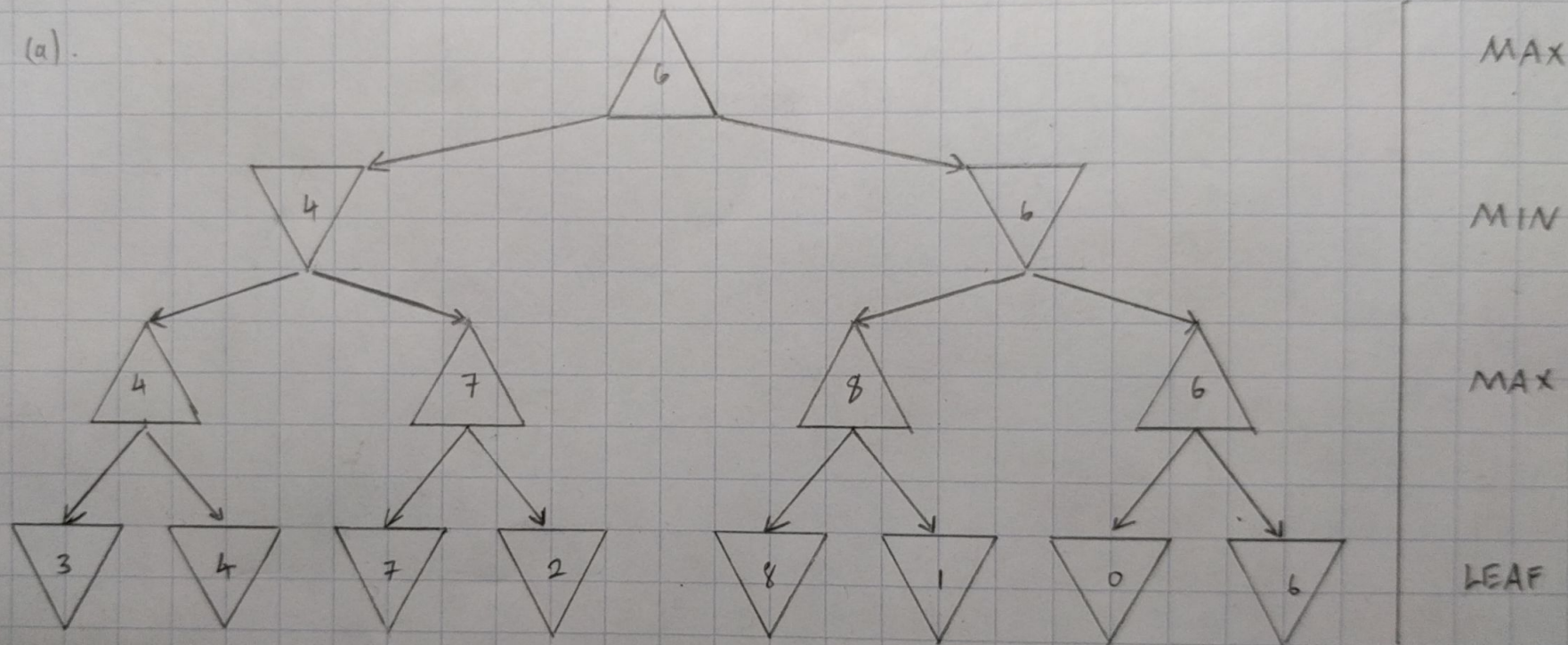
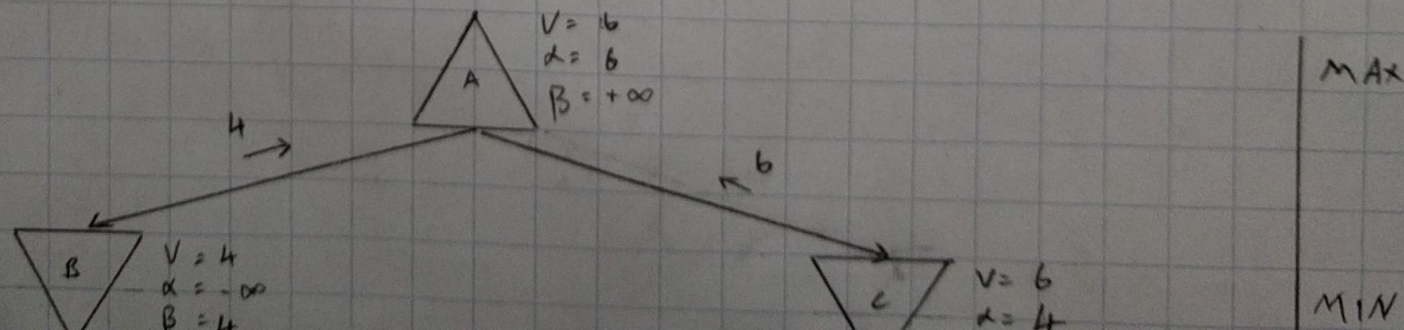


1. (a).

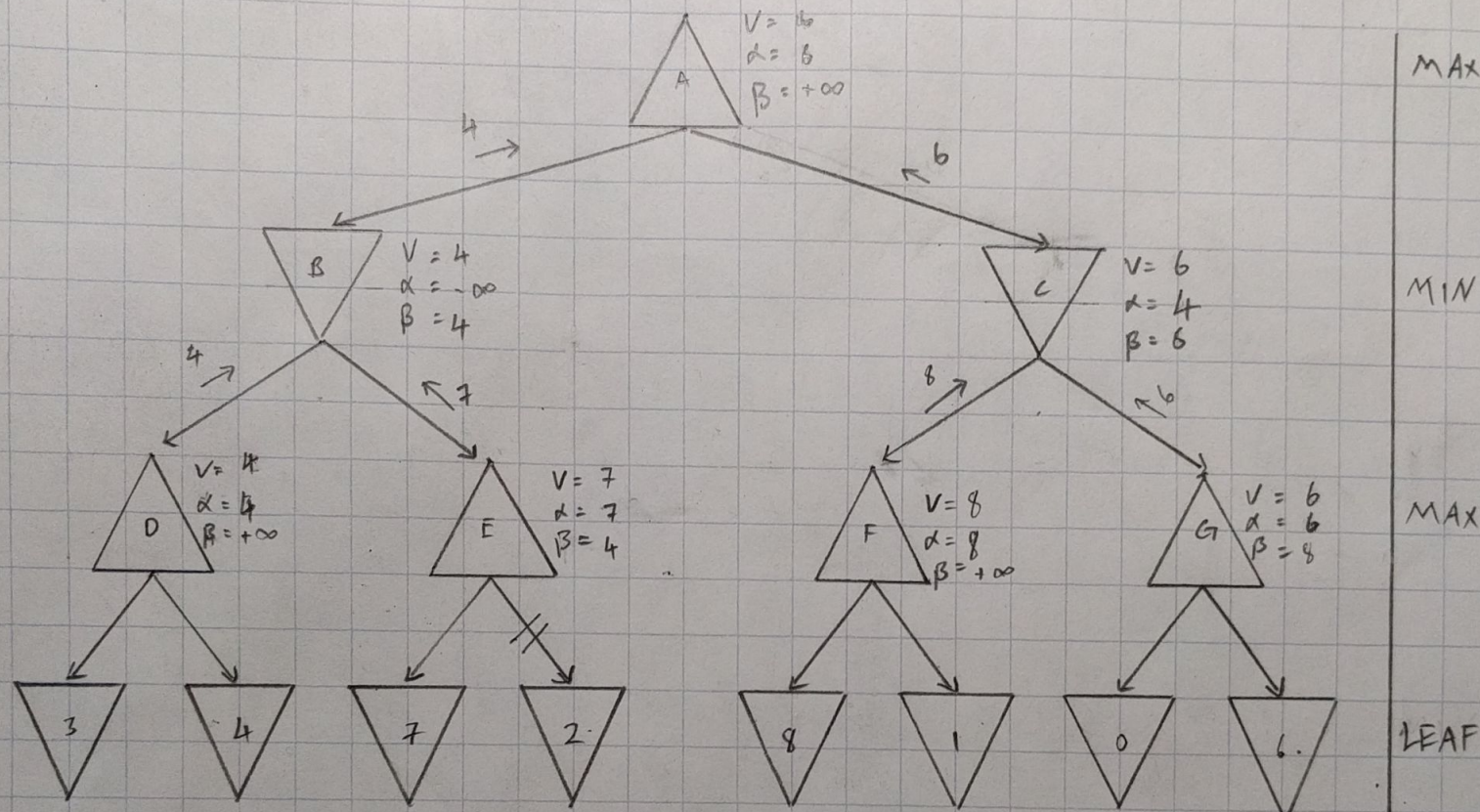


(b)  $\alpha$ : best already-explored option along path to the root for maximizer.  
 $\beta$ : best already-explored option along path to the root for minimizer.





- (b)  $\alpha$ : best already-explored option along path to the root for maximizer.  
 $\beta$ : best already-explored option along path to the root for minimizer.



Max-Value( $s, \alpha, \beta$ ):

if terminal( $s$ ): return  $V(s)$ ;

$V = -\infty$ ;

for  $c$  in next-states( $s$ ):

$v' = \text{Min-Value}(c, \alpha, \beta)$ ;

if  $v' > V$ :  $V = v'$ ;

if  $v' > \beta$ : return  $V$ ;

if  $v' > \alpha$ :  $\alpha = v'$ ;

return  $V$ ;

Min-Value( $s, \alpha, \beta$ ):

if terminal( $s$ ): return  $V(s)$ ;

$V = +\infty$ ;

for  $c$  in next-states( $s$ ):

$v' = \text{Max-Value}(c, \alpha, \beta)$ ;

if  $v' < V$ :  $V = v'$ ;

if  $v' \leq \alpha$ : return  $V$ ;

if  $v' < \beta$ :  $\beta = v'$ ;

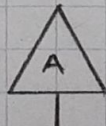
return  $V$ ;

(c) The node with value 2 is pruned, as shown on the diagram.

(d) Alpha-beta pruning is simply a more efficient implementation of Minimax, and in fact allows us to forego certain subtrees while still keeping the same final result.

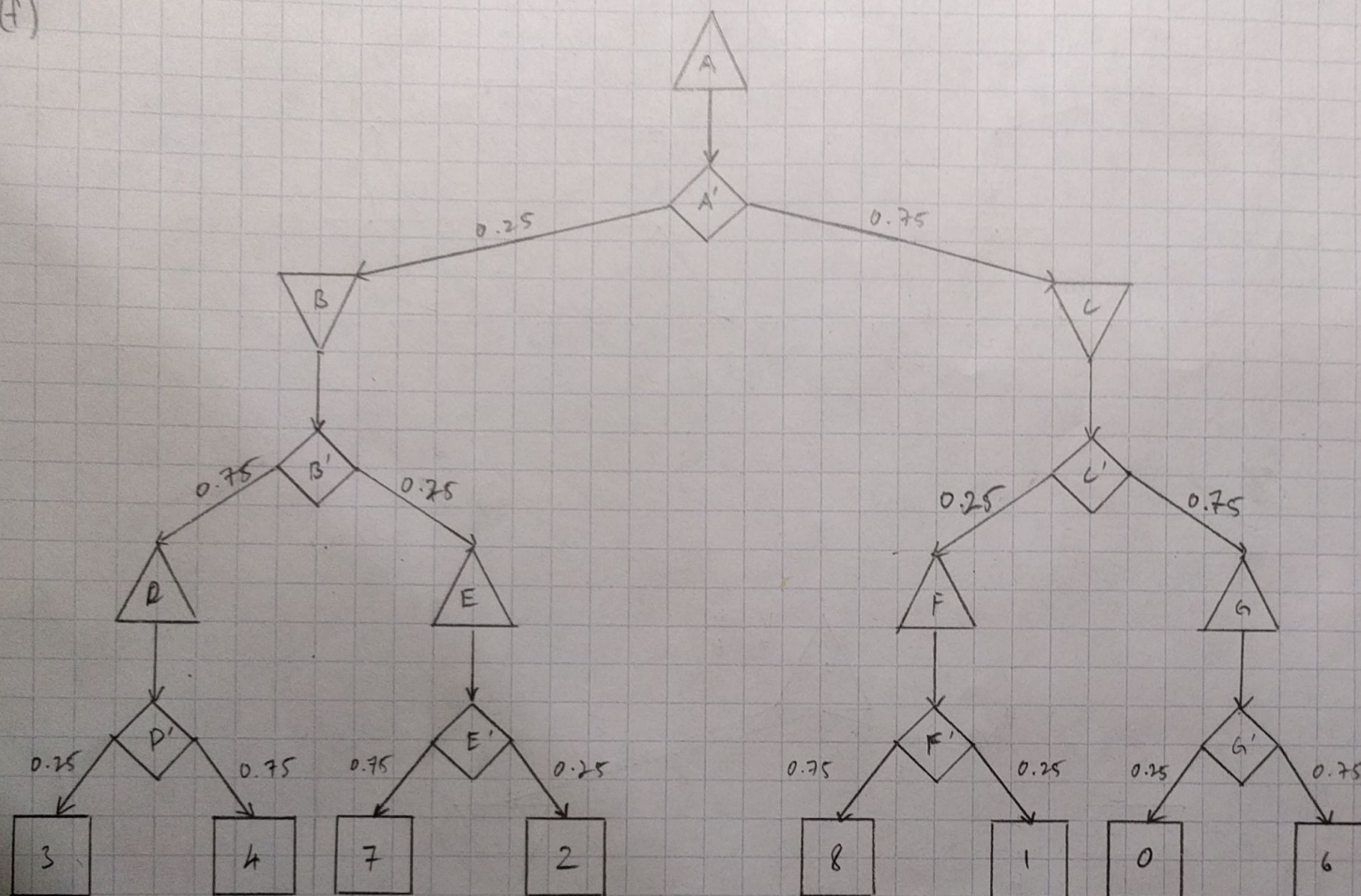
$$\begin{aligned} \text{(e). } P(\text{optimal choice}) &= P(\text{heads}) + P(\text{tails}) \cdot P(\text{optimal choice} \mid \text{tails}) \\ &= 0.5 + (0.5) \cdot (0.5) \\ &= 0.75. \end{aligned}$$

(f)





(4)



(g).  $E(D) = 0.25(3) + 0.75(4)$   
 $= 3.75$

$$E(E) = 0.75(7) + 0.25(2)$$

$$= 5.75$$

$$E(F) = 0.75(8) + 0.25(1)$$

$$= 6.25$$

$$E(G) = 0.75(6) + 0.25(0)$$

$$= 4.50$$

$$E(B) = 0.75(E(D)) + 0.25(E(E))$$

$$= 4.25$$

$$E(C) = 0.25(E(F)) + 0.75(E(G))$$

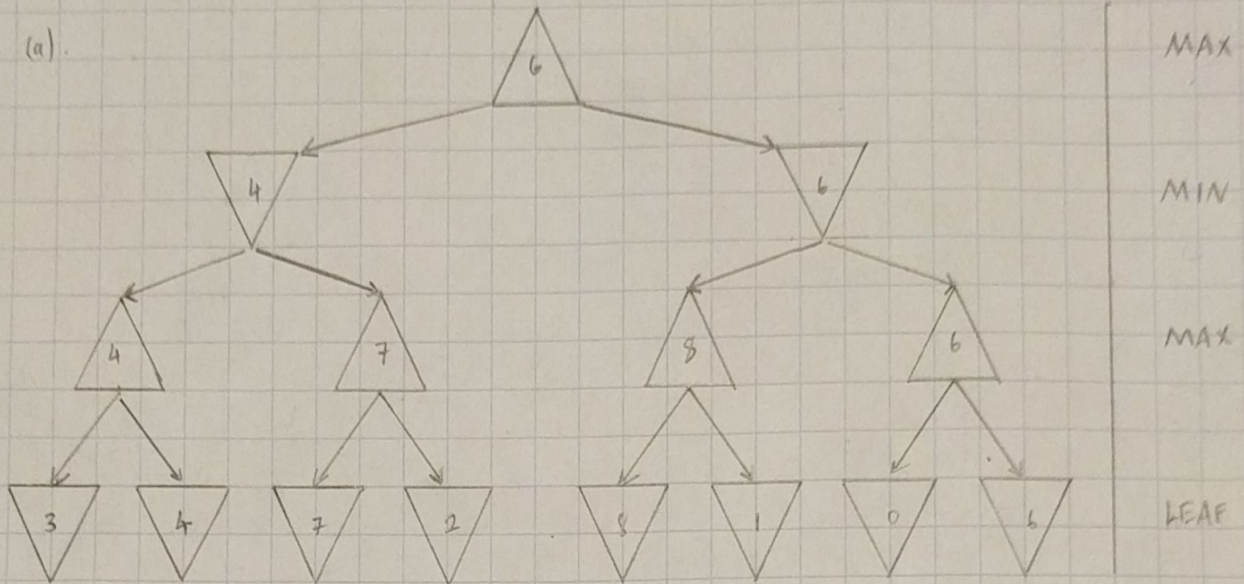
$$= 4.94$$

$$E(A) = 0.25(E(B)) + 0.75(E(C))$$

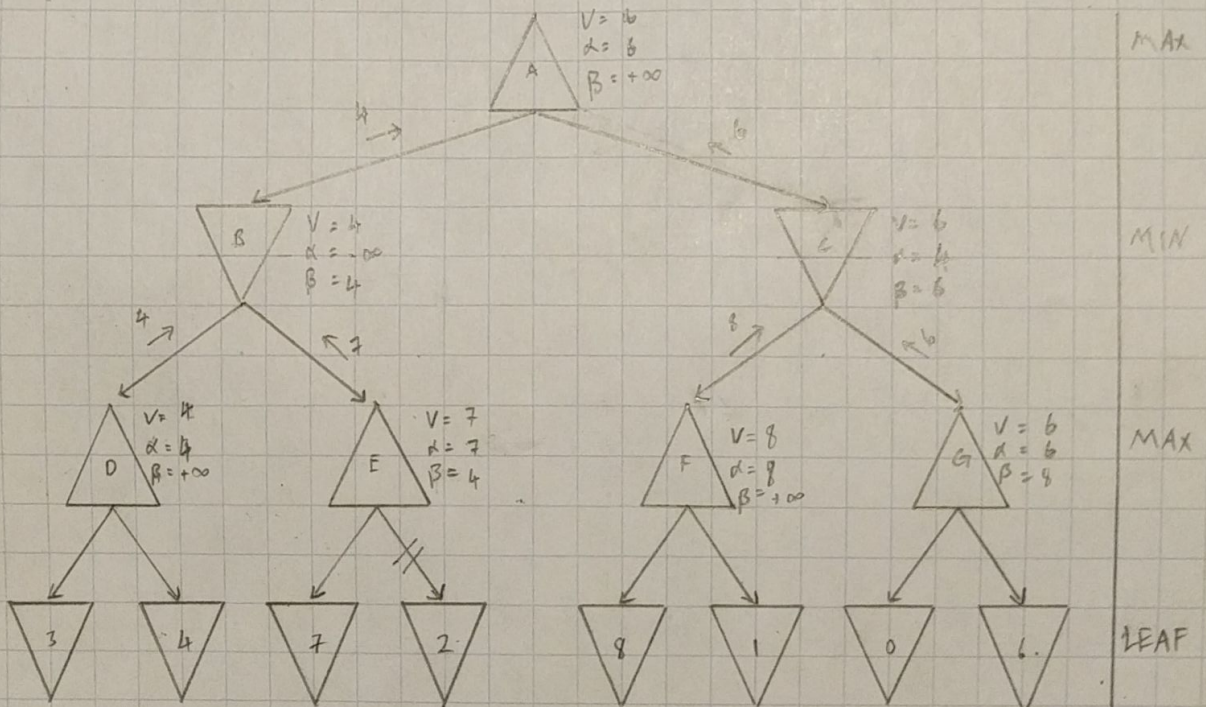
$$= 4.77$$



1. (a).



- (b)  $\alpha$ : best already-explored option along path to the root for maximizer.  
 $\beta$ : best already-explored option along path to the root for minimizer.



Max-Value( $s, \alpha, \beta$ ):

if terminal( $s$ ): return  $V(s)$ ;

$V = -\infty$ ;

for  $c$  in next-states( $s$ ):

$v' = \text{Min-Value}(c, \alpha, \beta)$ ;

if  $v' > V$ :  $V = v'$ ;

if  $v' > \beta$ : return  $V$ ;

if  $v' > \alpha$ :  $\alpha = v'$ ;

return  $V$ ;

Min-Value( $s, \alpha, \beta$ ):

if terminal( $s$ ): return  $V(s)$ ;

$V = +\infty$ ;

for  $c$  in next-states( $s$ ):

$v' = \text{Max-Value}(c, \alpha, \beta)$ ;

if  $v' < V$ :  $V = v'$ ;

if  $v' \leq \alpha$ : return  $V$ ;

if  $v' < \beta$ :  $\beta = v'$ ;

return  $V$ ;

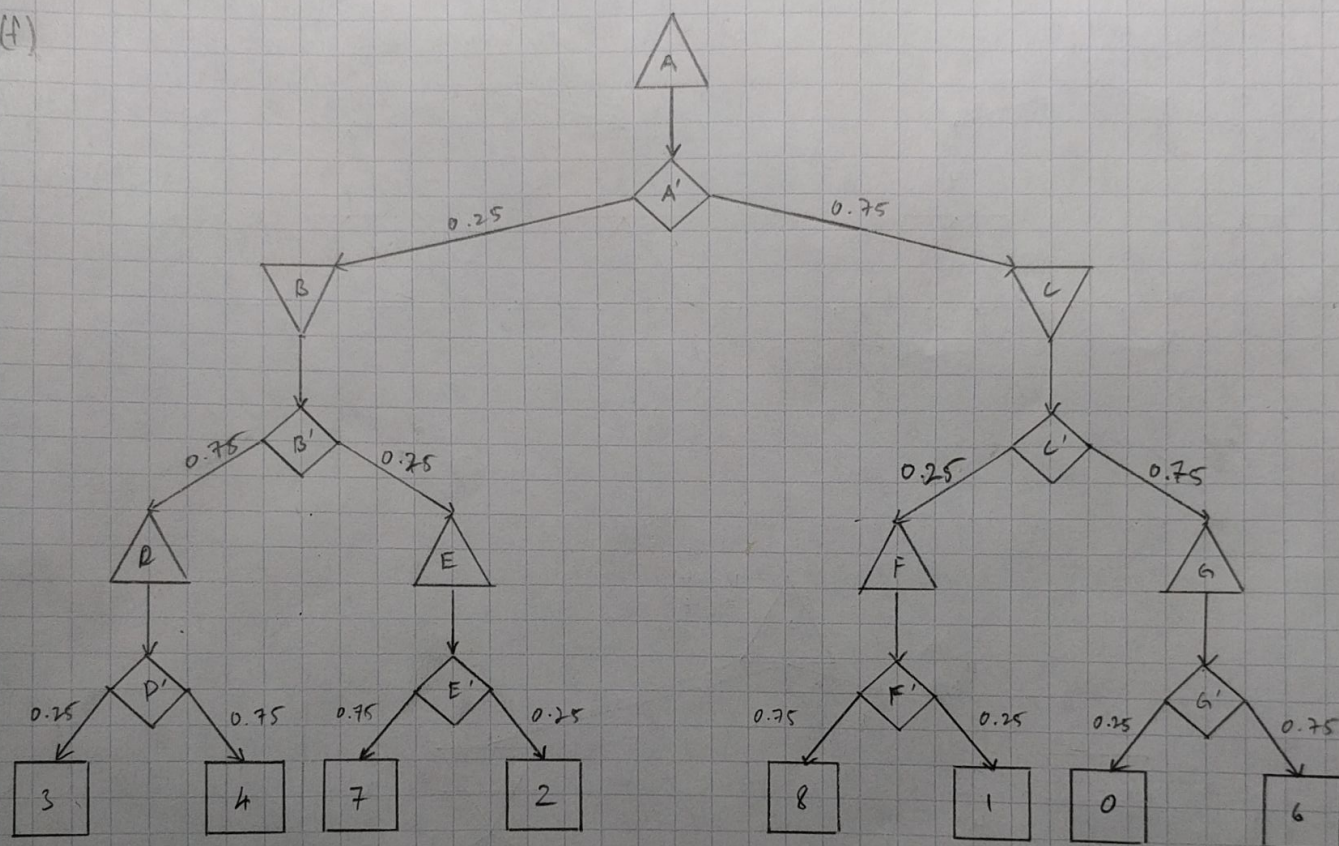


(c) The node with value 2 is pruned, as shown on the diagram.

(d) Alpha-beta pruning is simply a more efficient implementation of Minimax, and in fact allows us to forego certain solutions while still keeping the same final result.

$$\begin{aligned}
 (e) \quad P(\text{optimal choice}) &= P(\text{heads}) + P(\text{tails}) \cdot P(\text{optimal choice} \mid \text{tails}) \\
 &= 0.5 + (0.5) \cdot (0.5) \\
 &= 0.75.
 \end{aligned}$$

(f)



$$\begin{aligned}
 (g) \quad E(D) &= 0.25(3) + 0.75(4) \\
 &= 3.75
 \end{aligned}$$

$$\begin{aligned}
 E(E) &= 0.75(7) + 0.25(2) \\
 &= 5.75
 \end{aligned}$$

$$\begin{aligned}
 E(F) &= 0.75(8) + 0.25(1) \\
 &= 6.25
 \end{aligned}$$

$$\begin{aligned}
 E(G) &= 0.75(6) + 0.25(0) \\
 &= 4.50
 \end{aligned}$$

$$\begin{aligned}
 E(B) &= 0.75(E(D)) + 0.25(E(E)) \\
 &= 4.25
 \end{aligned}$$

$$\begin{aligned}
 E(C) &= 0.25(E(F)) + 0.75(E(G)) \\
 &= 4.94
 \end{aligned}$$

$$\begin{aligned}
 E(A) &= 0.25(E(B)) + 0.75(E(C)) \\
 &= 4.77
 \end{aligned}$$