

GAME THEORY

→ Lower bound on efficiency of randomized algorithms

→ Example: Tree evaluation

		Bob			
		R	P	S	
Alice	R	0	-1	1	→ Alice is trying to maximize outcome α
	P	1	0	-1	→ Bob is trying to minimize outcome α
	S	-1	1	0	

A Game evaluation matrix

Generally GEM $[M_{ij}]$ of real numbers

If Alice chooses strategy i , in the worst case she gets $\min_j [M_{ij}]$

If Bob chooses strategy j , in the worst case he gets $\max_i [M_{ij}]$

Alice's best strategy is $\max_i \min_j [M_{ij}] = \alpha_A$

Bob's best strategy is $\min_j \max_i [M_{ij}] = \alpha_B$

Bob's best strategy is $\min_j \max_i \{M_{ij}\} = 0_B$

There are games for which $0_A = 0_B$ (equilibrium)

Alice

	↓	↓	↓
	0	-1	-2
	1	0	-1
→	2	1	0

MIXED STRATEGIES

Alice's strategy = probability distribution over rows p

Bob's strategy = probability distribution over columns q

} Column vectors

$$p^T M q = \sum_{i,j} p_i q_j M_{ij} = \text{Expected value of game } M \text{ with strategies } p \text{ and } q.$$

For fixed strategy of Alice p she is guaranteed to achieve at least $\min_q p^T M q$.

Fixed q guarantees Bob $\max_p p^T M q$

Alice's best strategy $\max_p \min_q p^T M q = 0_A$

Bob's best strategy $\min_q \max_p p^T M q = 0_B$

Von Neumann's theorem

$$\forall M \quad \max_P \min_q p^T M q = \min_q \max_P p^T M q$$

Loomis' theorem

$$\forall M \quad \max_P \min_k p^T M e_k = \min_q \max_j e_j^T M q$$

k \downarrow
ith position

$$e_i = (0, \dots, 1, \dots, 0)$$

Proof sketch \hookrightarrow $a = p^T M$

$$\text{for fixed } p : \min_q p^T M q = \min_q a \cdot q = a_1 q_1 + \dots + a_n q_n$$

find smallest a_i

and set $q_i = 1$ and others $q = 0$.

inputs

	A_1	A_2	A_3	...	A_n
I_0	$C(I_0, A_1)$	$C(I_0, A_2)$			
I_1	$C(I_1, A_1)$				
\vdots					
\vdots					
\vdots					
I_n					

deterministic algorithms
 \checkmark our randomized algorithm
 is choosing from

In |

Choose probability of inputs p

and probability of choosing deterministic algorithms q

$E(C(I_p, A_q))$ = expected running time for input distribution p
and rand. algorithm characterized by q .

$$= p^T M q$$

VN's thm:

$$\max_p \min_q E(C(I_p, A_q)) = \min_q \max_p E(C(I_p, A_q))$$

Loomis' thm:

$$\cancel{\max_p} \min_{A_i \in \mathcal{A}} E(C(I_p, A_i)) = \cancel{\min_q} \max_{i \in I} E(C(I_i, A_q))$$

$$\forall_{p, q} \min_{A_i \in \mathcal{A}} E(C(I_p, A_i)) \leq \max_{i \in I} E(C(I_i, A_q)) \quad \square$$

for chosen input distribution p
find the best deterministic algorithm

for given rand algorithm A_q
find the worst input

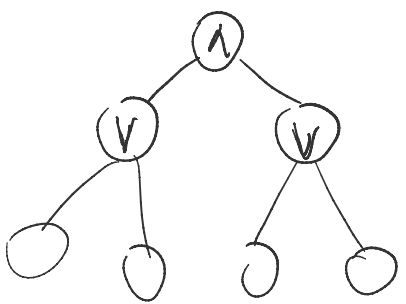
find the best deterministic algorithm

find the worst input

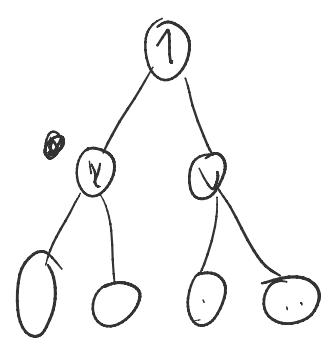
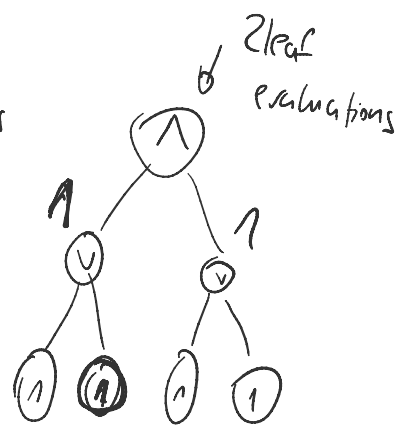
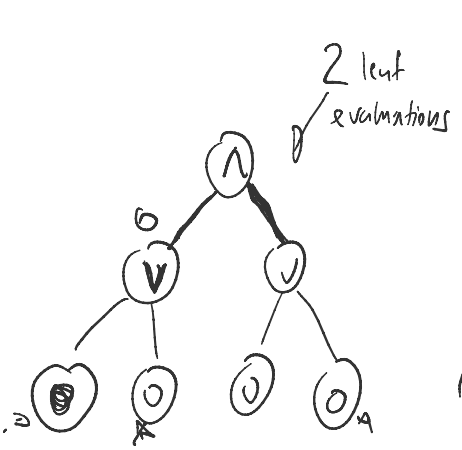
↓
lower bound

↓
We are interested in this

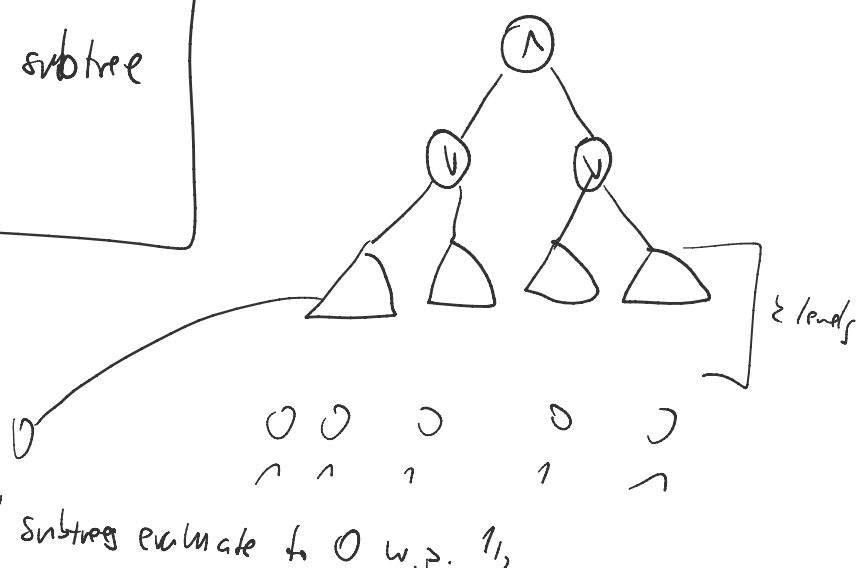
Tree evaluation example



Example of input distribution
 all 0's w.p. $\frac{1}{2}$ (all nodes evaluate to 0)
 all 1's w.p. $\frac{1}{2}$ (all nodes evaluate to 1)



4 choices of first leaf
 2 choices for leaf in the other subtree
 = 8 algorithms



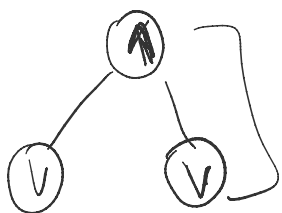
All subtrees evaluate to 0 w.p. $1/2$

All subtrees evaluate to 1 w.p. $1/2$

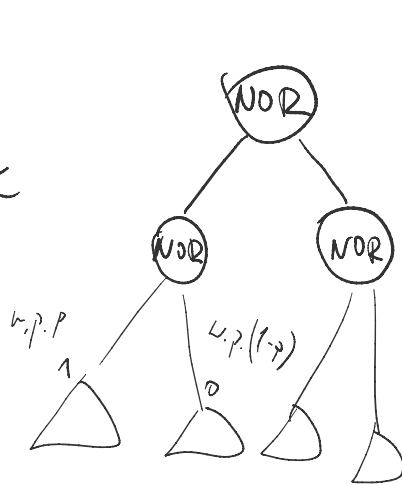
the best deterministic algorithm for any chosen input takes 2^L evaluations.

Ⓛ min max theorems (Loomis's)

Any randomized algorithm needs at least 2^L leaf evaluations.



\approx



$$(a \vee b) \wedge (c \vee d)$$

\equiv

$$(a \text{ NOR } b) \text{ NOR } (c \text{ NOR } d)$$

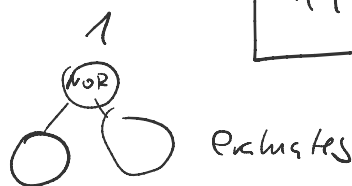
ab	a NOR b	c	d
00	1	0	0
01	0	0	0
10	0	0	0
11	0	0	0

$$Pr(\text{leaf} = 1) = p$$

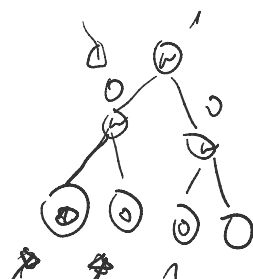
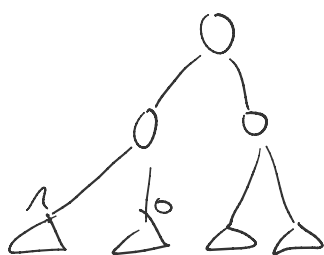
$$Pr(\text{leaf} = 0) = 1-p$$

$(1-p)^2 = p \Rightarrow$ probability that

to 1 is equal to p



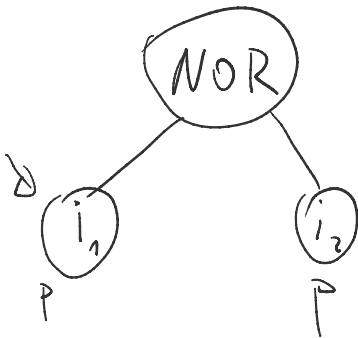
$$p = \frac{3 - \sqrt{5}}{2}$$



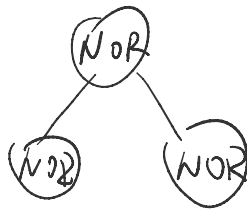
	0	1
$(1-p)^4 \rightarrow$	0000 (4)	0, 14
$(1-p)^3 \cdot p$	0001 (6)	0, 05
$(1-p)^2 \cdot p^2$	0010 (3)	...
	0011 (3)	...

found down

Expectation $2 < 2,52 < 3$
 $< 2,61 < 3$



$p + (1-p) \cdot 2 \rightarrow$ each nor will
 take on average $p + (1-p) \cdot 2 = (2-p) < 1,61$



$$p \cdot (2-p) + (1-p) \cdot 2 \cdot (2-p) = (2-p)^2$$

$< 2,61$