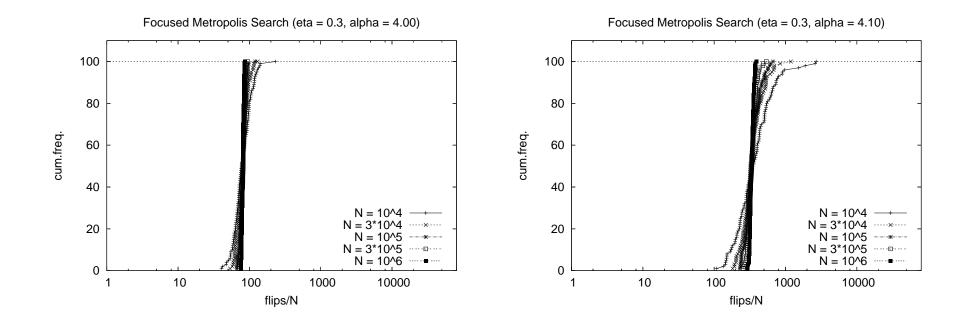
# **FMS experiments (3-SAT)**



Normalised solution times for FMS,  $\alpha = 3.8 \dots 4.3$ . Left: complete data; right: medians and quartiles.



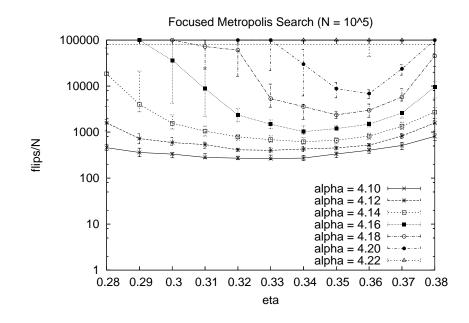
# **FMS linear scaling**



Cumulative solution time distributions for FMS with  $\eta = 0.3$ .



#### **FMS optimal acceptance ratio?**

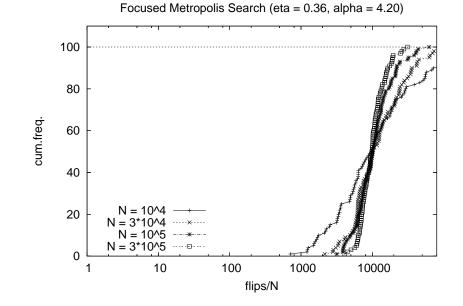


Normalised solution times for FMS with  $\eta = 0.28 \dots 0.38$ ,  $\alpha = 4.10 \dots 4.22$ .



Local Search Algorithms for Random Satisfiability – 25/30

### FMS optimal acceptance ratio cont'd



Cumulative solution time distributions for FMS with  $\eta = 0.36$ ,  $\alpha = 4.20$ .



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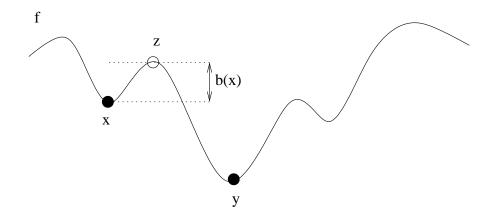
For FRRT: landscape structure?

For FMS: contact processes?



#### **Combinatorial landscapes**

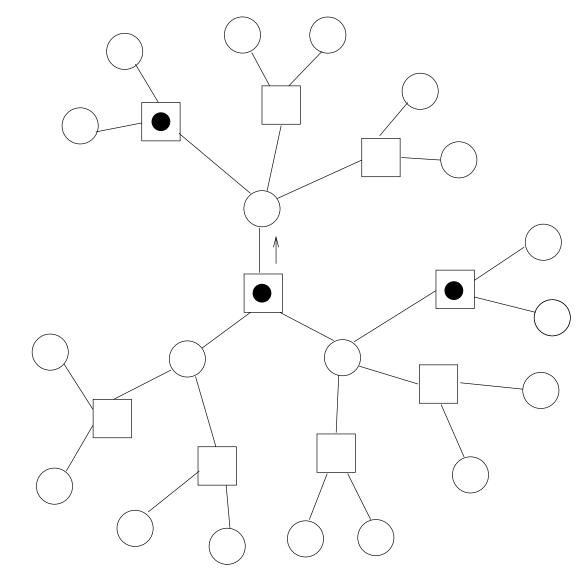
Reidys & Stadler (SIAM Rev. 2002)



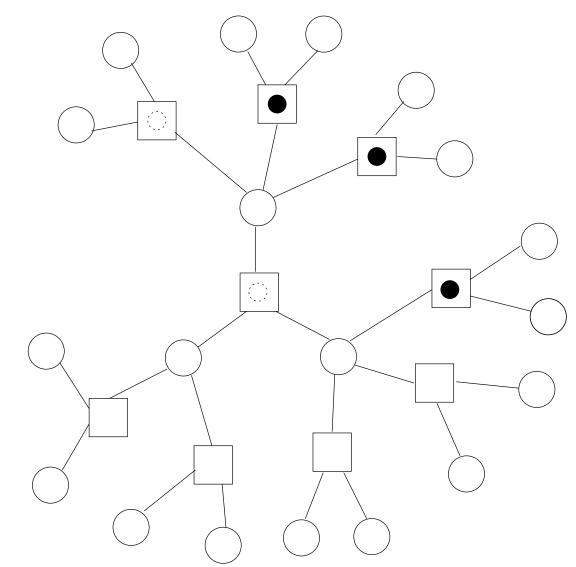
**barrier height from** x to y:  $b(x, y) = \min\{\max\{f(z) - f(x), 0 \mid z \in p\} \mid p \text{ an } x\text{-}y \text{ path}\}$ 

■ barrier height of 
$$x \notin Opt$$
.  
 $b(x) = \min\{b(x, y) \mid f(y) < f(x)\}$ 

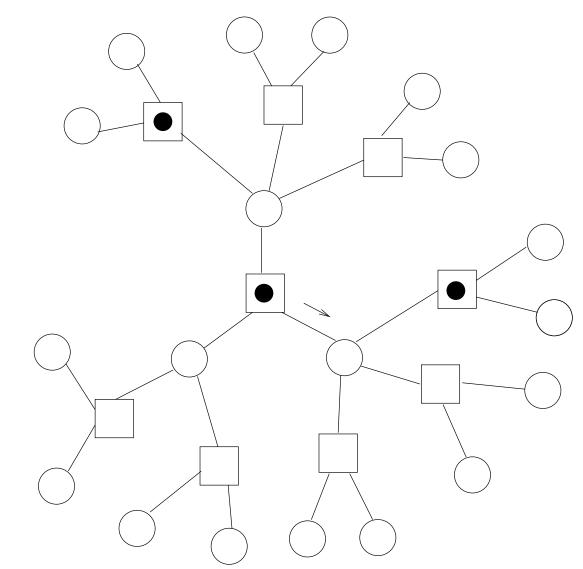
■ *depth* of a landscape:  
$$D_f = \max\{b(x) \mid x \notin \mathsf{Opt}\}$$



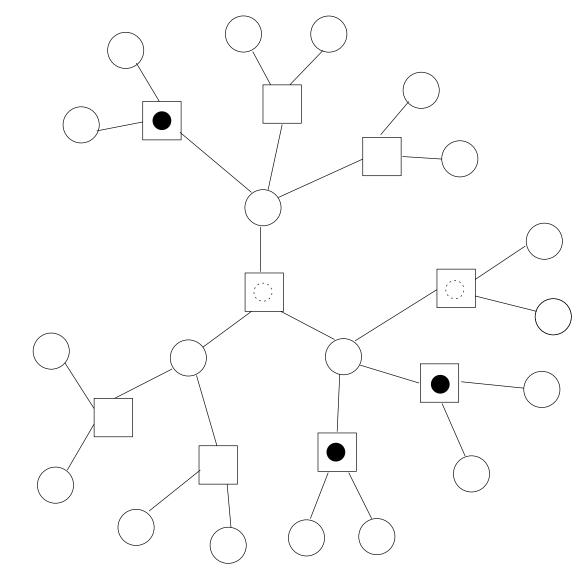














#### References

# References

- [1] S. Seitz, P. Orponen: An efficient local search method for random 3-satisfiability. *Proc. LICS'03 Workshop on Typical Case Complexity and Phase Transitions (Ottawa, Canada, June 2003).* Elsevier Electronic Notes in Discrete Mathematics Vol. 16.
- [2] S. Seitz, M. Alava, P. Orponen: Threshold behaviour of WalkSAT and focused Metropolis search on random 3-satisfiability. *Proc. 8th Intl. Conf. on Theory and Applications* of Satisfiability Testing (St. Andrews, Scotland, June 2005). Springer-Verlag, Berlin, to appear.



[3] S. Seitz, M. Alava, P. Orponen: Focused local search algorithms for random 3-satisfiability. To appear.