

Foundations of Probabilistic Proofs

A course by **Alessandro Chiesa**

Lecture 01

Intro to IPs

What are Mathematical Proofs?

One answer: an **approximation of understanding**.

"A proof is whatever convinces me." (Shimon Even, 1978) [Stories about Shimon Even by Oded Goldreich]

Logic formalizes the notion of "proof" so it can be studied using mathematics itself.

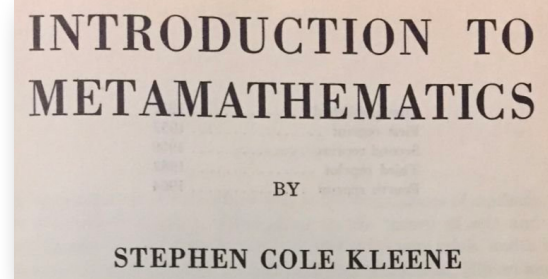
In particular this leads to **METAMATHEMATICS**.

A **formal system** is a tuple **(alphabet, grammar, axioms, inference rules)**.

A **(true) theorem** is a sentence that has a **(valid) proof**:

a list of sentences whose last sentence is the theorem such that every sentence is an axiom, an assumption, or derived from prior sentences.

a logical derivation
from axioms & assumptions



Fundamental question: **HILBERT'S ENTSCHEIDUNGSPROBLEM**

is there a procedure to determine if a sentence is a theorem?

NO no such
procedure exists

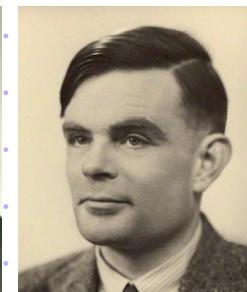
1931: Gödel $\begin{cases} \text{IT1: every strong enough formal system is not complete} \\ \text{IT2: every strong enough formal system cannot prove its own consistency} \end{cases}$

1935: Church (via λ -calculus)

1936: Turing (via Turing machines)

$\forall$ sentence x , x or $\bar{x}$ has a proof

$\forall$ sentence x , at most one of x or $\bar{x}$ has a proof



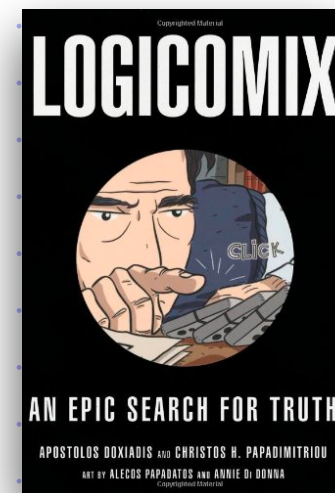
Proofs and Computation

Mathematical proofs were implicitly always **about computation**.

Formulating (and answering) the Entscheidungsproblem made this explicit.

Computation is formalized via **Turing machines** (and other equivalent models).

This enables the study of **COMPUTABILITY THEORY** and **COMPLEXITY THEORY**.



Undecidability of a language rules out any mathematical proof.

Languages with **NONDETERMINISTIC WITNESSES** correspond to theorems with mathematical proofs:

A language L is in **NTIME** $[T]$ iff $\exists$ ^{verifier} V machine M that runs in time $T(|x|)$ s.t.

• **completeness**: $\forall$ ^{theorem} instance $x \in L \exists$ $T(|x|)$ -size ^{proof} witness w $V(x, \pi) = 1$
 $M(x, w) = 1$

• **soundness**: $\forall$ ^{theorem} instance $x \notin L \forall$ $T(|x|)$ -size ^{proof} witness w $V(x, \pi) = 0$
 $M(x, w) = 0$

The NTIME-hierarchy theorem tells us that checking a witness may take **arbitrarily long**:

theorem: $\text{NTIME}[o(T)] \subsetneq \text{NTIME}[T]$ [precisely: $\text{NTIME}[f(n)] \subsetneq \text{NTIME}[g(n)] \forall$ time-constructible f, g with $f(n+1) = o(g(n))$]

Hence **EFFICIENTLY-VERIFIABLE** witnesses better capture mathematical proofs:

$\text{NP} = \bigcup_{c \in \mathbb{N}} \text{NTIME}[n^c]$ nondeterministic polynomial time

Efficient Mathematical Proofs = NP

The definition of the complexity class **NP** (nondeterministic polynomial time):

$L \in NP \iff \exists$ polynomial-time ^{verifier V} decider D s.t.

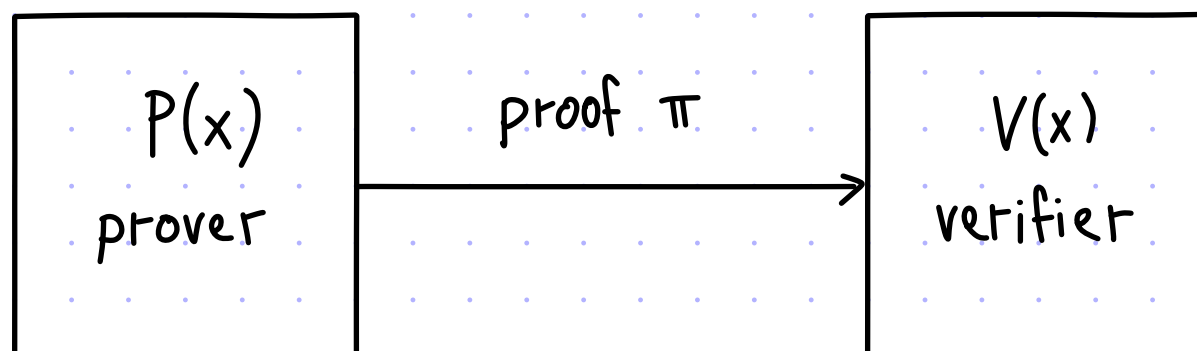
^{completeness:} ① ^{theorem} $\forall$ instance $x \in L \exists$ poly($|x|$)-size ^{proof} witness w $V(x, \pi) = 1$
 $D(x, w) = 1$

^{soundness:} ② ^{theorem} $\forall$ instance $x \notin L \forall$ poly($|x|$)-size ^{proof} witness w $V(x, \pi) = 0$
 $D(x, w) = 0$

Example: $L = SAT$

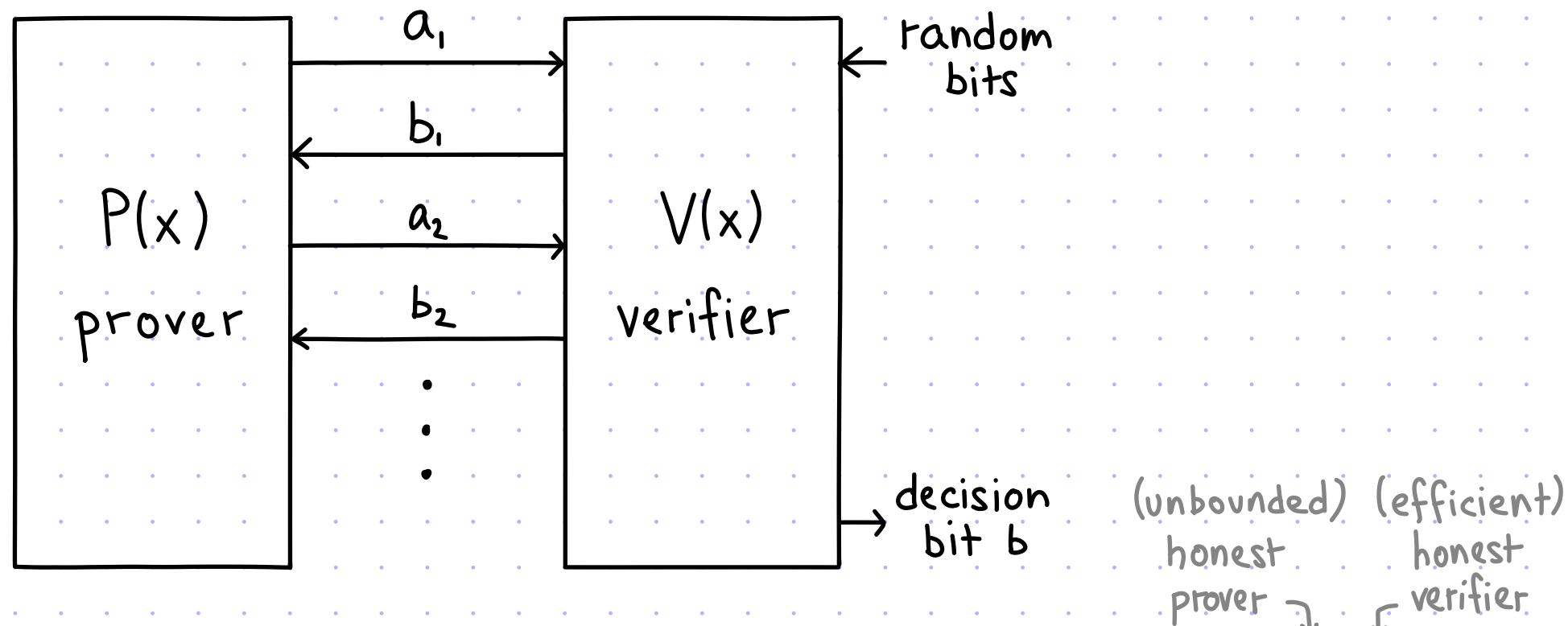
- x is a boolean formula $\phi(x_1, \dots, x_n)$
- w is an assignment $(a_1, \dots, a_n) \in \{0, 1\}^n$
- D checks that $\phi(a_1, \dots, a_n) = \text{true}$

Hence NP captures **traditional (efficient) mathematical proofs**:



Interactive Proofs

A revolutionary idea: the verifier may use randomness and interact with the prover.



An **interactive proof** for a language L is a pair (P, V) such that:

① completeness: $\forall x \in L \quad \Pr_{r_p, r_v} [\langle P(x; r_p), V(x; r_v) \rangle = 1] = 1.$

② soundness: $\forall x \notin L \quad \forall \tilde{P} \quad \Pr_{r_v} [\langle \tilde{P}, V(x; r_v) \rangle = 1] \leq 1/2.$

the "best" randomness can be hardcoded in $\tilde{P}$

more generally:

$\geq 1 - \epsilon_c$

$\leq \epsilon_s$

and it suffices
to have
 $1 - \epsilon_c - \epsilon_s \geq \frac{1}{\text{poly}}$

What Is The Power Of Interactive Proofs?

Somewhat degenerate if we leverage **only interaction** or **only randomness**:

		interaction	
		no	yes
randomness	no	NP	NP
	yes	MA	IP

↖ believed to equal NP (strong PRGs $\rightarrow$ MA = NP)

Hence we should leverage interaction and randomness simultaneously.

We wish to understand:

Which languages have interactive proofs?

Are there any beyond NP (and MA)?

Isomorphisms Between Graphs

Let $G_0 = (V, E_0)$ and $G_1 = (V, E_1)$ be two graphs on vertices V .

def: $G_0 \equiv G_1$ (G_0 & G_1 are **isomorphic**) if $\exists$ permutation $\pi: V \rightarrow V$ s.t.

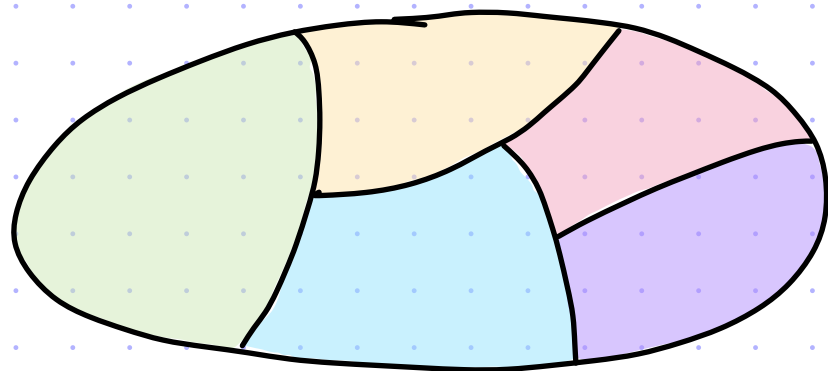
$$(u, v) \in E_0 \iff (\pi(u), \pi(v)) \in E_1.$$

If so, we write $G_1 = \pi(G_0)$.

The isomorphism relation is an **EQUIVALENCE RELATION**:

- it is **reflexive**: $G \equiv G$ (via the identity permutation)
- it is **symmetric**: $G_1 = \pi(G_0) \iff G_0 = \pi^{-1}(G_1)$
- it is **transitive**: $G_1 = \pi_1(G_0) \wedge G_2 = \pi_2(G_1) \rightarrow G_2 = (\pi_2 \circ \pi_1)(G_0)$

Hence the relation partitions all graphs into **EQUIVALENCE CLASSES**:



Languages for Graph Isomorphism

The graph isomorphism relation induces two languages:

$$GI := \{ (G_0, G_1) \mid G_0 \cong G_1 \} \quad GNI := \{ (G_0, G_1) \mid G_0 \not\cong G_1 \}$$

Examples:

• $\left(\begin{array}{c} \text{Star graph } G_1 \\ \text{Cycle graph } G_0 \end{array} \right) \in GI. \quad \text{Why?} \quad \pi = \left\{ \begin{array}{l} 1 \rightarrow 1 \\ 3 \rightarrow 2 \\ 5 \rightarrow 3 \\ 2 \rightarrow 4 \\ 4 \rightarrow 5 \end{array} \right\}$

• $\left(\begin{array}{c} \text{House graph } G_1 \\ \text{Square graph } G_0 \end{array} \right) \in GNI. \quad \text{Why?} \quad G_1 \text{ has a triangle but } G_0 \text{ does not}$

More generally, $GI \in NP$, and so $GNI \in coNP$.

But it is not known if GI (or GNI) is in P .

Q: How to prove that $G_0 \not\cong G_1$?

In general, it is harder to see than in the above example.

Interactive Proof for Graph Non-Isomorphism

[1/2]

theorem: $GNI \in IP$

$P(G_0, G_1)$

find $\tilde{b}$ s.t.

$H \equiv G_{\tilde{b}}$

$\xleftarrow{H}$
 $\xrightarrow{\tilde{b}}$

$V(G_0, G_1)$

$b \leftarrow \{0, 1\}$

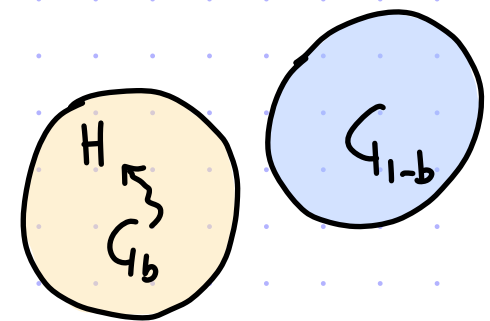
$\pi \leftarrow \{\text{permutations on vertices}\}$

$H := \pi(G_b)$

$\tilde{b} \stackrel{?}{=} b$

Completeness: Suppose that $(G_0, G_1) \in GNI$ (i.e., $G_0 \neq G_1$).

Then G_b and G_{1-b} are in different equivalence classes:



The honest prover determines b by finding out which graph H is isomorphic to.

NOTE: for now we ignore the efficiency of the honest prover.

Interactive Proof for Graph Non-Isomorphism

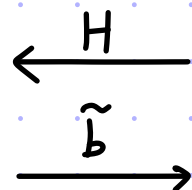
[2/2]

theorem: $GNI \in IP$

$P(G_0, G_1)$

find $\tilde{b}$ s.t.

$H \equiv G_{\tilde{b}}$



$V(G_0, G_1)$

$b \leftarrow \{0, 1\}$

$\pi \leftarrow \{\text{permutations on vertices}\}$

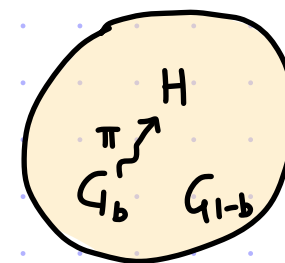
$H := \pi(G_b)$

$\tilde{b} \stackrel{?}{=} b$

Soundness: Suppose that $(G_0, G_1) \notin GNI$ (i.e., $G_0 \equiv G_1$).

The random variable $\pi(G_b)$ is identical to $\pi(G_{1-b})$:

Hence $H := \pi(G_b)$ and b are **independent**.



We conclude that $\Pr[\tilde{b} = b] = 1/2$ regardless of how a malicious prover chooses $\tilde{b}$ based on H .

NOTE: it is crucial that b is secret... but later we learn how to avoid "private randomness"

Upper Bound on IP

[1/4]

theorem: $IP \subseteq PSPACE$ ← languages decidable in polynomial space

Let $L \in IP$, and let (P, V) be an IP for L .

We show that $L \in PSPACE$.

Fix an instance x and define $q_x := \max_{\tilde{P}} \Pr [\langle \tilde{P}, V(x; r) \rangle = 1]$. maximum winning probability

If $x \in L$ then $q_x = 1$.
If $x \notin L$ then $q_x \leq 1/2$. } It suffices to compute q_x in polynomial space.

PROBLEM: we cannot iterate over ALL provers $\tilde{P}$ because
this includes those that require large space to run

IDEA: any interaction transcript has polynomial size (the IP verifier reads it)
so we CAN iterate over all transcripts in polynomial space

We show that the **optimal prover strategy** is computable
in polynomial space, and so is the probability q_x .

Upper Bound on IP

[2/4]

The **optimal prover** is defined as follows:

$P^*(x, (a_1, b_1, \dots, a_i, b_i))$ outputs a_{i+1}^* that maximizes the probability that $P^*(x)$ convinces $V(x)$ conditioned on the first i rounds being $(a_1, b_1, \dots, a_i, b_i)$.

claim: $P^* \in \text{PSPACE} \rightarrow q_x \in \text{PSPACE}$

proof: The optimality of P^* implies that $q_x = \frac{\sum_{r \in R} d(x, r)}{|R|}$ where:

- R are the possible random strings of the IP verifier V ,
- $d(x, r)$ is the decision bit of $V(x; r)$ when interacting with P^* .

Note that $d(x, r)$ is computable in polynomial space:

$$\begin{aligned} a_1^* &:= P^*(x, \perp) & a_2^* &:= P^*(x, (a_1^*, b_1)) & \dots & a_k^* &:= P^*(x, (a_1^*, b_1, \dots, a_{k-1}^*, b_{k-1})) \\ b_1 &:= V(x, r, a_1^*) & b_2 &:= V(x, r, a_1^*, a_2^*) & \dots & b_k &:= V(x, r, a_1^*, \dots, a_k^*) \end{aligned}$$

Indeed:

- each invocation of P^* is in polynomial space (by assumption)
- each invocation of V is in polynomial time (by definition)

Hence $A(x) :=$

1. Initialize $c := 0$.
2. For each $r \in R$, $c := c + d(x, r)$.
3. Output $c/|R|$.

runs in polynomial space.

Upper Bound on IP

[3/4]

claim: $P^* \in PSPACE$

proof: Given a transcript $tr = (a_1, b_1, \dots, a_i, b_i)$ of i rounds, define:

$$R[x, tr] := \left\{ r \in R \mid \begin{array}{l} b_1 = V(x, r, a_1) \\ b_2 = V(x, r, a_1, a_2) \\ \vdots \\ b_i = V(x, r, a_1, \dots, a_i) \end{array} \right\} \quad \text{set of random strings consistent with } (x, tr)$$

Membership in $R[x, tr]$ can be checked in polynomial time, and thus polynomial space.

The proof is by (reverse) induction on $i \in \{0, 1, \dots, k-1\}$.

Base case is $i = k-1$.

By definition of P^* ,

$$P^*(x, tr) = P^*(x, (a_1, b_1, \dots, a_{k-1}, b_{k-1})) = \arg \max_{a_k} \mathbb{P}_r [V(x, r, a_1, \dots, a_{k-1}, a_k) = 1]$$

We can iterate over all prover messages a_k and all random strings r in polynomial space. (By reusing space for every a_k and r .)

Upper Bound on IP

[4/4]

claim: $P^* \in \text{PSPACE}$

proof: (continued)

Inductive case is $i < k-1$. (We assume that $P^* \in \text{PSPACE}$ for $|tr| > i$.)

By definition of P^* ,

$$P^*(x, tr) = P^*(x, (a_1, b_1, \dots, a_i, b_i)) = \arg \max_{a_{i+1}} \Pr_{r \in R[x, tr]} [V(x, r, a_1, \dots, a_i, a_{i+1}, a_{i+2}^*, \dots, a_k^*) = 1]$$

where $a_{i+2}^*, \dots, a_k^*$ are optimal prover messages for (x, tr, r, a_{i+1}) :

$$b_{i+1} := V(x, r, a_1, \dots, a_i, a_{i+1}) \quad \text{in polynomial time}$$

$$a_{i+2}^* := P^*(x, (a_1, b_1, \dots, a_i, b_i, a_{i+1}, b_{i+1})) \quad \text{in polynomial space (inductive assumption)}$$

$$b_{i+2} := V(x, r, a_1, \dots, a_i, a_{i+1}, a_{i+2}^*) \quad \text{in polynomial time}$$

$$\vdots$$
$$a_k^* := P^*(x, (a_1, b_1, \dots, a_i, b_i, a_{i+1}, b_{i+1}, a_{i+2}^*, b_{i+2}, \dots, a_{k-1}^*, b_{k-1})) \quad \text{in polynomial space (inductive assumption)}$$

We can iterate over all prover messages a_{i+1} and all random strings r .

We conclude that P^* is computable in polynomial space.



Error Reduction

[1/3]

How to **reduce** the completeness error ϵ_c and/or soundness error ϵ_s of an IP?

Idea: Run the IP t times in sequence and **(somehow)** decide based on that.

For every IP prover $\tilde{P}_t$, define the random variables $(Z_i(x, \tilde{P}_t))_{i \in [t]} :=$ "i-th IP verifier accepts".

The RVs are independently and identically distributed.

Moreover:

- $x \in L \rightarrow \forall i \in [t] \Pr[Z_i(x, P_t) = 1] \geq 1 - \epsilon_c.$
- $x \notin L \rightarrow \forall i \in [t] \forall \tilde{P}_t \Pr[Z_i(x, \tilde{P}_t) = 1] \leq \epsilon_s.$

The case of **PERFECT COMPLETENESS** ($\epsilon_c = 0$):

$$V_{\text{AND}}(x; (s_1, \dots, s_t)) := \bigwedge_{i \in [t]} V(x; s_i)$$

• perfect completeness is preserved: $\epsilon'_c := 0$

$$\Pr[\langle P_t(x), V_{\text{AND}}(x; (s_1, \dots, s_t)) \rangle = 0] = \Pr[\bigwedge_{i \in [t]} Z_i(x, P_t) = 0] = 1 - \prod_{i \in [t]} \Pr[Z_i(x, P) = 1] = 1 - 1 = 0$$

• soundness error decays exponentially: $\epsilon'_s := \epsilon_s^t$

$$\Pr[\langle \tilde{P}_t, V_{\text{AND}}(x; (s_1, \dots, s_t)) \rangle = 1] = \Pr[\bigwedge_{i \in [t]} Z_i(x, \tilde{P}_t) = 1] = \prod_{i \in [t]} \Pr[Z_i(x, \tilde{P}_t) = 1] \leq \prod_{i \in [t]} \epsilon_s$$

Error Reduction

[2/3]

How to **reduce** the completeness error ϵ_c and/or soundness error ϵ_s of an IP?

Idea: Run the IP t times in sequence and **(somehow)** decide based on that.

What about the case of **IMPERFECT COMPLETENESS** ($\epsilon_c > 0$)?

The AND verifier **increases** the completeness error: $\epsilon_c' := 1 - (1 - \epsilon_c)^t \leq t \cdot \epsilon_c$.

→ This option demands small ϵ_c to begin with.

Alternatively, consider the OR verifier: $V_{\text{OR}}(x; (g_1, \dots, g_t)) := \bigvee_{i \in [t]} V(x; g_i)$

- completeness error decays exponentially: $\epsilon_c' := \epsilon_c^t$

$$\Pr[\langle P_t(x), V_{\text{OR}}(x; (g_1, \dots, g_t)) \rangle = 0] = \Pr[\bigvee_{i \in [t]} Z_i(x, P_t) = 0] = \prod_{i \in [t]} \Pr[Z_i(x, P_t) = 0] \leq \prod_{i \in [t]} \epsilon_c.$$

- soundness error increases: $\epsilon_s' := 1 - (1 - \epsilon_s)^t \leq t \cdot \epsilon_s$

$$\Pr[\langle \tilde{P}_t, V_{\text{OR}}(x; (g_1, \dots, g_t)) \rangle = 1] = \Pr[\bigvee_{i \in [t]} Z_i(x, \tilde{P}_t) = 1] = 1 - \prod_{i \in [t]} \Pr[Z_i(x, \tilde{P}_t) = 0] \leq 1 - \prod_{i \in [t]} (1 - \epsilon_s).$$

→ This option demands small ϵ_s to begin with.

What if neither ϵ_c nor ϵ_s is small (e.g. $\epsilon_c = 1/3$ and $\epsilon_s = 1/3$)?

Error Reduction

[3/3]

How to **reduce** the completeness error ϵ_c and/or soundness error ϵ_s of an IP?

Idea: Run the IP t times in sequence and **(somehow)** decide based on that.

The random variable $Z(x, \tilde{P}) := \frac{1}{t} \sum_{i \in [t]} Z_i(x, \tilde{P})$ has mean $\mathbb{E}[Z(x, \tilde{P})] = \mathbb{E}[Z_i(x, \tilde{P})]$.

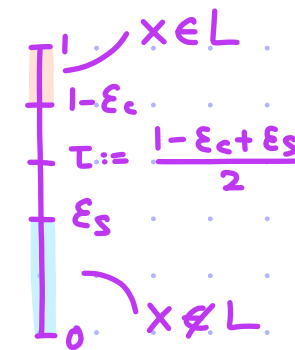
By a **Chernoff bound**, $Z(x, \tilde{P})$ concentrates around its mean:

$$\forall \gamma \geq 0 \quad \Pr[|Z(x, \tilde{P}) - \mathbb{E}[Z(x, \tilde{P})]| \geq \gamma] \leq 2 \cdot e^{-\frac{t\gamma^2}{4}}.$$

This motivates the MAJ verifier:

$V_{\text{MAJ}}(x; (g_1, \dots, g_t)) :=$

1. Set the threshold $\tau := \frac{1 - \epsilon_c + \epsilon_s}{2}$.
2. For every $i \in [t]$, compute $b_i := V(x; g_i)$.
3. If $\frac{1}{t} \sum_{i \in [t]} b_i \geq \tau$ output 1; else output 0.



$$\bullet x \in L \rightarrow \Pr[\langle P(x), V_{\text{MAJ}}(x) \rangle = 0] = \Pr[Z(x, P) < \tau] \stackrel{\mathbb{E}[Z(x, P)] \geq 1 - \epsilon_c}{\leq} \Pr[|Z(x, P) - \mathbb{E}[Z(x, P)]| \geq \frac{1 - \epsilon_c - \epsilon_s}{2}] \stackrel{\text{Chernoff bound}}{\leq} 2 \cdot e^{-t \cdot (1 - \epsilon_c - \epsilon_s)^2}.$$

$$\bullet x \notin L \rightarrow \Pr[\langle \tilde{P}, V_{\text{MAJ}}(x) \rangle = 1] = \Pr[Z(x, \tilde{P}) \geq \tau] \stackrel{\mathbb{E}[Z(x, \tilde{P})] \leq \epsilon_s}{\leq} \Pr[|Z(x, \tilde{P}) - \mathbb{E}[Z(x, \tilde{P})]| \geq \frac{1 - \epsilon_c - \epsilon_s}{2}] \stackrel{\text{Chernoff bound}}{\leq} 2 \cdot e^{-t \cdot (1 - \epsilon_c - \epsilon_s)^2}.$$

Hence if $t \geq \frac{\ln 2/\epsilon}{(1 - \epsilon_c - \epsilon_s)^2}$ then $\epsilon'_c, \epsilon'_s \leq \epsilon$.

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- [Hoeffding](#) and [Chernoff](#) concentration inequalities.