Probability and Computing – Lower bounds using Yao's Principle

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Lecture Notes by Worsch

Some of this lecture's content is covered in Thomas Worsch's notes from 2019.

Content

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Prisoner's Dilemma

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		👺	
		🤐	🗨
😈	🤐	-1\-1	-3\0
	🗨	0\-3	-2\-2

Setting

- *strategies* 🤐 and 🗨 available to both *players*
- table shows *payoffs* for players depending on chosen strategies
- here: always better to choose 🗨
  $\hookrightarrow$ pair (🗨, 🗨) is unique *equilibrium*

Definition: Equilibrium

Combination of strategies such that no one can profit by unilaterally switching his or her own strategy.

A cat and mouse game

		🐱	
		🧀	🧶
🐭	🧀	-4\2	2\1
	🕳	0\0	0\1

Someone always regrets their decision

🐭	🐱	reaction
🧀	🧀	🐭 should have played 🕳
🕳	🧀	🐱 should have played 🧶
🕳	🧶	🐭 should have played 🧀
🧀	🧶	🐱 should have played 🧀

$\hookrightarrow$ No combination of *pure* strategies is an *equilibrium*.

Equilibrium

Combination of strategies such that no one can profit by unilaterally switching his or her own strategy.

Nash Equilibria

What a Game *is*

- Finite sets S_1, S_2 of *pure strategies*.
- Utility functions $u_1, u_2 : S_1 \times S_2 \to \mathbb{R}$.

How a Game is played

- Players pick a strategy simultaneously
  $\hookrightarrow$ gives pair $(s_1, s_2) \in S_1 \times S_2$.
- Player 1 gets payoff $u_1(s_1, s_2)$ and player 2 gets $u_2(s_1, s_2)$.

Existence of Mixed-Strategy Nash Equilibria

There exist distributions $\mathcal{S}_1$ on S_1 and $\mathcal{S}_2$ on S_2, called *mixed strategies* such that $(\mathcal{S}_1, \mathcal{S}_2)$ is an equilibrium:

$$\text{player 1 cannot increase expected payoff: } \mathbb{E}_{s_1 \sim \mathcal{S}_1, s_2 \sim \mathcal{S}_2}[u_1(s_1, s_2)] = \max_{s_1 \in S_1} \mathbb{E}_{s_2 \sim \mathcal{S}_2}[u_1(s_1, s_2)].$$

$$\text{player 2 cannot increase expected payoff: } \mathbb{E}_{s_1 \sim \mathcal{S}_1, s_2 \sim \mathcal{S}_2}[u_2(s_1, s_2)] = \max_{s_2 \in S_2} \mathbb{E}_{s_1 \sim \mathcal{S}_1}[u_2(s_1, s_2)].$$

Remark: Theorem holds for $n \geq 3$ players as well.

Nash Equilibrium in Cat & Mouse Game

		🐱	
		🧀	🧶
🐭	🧀	-4\2	2\1
	🕳	0\0	0\1

Equilibrium

$\mathcal{S}_{🐭} = \{$ 🧀 $: \frac{1}{2},$ 🕳 $: \frac{1}{2}\}$

$\mathcal{S}_{🐱} = \{$ 🧀 $: \frac{1}{3},$ 🧶 $: \frac{2}{3}\}$

Verification of Equilibrium Property: Calculating Expected Payoffs

for 🐭:

- playing 🧀 gives expected payoff
  $\frac{1}{3} \cdot (-4) + \frac{2}{3} \cdot 2 = 0$
- playing 🕳 gives expected payoff
  $\frac{1}{3} \cdot 0 + \frac{2}{3} \cdot 0 = 0$
- playing $\mathcal{S}_{🐭}$ is a mix of both
  $\hookrightarrow$ also expected payoff 0.

for 🐱:

- playing 🧀 gives expected payoff
  $\frac{1}{2} \cdot 2 + \frac{1}{2} \cdot 0 = 1$
- playing 🧶 gives expected payoff
  $\frac{1}{2} \cdot 1 + \frac{1}{2} \cdot 1 = 1$
- playing $\mathcal{S}_{🐱}$ is a mix of both
  $\hookrightarrow$ also expected payoff 1.

Content

Two Player Zero Sum Games and their Matrix Formulation

- Finite sets of pure strategies
  - S_1 for player 1
  - S_2 for player 2
- utility function $u : S_1 \times S_2 \to \mathbb{R}$
  - player 1 gets $u(s_1, s_2)$
  - player 2 gets $-u(s_1, s_2)$

- Implicit sets of pure strategies
  - $S_1 = [n]$ for the *row player*
  - $S_2 = [m]$ for the *column players*
- matrix $M \in \mathbb{R}^{n \times m}$
  - row player gets M_{s_1, s_2}
  - column player gets $-M_{s_1, s_2}$

		🤓		
		🪨	📄	✂
	🪨	0	-1	1
👧	📄	1	0	-1
	✂	-1	1	0

Unique equilibrium of 🪨 📄 ✂

$\mathcal{S}_1 = \mathcal{S}_2 = \{$ 🪨 $: \frac{1}{3},$ 📄 $: \frac{1}{3},$ ✂ $: \frac{1}{3} \}$

Two Player Zero Sum Games and their Matrix Formulation

- Finite sets of pure strategies
  - S_1 for player 1
  - S_2 for player 2
- utility function $u : S_1 \times S_2 \to \mathbb{R}$
  - player 1 gets $u(s_1, s_2)$
  - player 2 gets $-u(s_1, s_2)$

- Implicit sets of pure strategies
  - $S_1 = [n]$ for the *row player*
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- matrix $M \in \mathbb{R}^{n \times m}$
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  - column player gets $-M_{s_1, s_2}$

		🤓 🪨	🤓 📄	🤓 ✂️
👧	🦎	-1	1	-1
👧	🖖	1	-1	1

Equilibria of 🪨 📄 ✂️ 🦎 🖖

Work it out yourself!

Nash Equilibria for Two-Player Zero-Sum Games

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Nash's Theorem (1950), Special Case for Two-Player Zero-Sum Games

For any $M \in \mathbb{R}^{n \times m}$ there exist distributions $\mathcal{S}_1^*$ on $[n]$ and $\mathcal{S}_2^*$ on $[m]$ such that

$$\mathbb{E}_{s_1 \sim \mathcal{S}_1^*, s_2 \sim \mathcal{S}_2^*}[M_{s_1,s_2}] = \max_{s_1 \in [n]} \mathbb{E}_{s_2 \sim \mathcal{S}_2^*}[M_{s_1,s_2}] = \min_{s_2 \in [m]} \mathbb{E}_{s_1 \sim \mathcal{S}_1^*}[M_{s_1,s_2}].$$

Intuition: When the players play according to $\mathcal{S}_1^*$ and $\mathcal{S}_2^*$, then no player can benefit by deviating from his strategy.

Corollary: Loomis (1946) Von Neumann (1928)

For any $M \in \mathbb{R}^{n \times m}$ we have

$$\max_{\mathcal{S}_1} \min_{s_2 \in [m]} \mathbb{E}_{s_1 \sim \mathcal{S}_1}[M_{s_1,s_2}] = \min_{\mathcal{S}_2} \max_{s_1 \in [n]} \mathbb{E}_{s_2 \sim \mathcal{S}_2}[M_{s_1,s_2}]$$

(where $\mathcal{S}_1$ and $\mathcal{S}_2$ are distributions on $[n]$ and $[m]$, respectively)

Next: Proof of Loomis' Theorem assuming Nash's Theorem.

Intuition

No first-mover disadvantage if

- first player plays mixed strategy
- second player (wlog) pure strategy

Lemma: First Mover's Disadvantage

Lemma Φ: Exchanging min and max

Let X and Y be sets and $u : X \times Y \to \mathbb{R}$ a function. In our setting[1]

$$\max_{y \in Y} \min_{x \in X} u(x,y) \leq \min_{x \in X} \max_{y \in Y} u(x,y)$$

[1] In general min and max may not be well-defined...

Proof.

$$\max_{y \in Y} \min_{x \in X} u(x,y) = \min_{x \in X} u(x,y^*) \leq \min_{x \in X} \max_{y \in Y} u(x,y). \qquad \square$$

Relevance

Being the second player to choose is never a disadvantage.

Lemma: When *pure* strategies are sufficient

Lemma Δ: Minima over sets of distributions

Let X be a set and $u : X \to \mathbb{R}$ a function. Let **D** be the set of all distributions on X. In our setting:

$$\min_{x \in X} u(x) = \min_{\mathcal{X} \in \mathbf{D}} \mathbb{E}_{x \sim \mathcal{X}}[u(x)].$$

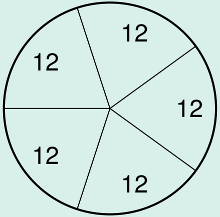
Relevance for us

The last player to choose a strategy may always chose a pure strategy.

Proof by Example

Here is a list of numers $X = \{12, 42, 73, 101\}$.

- Task 1: Find the minimum!
  $\hookrightarrow$ Duh, it's 12.
- Task 2: Design a wheel of fortune involving only numbers from X with minimum expectation!
  $\hookrightarrow$ Duh, take 12 everywhere.



Proof of Loomis's Theorem

Corollary: Loomis (1946) Von Neumann (1928)

For any $M \in \mathbb{R}^{n\times m}$ we have

$$\max_{\mathcal{S}_1} \min_{s_2\in[m]} \mathbb{E}_{s_1\sim\mathcal{S}_1}[M_{s_1,s_2}] = \min_{\mathcal{S}_2} \max_{s_1\in[n]} \mathbb{E}_{s_2\sim\mathcal{S}_2}[M_{s_1,s_2}]$$

Let $\mathcal{S}_1^*$ and $\mathcal{S}_2^*$ be the mixed strategies from Nash's Theorem.

$$\begin{aligned}
& \min_{\mathcal{S}_2} \max_{s_1\in[n]} \mathbb{E}_{s_2\sim\mathcal{S}_2}[M_{s_1,s_2}] \\
\le\ & \max_{s_1\in[n]} \mathbb{E}_{s_2\sim\mathcal{S}_2^*}[M_{s_1,s_2}] \\
=\ & \min_{s_2\in[m]} \mathbb{E}_{s_1\sim\mathcal{S}_1^*}[M_{s_1,s_2}] && \text{Nash's Theorem} \\
=\ & \min_{\mathcal{S}_2} \mathbb{E}_{s_1\sim\mathcal{S}_1^*, s_2\sim\mathcal{S}_2}[M_{s_1,s_2}] && \text{Lemma } \Delta \\
\le\ & \max_{\mathcal{S}_1} \min_{\mathcal{S}_2} \mathbb{E}_{s_1\sim\mathcal{S}_1, s_2\sim\mathcal{S}_2}[M_{s_1,s_2}] \\
=\ & \max_{\mathcal{S}_1} \min_{s_2\in[m]} \mathbb{E}_{s_1\sim\mathcal{S}_1}[M_{s_1,s_2}] && \text{Lemma } \Delta \\
\le\ & \min_{\mathcal{S}_2} \max_{\mathcal{S}_1} \mathbb{E}_{s_1\sim\mathcal{S}_1, s_2\sim\mathcal{S}_2}[M_{s_1,s_2}] && \text{Lemma } \Phi\text{: moving first no } \textit{disadvantage} \\
=\ & \min_{\mathcal{S}_2} \max_{s_1\in[n]} \mathbb{E}_{s_2\sim\mathcal{S}_2}[M_{s_1,s_2}] && \text{Lemma } \Delta
\end{aligned}$$

Start and end with same term. Hence all "$\le$" are "$=$". Hence terms of interest are "$=$". □

Content

Algorithm Design as a 2-Player Zero-Sum Game

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Setting

For a given computational problem P let

- **Algos**: *finite* set of deterministic algorithms
- **Inputs**: *finite* set of inputs
- $C(A, I) \in \mathbb{R}$ cost of $A \in$ **Algos** on $I \in$ **Inputs**.

A Two-Player Zero-Sum Game

- Designer chooses (randomised) algorithm, i.e. a distribution on **Algos**.
  $\hookrightarrow$ Goal: Minimise (expected) cost.
- Adversary chooses (randomised) input, i.e. a distribution on **Inputs**.
  $\hookrightarrow$ Goal: Maximise (expected) cost.

Example: Sorting

For given $n \in \mathbb{N}$ (finite, though possibly $n \to \infty$ later)

- $P =$ "sort n numbers comparison-based"
- $C(A, I) =$ # of comparisons of A for input I
- **Inputs** $= S_n$ //permutations of $[n]$
- **Algos** $=$ e.g. suitable set of decision trees

Sorting (x, y, z)

Algorithm Designer	Adversary: $(1,2,3)$	$(3,1,2)$	$(2,3,1)$	$\dots$
$x < y$ then $y < z$ then $z < x$	2	3	3	
$y < z$ then $z < x$ then $x < y$	3	2	3	
$\dots$				

Recall: Exercise Sheet 0, Exercise 1.

Randomised Complexity and Yao's Principle

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Definition: Randomised Complexity

$$\mathcal{C} := \min_{\mathcal{A} \text{ dist. on } \textbf{Algos}} \max_{I \in \textbf{Inputs}} \mathbb{E}_{A\sim\mathcal{A}}[C(A, I)] \qquad \text{designer moves first}$$

$$\overset{\text{Loomis}}{=} \max_{\mathcal{I} \text{ dist. on } \textbf{Inputs}} \min_{A \in \textbf{Algos}} \mathbb{E}_{I\sim\mathcal{I}}[C(A, I)] \qquad \text{adversary moves first}$$

Yao's Principle: (Upper and) Lower Bounds on $\mathcal{C}$

Let $\mathcal{A}_0$ be a distribution on **Algos** and $\mathcal{I}_0$ a distribution on **Inputs**. Then

$$\max_{I \in \textbf{Inputs}} \mathbb{E}_{A\sim\mathcal{A}_0}[C(A, I)] \geq \mathcal{C} \geq \min_{A \in \textbf{Algos}} \mathbb{E}_{I\sim\mathcal{I}_0}[C(A, I)].$$

Tightness: Loomis implies that "$=$" is possible.

$\hookrightarrow$ Can attain lower bounds on $\mathcal{C}$ by thinking about deterministic algorithm only!

Content

Computational Problem: $\bar{\wedge}$-Tree-Evaluation

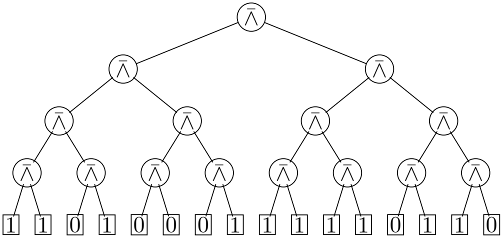
Problem: Evaluate $\bar{\wedge}$-Tree of depth d

- **Inputs** $= \{0, 1\}^n$ for $n = 2^d$. Specify bits at leafs.
- **Algos** $=$ Algorithms computing value at root.
- $C(A, I) = \#$ bits of I that A examines
  $\hookrightarrow$ query complexity of A on I

Goal

Bound randomised query complexity

$$\mathcal{C} = \min_{\mathcal{A} \text{ dist. on } \textbf{Algos}} \ \max_{I \in \textbf{Inputs}} \mathbb{E}_{A \sim \mathcal{A}}[C(A, I)].$$



Computational Problem: $\bar{\wedge}$-Tree-Evaluation

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Goal

Bound randomised query complexity

$$\mathcal{C} = \min_{\mathcal{A} \text{ dist. on } \textbf{Algos}} \; \max_{I \in \textbf{Inputs}} \mathbb{E}_{A \sim \mathcal{A}}[C(A, I)].$$

Example and possible formalisation of **Algos** (that we won't use)

Each $A \in$ **Algos** corresponds to a *decision tree*. In the example:

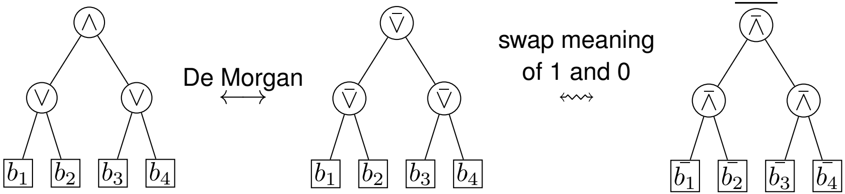
- $C(A, (1, 0, 1, 0)) = 4$
- $C(A, (0, 1, 0, 1)) = 2$

Each leaf queried at most once per path
$\Rightarrow$ depth $\leq n \Rightarrow |\textbf{Algos}| < \infty$

What we already know

$\wedge$-$\vee$-trees are $\overline{\vee}$-trees are $\overline{\wedge}$-trees

See exercise sheet 1 (“Die Wälder von NORwegen”)



What we already know

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$\wedge$-$\vee$-trees are $\bar{\vee}$-trees are $\bar{\wedge}$-trees

See exercise sheet 1 (“Die Wälder von NORwegen”)

Deterministic Query Complexity is n (Lecture 1, Slide 8)

For all $A \in$ **Algos** there exists $I \in$ **Inputs** such that $C(A, I) = n$.

Randomised Query Complexity is $\mathcal{O}(n^{\log_4(3)}) \approx \mathcal{O}(n^{0.792})$ (Lecture 1, Slide 10)

Let $\mathcal{A}$ be the randomised algorithm that evaluates one of the two depth $d-1$ subtrees at random (recursively) and, if that yields 1, also evaluates the other subtree (recursively).

$$\max_{I \in \textbf{Inputs}} \mathbb{E}_{A \sim \mathcal{A}}[C(A, I)] = \mathcal{O}(3^{d/2}) = \mathcal{O}(n^{\log_4(3)}).$$

Goal: Show lower bound of $\Omega(\varphi^d) \approx \Omega(n^{0.694})$ using Yao’s Principle (φ is the golden ratio).

Remark: actual complexity is $\Theta(n^{\log_4(3)})$, but that’s more difficult.

Warm Up: A simple lower bound

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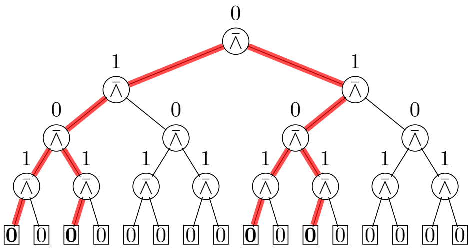
Observation

For any even $d \in \mathbb{N}$ and $A \in$ **Algos** we have $C(A, (0, \dots, 0)) \geq 2^{d/2}$.



Proof

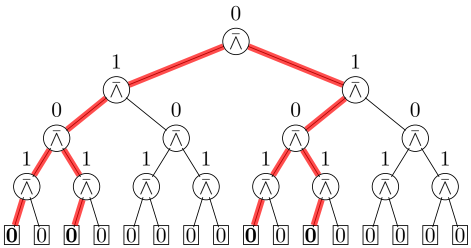
- in the end A knows that the root is 0.
- knowing a 0 requires knowing that both children are 1.
- Knowing a 1 requires knowing of one child that it is 0.

$\hookrightarrow$ A knows of $\geq 2^{d/2}$ leafs that they are 0 and must have checked them.

Warm Up: A simple lower bound

Observation

For any even $d \in \mathbb{N}$ and $A \in$ **Algos** we have $C(A, (0, \ldots, 0)) \geq 2^{d/2}$.

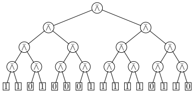


Corollary: Randomised Complexity is $\Omega(\sqrt{n})$

$$\begin{aligned}
\mathcal{C} &= \min_{\mathcal{A} \text{ dist. on } \textbf{Algos}} \ \max_{I \in \textbf{Inputs}} \mathbb{E}_{A \sim \mathcal{A}}[C(A, I)] \\
&\geq \min_{\mathcal{A} \text{ dist. on } \textbf{Algos}} \mathbb{E}_{A \sim \mathcal{A}}[C(A, (0, \ldots, 0))] \\
&\geq \min_{\mathcal{A} \text{ dist. on } \textbf{Algos}} \mathbb{E}_{A \sim \mathcal{A}}[2^{d/2}] \\
&\geq 2^{d/2} = 2^{\log_2(n)/2} = n^{1/2}.
\end{aligned}$$

Note Yao's spirit: Lower bound on *randomised complexity* from result on *deterministic algorithms*.

A stronger lower bound



Theorem (Tarsi 1984)

For any $p \in [0, 1]$ simpleEval is optimal for input distribution $\mathcal{I}_p$, i.e.

$$\min_{A \in \mathbf{Algos}} \mathbb{E}_{I \sim \mathcal{I}_{p_0}}[C(A, I)] = \mathbb{E}_{I \sim \mathcal{I}_{p_0}}[C(\text{simpleEval}, I)].$$

Lemma

If $p_0 = \frac{\sqrt{5}-1}{2}$ and φ is the golden ratio then

$$\mathbb{E}_{I \sim \mathcal{I}_{p_0}}[C(\text{simpleEval}, I)] = (1 + p_0)^d = \varphi^d.$$

Corollary: $\mathcal{C} = \Omega(\varphi^d) \approx \Omega(n^{0.694})$

$$\mathcal{C} \overset{\text{Yao}}{\geq} \min_{A \in \mathbf{Algos}} \mathbb{E}_{I \sim \mathcal{I}_{p_0}}[C(A, I)] \overset{\text{Tarsi}}{=} \mathbb{E}_{I \sim \mathcal{I}_{p_0}}[C(\text{simpleEval}, I)]$$

$$\overset{\text{Lemma}}{=} \varphi^d = \varphi^{\log_2 n} = n^{\log_2 \varphi} \approx n^{0.694}.$$

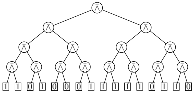
Independent Bernoulli Inputs

Let $\mathcal{I}_p = Ber(p)^n$ be the distribution where leafs are assigned independently values with distribution $Ber(p)$.

Deterministic Algorithm

Algorithm simpleEval(T)**:**
- **if** $T = \mathrm{leaf}(b)$ **then**
  - **return** b
- **else**
  - $(T_\ell, T_r) \leftarrow T$
  - **if** *simpleEval(T_ℓ) = 0* **then**
    - **return** 1
  - **else**
    - **return** $\neg$simpleEval(T_r)

Proof of Lemma: Cost of simpleEval on $\mathcal{I}_{p_0}$



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Lemma

If $p_0 = \frac{\sqrt{5}-1}{2}$ and φ is the golden ratio then

$$\mathbb{E}_{I\sim\mathcal{I}_{p_0}}[C(\text{simpleEval}, I)] = (1+p_0)^d = \varphi^d.$$

Proof (cf. Exercise “Die Wälder von NORwegen”)

- $p_0 = \frac{\sqrt{5}-1}{2}$ is the solution to $p = 1 - p^2$.
- If $a, b \sim Ber(p_0)$ then $a\bar{\wedge}b \sim Ber(1-p_0^2) = Ber(p_0)$.
- For $I \sim \mathcal{I}_{p_0}$ the probability that an *internal* tree node evaluates to 1 is p_0.
- Let $c_d := \mathbb{E}_{I\sim\mathcal{I}_{p_0}}[C(\text{simpleEval}, I)]$ for trees of depth d. Then
  - $c_0 = 1$ // tree of depth 0 is just the leaf
  - $c_d = c_{d-1} + p_0 \cdot c_{d-1} = (1+p_0)c_{d-1} \overset{\text{Ind.}}{=} (1+p_0)(1+p_0)^{d-1} = (1+p_0)^d$
    // Always one recursive call, with probability p a second one.

Deterministic Algorithm

Algorithm simpleEval(T)**:**
- **if** $T = \text{leaf}(b)$ **then**
  - **return** b
- **else**
  - $(T_\ell, T_r) \leftarrow T$
  - **if** *simpleEval(T_ℓ) = 0* **then**
    - **return** 1
  - **else**
    - **return** $\neg$simpleEval(T_r)

Content

Tarsi's Theorem

Theorem (Tarsi 1984)

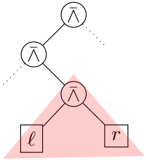
For any $p \in [0,1]$ simpleEval is optimal for input distribution $\mathcal{I}_p$, i.e.

$$\min_{A \in \textbf{Algos}} \mathbb{E}_{I \sim \mathcal{I}_{p_0}}[C(A, I)] = \mathbb{E}_{I \sim \mathcal{I}_{p_0}}[C(\text{simpleEval}, I)].$$

Proof idea:

- Take optimal Algorithm A.
- Transform A into simpleEval step by step.
- Show: Expected query complexity never increases.

Lemma: Evaluating Superleafs like simpleEval



Definition: Superleafs

A *superleaf* consists of two sibling leafs and their parent.

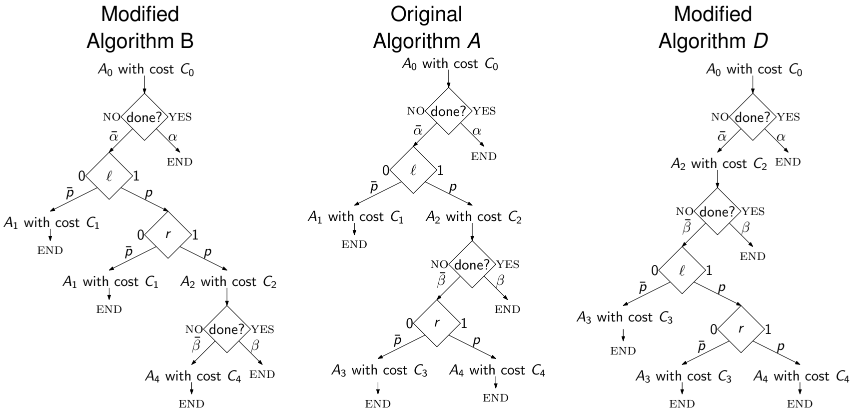
Lemma

For any $p \in [0, 1]$ and any $A \in$ **Algos** there exists $A' \in$ **Algos** such that

- $\mathbb{E}_{I \sim \mathcal{I}_p}[C(A', I)] \leq \mathbb{E}_{I \sim \mathcal{I}_p}[C(A, I)]$
- A' behaves on any superleaf $T = (\ell, r)$ like simpleEval:
  - i never visits r before ℓ
  - ii never visits r if $\ell = 0$
  - iii immediately visits r after visiting ℓ if $\ell = 1$

Proof Idea

- We fix every superleaf one by one. Let T be superleaf that needs fixing.
- Property i: Switch roles of ℓ and r if needed. Does not change the expected cost.
- Property ii: r does not contribute to result. Not visiting r *reduces* expected cost.
- Property iii: More difficult. See next slide.



$$C_A := \mathbb{E}[C(A, I)] = \mathbb{E}[C_0 + \bar{\alpha} \cdot (1 + \bar{p}C_1 + p \cdot (C_2 + \bar{\beta}(1 + \bar{p}C_3 + pC_4)))]$$
$$C_B := \mathbb{E}[C(B, I)] = \mathbb{E}[C_0 + \bar{\alpha} \cdot (1 + \bar{p}C_1 + p \cdot (1 + \bar{p}C_1 + p(C_2 + \bar{\beta}C_4)))]$$
$$C_D := \mathbb{E}[C(D, I)] = \mathbb{E}[C_0 + \bar{\alpha} \cdot (C_2 + \bar{\beta}(1 + \bar{p}C_3 + p(1 + \bar{p}C_3 + pC_4)))]$$

$$(C_B - C_A) + p \cdot (C_D - C_A) = \ldots = 0$$
$$\Rightarrow C_B - C_A \leq 0 \vee C_D - C_A \leq 0$$

$\Rightarrow$ B or D (or both) are at least as good as A and both visit superleaf (ℓ, r) as desired.

Theorem (Tarsi 1984)

For any $p \in [0,1]$ simpleEval is optimal for input distribution $\mathcal{I}_p$, i.e.

$$\min_{A \in \textbf{Algos}} \mathbb{E}_{I \sim \mathcal{I}_{p_0}}[C(A, I)] = \mathbb{E}_{I \sim \mathcal{I}_{p_0}}[C(\text{simpleEval}, I)].$$

We use induction on d. For $d = 0$ simpleEval is clearly optimal. Let now $d \geq 1$.
Let $A \in$ **Algos** be an algorithm minimising $\mathbb{E}_{I \sim \mathcal{I}_p}[C(A, I)]$.
By Lemma: There exists $A' \in$ **Algos** that behaves like simpleEval on superleafs such that

$$\mathbb{E}_{I \sim \mathcal{I}_p}[C(A', I)] \leq \mathbb{E}_{I \sim \mathcal{I}_p}[C(A, I)].$$

Let L' be the number of superleafs visited by A' and L the number of superleafs visited by simpleEval.
Superleafs evaluate to 1 with probability $1 - p^2$ independently and are in a complete binary tree of depth $d - 1$.

Apply induction for $d' = d - 1$ and $p' = 1 - p^2$.

$$\mathbb{E}_{I \sim \mathcal{I}_p}[L] \overset{\text{Ind.}}{\leq} \mathbb{E}_{I \sim \mathcal{I}_p}[L'].$$

The expected cost for evaluating a superleaf is $1 + p$.
Hence

$$\mathbb{E}_{I \sim \mathcal{I}_p}[C(A', I)] = (1 + p)\mathbb{E}[L']$$
$$\mathbb{E}_{I \sim \mathcal{I}_p}[C(A, I)] = (1 + p)\mathbb{E}[L]$$

Finally we obtain:

$$\mathbb{E}_{I \sim \mathcal{I}_p}[C(\text{simpleEval}, I)] = (1 + p)\mathbb{E}[L] \leq (1 + p)\mathbb{E}[L']$$
$$= \mathbb{E}_{I \sim \mathcal{I}_p}[C(A', I)] \leq \mathbb{E}_{I \sim \mathcal{I}_p}[C(A, I)].$$

Hence, simpleEval is optimal for $\mathcal{I}_p$. □

Content

Ski Rental – A Prototypical Online Problem

Setting: You are on a ski trip

Trip lasts for unknown number of days $I \in \mathbb{N}$ ("as long as there is snow").

Every day, if no skis bought yet:

- RENT skis for one day for cost 1 *or*
- BUY skis for cost $B \in \mathbb{N}$.

Goal: Minimise Competitive Ratio

The *competitive ratio* of distribution $\mathcal{A}$ on **Algos** is

$$C_{\mathcal{A}} = \sup_{I \in \textbf{Inputs}} \frac{\mathbb{E}_{A \sim \mathcal{A}}[C(A, I)]}{\mathrm{OPT}(I)}.$$

Framing using Online Algorithms

- **Inputs** $= \mathbb{N}$: number of days (not known in advance)
- **Algos** $= \mathbb{N}$: specify day for choosing BUY
- cost for $A \in$ **Algos** on $I \in$ **Inputs**:

$$C(A, I) = \begin{cases} I & \text{if } I < A \\ A - 1 + B & \text{otherwise.} \end{cases}$$

- cost of optimum *offline* solution

$$\mathrm{OPT}(I) = \begin{cases} I & \text{if } I < B \\ B & \text{otherwise.} \end{cases}$$

Break-Even is the best deterministic algorithm

Karlsruhe Institute of Technology

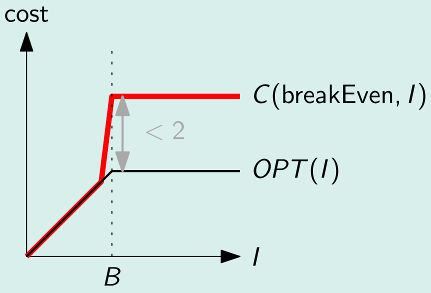
Observation

The algorithm breakEven $:= B$ has competitive ratio $\frac{2B-1}{B} \approx 2$.
All other $A \in$ **Algos** have competitive ratio ≥ 2.

Recall

B is the cost to BUY.

Proof



The worst ratio for breakEven is attained for input $I = B$.

$$C_{\text{breakEven}} = \sup_{I \in \mathbb{N}} \frac{C(\text{breakEven}, I)}{\mathrm{OPT}(I)} = \frac{C(\text{breakEven}, B)}{\mathrm{OPT}(B)}$$
$$= \frac{B - 1 + B}{B} = \frac{2B - 1}{B}.$$

Break-Even is the best deterministic algorithm

KIT Karlsruhe Institute of Technology

Observation

The algorithm breakEven $:= B$ has competitive ratio $\frac{2B-1}{B} \approx 2$.
All other $A \in$ **Algos** have competitive ratio ≥ 2.

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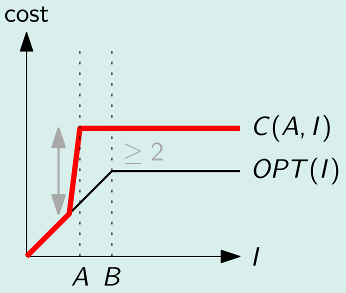


The worst ratio for $A \in$ **Algos** with $A < B$ is attained for input $I = A$.

$$C_A = \sup_{I \in \mathbb{N}} \frac{C(A, I)}{\mathrm{OPT}(I)} = \frac{C(A, A)}{\mathrm{OPT}(A)} = \frac{A - 1 + B}{A} = 1 + \frac{B-1}{A} \geq 1 + 1 = 2.$$

Break-Even is the best deterministic algorithm

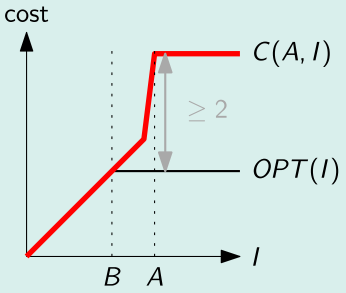
Observation

The algorithm breakEven $:= B$ has competitive ratio $\frac{2B-1}{B} \approx 2$.
All other $A \in$ **Algos** have competitive ratio ≥ 2.

Recall

B is the cost to BUY.

Proof



The worst ratio for $A \in$ **Algos** with $A > B$ is attained for input $I = A$.

$$C_A = \sup_{I \in \mathbb{N}} \frac{C(A, I)}{\mathrm{OPT}(I)} = \frac{C(A, A)}{\mathrm{OPT}(A)} = \frac{A - 1 + B}{B} = 1 + \frac{A-1}{B} \geq 1 + 1 = 2.$$

A randomised algorithm can beat break-even

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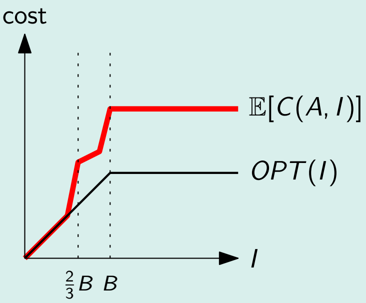
Observation (assuming wlog that B is a multiple of 3)

The randomised algorithm $\mathcal{A} = \mathcal{U}(\{\frac{2}{3}B, B\})$ has competitive ratio $\approx 1 + \frac{5}{6}$.

Proof



The competitive ratio of $\mathcal{A}$ “spikes” for inputs $\frac{2}{3}B$ and B. It is decreasing in between and constant after B.

$$\mathbb{E}_{A\sim\mathcal{A}}[C(A, \tfrac{2}{3}B)] = \underbrace{\tfrac{2}{3}B - 1}_{\text{rent}} + \underbrace{\tfrac{1}{2}(1 + B)}_{\text{rent or buy}} < \tfrac{7}{6}B, \qquad \mathrm{OPT}(\tfrac{2}{3}B) = \tfrac{2}{3}B,$$

$$\mathbb{E}_{A\sim\mathcal{A}}[C(A, B)] = \underbrace{B}_{\text{buy}} + \underbrace{\tfrac{2}{3}B - 1}_{\text{rent}} + \underbrace{\tfrac{1}{2}(\tfrac{1}{3}B)}_{\text{maybe rent}} < \tfrac{11}{6}B, \qquad \mathrm{OPT}(B) = B.$$

Hence $C_{\mathcal{A}} = \sup_{I\in\mathbb{N}} \frac{\mathbb{E}_{A\sim\mathcal{A}}[C(A, I)]}{\mathrm{OPT}(I)} \leq \max\left\{\frac{7/6}{2/3}, \frac{11/6}{1}\right\} = \max\left\{\frac{7}{4}, \frac{11}{6}\right\} = \frac{11}{6}$.

What's next?

Goal: Lower bound

No randomised algorithm has competitive ratio better than ≈ 1.582.

Yao's Principle for Online Algorithms

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Theorem (see Online Optimization Lecture, Corollary 3.8, Prof. Yann Disser, Darmstadt, 2023)

For any distribution $\mathcal{A}_0$ on **Algos** and any distribution $\mathcal{I}_0$ on **Inputs** we have

$$C_{\mathcal{A}_0} \overset{\text{def}}{=} \sup_{I \in \textbf{Inputs}} \frac{\mathbb{E}_{A \sim \mathcal{A}_0}[C(A, I)]}{\mathrm{OPT}(I)} \geq \frac{\inf_{A \in \textbf{Algos}} \mathbb{E}_{I \sim \mathcal{I}_0}[C(A, I)]}{\mathbb{E}_{I \sim \mathcal{I}_0}[\mathrm{OPT}(I)]}.$$

Remark

- Yao's principle exists for other settings as well.
- Proof of "$\geq$" relatively easy to prove.
- Tightness typically follows from duality of optimisation problems or fixed point theorems.
  (though I'm not sure how it works here)

A hard distribution for Ski-Rental: Intuition

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$$\mathcal{I}_0 := Geo(\tfrac{1}{B}).$$

Why $\mathcal{I}_0$?

- distribution is **memoryless**.
  Assume no skis bought on day i: Minimising expected *future* cost is the same problem as on day 1.
  $\hookrightarrow$ wlog: either buy right away or not at all.
- **expectation** tuned such that

$$\mathbb{E}_{I\sim\mathcal{I}_0}[C(\text{never buy}, I)] = \mathbb{E}_{I\sim\mathcal{I}_0}[C(\text{immediately buy}, I)] = B.$$

$\hookrightarrow$ all strategies equally good

A hard distribution for Ski-Rental: Analysis

Lemma

Let $\mathcal{I}_0 := \mathit{Geo}(\frac{1}{B})$ *and* $q := 1 - \frac{1}{B} =$ "Pr[❄]". *Then*

- i $\mathbb{E}_{I\sim\mathcal{I}_0}[C(A,I)] = B$ *for all* $A \in \mathbb{N}$.
- ii $\mathbb{E}_{I\sim\mathcal{I}_0}[\mathrm{OPT}(I)] = B(1-(1-\frac{1}{B})^B)$.

Seen before:

Any random variable X with values in $\mathbb{N}$ satisfies
$$\mathbb{E}[X] = \sum_{j\geq 1} \Pr[X \geq j].$$

Proof of (i)

$$\mathbb{E}_{I\sim\mathcal{I}_0}[C(A,I)] = \mathbb{E}_{I\sim\mathcal{I}_0}\left[\sum_{i\in\mathbb{N}} \text{cost on day } i\right] = \sum_{i\in\mathbb{N}} \mathbb{E}_{I\sim\mathcal{I}_0}[\text{cost on day } i] = \sum_{i=1}^{A-1} \underbrace{\Pr[I \geq i]\cdot 1}_{\text{rent}} + \underbrace{\Pr[I \geq A]\cdot B}_{\text{buy}}$$

$$= \sum_{i=1}^{A-1} q^{i-1} + q^{A-1}\cdot B = \sum_{i=0}^{A-2} q^{i} + q^{A-1}\cdot B = \frac{1-q^{A-1}}{1-q} + q^{A-1}\cdot B$$

$$= (1-q^{A-1})B + q^{A-1}\cdot B = B.$$

A hard distribution for Ski-Rental: Analysis

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Lemma

Let $\mathcal{I}_0 := \textit{Geo}(\frac{1}{B})$ *and* $q := 1 - \frac{1}{B} =$ "Pr[❄]". *Then*

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- ii $\mathbb{E}_{I\sim\mathcal{I}_0}[\mathrm{OPT}(I)] = B(1 - (1 - \frac{1}{B})^B)$.

Seen before:

Any random variable X with values in $\mathbb{N}$ satisfies

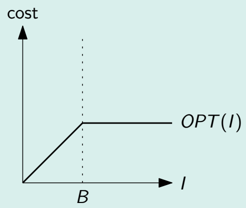
$$\mathbb{E}[X] = \sum_{j\geq 1} \Pr[X \geq j].$$

Proof of (ii)

$$\mathbb{E}_{I\sim\mathcal{I}_0}[\mathrm{OPT}(I)] = \sum_{j\geq 1} \Pr[\mathrm{OPT}(I) \geq j] = \sum_{j=1}^{B} \Pr[\mathrm{OPT}(I) \geq j]$$

$$= \sum_{j=1}^{B} \Pr[I \geq j] = \sum_{j=1}^{B} q^{j-1} = \sum_{j=0}^{B-1} q^j$$

$$= \frac{1 - q^B}{1 - q} = B(1 - (1 - \tfrac{1}{B})^B).$$



Note: $\mathrm{OPT}(I) = I$ for $I \in [B]$.

A hard distribution for Ski-Rental: Analysis

Lemma

Let $\mathcal{I}_0 := Geo(\frac{1}{B})$ *and* $q := 1 - \frac{1}{B} =$ "Pr[❄]". *Then*

- i $\mathbb{E}_{I\sim\mathcal{I}_0}[C(A, I)] = B$ *for all* $A \in \mathbb{N}$.
- ii $\mathbb{E}_{I\sim\mathcal{I}_0}[\mathrm{OPT}(I)] = B(1 - (1 - \frac{1}{B})^B)$.

Seen before:

Any random variable X with values in $\mathbb{N}$ satisfies

$$\mathbb{E}[X] = \sum_{j\geq 1} \Pr[X \geq j].$$

Lower bound for Ski-Rental

By Yao's theorem any randomised algorithm $\mathcal{A}$ for ski-rental has competitive ratio at least

$$c_{\mathcal{A}} \geq \frac{\inf_{A\in\textbf{Algos}} \mathbb{E}_{I\sim\mathcal{I}_0}[C(A, I)]}{\mathbb{E}_{I\sim\mathcal{I}_0}[\mathrm{OPT}(I)]} = \frac{B}{B(1 - (1 - \frac{1}{B})^B)} = \frac{1}{1 - (1 - \frac{1}{B})^B}.$$

For large B the lower bound converges to $\lim_{B\to\infty} \frac{1}{1-(1-\frac{1}{B})^B} = \frac{1}{1-1/e} = \frac{e}{e-1} \approx 1.582$.

Upper bound for Ski-Rental

Remark: The lower bound is tight (Karlin et al. 1994)

There exists a distribution $\mathcal{A}$ on $[B]$ such that $c_{\mathcal{A}} \leq \frac{e}{e-1}$.

Applications

Very basic online question:

Should I pay a small possibly recurring cost or a large one time cost?

Occurs in:

- Cache management.
- Networking.
- Scheduling.
- ...

Conclusion

Algorithm Design as a Two-Player Game

- “we” choose algorithm to minimise cost
- “adversary” chooses input to maximise cost
- Nash/Loomis: It does not matter who moves first
  if mixed strategy is allowed for first player.

Yao’s Principle

Lower bound on worst-case expected cost of *any randomised algorithm* $\mathcal{A}_0$ by analying *any deterministic algorithm* on specific input distribution $\mathcal{I}_0$.

$$\max_{I \in \textbf{Inputs}} \mathbb{E}_{A \sim \mathcal{A}_0}[C(A, I)] \geq \mathcal{C} \geq \min_{A \in \textbf{Algos}} \mathbb{E}_{I \sim \mathcal{I}_0}[C(A, I)].$$

Can narrow down randomised complexity $\mathcal{C}$ of underlying problem from both sides.

Anhang: Mögliche Prüfungsfragen I

Spieltheorie:

- Was ist ein Zwei-Spieler-Spiel im Sinne der Spieltheorie?
- Was ist ein Nash-Equilibrium?
- Gibt es immer ein Nash-Equilibrium?
- Was ist ein Nullsummenspiel?
- Was besagt der Satz von Nash (für Zwei-Spieler Nullsummenspiele)?
- Was besagt der Satz von Loomis?
- Beweise den Satz von Loomis! (anspruchsvolle Aufgabe)

Yaos Prinzip:

- Worin besteht die Verbindung zwischen Spieltheorie und dem Entwurf von Algorithmen?
- Wie ist die randomisierte Komplexität (bzgl. einer Kostenfunktion C) normalerweise definiert? Welche andere Sichtweise ergibt sich darauf durch den Satz von Loomis?
- Formuliere Yaos Prinzip! Wofür ist es nützlich?

Anhang: Mögliche Prüfungsfragen II

Anwendung auf $\overline{\wedge}$-Bäume:

- Welches Ziel haben wir uns bei der Auswertung von $\overline{\wedge}$-Bäumen gesetzt? (Anfragekomplexität minimieren)
- Welche Worst-Case Kosten lassen sich mit einem deterministischen Algorithmus erreichen?
- Können randomisierte Algorithmen das besser? Wie?
- Man kann sich recht leicht überlegen, dass die randomisierte Komplexität $\Omega(\sqrt{n})$ beträgt. Wie ging das?
- Wir haben auch eine schärfere Analyse gesehen. Welche Komponenten hatte diese? Insbesondere: Wie kommt dabei Yao Prinzip zur Anwendung?
- Was besagt der Satz von Tarsi?

Ski-Rental-Problem:

- Formuliere das Ski-Rental Problem.
- Wie nennt man diese Art von Problem? (*Online* Problem)
- Spielt das nur im Wintersport eine Rolle? (nur Stichworte)
- Wie ist der kompetitive Faktor definiert?

Anhang: Mögliche Prüfungsfragen III

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- Was ist der beste deterministische Algorithmus? Wie kann man das einsehen?
- Gibt es einen randomisierten Algorithmus der Break-Even schlagen kann? (nur die Idee)
- Formuliere Yaos Prinzip für Online Algorithmen.
- Welche Eingabeverteilung haben wir für die untere Schranke für Ski-Rental zugrunde gelegt? Was ist die Intuition?
- Welche Kosten ergeben sich für Online und Offline Algorithmen für diese Eingabeverteilung? Was lässt sich entsprechend über den kompetitiven Faktor sagen?