

Adversarial Search

CS5491: Artificial Intelligence
ZHICHAO LU

Content Credits: Prof. Wei's CS4486 Course
and Prof. Boddeti's AI Course

TODAY

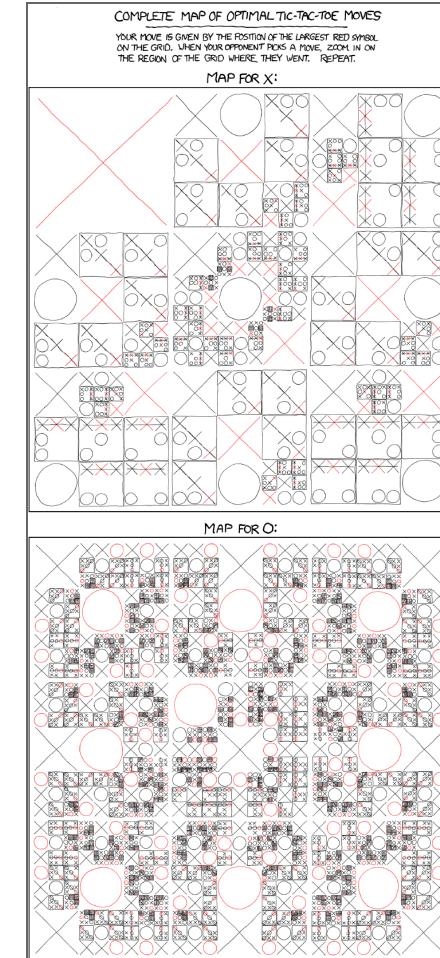
Adversarial Games

Minimax Games

$\alpha - \beta$ pruning

Reading

- Today's Lecture: RN Chapter 5.1-5.5



XKCD

AGENTS INTERACTING WITH AGENTS



GAME PLAYING STATE-OF-THE-ART

Checkers: 1950: First computer player. 1994: First computer champion: Chinook ended 40-year-reign of human champion Marion Tinsley using complete 8-piece endgame. 2007: Checkers solved.

Chess: 1997: Deep Blue defeats human champion Gary Kasparov in a six-game match. Deep Blue examined 200M positions per second, used very sophisticated evaluation and undisclosed methods for extending some lines of search up to 40 layers. Current programs are even better, if less historic.

Go: Go: Human champions are now starting to be challenged by machines. In go, $b > 300$. Classic programs use pattern knowledge bases, but big recent advances use Monte Carlo (randomized) expansion methods.

- 2016: Alpha Go defeats human champion. Uses Monte Carlo Tree Search, learned evaluation function.

ADVERSARIAL GAMES

TYPES OF GAMES

Many different kinds of games.

Axes:

- › Deterministic or stochastic?
- › One, two, or more players?
- › Zero sum?
- › Perfect information (can you see the state)?

Want algorithms for calculating a strategy (policy) which recommends a move from each state.

DETERMINISTIC GAMES

Many possible formalizations, one is:

- › **States** S (start at s_0)
- › **Players** $P = \{1, \dots, N\}$ (usually take turns)
- › **Actions** A (may depend on player / state)
- › **Transition Function** $S \times A \rightarrow S$
- › **Terminal Test** $S \rightarrow \{t, f\}$
- › **Terminal Utilities** $S \times P \rightarrow R$

Solution for a player is a policy: $S \rightarrow A$

GAME THEORY

Zero-Sum Games

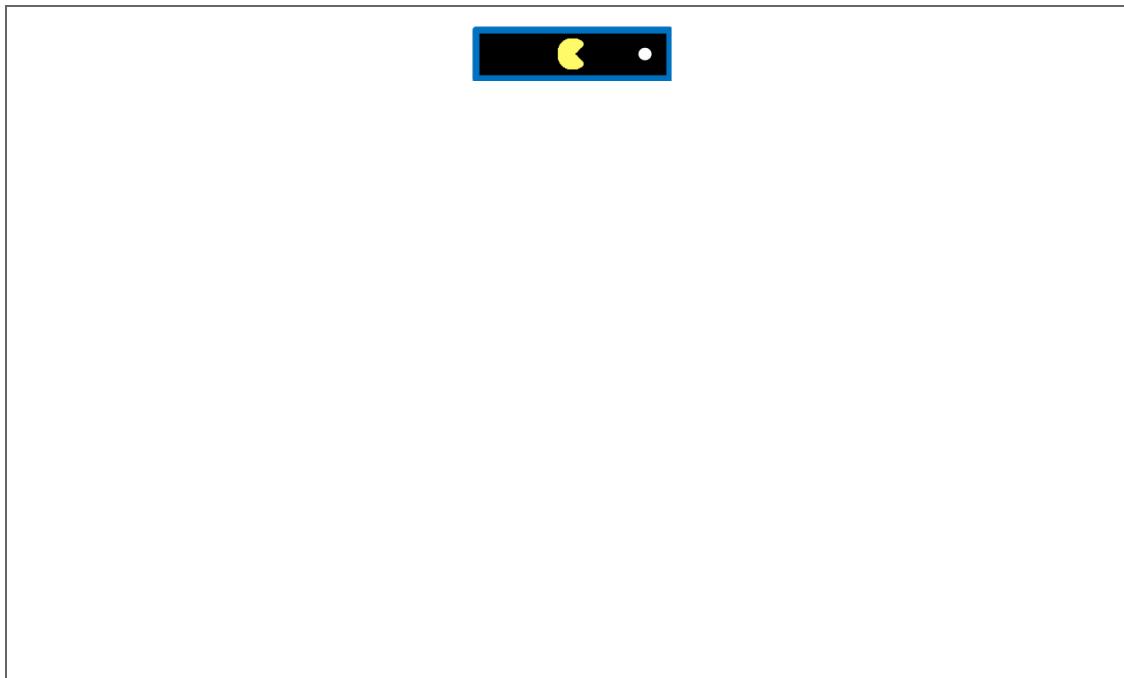
- Agents have opposite utilities (values on outcomes)
- Lets us think of a single value that one maximizes and the other minimizes
- Adversarial, pure competition

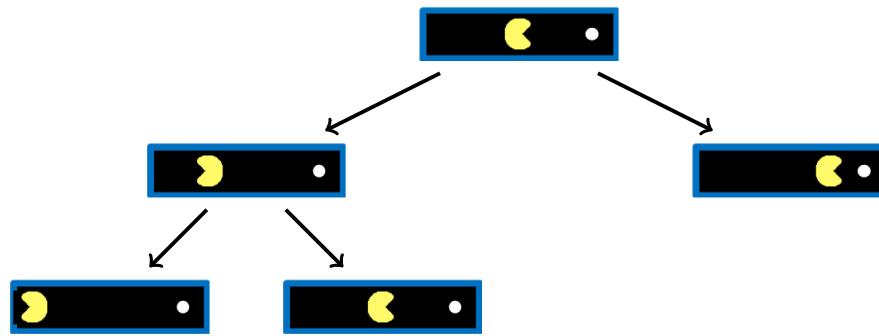
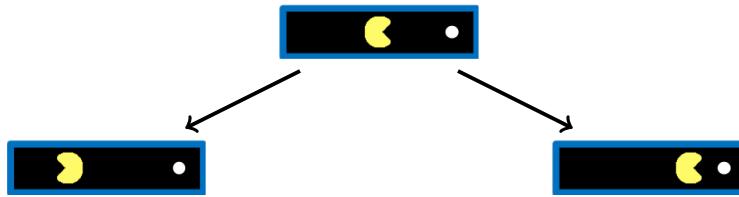
General Games

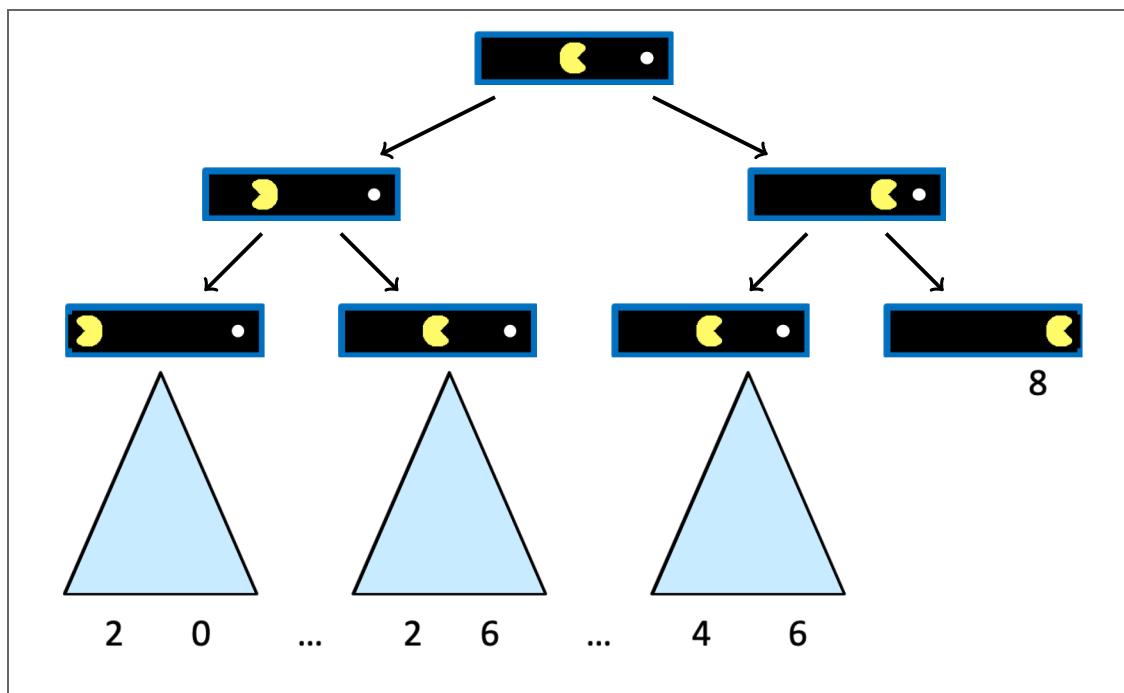
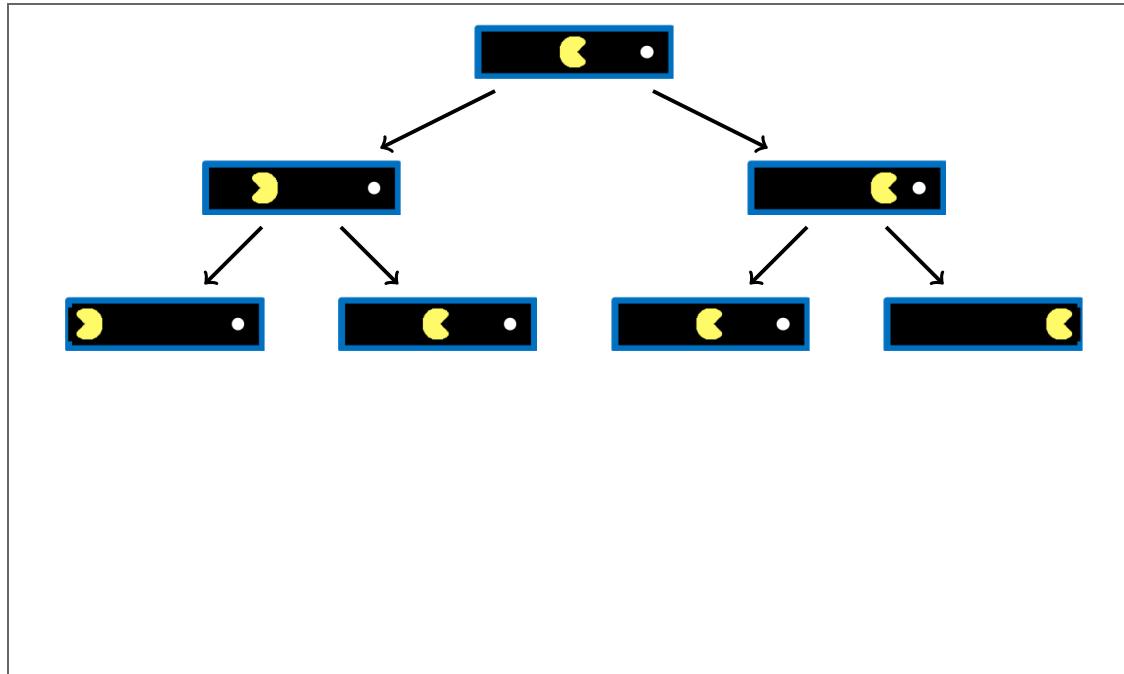
- Agents have independent utilities (values on outcomes)
- Cooperation, indifference, competition, and more are all possible
- More later on non-zero-sum games

ADVERSARIAL SEARCH

SINGLE-AGENT TREES







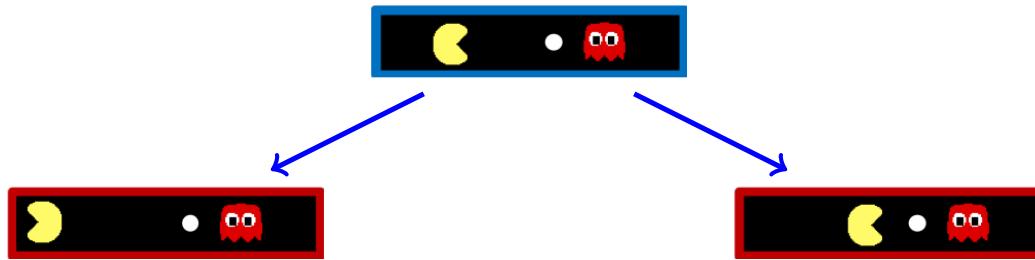
Value of State: The best achievable outcome (utility) from that state

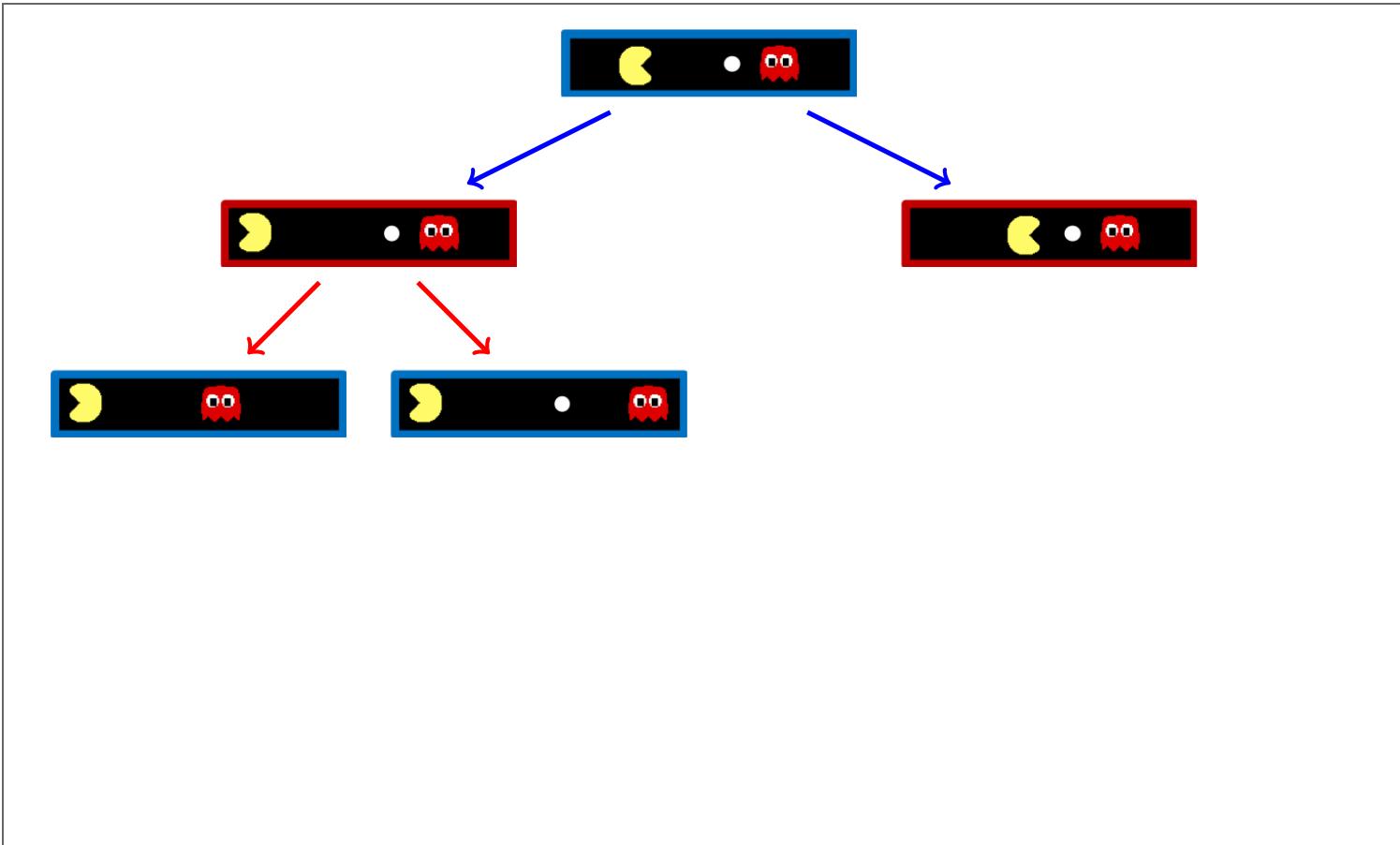
Terminal States: $V(s)$ known

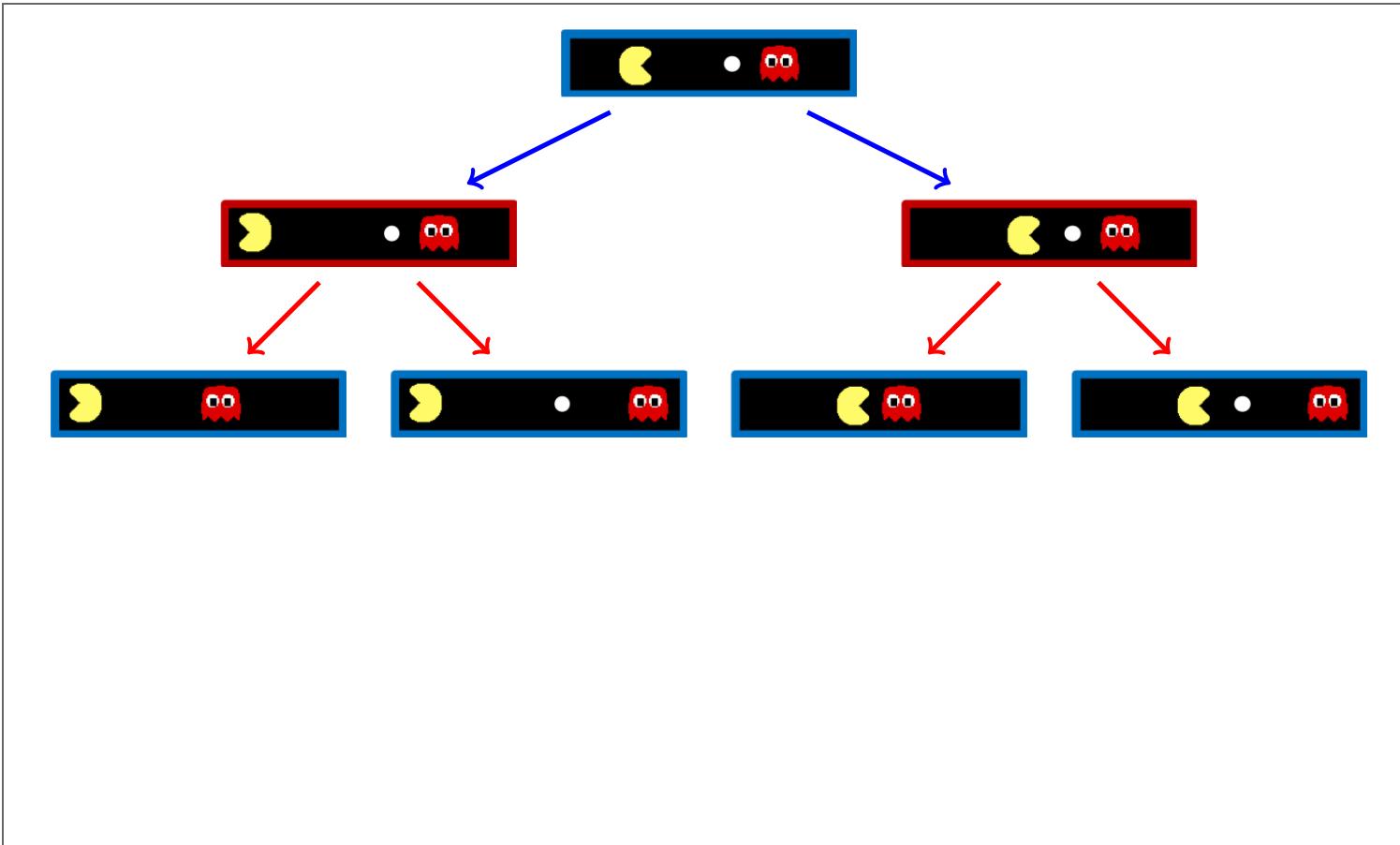
Non-Terminal States: $V(s) = \max_{s' \in \text{children}(s)} V(s')$

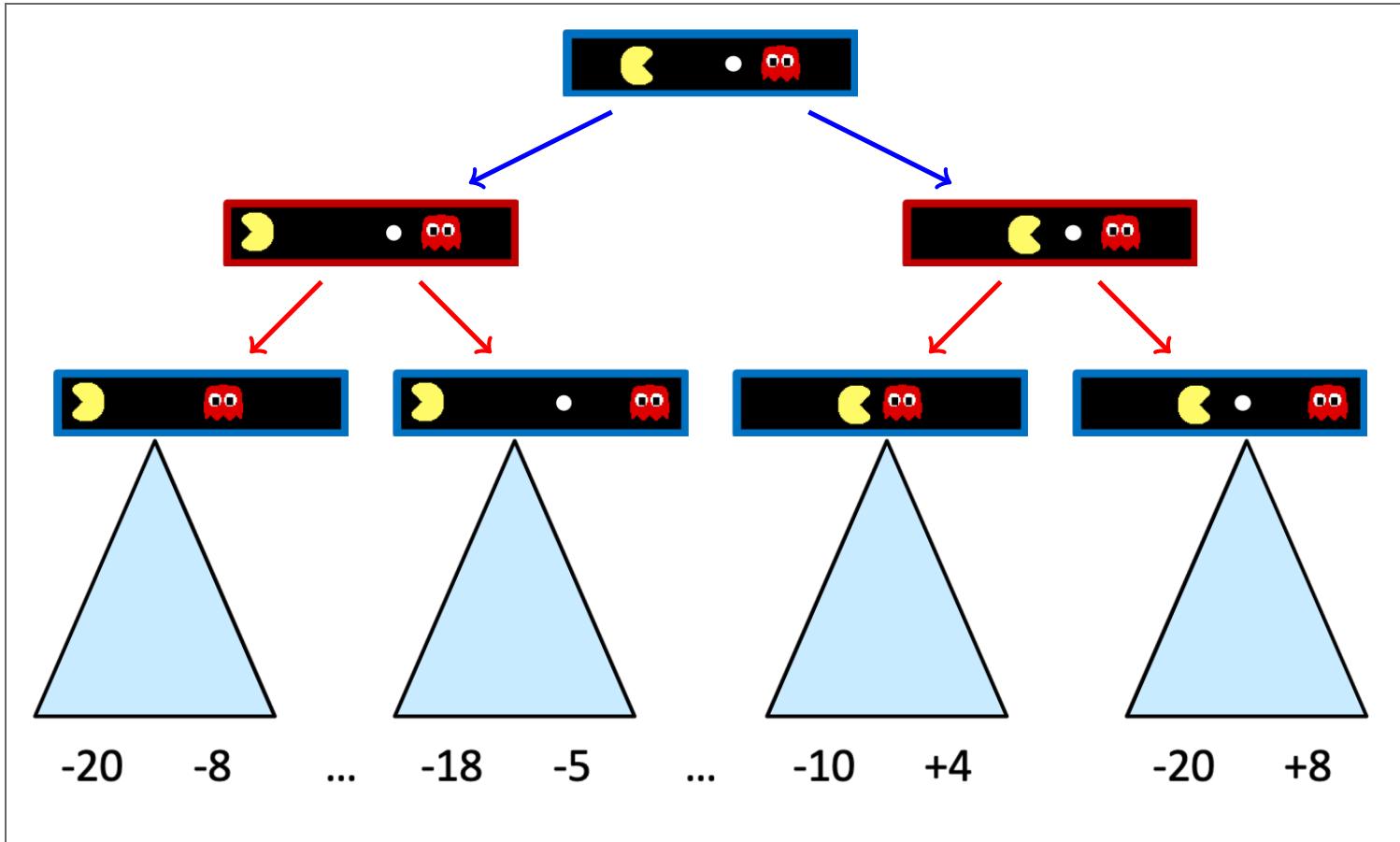
ADVERSARIAL GAME TREES



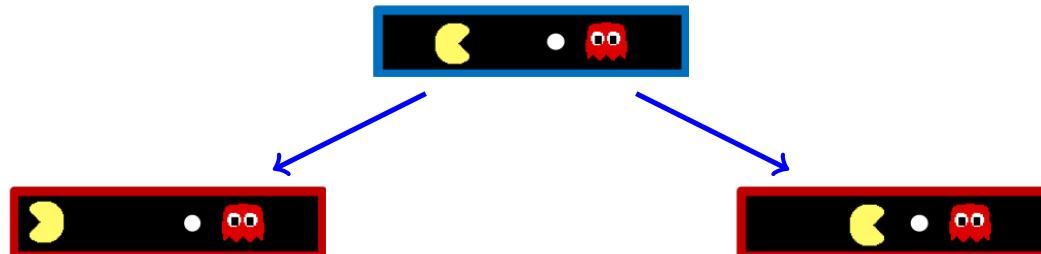


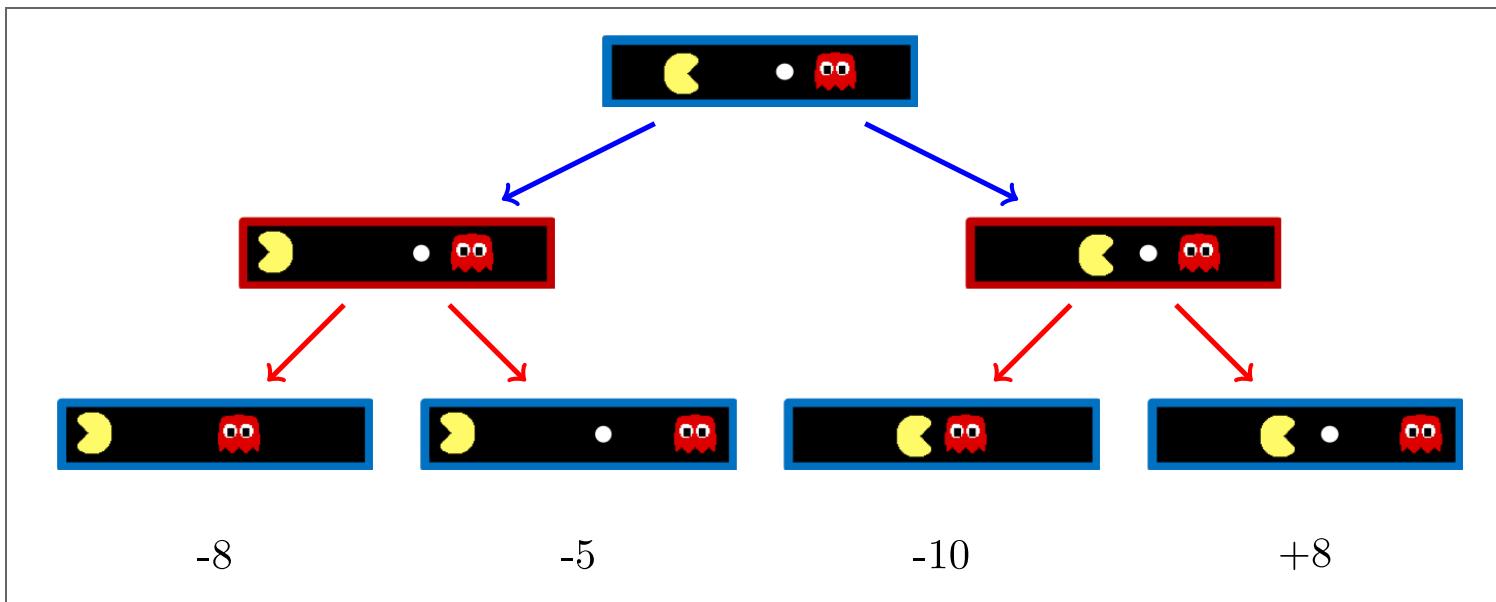
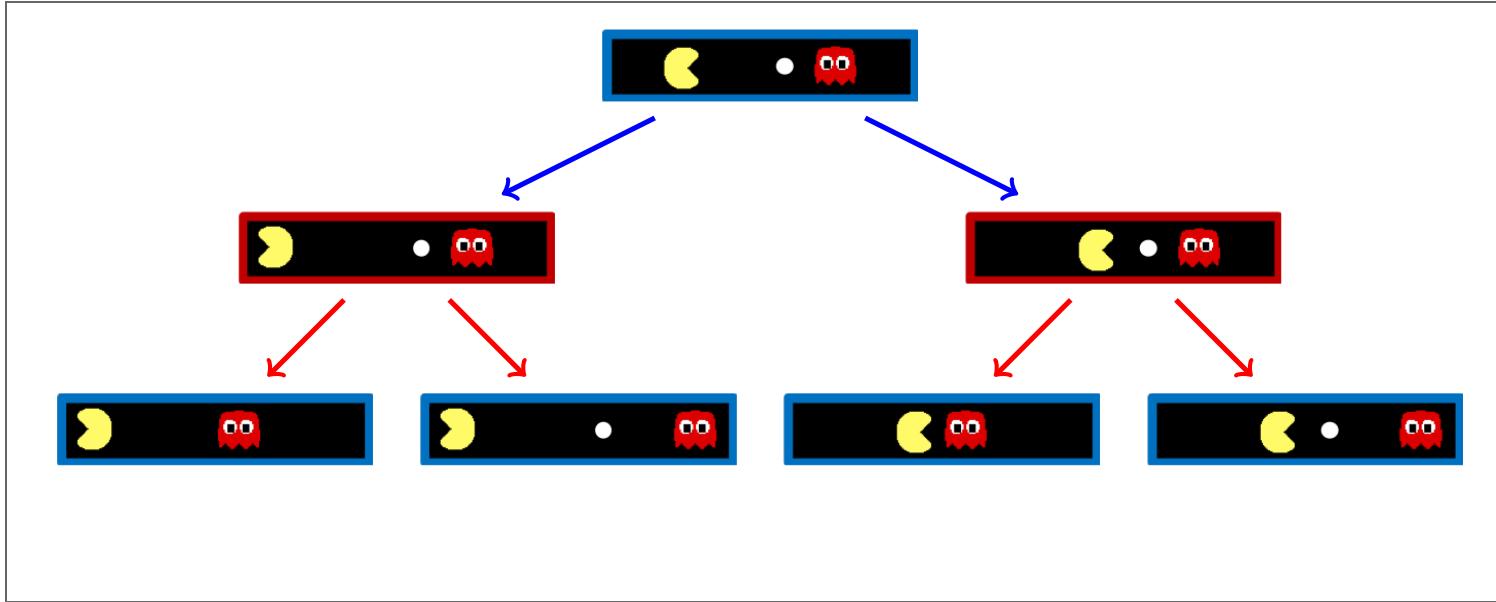






MINIMAX VALUES



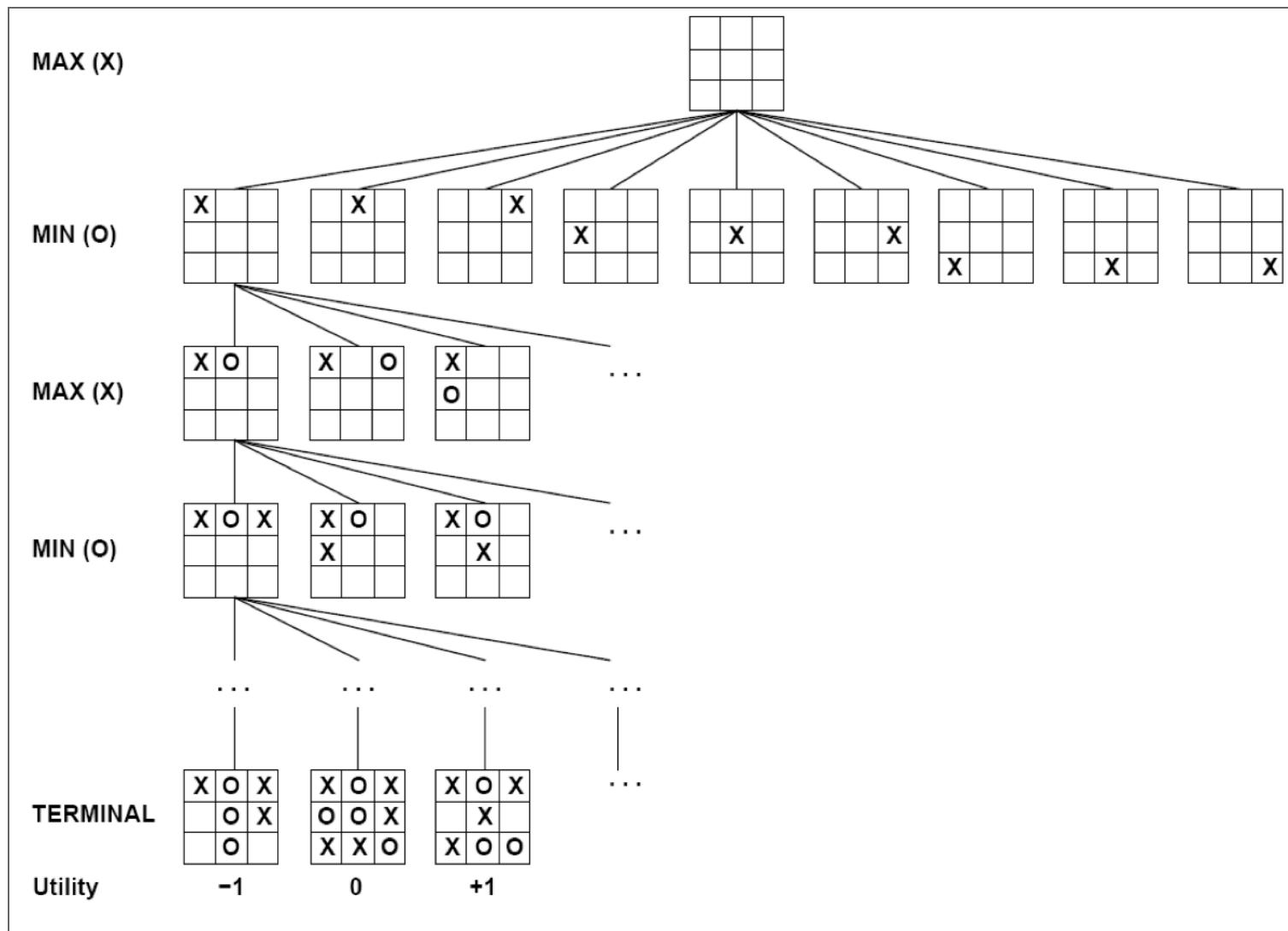


States Under Agent's Control: $V(s) = \max_{s' \in \text{successors}(s)} V(s')$

States Under Opponent's Control: $V(s') = \min_{s \in \text{successors}(s')} V(s)$

Terminal States: $V(s)$ known

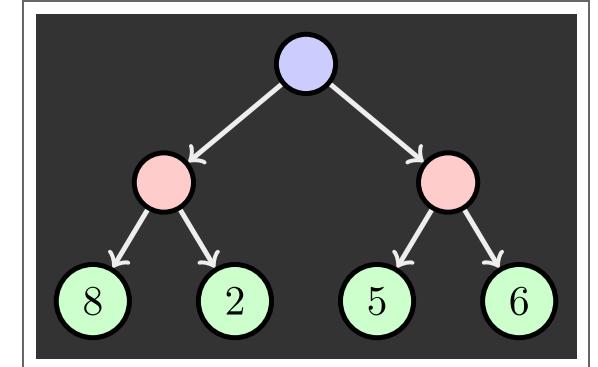
TIC-TAC TOE



ADVERSARIAL SEARCH (MINIMAX)

Deterministic, zero-sum games:

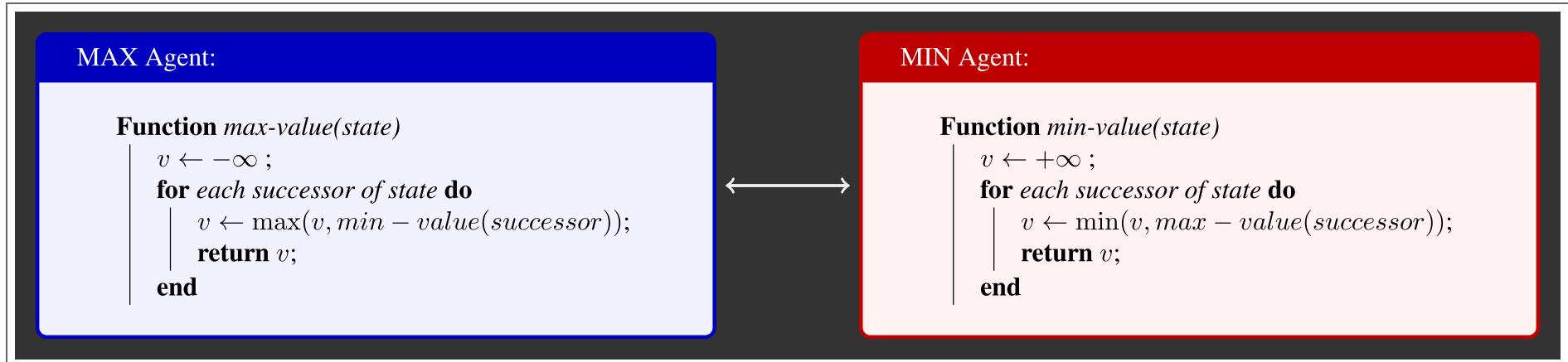
- › Tic-tac-toe, chess, checkers
- › One player maximizes result
- › The other minimizes result



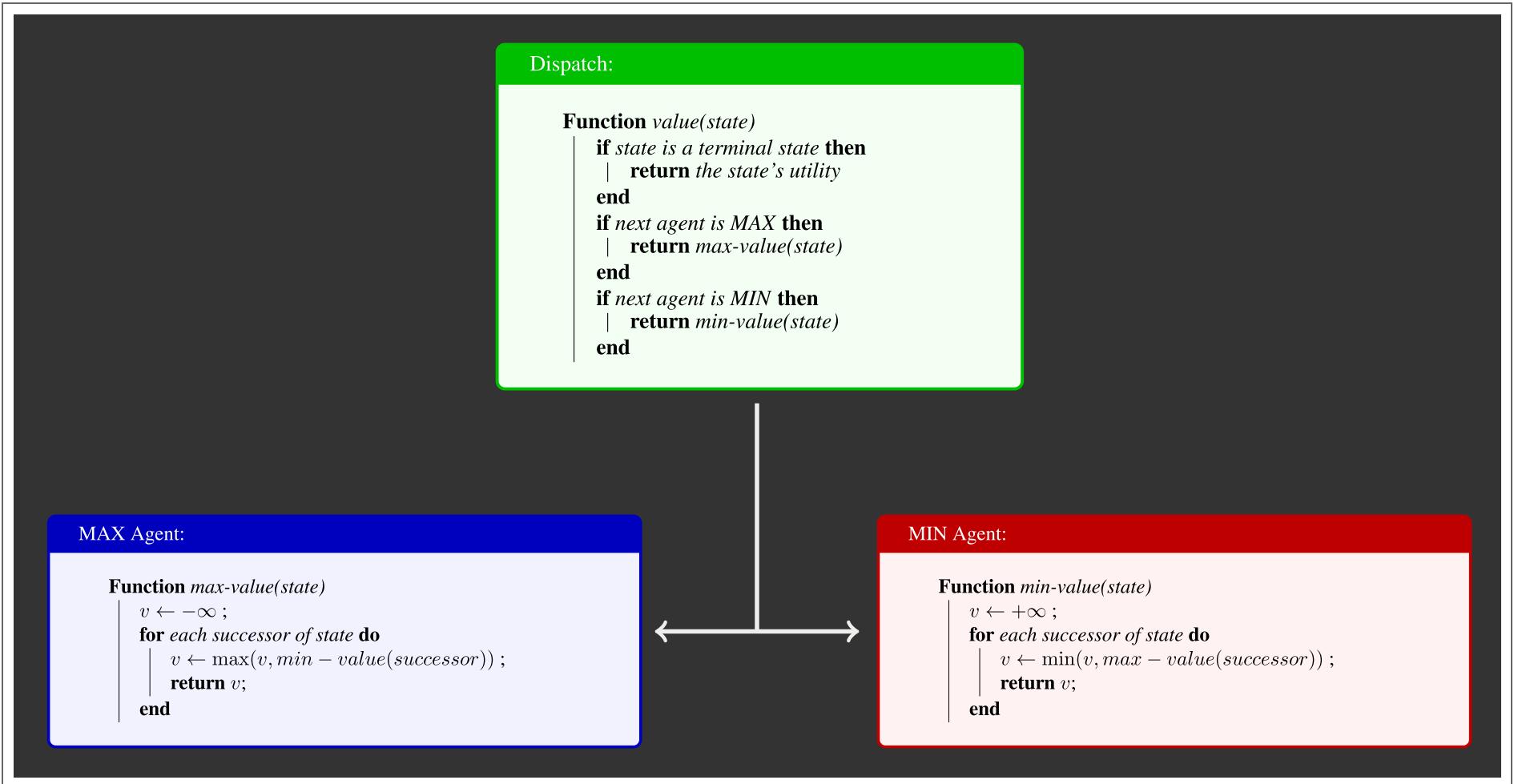
Minimax Search:

- › A state-space search tree
- › Players alternate turns
- › Compute each node's **minimax value**: the best achievable utility against a rational (optimal) adversary

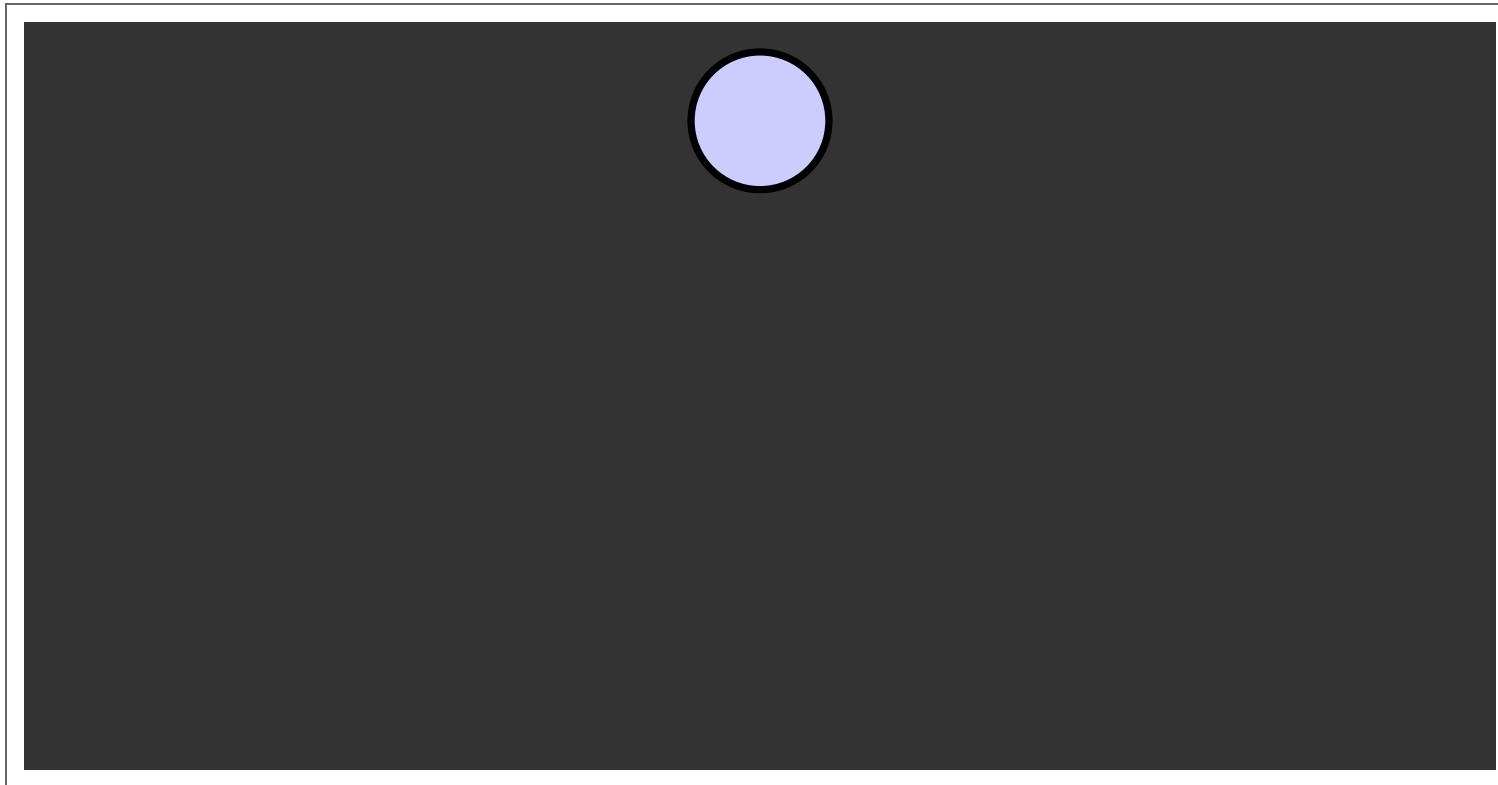
MINIMAX IMPLEMENTATION

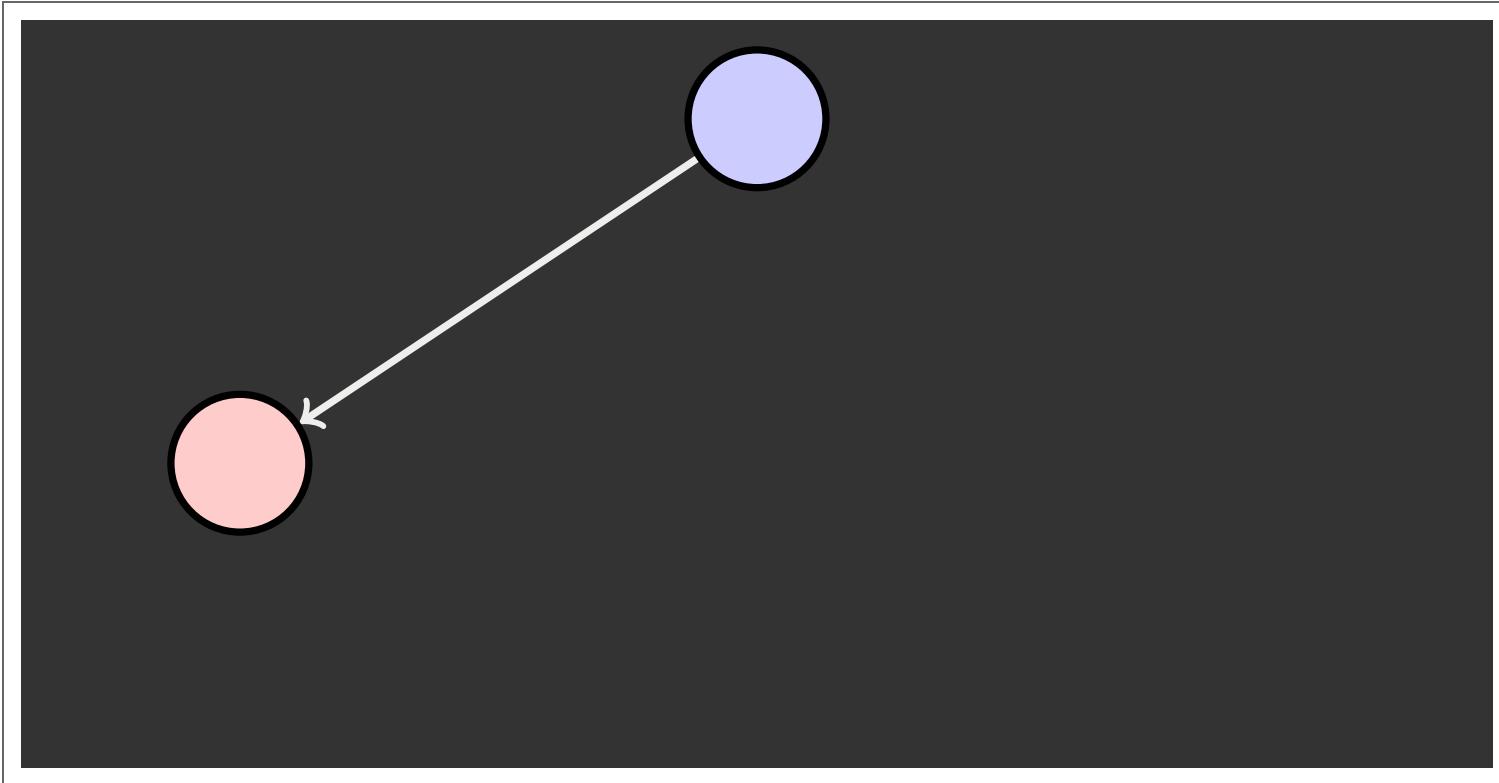


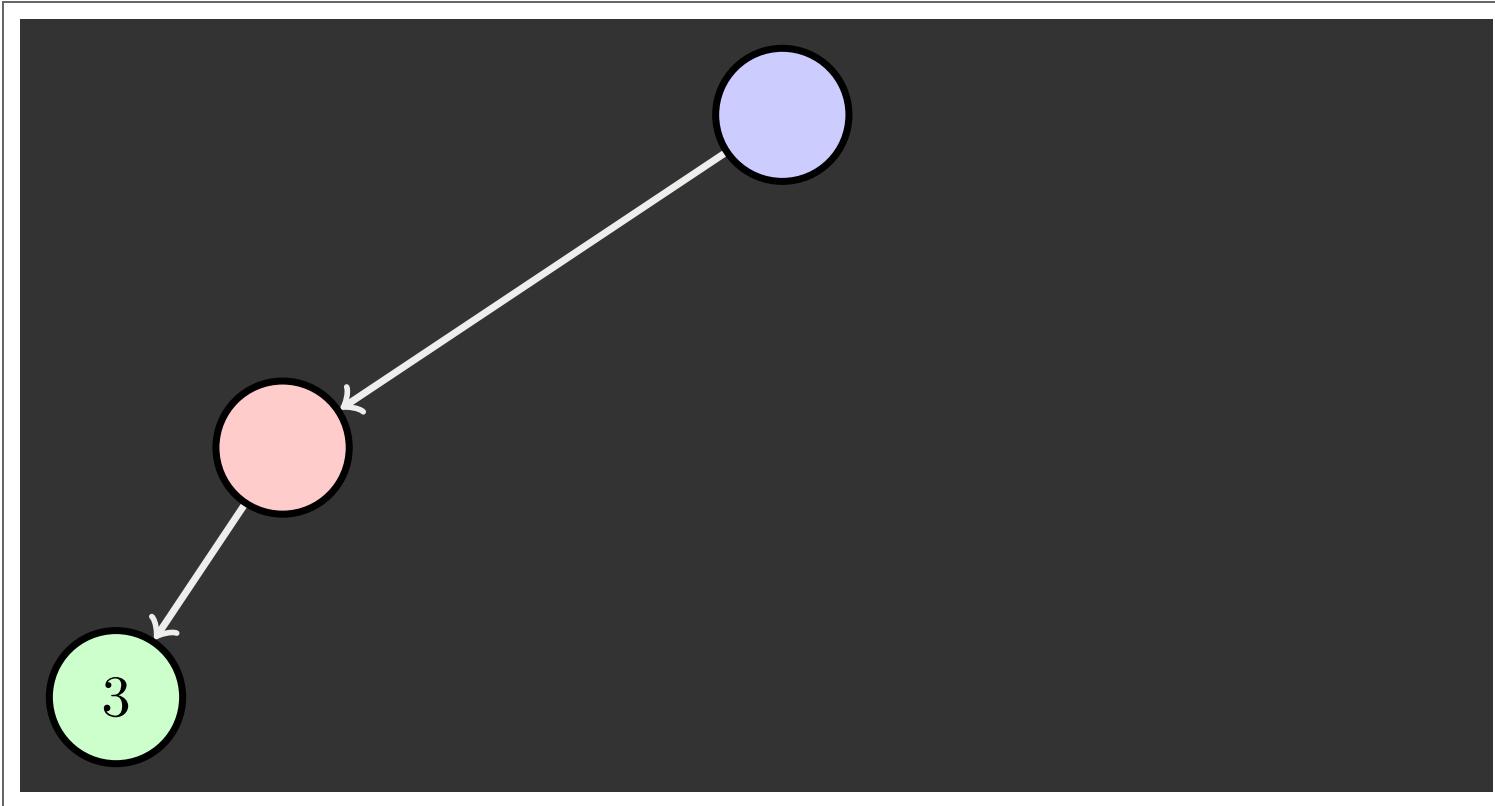
MINIMAX IMPLEMENTATION (DISPATCH)

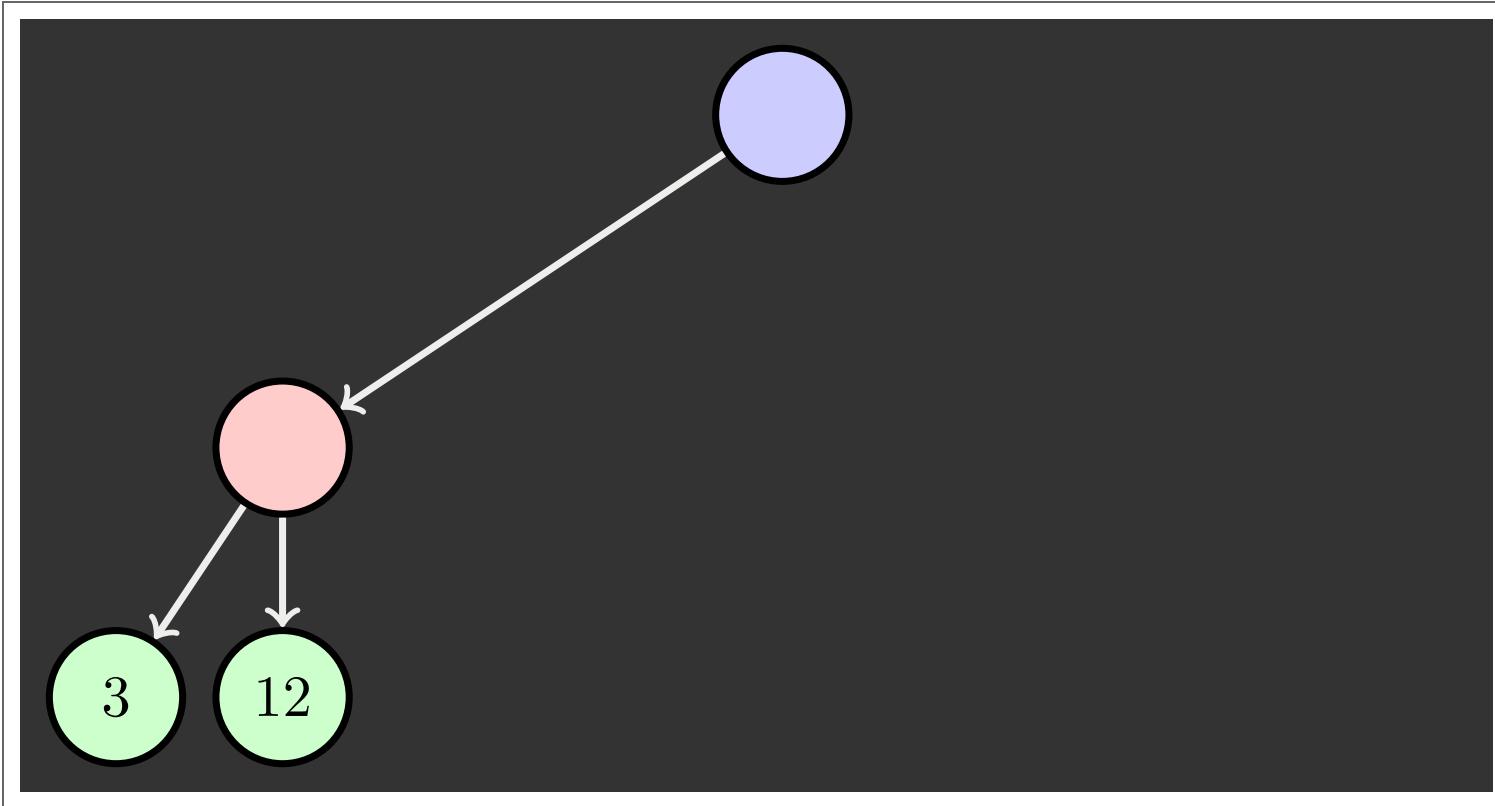


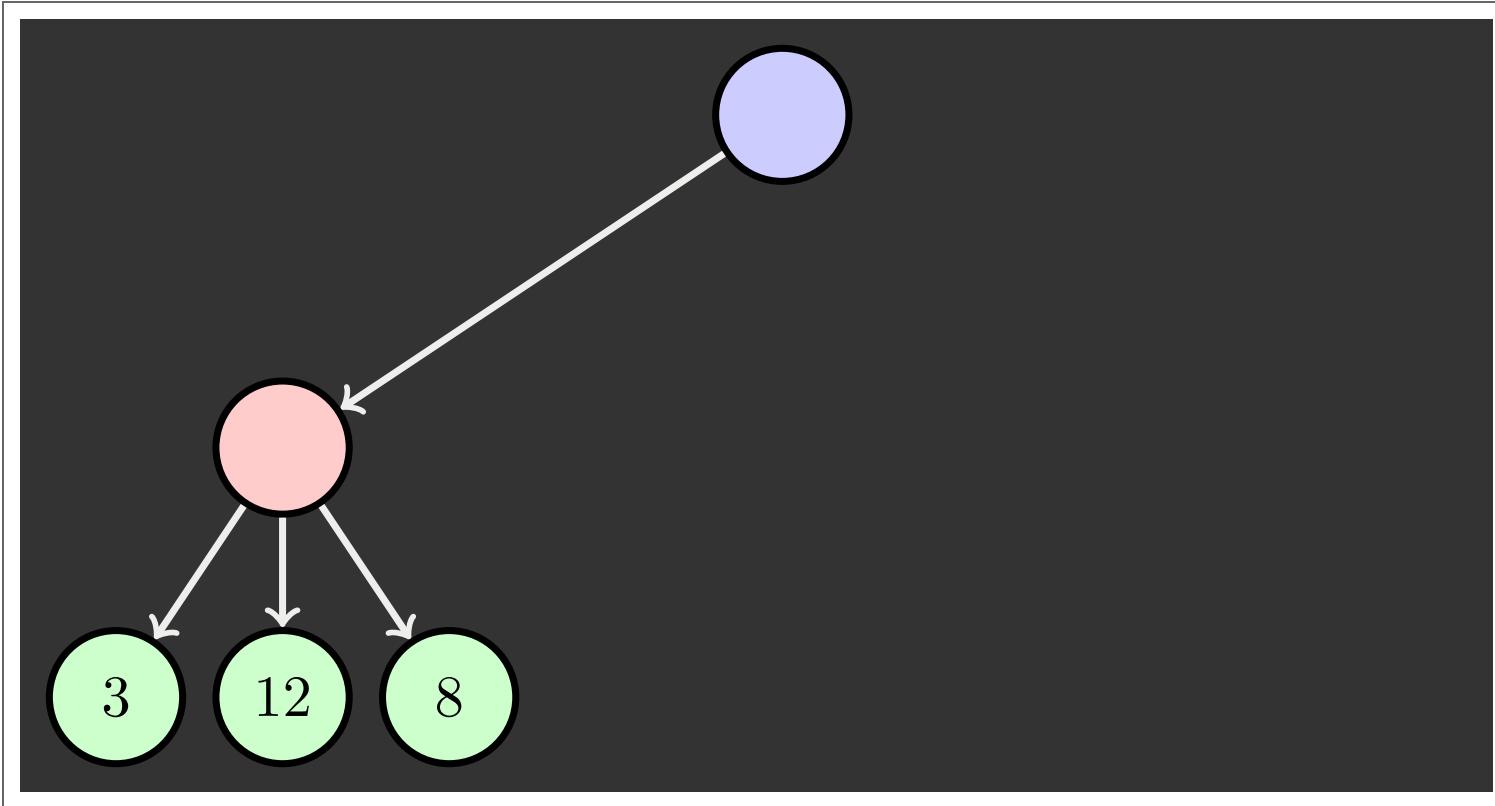
MINIMAX EXAMPLE

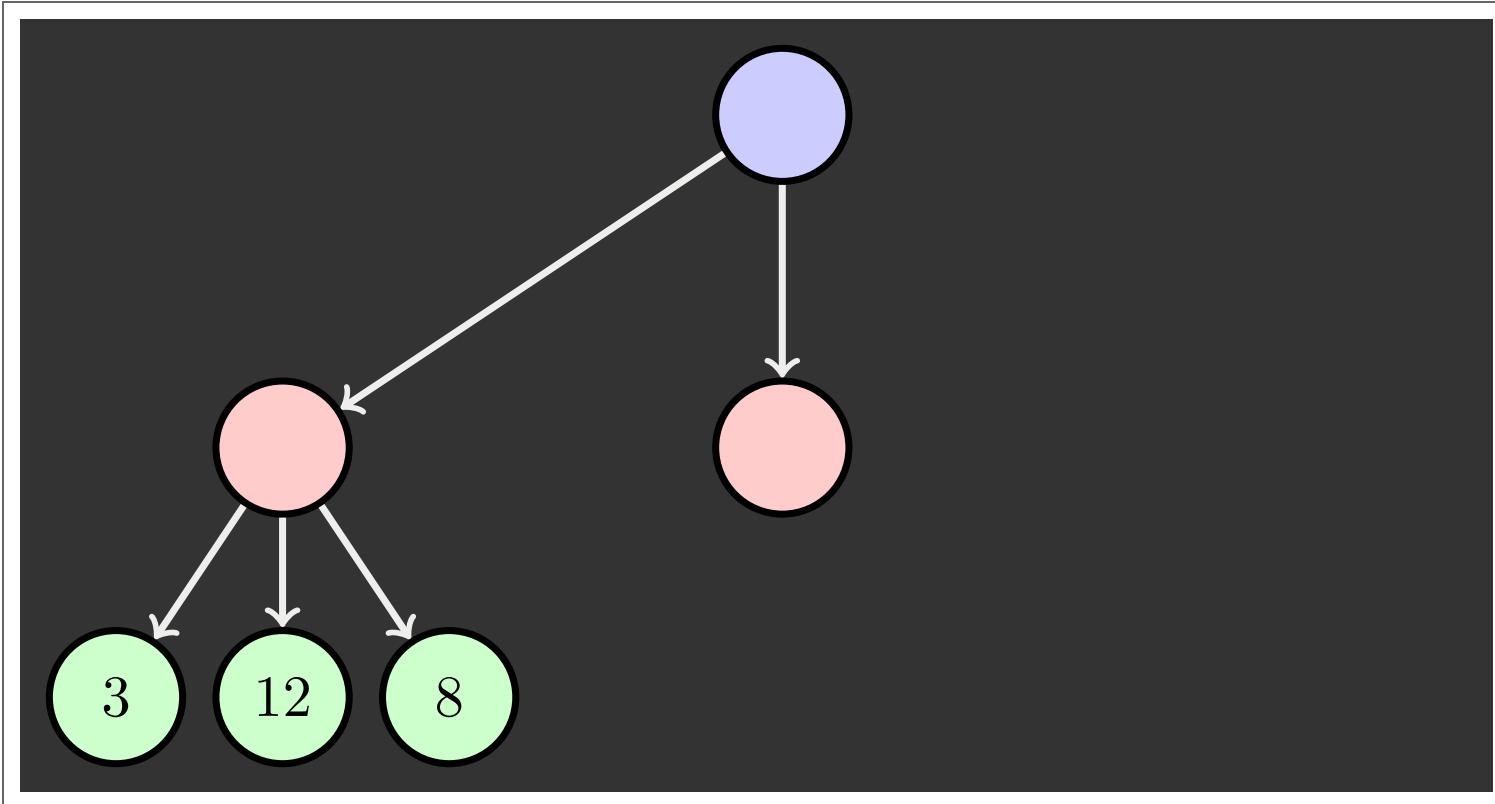


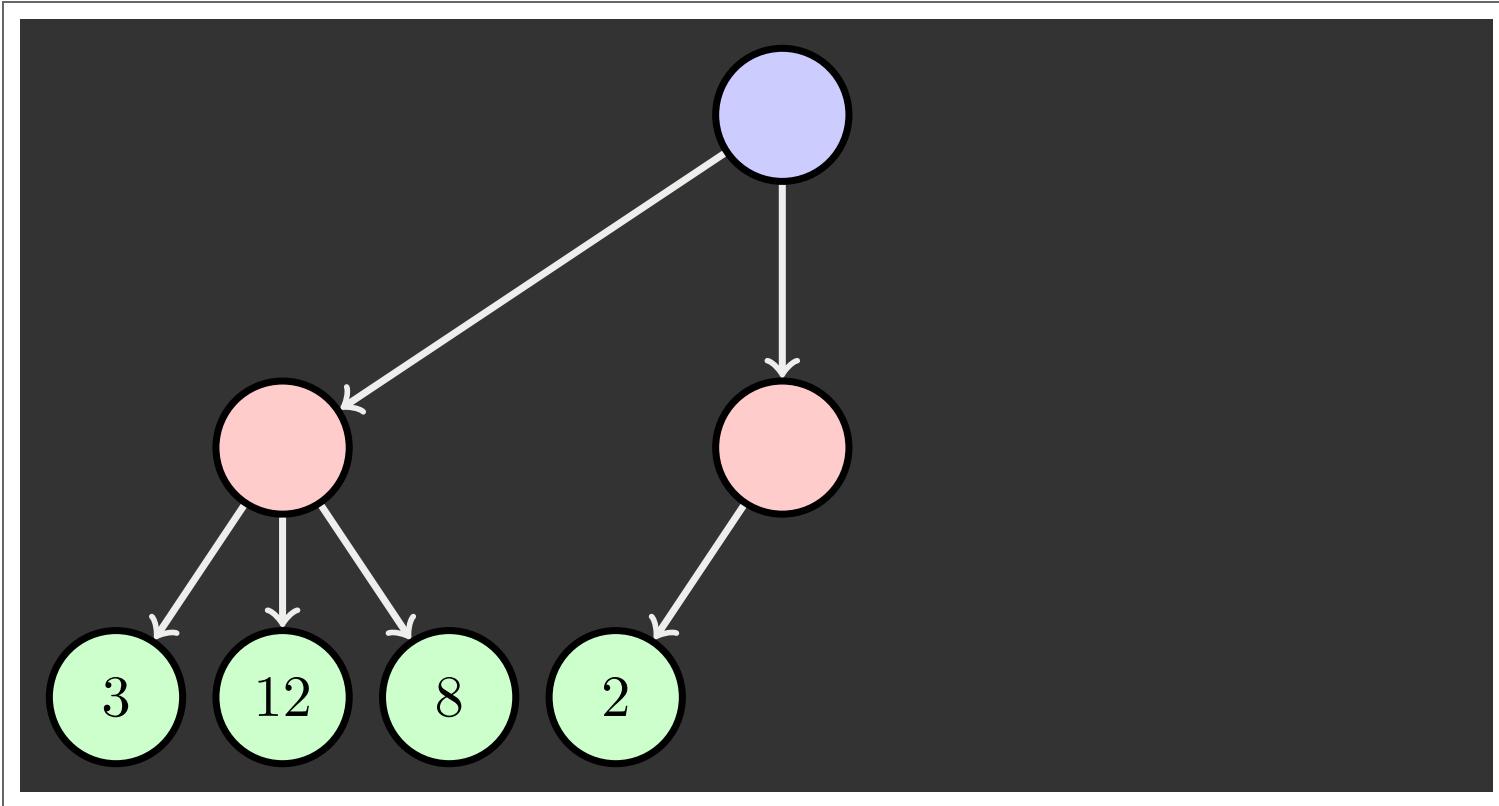


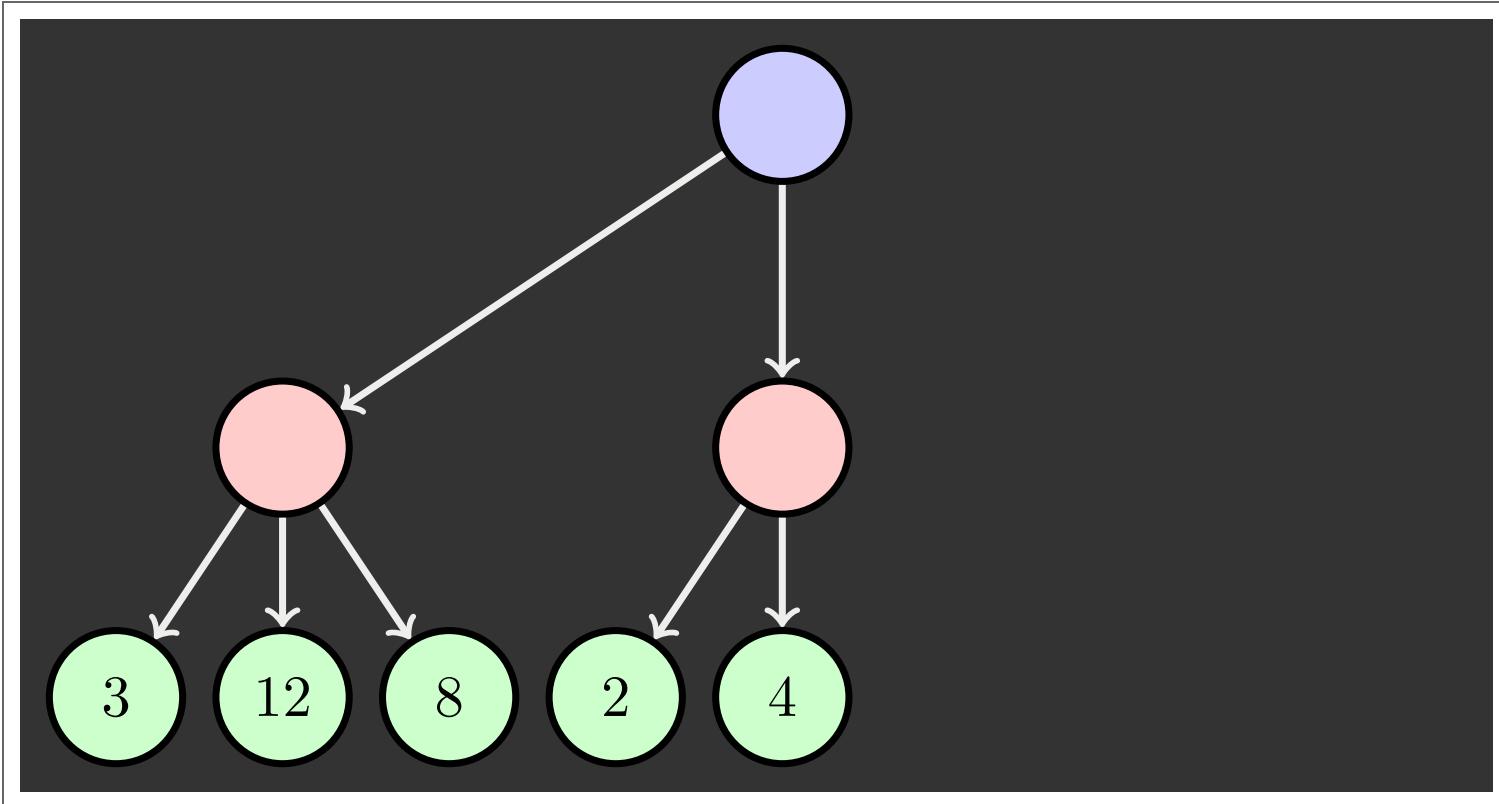


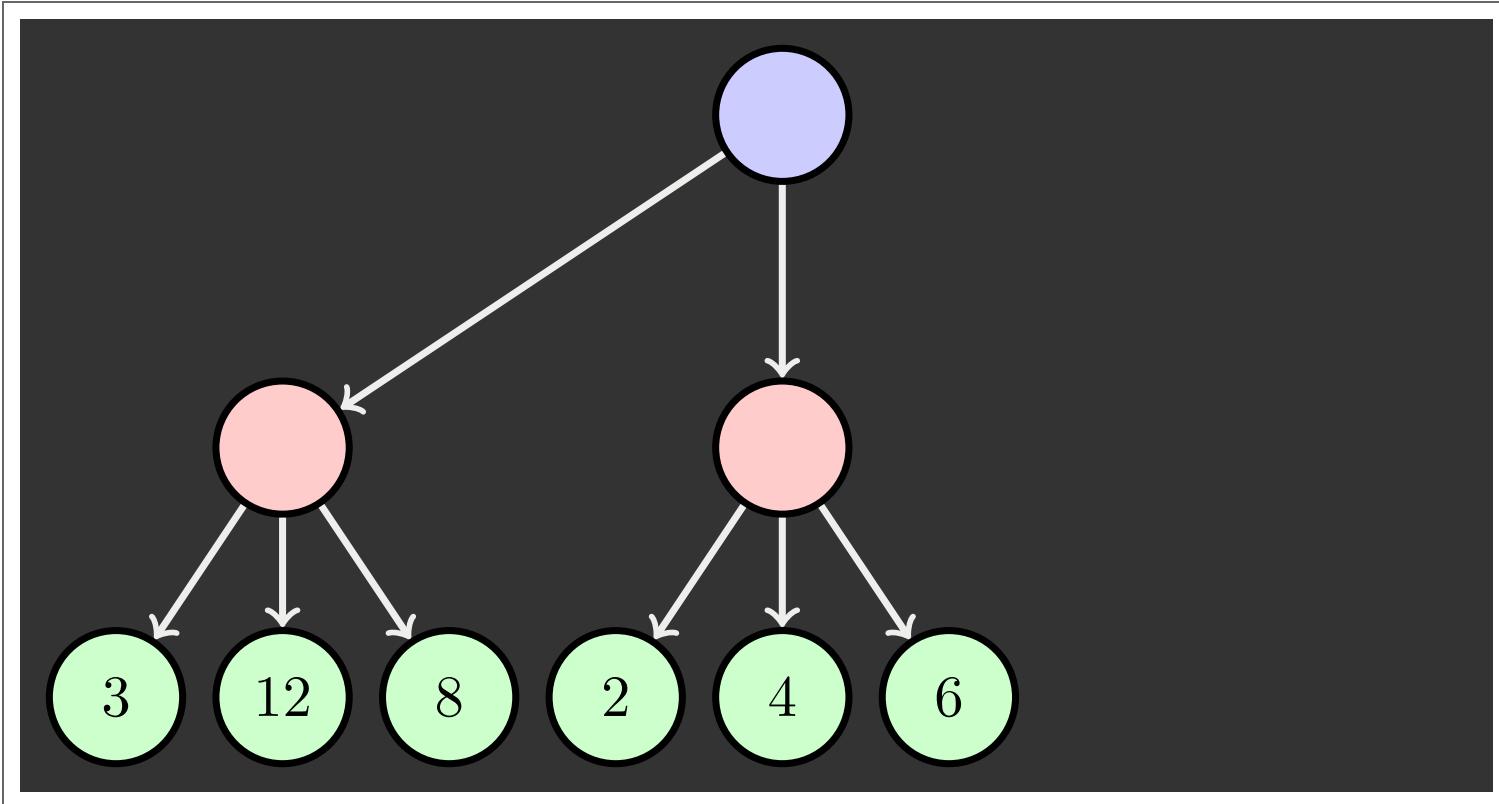


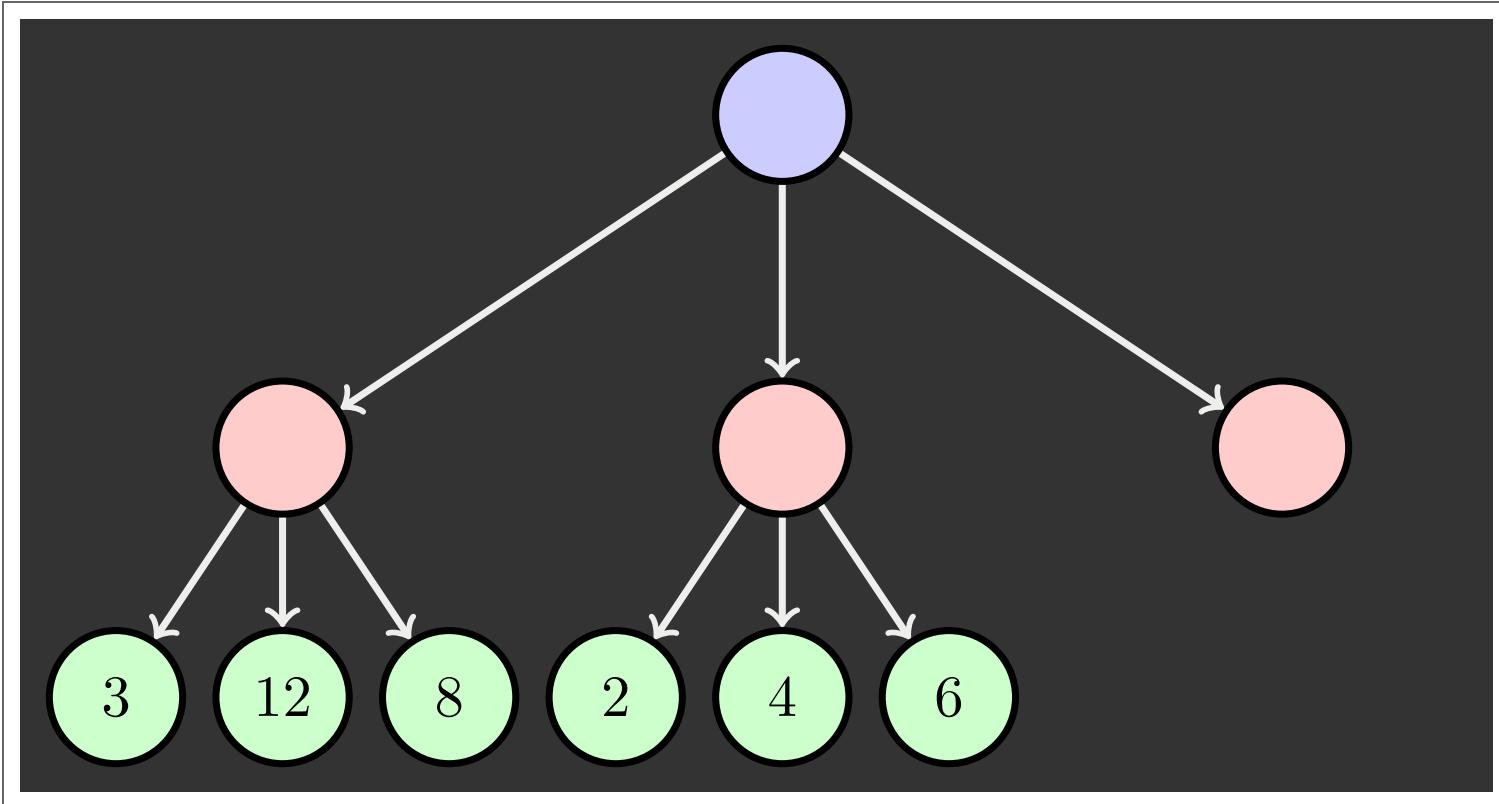


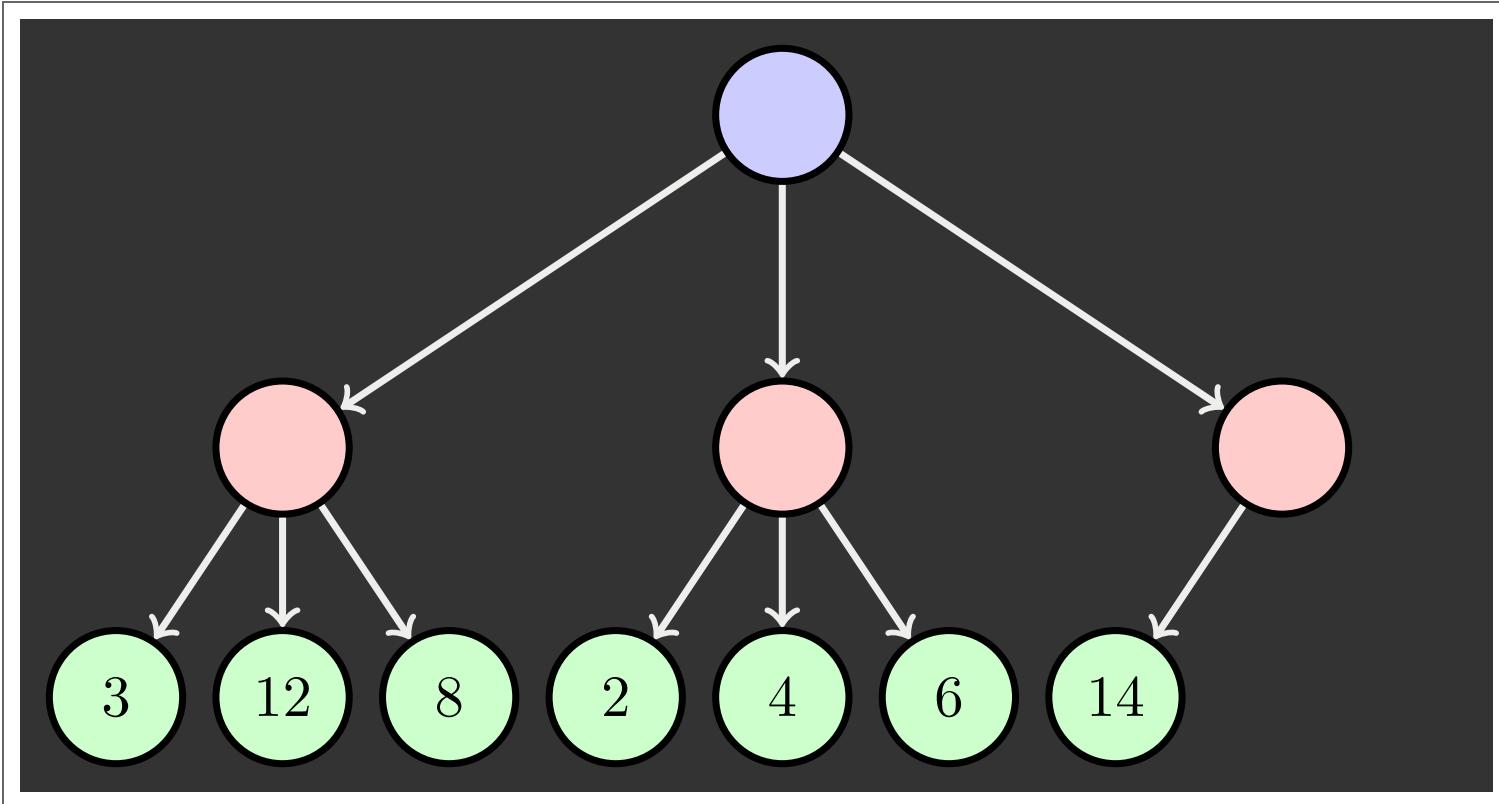


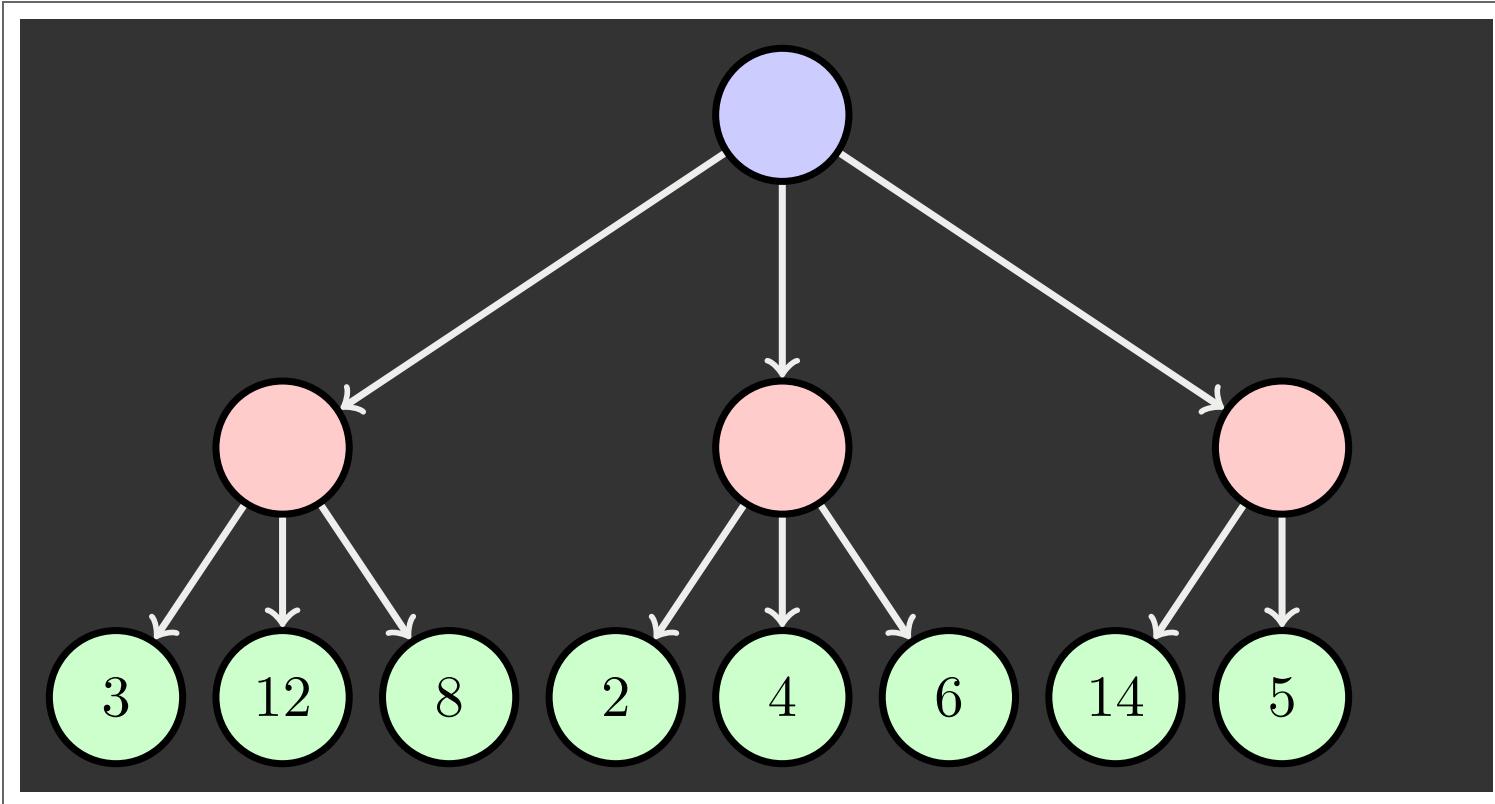


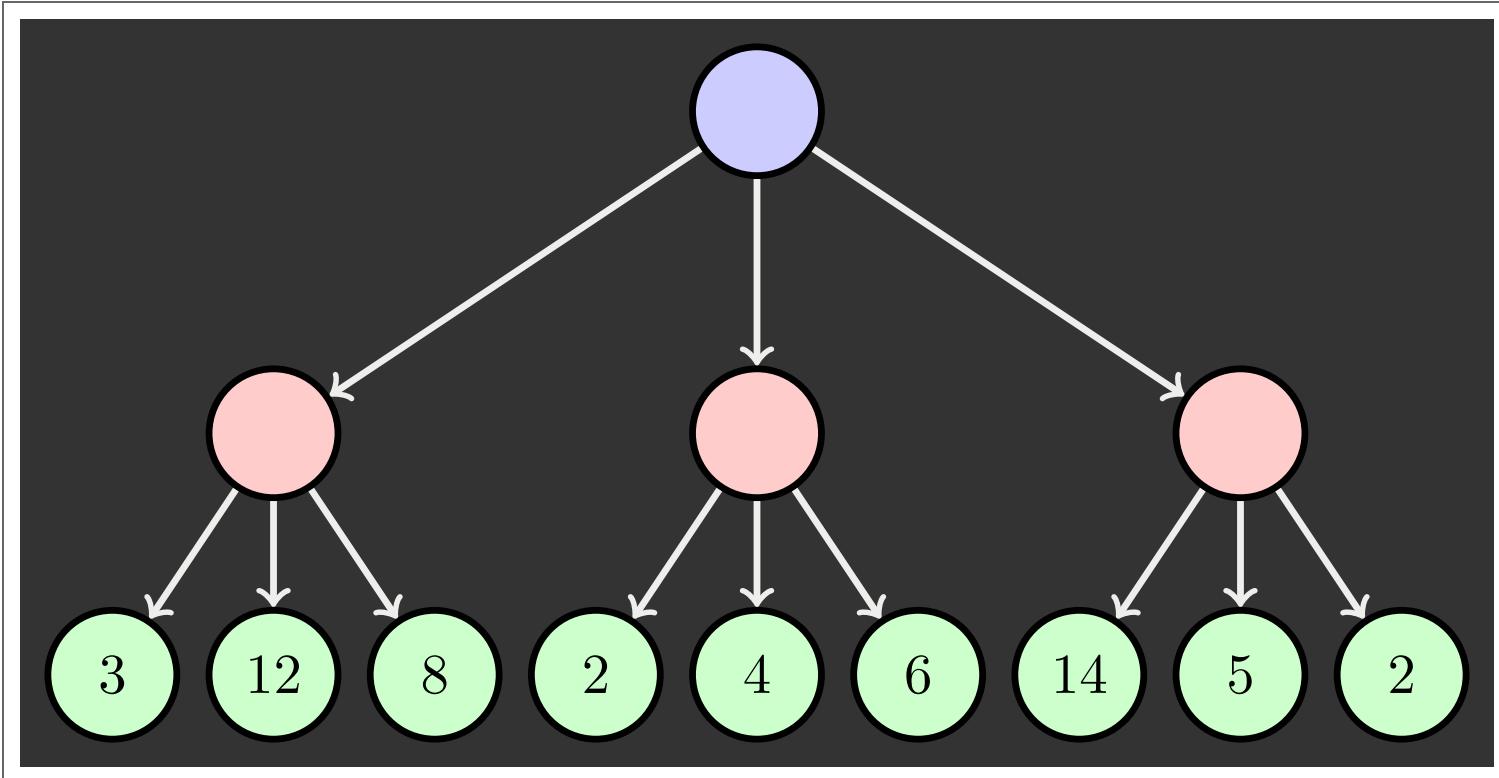




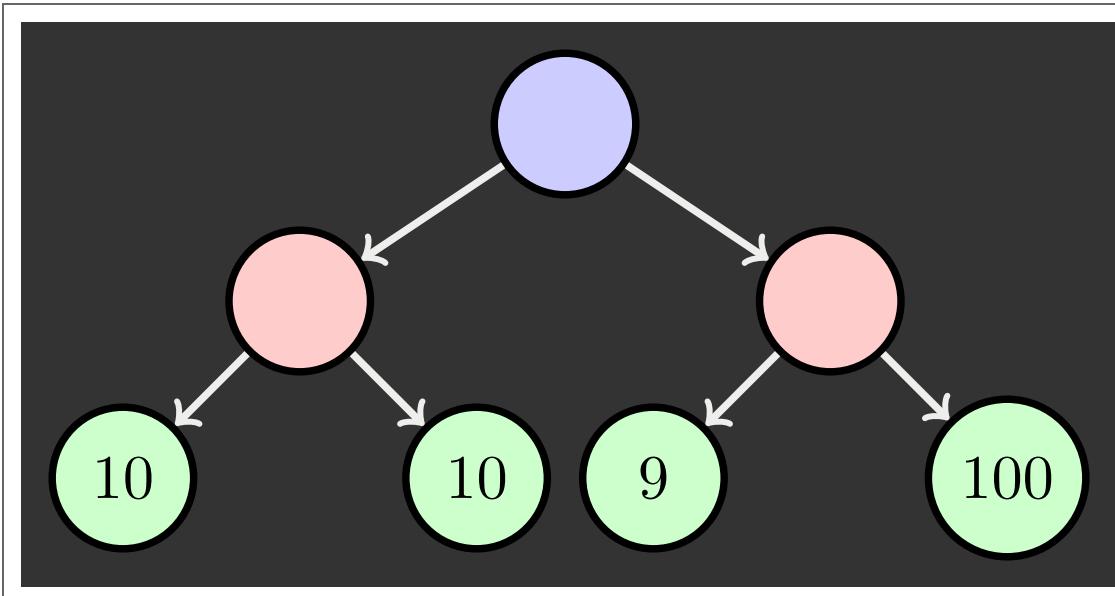








MINIMAX PROPERTIES



Optimal against a perfect player. Otherwise?

MINIMAX EFFICIENCY

How efficient is minimax?

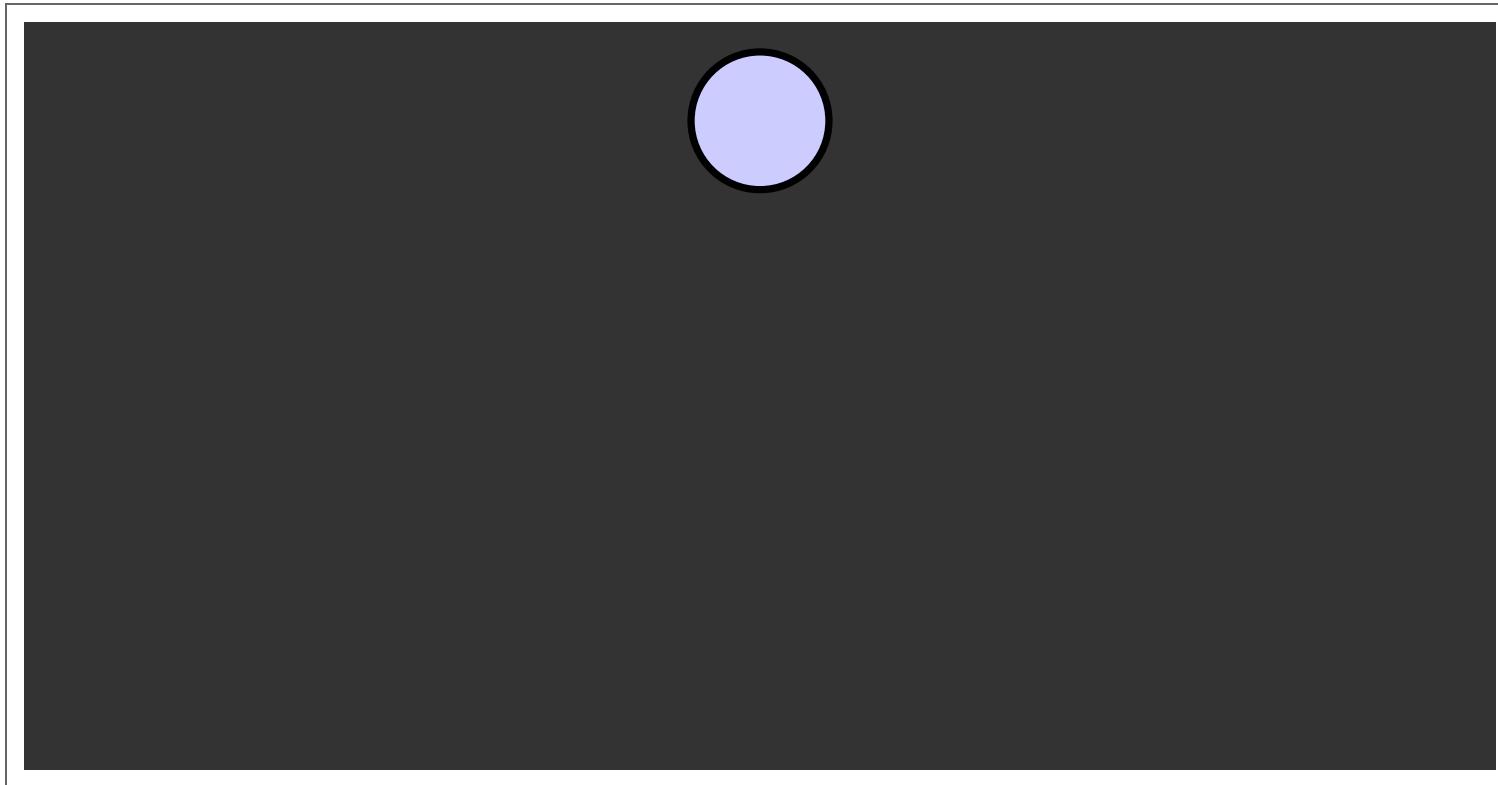
- › Just like (exhaustive) DFS
- › Time: $\mathcal{O}(b^m)$
- › Space: $\mathcal{O}(bm)$

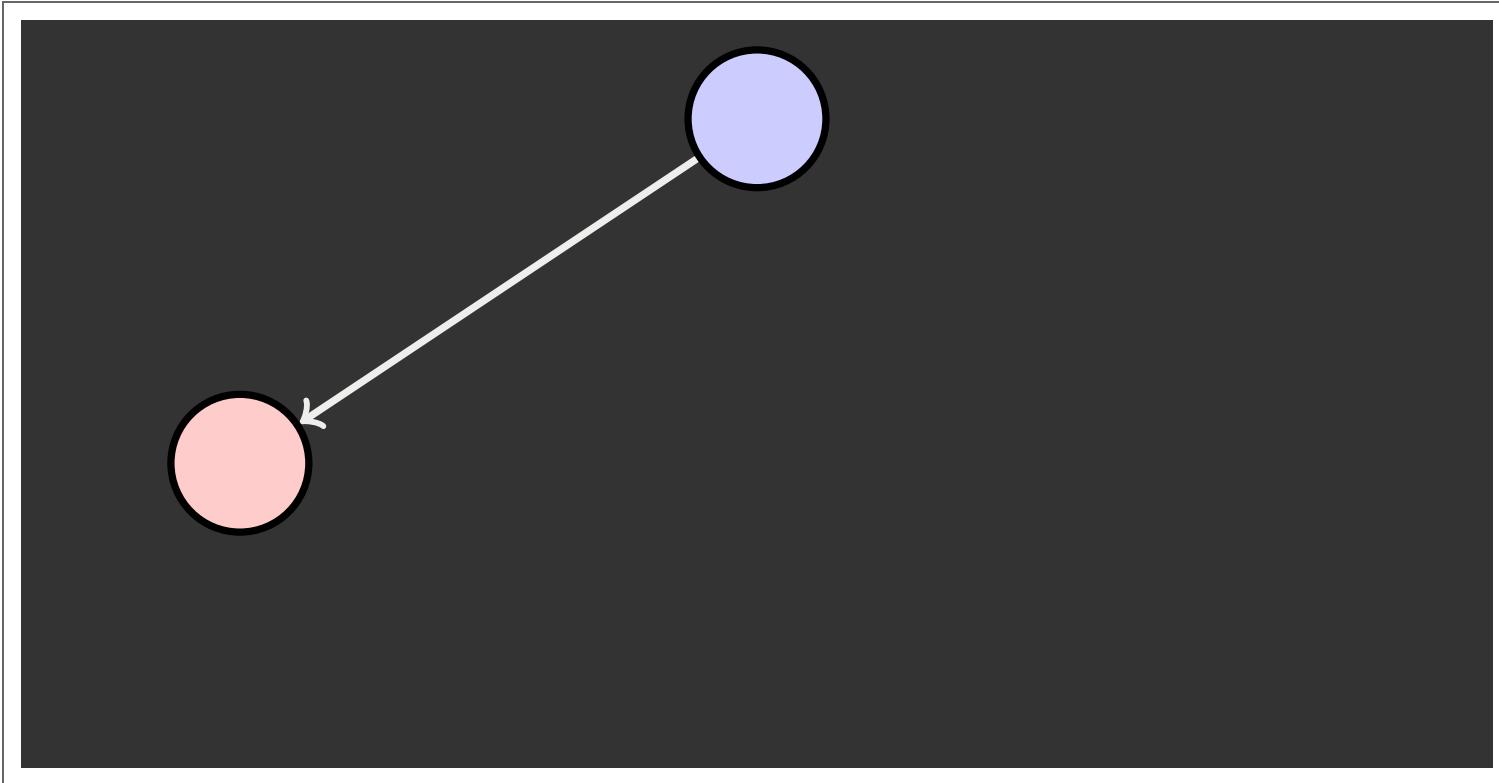
Example: For chess, $b \approx 35, m \approx 100$

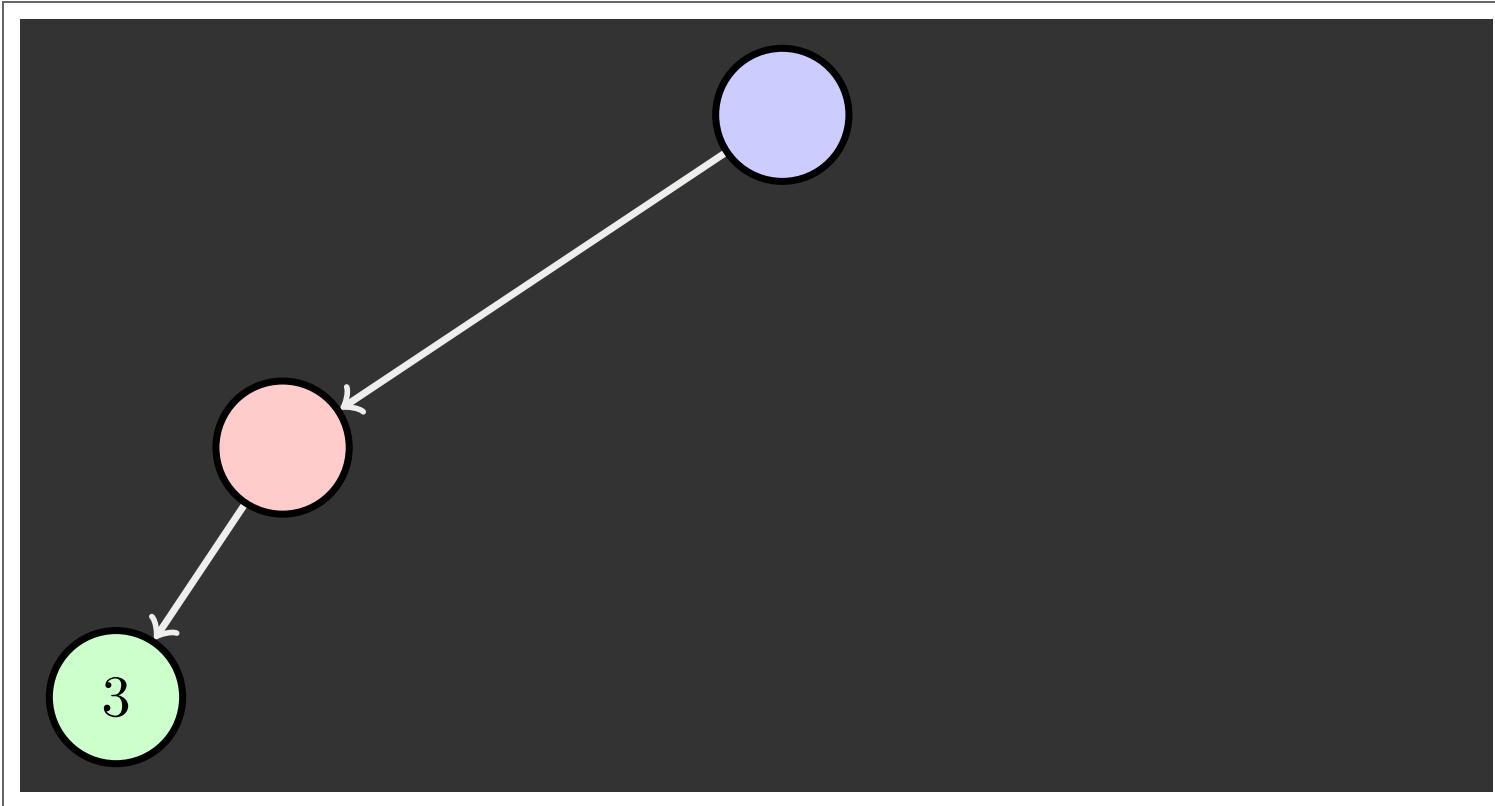
- › Exact solution is completely infeasible
- › But, do we need to explore the whole tree?

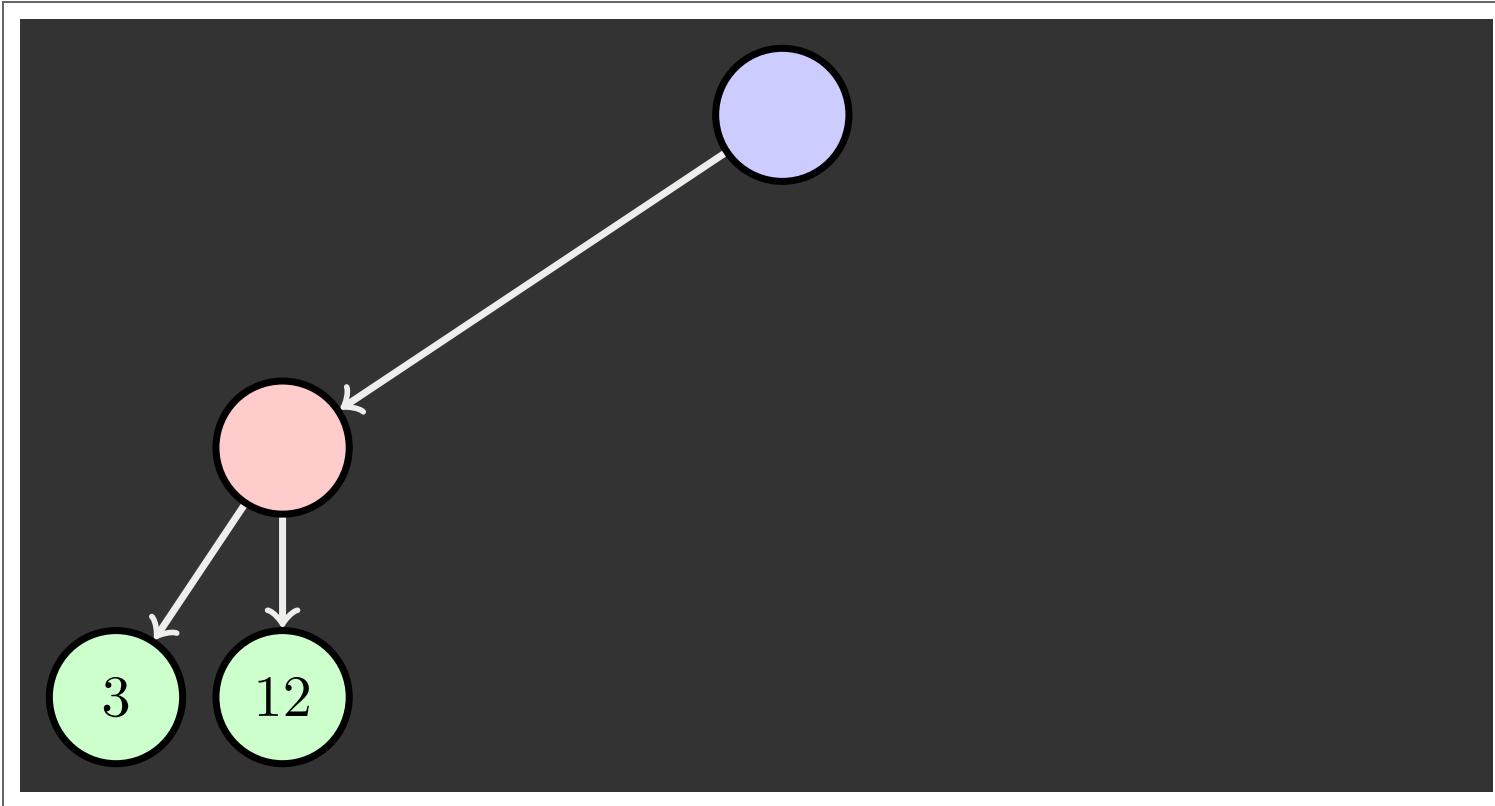
GAME TREE PRUNING

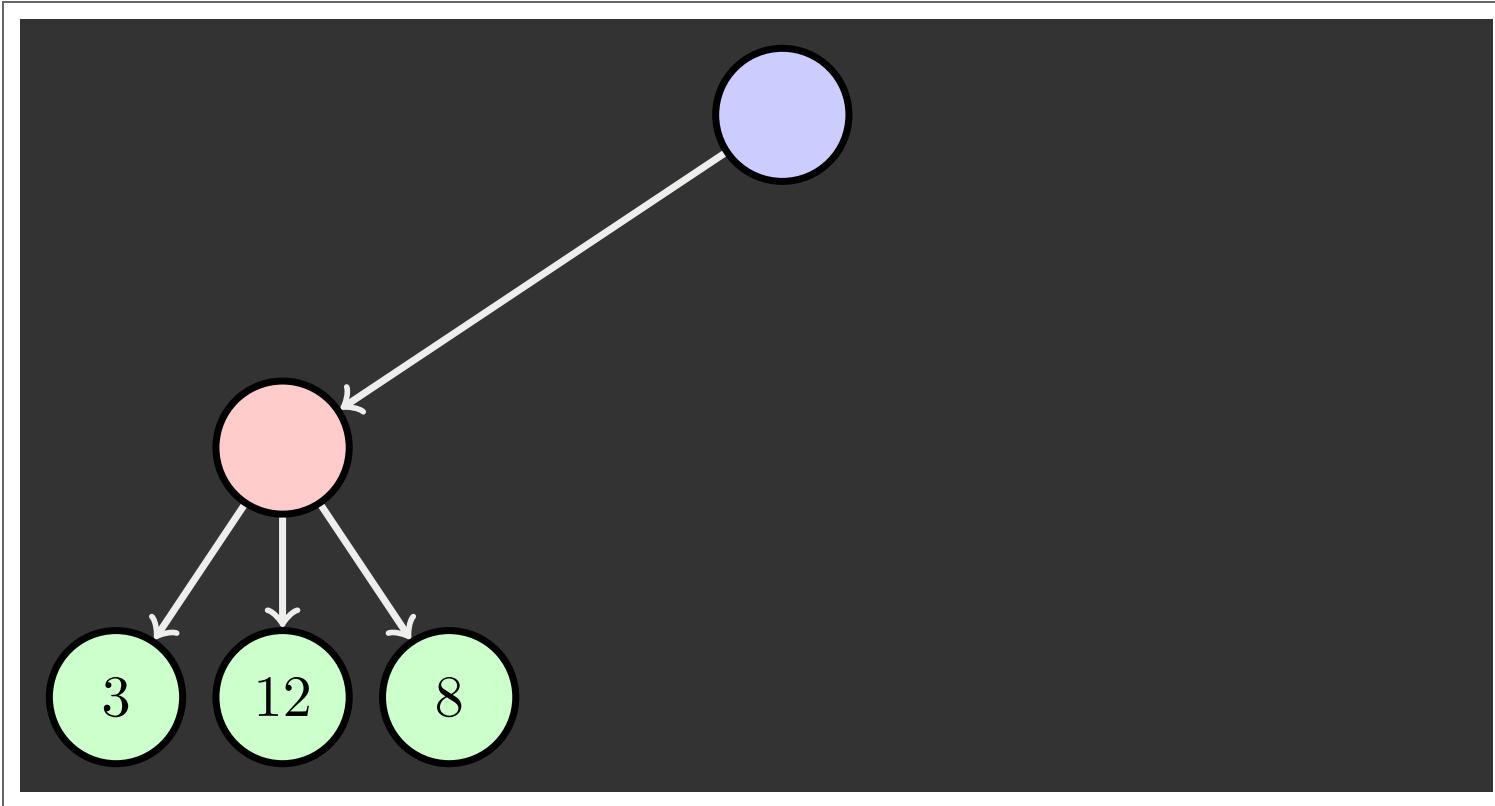
MINIMAX PRUNING

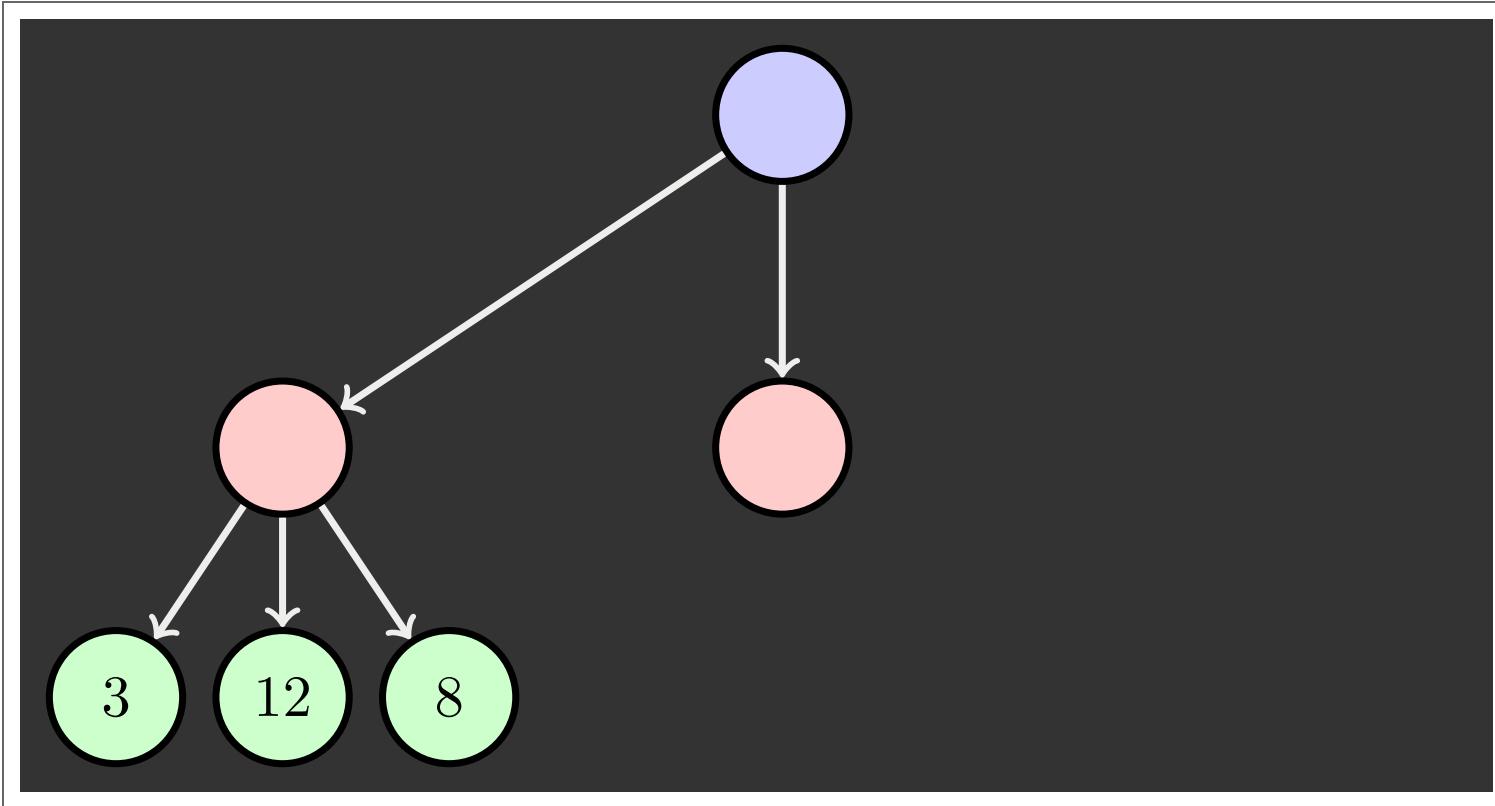


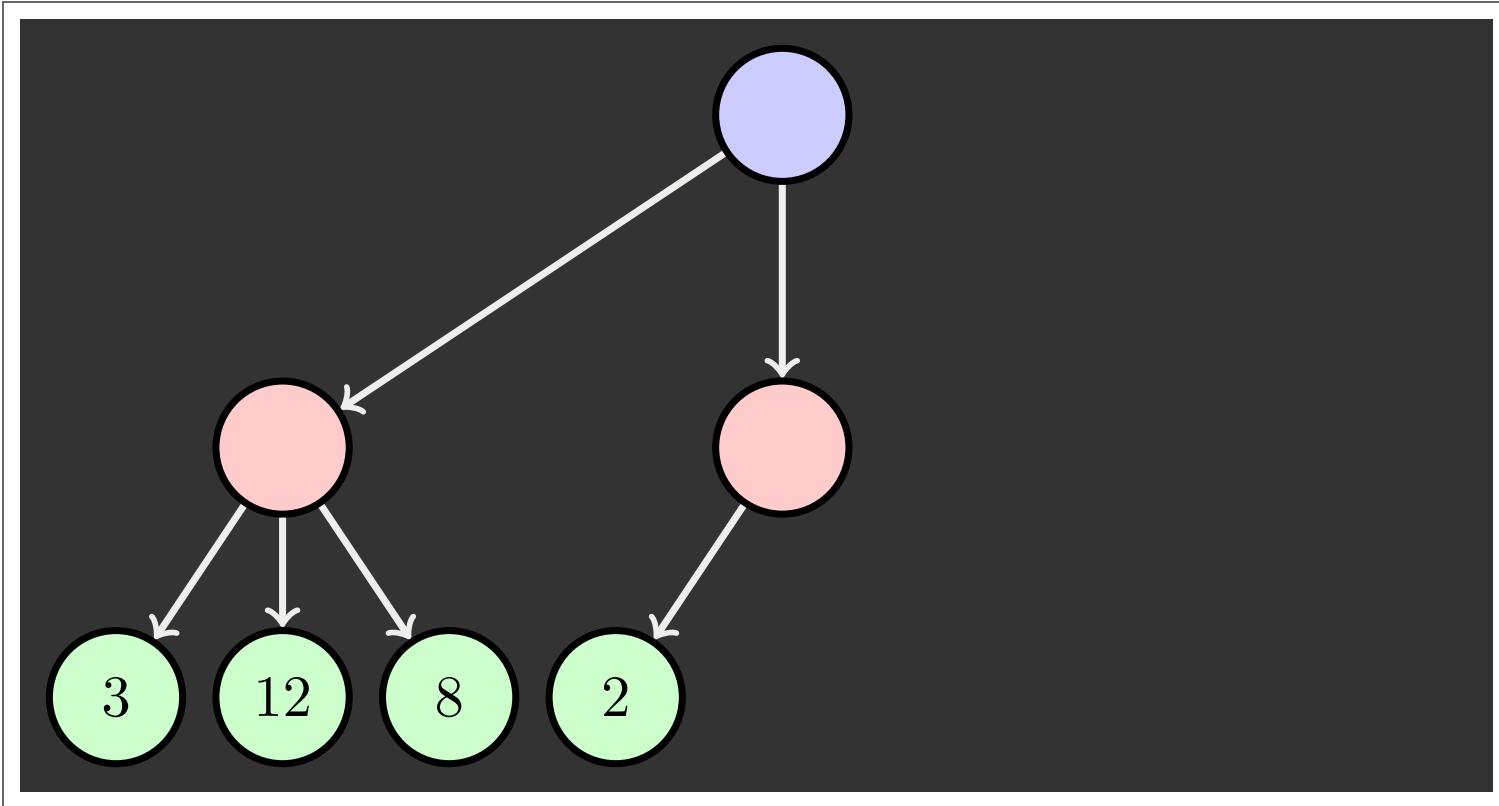


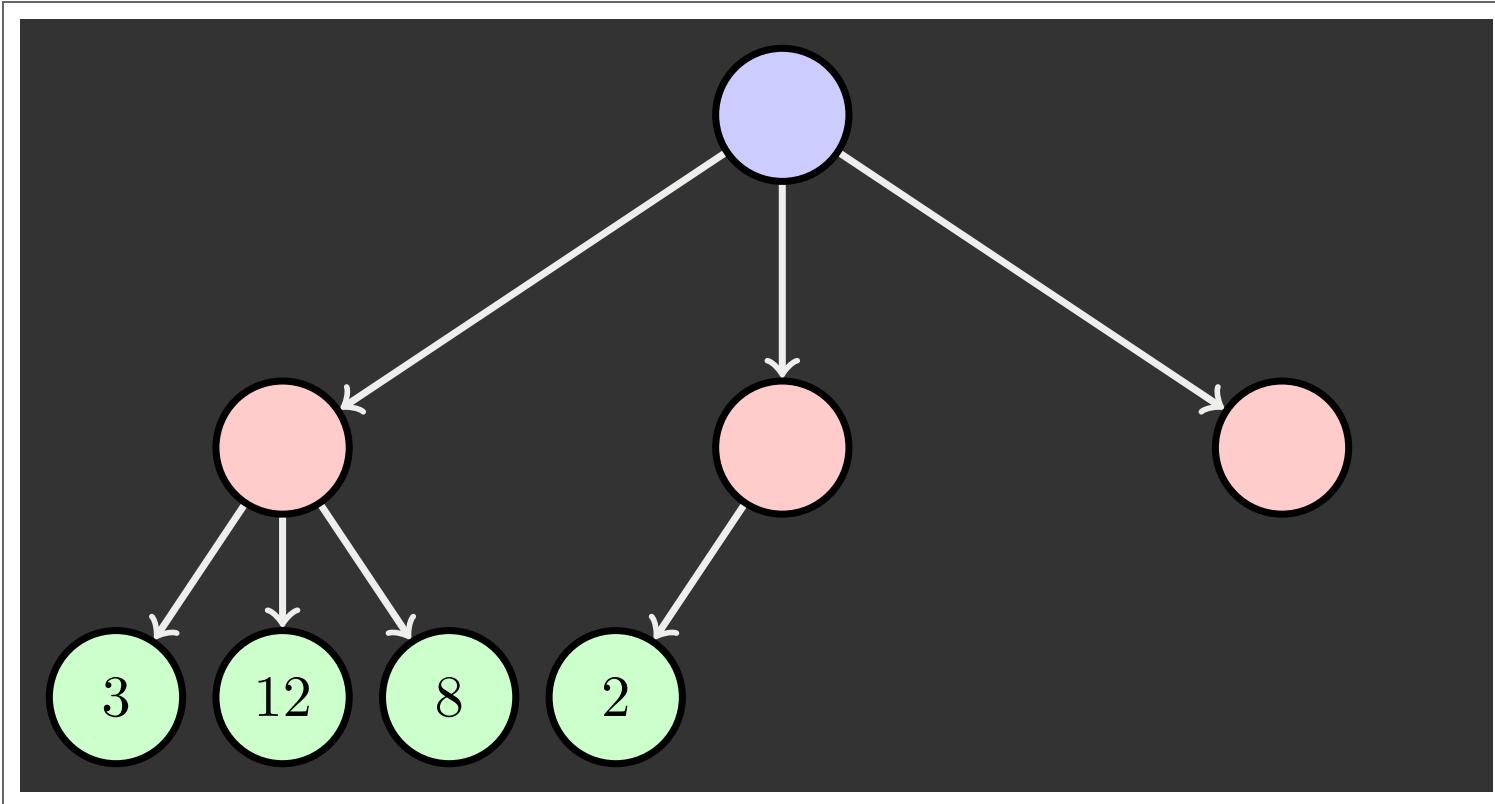


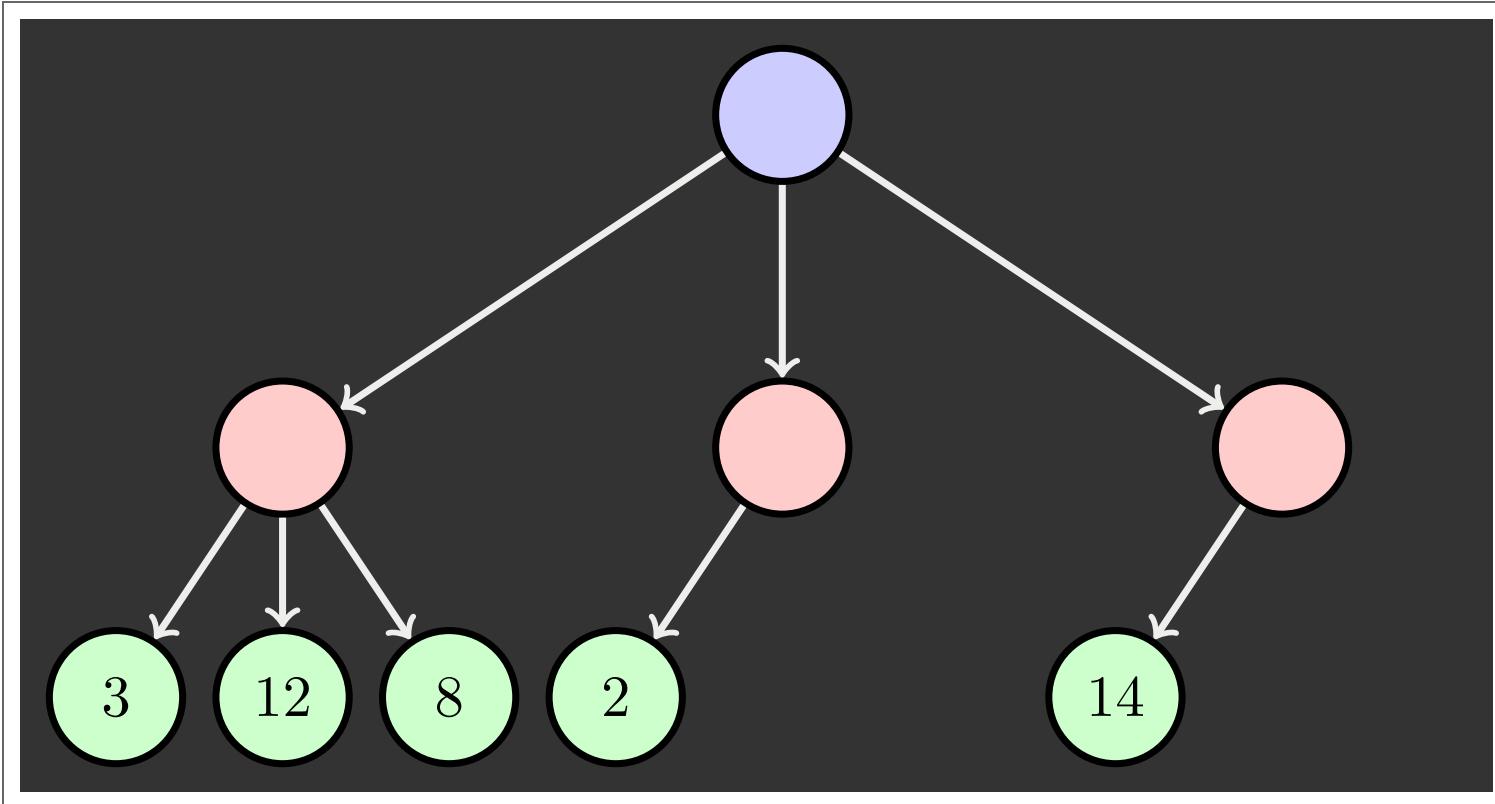


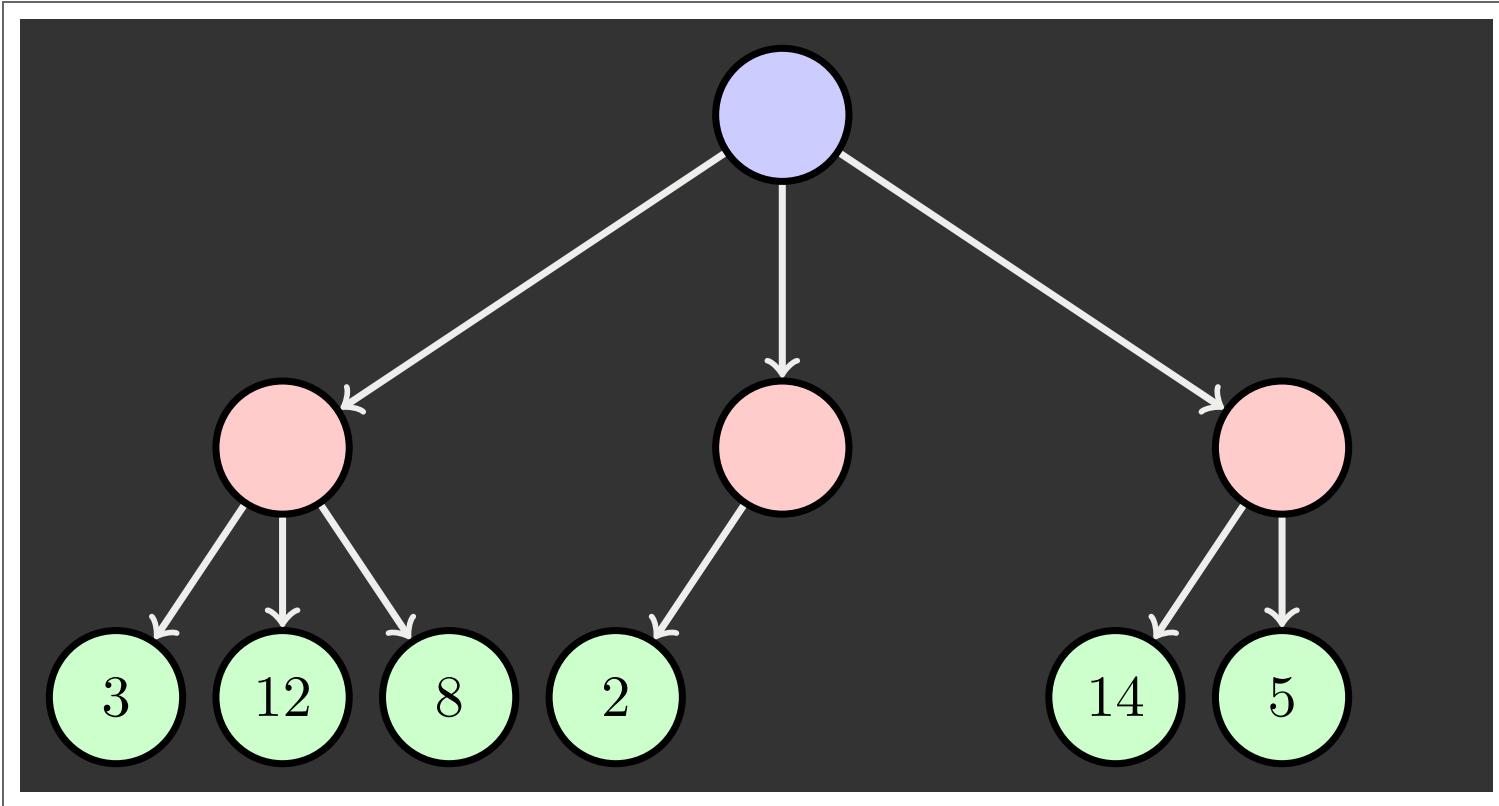


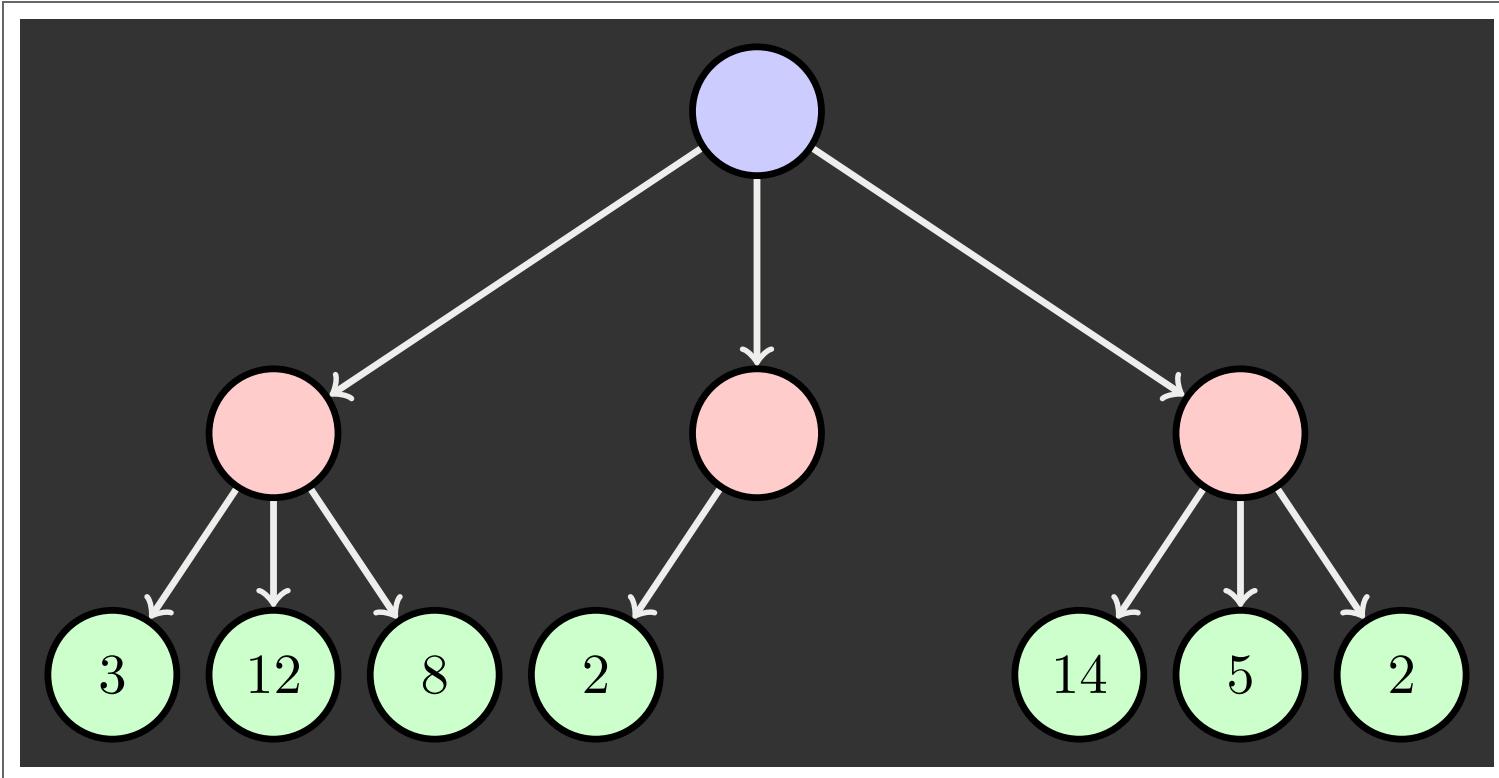












A – B PRUNING

General configuration (MIN version)

- › We are computing the *MIN – VALUE* at some node n
- › We are looping over n 's children
- › n 's estimate of the childrens' *min* is dropping
- › Who cares about n 's value? *MAX*
- › Let α be the best value that *MAX* can get at any choice point along the current path from the root.
- › If n becomes worse than α , *MAX* will avoid it, so we can stop considering n 's other children (it is already bad enough that it won't be played)

MAX version is symmetric

A – B IMPLEMENTATION

Dispatch:

α : MAX's best option on path to root

β : MIN's best option on path to root

MAX Agent:

```
def max-value(state,  $\alpha$ ,  $\beta$ ):  
    initialize  $v = -\infty$   
    for each successor of state:  
         $v = \max(v, \text{value(successor, } \alpha, \beta))$   
        if  $v \geq \beta$  return  $v$   
         $\alpha = \max(\alpha, v)$   
    return  $v$ 
```

MIN Agent:

```
def min-value(state,  $\alpha$ ,  $\beta$ ):  
    initialize  $v = +\infty$   
    for each successor of state:  
         $v = \min(v, \text{value(successor, } \alpha, \beta))$   
        if  $v \leq \alpha$  return  $v$   
         $\beta = \min(\beta, v)$   
    return  $v$ 
```

A – B PRUNING PROPERTIES

This pruning has **no effect** on minimax value computed for the root.

Values of intermediate nodes might be wrong

- › Important: children of the root may have the wrong value
- › So the most naïve version won't let you do action selection

Good child ordering improves effectiveness of pruning

With "perfect ordering":

- › Time complexity drops to $\mathcal{O}(b^{\frac{m}{2}})$
- › Doubles solvable depth
- › Full search of, e.g. chess, is still hopeless . . .

This is a simple example of **metareasoning** (computing about what to compute)

CONSTRAINED RESOURCES

Problem: In realistic games, cannot search to leaves.

Solution: Depth-limited search

- › Instead, search only to a limited depth in the tree
- › Replace terminal utilities with an evaluation function for non-terminal positions

Example:

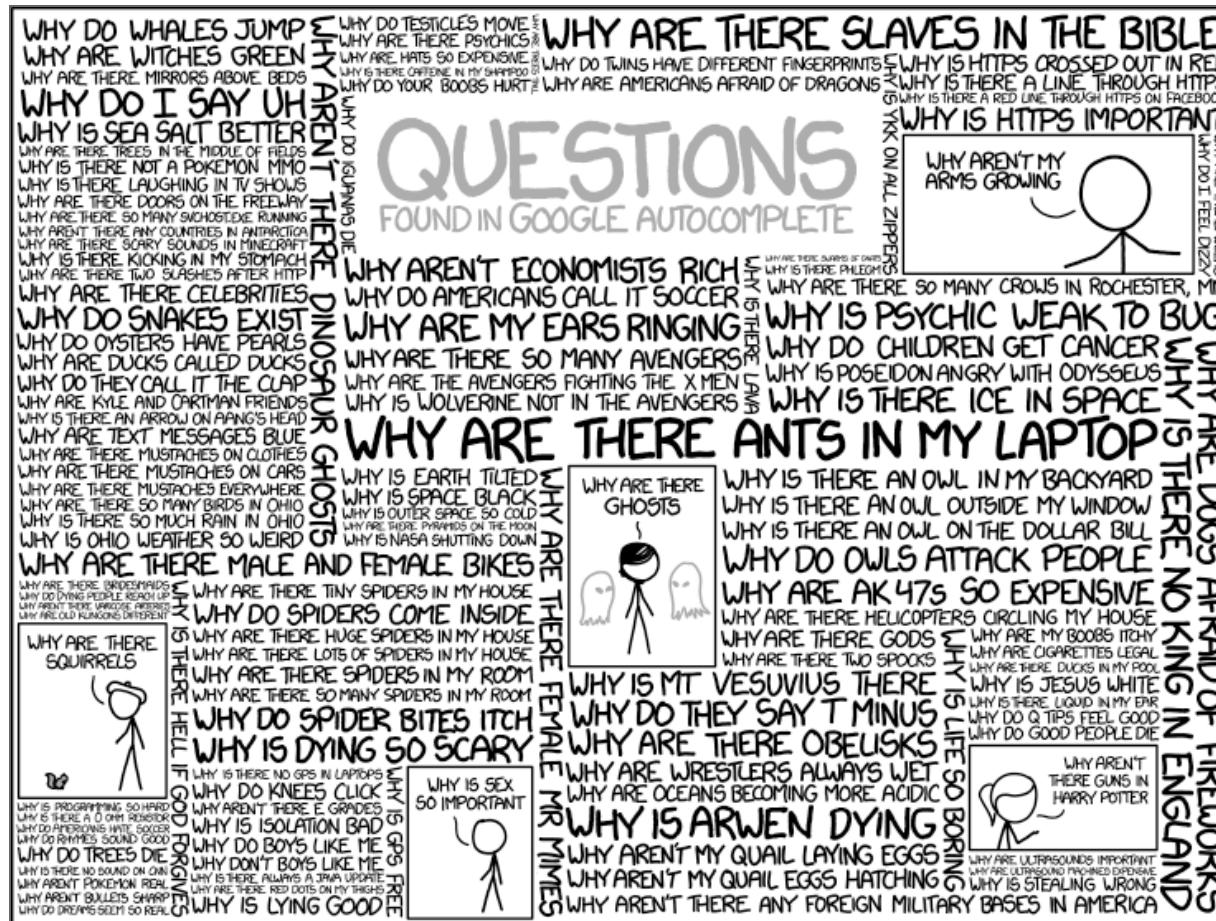
- › Suppose we have 100 seconds, can explore 10K nodes / sec
- › So can check 1M nodes per move
- › $\alpha - \beta$ reaches about depth 8 – decent chess program

Guarantee of optimal play is gone

More depth makes a BIG difference

Use iterative deepening for an anytime algorithm

Q & A



XKCD

Speaker notes

≡
Q & A

