

# 472 Recitation

Week 6

Problem set 2 due on this Friday at 5:00 PM

# Game search

Weakness of alpha-beta search:

- High branching factor
- Rely on good Evaluation function

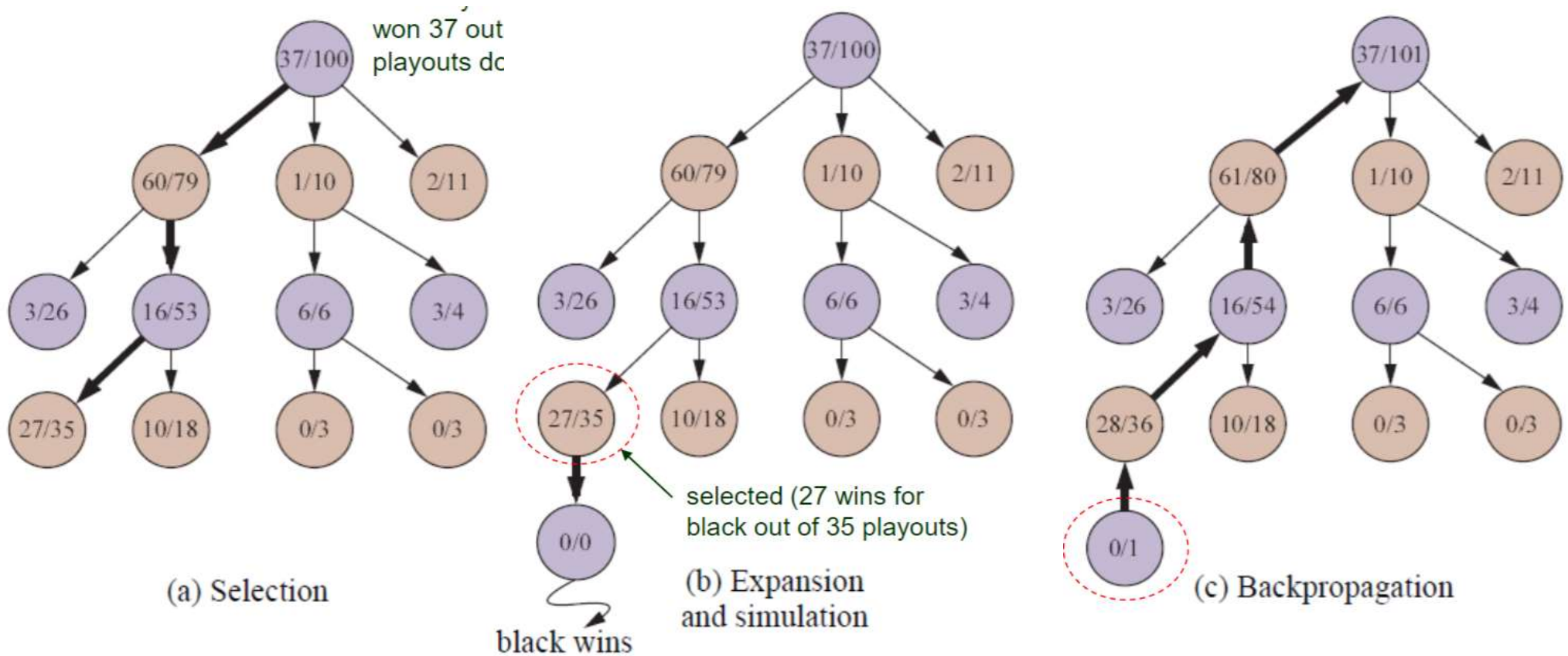


Monte Carlo Method

Idea: rely on repeated **random sampling** to obtain numerical results

For game: no heuristic evaluation function and the value of a state estimated as the **average utility** over a number of simulations of complete games

# Mento Carlo Method



# Mento Carlo Method

Upper confidence bound formula:

$$UCB(n) = \frac{U(n)}{N(n)} + C \times \sqrt{\frac{\log N(PARENT(n))}{N(n)}}$$

- MCTS has advantage over alpha-beta when  $b$  is high.
- MCTS is less vulnerable to a single error.
- MCTS can be applied to brand-new games via training by self-play.
- MCTS is less desired than alpha-beta on a game like chess with low  $b$  and good evaluation function.

# Constraint Satisfaction Problem

- A set of **variables**  $\mathcal{X} = \{X_1, \dots, X_n\}$ .
- A set of **domains**  $\mathcal{D} = \{D_1, \dots, D_n\}$ .
- A set of **constraints**  $\mathcal{C} = \{C_1, \dots, C_m\}$  that specifies allowable combination of values.

$$\blacklozenge C_j: \langle (v_i, v_j), \text{relation} \rangle$$

Assignment:  $\{X_i = v_i, X_j = v_j, \dots\}$

- **consistent** if no constraint is violated.
- **complete** if every variable is assigned a value.
- **partial** if some variables are unassigned.

A **solution** to a CSP is a consistent, complete assignment.

A **partial solution** is a partial assignment that is consistent.

# Formulate CSP

- A natural representation for a wide variety of problem.
- Fast and efficient CSP solvers.
- Ability of a CSP solver to reduce the search space significantly.

Upon violation by a partial assignment

- ◆ discard its further refinements,
- ◆ see which variables cause the violation,
- ◆ focus on those variables that matter.

Formulation of CSP is getting the variables, domains, and constraints from the problem description.

# Constraints

A *unary constraint* restricts the value of a single variable.

$\langle (SA), SA \neq \text{green} \rangle$

A *binary constraint* relates two variables.

$SA \neq WA$

A higher order constraint relate more variables.

A *global constraint* involves an arbitrary number of variables (but not necessarily all the variables).



# Constraint Propagation

Idea: Use constraints to reduce the number of legal values for a variable, which in turn reduce those for another variable, and so on.

A variable  $X_i$  is *arc-consistent* with respect to (w.r.t.) another variable  $X_j$  if for every value in  $D_i$  there exists a value in  $D_j$  that satisfies the binary constraint on the arc (i.e., edge  $(X_i, X_j)$ ).

The variable is *arc-consistent* if it is so w.r.t every other variable that it shares a binary constraint with.

The constraint graph is *arc-consistent* if every variable is arc consistent with every other variable.

**Any CSP can be transformed into a binary CSP.**

```

queue  $\leftarrow$  a queue of arcs, initially all the arcs in csp

while queue is not empty do
    ( $X_i, X_j$ )  $\leftarrow$  POP(queue)
    if REVISE(csp,  $X_i, X_j$ ) then
        if size of  $D_i = 0$  then return false
        for each  $X_k$  in  $X_i$ .NEIGHBORS -  $\{X_j\}$  do // propagate to other variables sharing a
            add ( $X_k, X_i$ ) to queue // constraint with  $X_i$  since its domain has
        // reduced.
return true

```

```
while queue is not empty do
```

$$(X_i, X_j) \leftarrow \text{POP}(\text{queue})$$

**if** REVERSE( $csp, X_i, X_j$ ) **then**

**if** size of  $D_i = 0$  **then return** *false*

```

for each  $X_k$  in  $X_i$ .NEIGHBORS -  $\{X_j\}$  do // propagate to other variables sharing a
    add  $(X_k, X_i)$  to queue // constraint with  $X_i$  since its domain has
rn true // reduced.

```

```
return true
```

```

revised  $\leftarrow$  false
for each  $x$  in  $D_i$  do
    if no value  $y$  in  $D_j$  allows  $(x,y)$  to satisfy the constraint between  $X_i$  and  $X_j$  then
        delete  $x$  from  $D_i$ 
        revised  $\leftarrow$  true
return revised

```

Domain size  $\leq d$ ,  $c$  binary constraints.

```
revised  $\leftarrow$  false
```

**for each**  $x$  **in**  $D_i$  **do**

**if no value  $y$  in  $D_j$  allows  $(x,y)$  to satisfy the constraint between  $X_i$  and  $X_j$  then**

delete  $x$  from  $D_i$ 
$$revised \leftarrow true$$
**return** *revised*

Domain size  $\leq d$ ,  $c$  binary constraints.

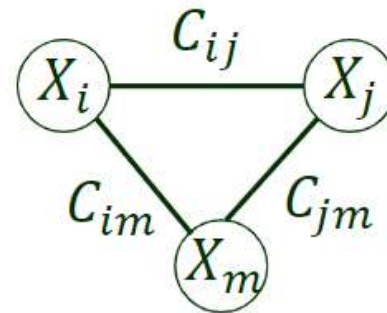
- Each arc inserted into the queue  $d$  times.
- Each checking takes  $O(d^2)$  time.

$O(cd^3)$

# Constraint Propagation

- ❖ Arc-consistency
- ❖ Path Consistency
- ❖ Bounds Propagation

$\{X_i, X_j\}$  is *path-consistent* w.r.t.  $X_m$  if for every assignment to  $X_i, X_j$  consistent with their constraint  $C_{ij}$  (if exists), there exists an assignment to  $X_m$  that satisfies the constraints  $C_{im}$  and  $C_{jm}$  between them and  $X_m$ .



# Backtracking Search

- ♣ Constraint propagation often ends with partial solutions.
- ♣ Backtracking search can be employed to extend them to full solutions.