Content

Gomoku Rule

- Gomoku:
  - Free Gomoku Rule: *Victoria* 15×15[1][2][3]
  - Standard Gomoku Rule: *Victoria* 15×15

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  - Free Renju Rule[4]
  - Soosyrv-8 Rule

Evolutionary Algorithm

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- Neuroevolution: genomes represent artificial neural networks[9][10]
- ...

Evolutionary Algorithm

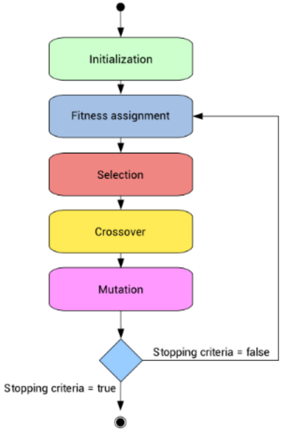

Figure: Flow chart of evolutionary algorithm

Genetic Algorithm[5]

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- Coding Scheme: coordinates of consecutive seven steps
  Representation: [(9,4), (7,6), (6,4), (7,7), (8,4), (7,4), (7,8)]

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Genetic Algorithm[5]

- Coding Scheme: coordinates of consecutive seven steps
  Representation: [(9,4), (7,6), (6,4), (7,7), (8,4), (7,4), (7,8)]
- Fitness function
- Selection: Roulette Wheel Selection

Genetic Algorithm

- Crossover: random crossover point
  Parent 1: (7,6) (5,5) (5,4) <u>(2,2) (6,5) (7,7) (4,4)</u>
  Parent 2: (5,7) (5,5) (2,4) <u>(7,7) (3,5) (4,4) (3,3)</u>
  Child 1: (7,6) (5,5) (5,4) <u>(7,7) (3,5) (4,4) (3,3)</u>
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Genetic Algorithm

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- Mutate: random mutate point
  Parent 3: (7,6) (5,5) (5,4) (2,2) (6,5) (7,7) (4,4)
  Child 3: (7,6) (5,5) (5,4) (1,1) (6,5) (7,7) (4,4)

Reinforcement Learning

Reinforcement Learning

- Temporal difference learning:[11][12]

Reinforcement Learning

- Temporal difference learning:[11][12]
- Q-learning

Reinforcement Learning

- Temporal difference learning:[11][12]
- Q-learning
- Deep Q-learning

Monte Carlo Tree Search[13][14][15]

- Selection
- Play-out
- Expansion
- Backpropagation

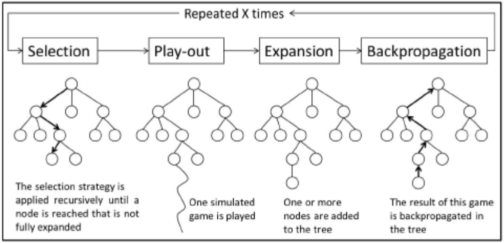
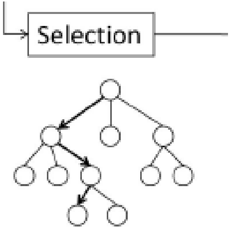
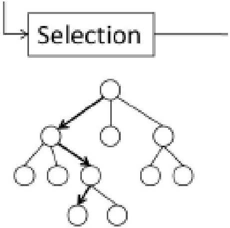


Figure: Flow chart of MCTS



The selection strategy is applied recursively until a node is reached that is not fully expanded

- Traverse down the tree from the root, according to a selection policy



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- Traverse down the tree from the root, according to a selection policy
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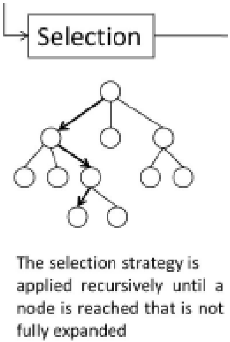
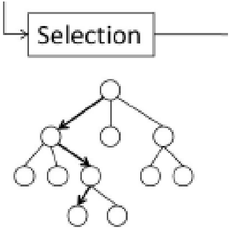
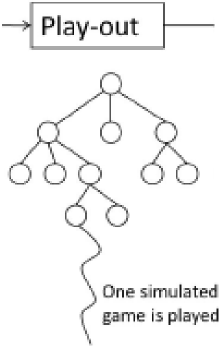


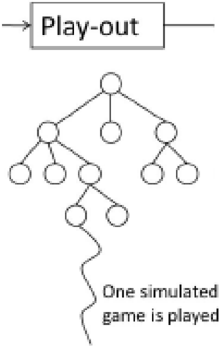
- Traverse down the tree from the root, according to a selection policy
- Until a node is reached that is not fully expanded
- Trade-off between exploration and exploitation



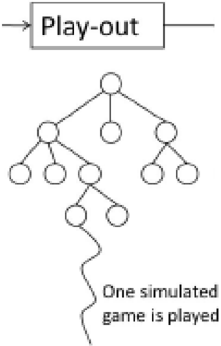
The selection strategy is applied recursively until a node is reached that is not fully expanded


Play-out
One simulated game is played

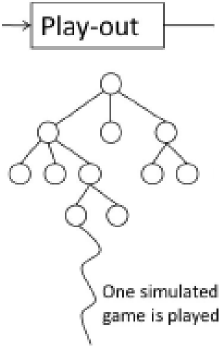
- Random game is played



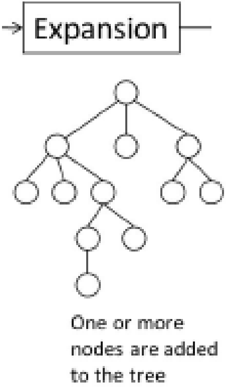
- Random game is played
- Roll-out policy



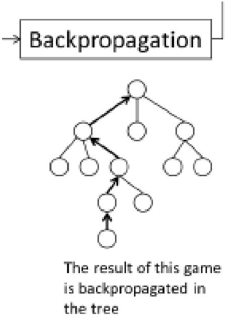
- Random game is played
- Roll-out policy
- Limited depth



- Expand the game tree with all nodes in play-out step



- Back propagate outcome and visit numbers



Solve Game

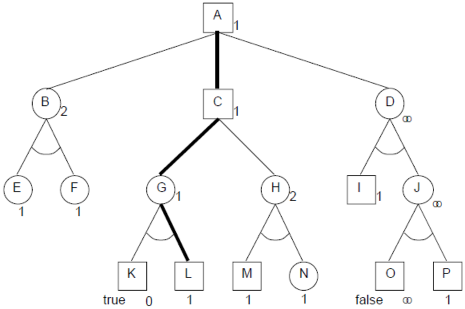
Solve Game

- Choose a knowledge re-presentation

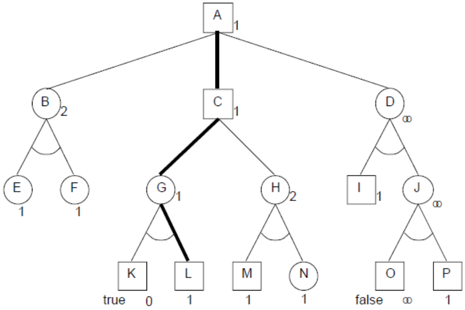
Solve Game

- Choose a knowledge re-presentation
- Perform a search: single-agent tree,game trees, `AND/OR` tree

AND/OR Tree

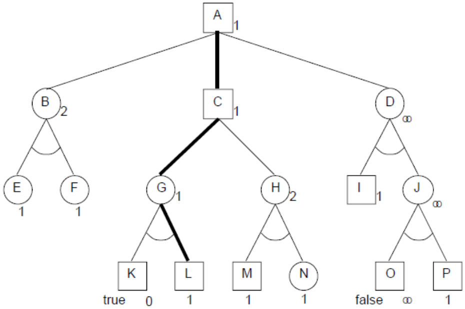


AND/OR Tree



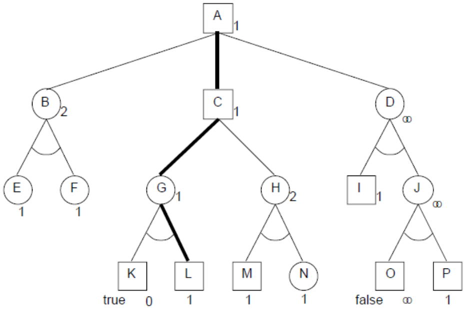
- Node value: TRUE,FALSE,UNKNOWN

AND/OR Tree



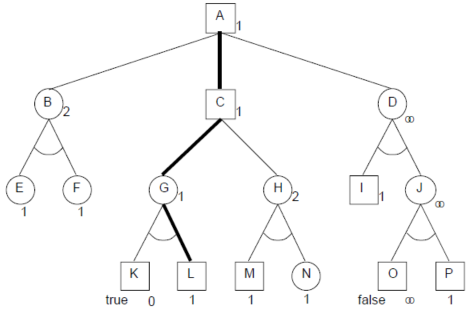
- Node value: TRUE,FALSE,UNKNOWN
- circle:AND, square:OR

Proof Number



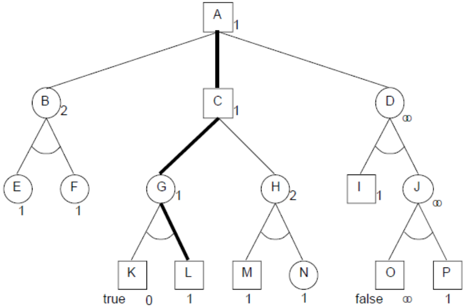
- circle:AND, square:OR

Proof Number



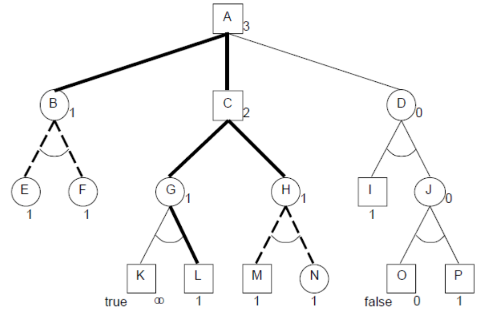
- For any AND/OR tree T a set of frontier nodes S is a proof set if proving all nodes within S proves T
- circle:AND, square:OR

Proof Number



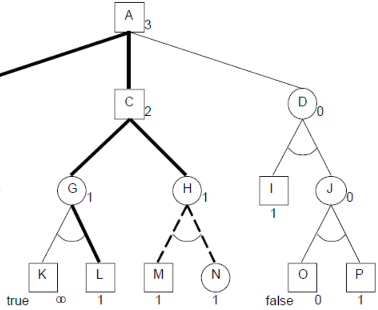
- For any AND/OR tree T a set of frontier nodes S is a proof set if proving all nodes within S proves T
- For any AND/OR tree T, the proof number of T is defined as the cardinality of the smallest proof set of T.
- circle:AND, square:OR

Disproof Number



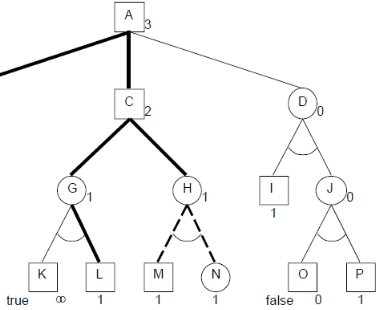
- circle:`AND`, square:`OR`

Disproof Number



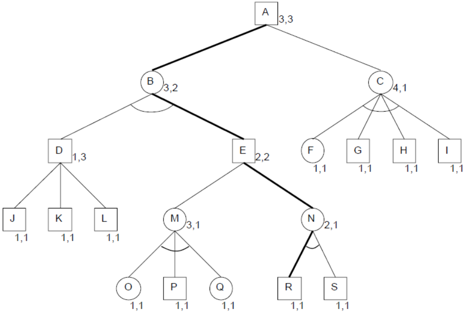
- For any AND/OR tree T a set of frontier nodes S is a disproof set if disproving all nodes within S disproves T
- circle:AND, square:OR

Disproof Number



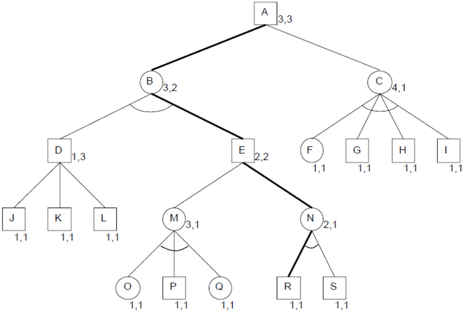
- For any AND/OR tree T a set of frontier nodes S is a disproof set if disproving all nodes within S disproves T
- For any AND/OR tree T, the disproof number of T is defined as the cardinality of the smallest disproof set of T.
- circle:AND, square:OR

Proof Number Search[3][16]



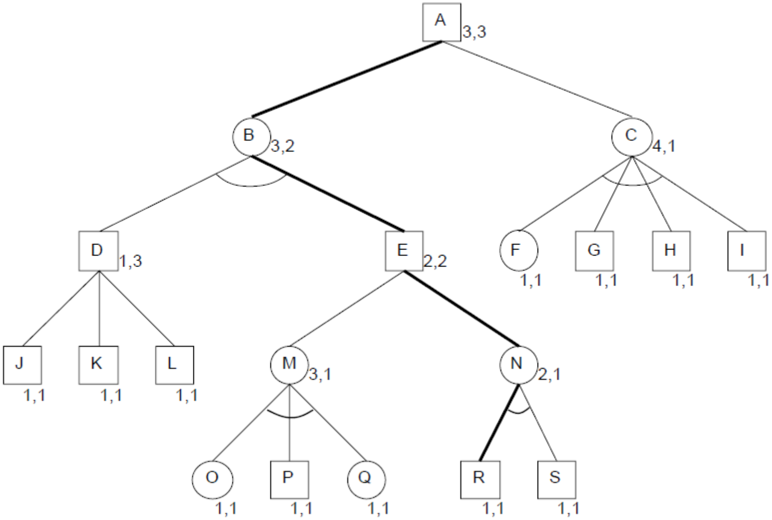
- circle:AND, square:OR

Proof Number Search[3][16]



- For any AND/OR tree T, a most-proving node of T is a frontier node of T, which by obtaining the value TRUE reduces T's proof number by 1, while by obtaining the value FALSE reduces T's disproof number by 1.
- circle:AND, square:OR

Proof Number Search



Dependency-based Search

Example: a production system consisting 11 rewriting rules $r_0, \ldots, r_{10}$

Dependency-based Search

Example: a production system consisting 11 rewriting rules $r_0, \ldots, r_{10}$

- $0 \xrightarrow{r_0} A, 1 \xrightarrow{r_0} B, 2 \xrightarrow{r_0} C, 3 \xrightarrow{r_0} D, 4 \xrightarrow{r_0} E, 5 \xrightarrow{r_0} F,$ $6 \xrightarrow{r_0} G, 7 \xrightarrow{r_0} H, 8 \xrightarrow{r_8} I, 9 \xrightarrow{r_9} J$

Dependency-based Search

Example: a production system consisting 11 rewriting rules $r_0, \ldots, r_{10}$

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- $ABCDEFGHIJ \xrightarrow{r_{10}} X$

Dependency-based Search

Example: a production system consisting 11 rewriting rules $r_0, \dots, r_{10}$

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- $ABCDEFGHIJ \xrightarrow{r_{10}} X$
- Initial state: 0123456789

Dependency-based Search

Example: a production system consisting 11 rewriting rules $r_0, \dots, r_{10}$

- $0 \xrightarrow{r_0} A, 1 \xrightarrow{r_0} B, 2 \xrightarrow{r_0} C, 3 \xrightarrow{r_0} D, 4 \xrightarrow{r_0} E, 5 \xrightarrow{r_0} F,$ $6 \xrightarrow{r_0} G, 7 \xrightarrow{r_0} H, 8 \xrightarrow{r_8} I, 9 \xrightarrow{r_9} J$
- $ABCDEFGHIJ \xrightarrow{r_{10}} X$
- Initial state: 0123456789
- Goal: X

Dependency-based Search

Dependency-based Search

- Attributes:
  $U = \{A(i,j,z) | 1 \leqslant i \leqslant j \leqslant 10, z \in \{A,\ldots,J,0,\ldots,9,X\}\}$

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  $U = \{A(i, j, z) | 1 \leqslant i \leqslant j \leqslant 10, z \in \{A, \ldots, J, 0, \ldots, 9, X\}\}$
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Dependency-based Search

- Attributes:
  $U = \{A(i,j,z) | 1 \leqslant i \leqslant j \leqslant 10, z \in \{A, \ldots, J, 0, \ldots, 9, X\}\}$
- Initial state
- Goal state: $\{A(1, 10, X)\}$

Dependency-based Search

- Attributes:
  $U = \{A(i,j,z) | 1 \leqslant i \leqslant j \leqslant 10, z \in \{A,\ldots,J,0,\ldots,9,X\}\}$
- Initial state
- Goal state: $\{A(1,10,X)\}$
- Operator U_f: f as a 3-tuple
  $< f^{pre}, f^{del}, f^{f^{add}} >, f^{pre}, f^{del}, f^{f^{add}} \subset U$ and $f^{del} \subset f^{pre}$
- $r_0 =< \{A(1,1,0)\}, \{A(1,1,0)\}, \{A(1,1,A)\} >$

Dependency-based Search

Dependency-based Search

- Paths U_p: Series of operators applicable to initial state $\{r_0, r_1\}$,$\{r_0, r_1, r_2\}$ is a path; $\{r_0, r_0\}$ isn't a path

Dependency-based Search

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Dependency-based Search

- Paths U_p: Series of operators applicable to initial state $\{r_0, r_1\}$,$\{r_0, r_1, r_2\}$ is a path; $\{r_0, r_0\}$ isn't a path
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- Path class: $U_p/_{\equiv}$: $\overline{\{r_0, r_1\}} = \{\{r_0, r_1\}, \{r_1, r_0\}\}$

Dependency-based Search

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- Path class: $U_p/_{\equiv}$: $\overline{\{r_0, r_1\}} = \{\{r_0, r_1\}, \{r_1, r_0\}\}$
- Key class U_k: A path class such that the last operator of all paths belonging to that path class is the same $\overline{\{r_0\}}, \ldots, \overline{\{r_9\}}, \overline{\{r_0, \ldots, r_9, r_{10}\}}$
- $\overline{\{r_0, r_1\}}$ is a path class but not a key class.

Solve Gomoku

Method: pn-search + db-search[17]

Solve Gomoku

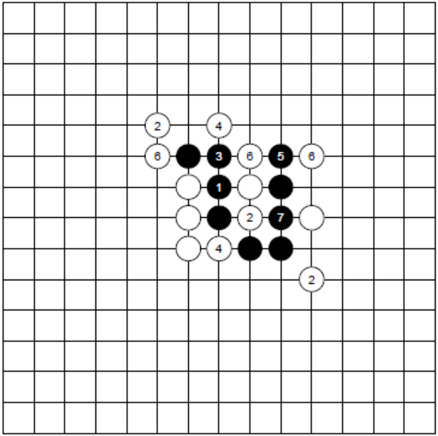
Method: pn-search + db-search[17]

- Attributes
- Initial state
- Goal state

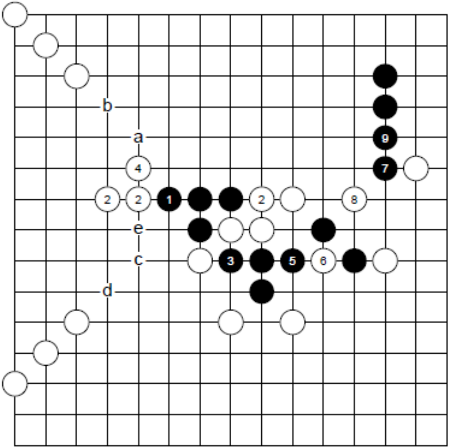
Solve Gomoku

Method: pn-search + db-search[17]

- Attributes
- Initial state
- Goal state
- Operator: transform into single-agent



Solve Gomoku



Minimax Algorithm

```
function MINIMAX-DECISION(state) returns an action
  return arg max_{a ∈ ACTIONS(s)} MIN-VALUE(RESULT(state, a))

function MAX-VALUE(state) returns a utility value
  if TERMINAL-TEST(state) then return UTILITY(state)
  v ← −∞
  for each a in ACTIONS(state) do
    v ← MAX(v, MIN-VALUE(RESULT(s, a)))
  return v

function MIN-VALUE(state) returns a utility value
  if TERMINAL-TEST(state) then return UTILITY(state)
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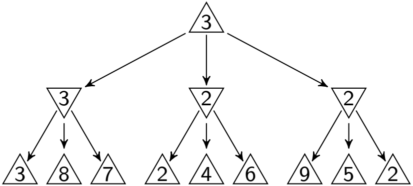
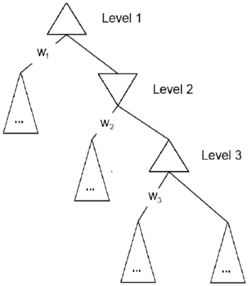
```

Figure: Pseudocode of minimax algorithm



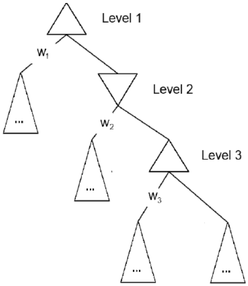
Meaning of α and β

- Consider a modification of alpha-beta pruning where you keep a list containing the best value, w_i, for the minimizer/maximizer (depending on the level) at each level up to and including the current level.
- Assume that the root node is always a max node.

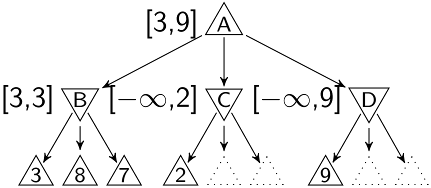


Meaning of α and β

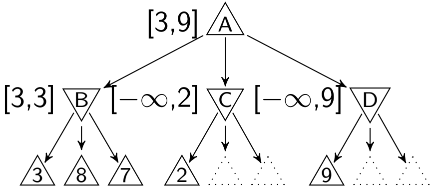
- Consider a modification of alpha-beta pruning where you keep a list containing the best value, w_i, for the minimizer/maximizer (depending on the level) at each level up to and including the current level.
- Assume that the root node is always a max node.
- What is the relationship between α,β and the list of $w_1, \ldots, w_n$ at a max node at the nth level of the tree



Meaning of α and β



Meaning of α and β



$[\alpha, \beta]$ is a closed interval as the estimation of utility value so far.

Pseudocode of alpha-beta pruning

```
function ALPHA-BETA-SEARCH(state) returns an action
  v ← MAX-VALUE(state, −∞, +∞)
  return the action in ACTIONS(state) with value v

function MAX-VALUE(state, α, β) returns a utility value
  if TERMINAL-TEST(state) then return UTILITY(state)
  v ← −∞
  for each a in ACTIONS(state) do
    v ← MAX(v, MIN-VALUE(RESULT(s,a), α, β))
    if v ≥ β then return v
    α ← MAX(α, v)
  return v

function MIN-VALUE(state, α, β) returns a utility value
  if TERMINAL-TEST(state) then return UTILITY(state)
  v ← +∞
  for each a in ACTIONS(state) do
    v ← MIN(v, MAX-VALUE(RESULT(s,a) , α, β))
    if v ≤ α then return v
    β ← MIN(β, v)
  return v
```

Figure: Pseudocode of alpha-beta pruning

Pseudocode of alpha-beta pruning

```
function ALPHA-BETA-SEARCH(state) returns an action
   v ← MAX-VALUE(state, −∞, +∞)
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```
function MAX-VALUE(state, α, β) returns a utility value
   if TERMINAL-TEST(state) then return UTILITY(state)
   v ← −∞
   for each a in ACTIONS(state) do
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      if v ≥ β then return v
      α ← MAX(α, v)
   return v
```

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      if v ≤ α then return v
      β ← MIN(β, v)
   return v
```

Figure: Pseudocode of alpha-beta pruning

- Each node inherit $[\alpha, \beta]$ from its parent node

Pseudocode of alpha-beta pruning

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  v ← −∞
  for each a in ACTIONS(state) do
    v ← MAX(v, MIN-VALUE(RESULT(s,a), α, β))
    if v ≥ β then return v
    α ← MAX(α, v)
  return v

function MIN-VALUE(state, α, β) returns a utility value
  if TERMINAL-TEST(state) then return UTILITY(state)
  v ← +∞
  for each a in ACTIONS(state) do
    v ← MIN(v, MAX-VALUE(RESULT(s,a) , α, β))
    if v ≤ α then return v
    β ← MIN(β, v)
  return v
```

Figure: Pseudocode of alpha-beta pruning

- Each node inherit $[\alpha, \beta]$ from its parent node
- For `MAX` node, β is fixed as β_{parent}, v is used to update α initialized as α_{parent}

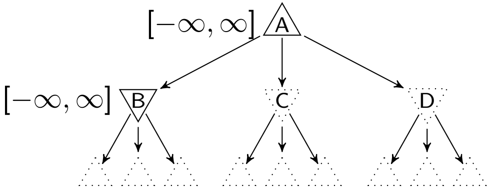
Pseudocode of alpha-beta pruning

```
function ALPHA-BETA-SEARCH(state) returns an action
  v ← MAX-VALUE(state, −∞, +∞)
  return the action in ACTIONS(state) with value v
________________________________________________________
function MAX-VALUE(state, α, β) returns a utility value
  if TERMINAL-TEST(state) then return UTILITY(state)
  v ← −∞
  for each a in ACTIONS(state) do
    v ← MAX(v, MIN-VALUE(RESULT(s,a), α, β))
    if v ≥ β then return v
    α ← MAX(α, v)
  return v
________________________________________________________
function MIN-VALUE(state, α, β) returns a utility value
  if TERMINAL-TEST(state) then return UTILITY(state)
  v ← +∞
  for each a in ACTIONS(state) do
    v ← MIN(v, MAX-VALUE(RESULT(s,a) , α, β))
    if v ≤ α then return v
    β ← MIN(β, v)
  return v
```

Figure: Pseudocode of alpha-beta pruning

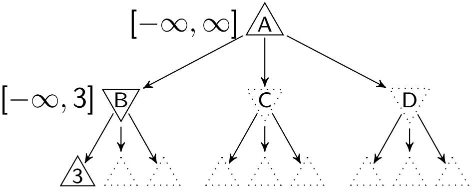
- Each node inherit $[\alpha, \beta]$ from its parent node
- For `MAX` node, β is fixed as β_{parent}, v is used to update α initialized as α_{parent}
- For `MIN` node, α is fixed as α_{parent}, v is used to update β initialized as β_{parent}

Example of alpha-beta pruning1



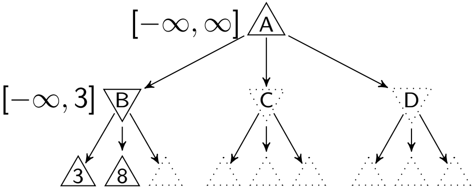
- For `MAX` node, β is fixed as β_{parent}, v is used to update α initialized as α_{parent}
- For `MIN` node, α is fixed as α_{parent}, v is used to update β initialized as β_{parent}

Example of alpha-beta pruning2



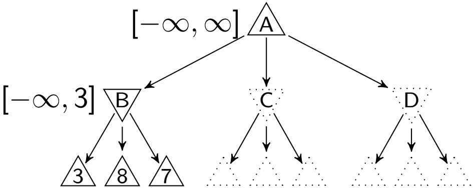
- For `MAX` node, β is fixed as β_{parent}, v is used to update α initialized as α_{parent}
- For `MIN` node, α is fixed as α_{parent}, v is used to update β initialized as β_{parent}

Example of alpha-beta pruning3



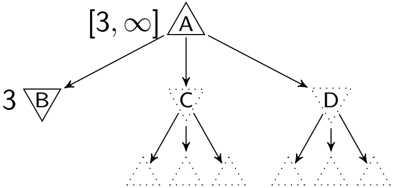
- For `MAX` node, β is fixed as β_{parent}, v is used to update α initialized as α_{parent}
- For `MIN` node, α is fixed as α_{parent}, v is used to update β initialized as β_{parent}

Example of alpha-beta pruning4



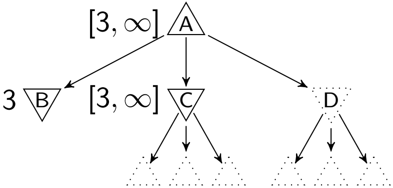
- For MAX node, β is fixed as β_{parent}, v is used to update α initialized as α_{parent}
- For MIN node, α is fixed as α_{parent}, v is used to update β initialized as β_{parent}

Example of alpha-beta pruning5



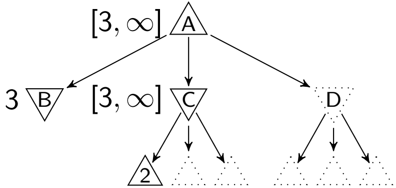
- For MAX node, β is fixed as β_{parent}, v is used to update α initialized as α_{parent}
- For MIN node, α is fixed as α_{parent}, v is used to update β initialized as β_{parent}

Example of alpha-beta pruning6



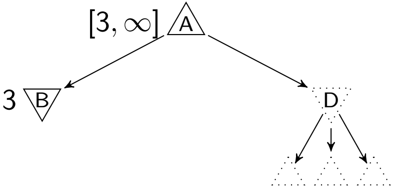
- For MAX node, β is fixed as β_{parent}, v is used to update α initialized as α_{parent}
- For MIN node, α is fixed as α_{parent}, v is used to update β initialized as β_{parent}

Example of alpha-beta pruning7



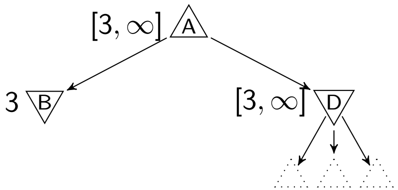
- For MAX node, β is fixed as β_{parent}, v is used to update α initialized as α_{parent}
- For MIN node, α is fixed as α_{parent}, v is used to update β initialized as β_{parent}

Example of alpha-beta pruning8



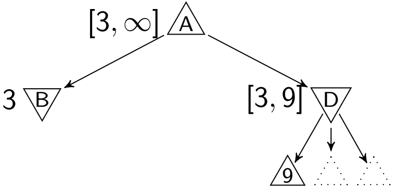
- For `MAX` node, β is fixed as β_{parent}, v is used to update α initialized as α_{parent}
- For `MIN` node, α is fixed as α_{parent}, v is used to update β initialized as β_{parent}

Example of alpha-beta pruning9



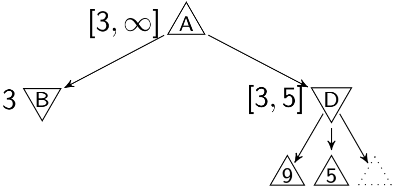
- For MAX node, β is fixed as β_{parent}, v is used to update α initialized as α_{parent}
- For MIN node, α is fixed as α_{parent}, v is used to update β initialized as β_{parent}

Example of alpha-beta pruning10



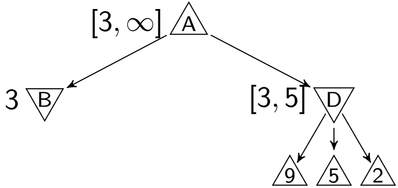
- For `MAX` node, β is fixed as β_{parent}, v is used to update α initialized as α_{parent}
- For `MIN` node, α is fixed as α_{parent}, v is used to update β initialized as β_{parent}

Example of alpha-beta pruning11



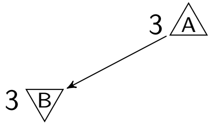
- For MAX node, β is fixed as β_{parent}, v is used to update α initialized as α_{parent}
- For MIN node, α is fixed as α_{parent}, v is used to update β initialized as β_{parent}

Example of alpha-beta pruning12



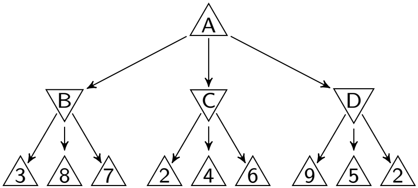
- For MAX node, β is fixed as β_{parent}, v is used to update α initialized as α_{parent}
- For MIN node, α is fixed as α_{parent}, v is used to update β initialized as β_{parent}

Example of alpha-beta pruning13

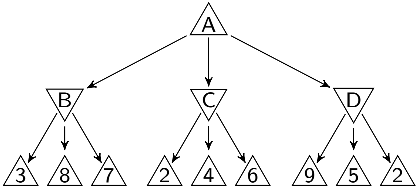


- For MAX node, β is fixed as β_{parent}, v is used to update α initialized as α_{parent}
- For MIN node, α is fixed as α_{parent}, v is used to update β initialized as β_{parent}

Input of Practice

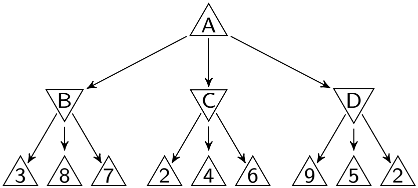


Input of Practice



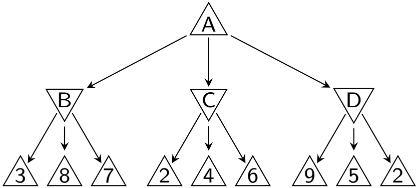
- First line: The role of the root node(1 for `MAX` node and 0 for `MIN` node) and the depth of the tree
- Example: 1 3

Input of Practice

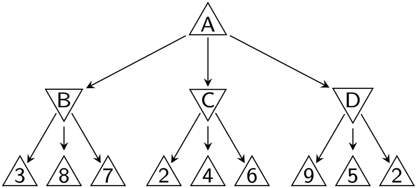


- First line: The role of the root node(1 for `MAX` node and 0 for `MIN` node) and the depth of the tree
- Example: 1 3
- Second line: Tree Structure
- Example: [[3,8,7],[2,4,6],[9,5,2]]

Output of Practice

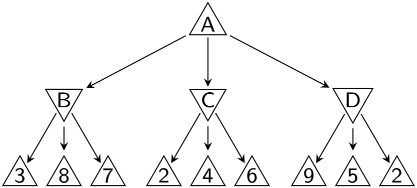


Output of Practice



- First line:The result for minimax search
- Example: 3

Output of Practice



- First line:The result for minimax search
- Example: 3
- Second line: Pruned nodes in order
- Example: 4 6

Gomoku Competition

- Gomoku Rule: Standard Gomoku Rule(exact five)
- Balanced opening from a set
- The board has 20x20 squares
- 30 seconds per move, 180 seconds per match
- 10 fixed AI, 12 matches with each one
- 3 points for a win

Gomoku Competition

- No more than 3 people a team
- Upload to test once a day
- Uploading file may not take more than 5 MB of space (zipped together with all necessary files) named as id.zip
- Only one CPU core
- No deep neural network
- No pondering

Gomoku Competition

- ftp://10.88.3.60
- Gomoku manager `http://gomocup.org/download-gomocup-manager/`
- AI `http://gomocup.org/download-gomoku-ai/`
- Python Template `https://github.com/stranskyjan/pbrain-pyrandom`
- Gomocup `http://gomocup.org/`

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