Probabilistic Computation

Lecture 13 BPP vs. PH





Probabilistic computation



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Pr[M(x)=yes]:

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XEL
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PTM for L: Pr[yes]:BPTM for L: Pr[yes]:



Probabilistic computation

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 x \u2294 L
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PTM for L: Pr[yes]:
BPTM for L: Pr[yes]:
RTM for L: Pr[yes]:











PP too powerful: NP \subseteq PP

RP, BPP, with bounded gap



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RP, BPP, with bounded gap

A realistic/useful computational model



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Today:



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Gap can be boosted from 1/poly to 1-1/exp

A realistic/useful computational model

Today:

ONP ⊈ BPP, unless PH collapses



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 PP = PP = PP PP = PP

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A realistic/useful computational model

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𝔅 BPP ⊆ Σ₂^P ∩ Π₂^P

Can randomized algorithms efficiently decide all NP problems?

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Then NP ⊆ BPP ⇒ NP ⊆ P/poly

 $\varnothing \Rightarrow \mathsf{PH} = \Sigma_2^{\mathsf{P}}$

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rX						
		X	X			
						X
						\checkmark
		\checkmark	X	\checkmark	\checkmark	\checkmark
	\checkmark	\checkmark		\checkmark	X	\checkmark
	X	X		\checkmark		\checkmark
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	\checkmark	\checkmark	\checkmark	X	\checkmark	\checkmark
	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	X
	\checkmark	\checkmark				

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Then, can give that random tape as advice

rX						
		X	X			
						X
			\checkmark	\checkmark	V	\checkmark
			\mathbf{X}	\checkmark	\checkmark	\checkmark
				\checkmark	X	\checkmark
	X	X		\checkmark		\checkmark
	X		\checkmark	\checkmark	\checkmark	\checkmark
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	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark

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 - BPP: can make worst
 error probability < 2⁻ⁿ



BPP vs. PH

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BPP vs. PH

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So BPP ⊆ Σ₂^P ∩ Π₂^P

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Note: Neighborhood of r is small (polynomially large), so can go through all of them in polynomial time





Space of random tapes = {0,1}^m Yes_x = {r| M(x,r)=yes }

(x∈L: |Yes_×|>(1-2⁻ⁿ)2^m)





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∞ x∉L: Yes_x very small, so its few shifts cover only a small region

$\mathsf{BPP} \subseteq \Sigma_2^{\mathsf{P}}$

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Yes! For all large S (like Yes_x) can indeed find a P s.t. P(S) = {0,1}^m

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Yes! For all large S (like Yes_x) can indeed find a P s.t. P(S) = {0,1}^m
 In fact, most P work (if k big enough)!

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Probabilistic Method (finding hay in haystack)

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 \odot To prove $\exists P$ with some property

Define a probability distribution over all candidate P's and prove that the property holds with positive probability (often even close to one)

Probabilistic Method (finding hay in haystack)
 To prove 3P with some property

Define a probability distribution over all candidate P's and prove that the property holds with positive probability (often even close to one)

Distribution s.t. easy to prove positive probability of property holding

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Probabilistic method to find P = {u₁, u₂, ..., u_k}, s.t. for all large S, P(S) = {0,1}^m

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Distribution over P's: randomized experiment to generate P

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So (with $|S|>(1-2^{-n})2^{m}$ and k=m/n), ∃P, P(S) = {0,1}^m

x∈L: |Yes_×|>(1-2⁻ⁿ)2^m





x∉L: |Yes_x|<2⁻ⁿ2^m

Space of random strings = {0,1}^m Yes_x = {r| M(x,r)=yes }
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x∉L: |Yes_x|<2⁻ⁿ2^m

Space of random strings = {0,1}^m Yes_× = {r| M(x,r)=yes }

For each x∈L, ∃P (of size k=m/n) s.t. P(Yes_x)={0,1}^m



For each x∉L, P(Yes_x) ⊊ {0,1}^m





■ L = { x | ∃P $\forall r'$ for some r∈P⁻¹(r') M(x,r)=yes }

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 - Usual attempt: L = { (M,x,1⁺) | M(x)=yes in time t with probability > 2/3}
 - Is indeed BPP-Hard
 - But in BPP?
 - Just run M(x) for t steps and accept if it accepts?
 - If $(M.x.1^{\dagger})$ in L, we will indeed accept with prob. > 2/3

But M may not have a bounded gap. Then, if (M,x,1⁺) not in L, we may accept with prob. very close to 2/3.

BPTIME(n) ⊊ BPTIME(n¹⁰⁰)?

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But is true for BPTIME(T)/1





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BPP \subseteq $\Sigma_2^P \cap \Pi_2^P$

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Coming up

- Probabilistic computation
- BPP ⊆ P/poly (so if NP ⊆ BPP, then PH= Σ_2^P)
- Coming up
 - Basic randomized algorithmic techniques

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Basic randomized algorithmic techniques

Saving on randomness