# Probabilistic Computation

Lecture 13 Understanding BPP



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  - Pr[M(x)=yes]:

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 $x \not\in L$ 

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

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- BPTM for L: Pr[yes]:
- RTM for L: Pr[yes]:



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

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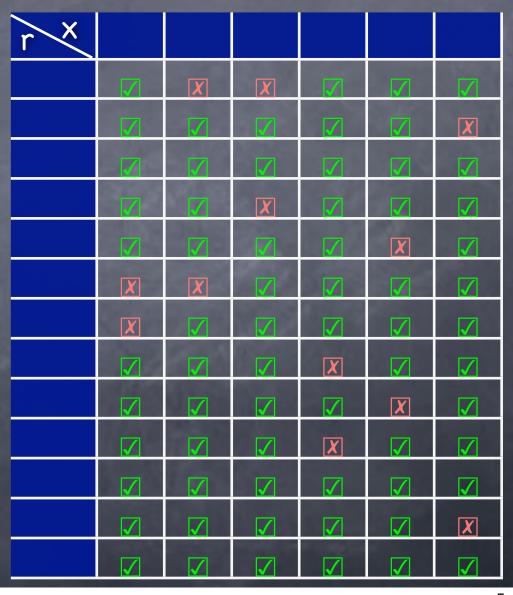
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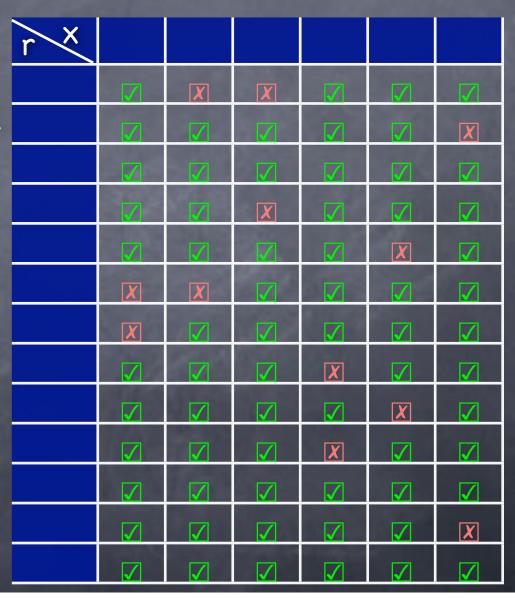
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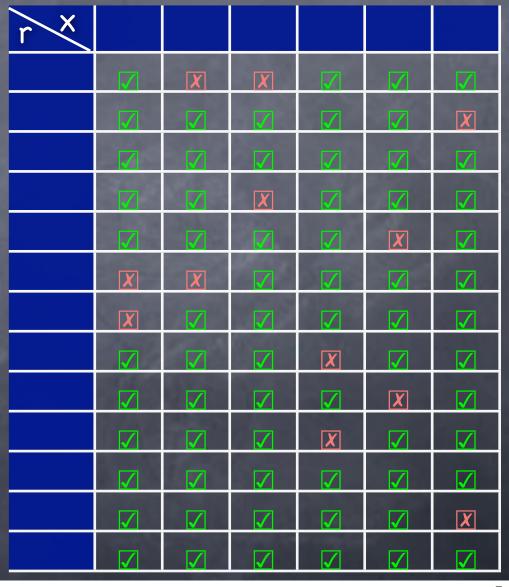
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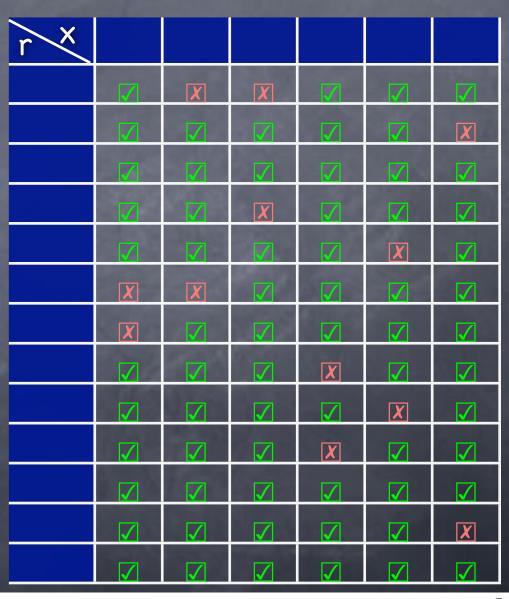
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  - BPP: can make worst error probability < 2<sup>-n</sup>



## BPP vs. PH

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- - $\odot$  So BPP  $\subseteq \Sigma_2^P \cap \Pi_2^P$

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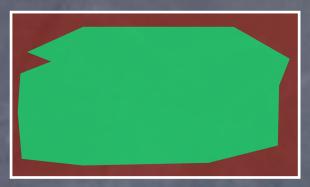
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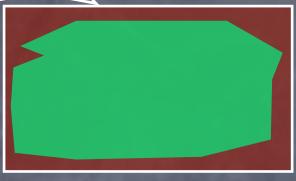
- $x \in L$ : "for almost all" r, M(x,r)=yes
- x∉L: M(x,r)=yes for very few r
- - If it were "for all", in coNP
  - □ L = { x| ∃a small "neighborhood",  $\forall z$ , for some r "near" z, M(x,r)=yes }
    - Note: Neighborhood of z is small (polynomially large), so can go through all of them in polynomial time





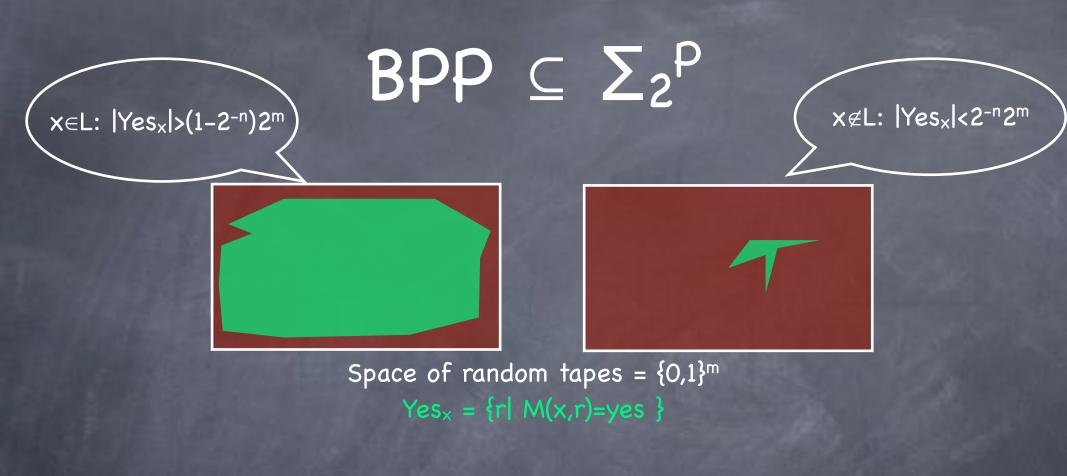
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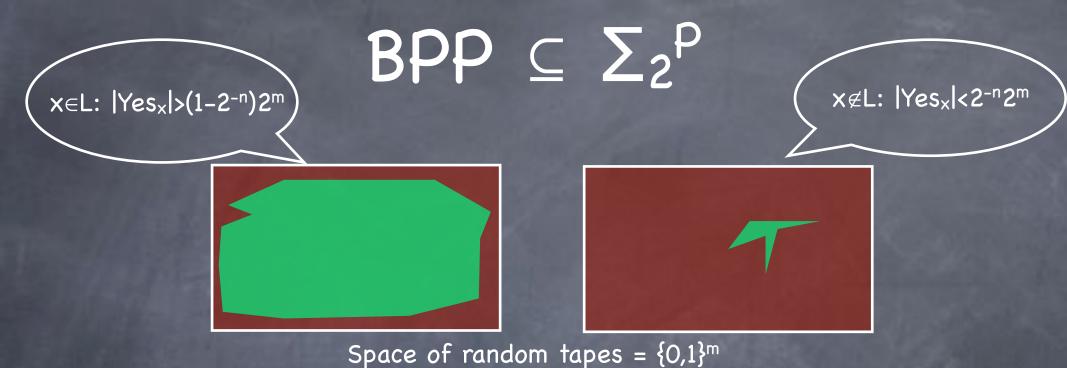
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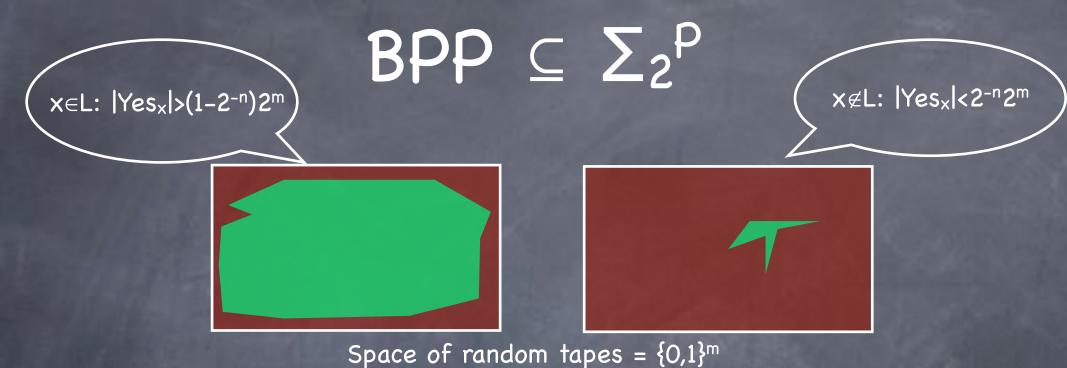
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 $Yes_{\times} = \{r | M(x,r) = yes \}$ 

- If z is a shift of  $r \in Yes_x$ , r is in the neighborhood of z
- x∉L: Yes<sub>x</sub> very small, so its few shifts cover only a small region

"A small set of shifts":  $P = \{u_1, u_2, ..., u_k\}$ 

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

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  - Yes! For all large S (like Yes<sub>x</sub>) can indeed find a P s.t. P(S) =  $\{0,1\}^m$

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  - - In fact, most P work (if k big enough)!

$$BPP \subseteq \Sigma_2^P$$

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

Probabilistic method to find  $P = \{u_1, u_2, ..., u_k\}$ , s.t. for all large S,  $P(S) = \{0,1\}^m$ 

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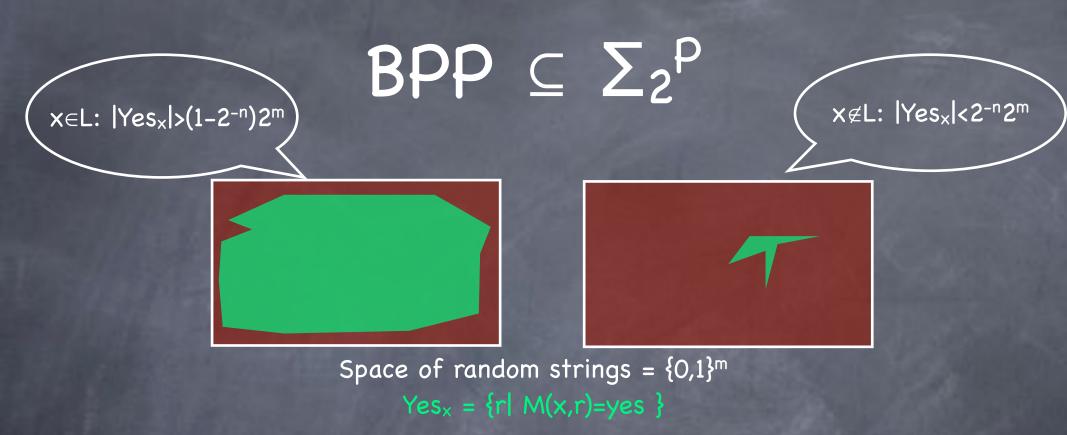
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  - $\begin{array}{lll} & \text{Pr}_{(\text{over P})}[P(S) \neq \{0,1\}^m] = \text{Pr}_{(\text{over P})}[\exists z \ z \not\in P(S)] \\ & \leq \Sigma_z \ \text{Pr}_{(\text{over P})}[z \not\in P(S)] = \Sigma_z \ \text{Pr}_{(\text{over u1..uk})}[\forall i \ z \oplus u_i \not\in S] \\ & = \Sigma_z \ \Pi_i \ \text{Pr}_{(\text{over ui})}[z \oplus u_i \not\in S] = \Sigma_z \ \Pi_i \ \text{Pr}_{(\text{over ui})}[u_i \not\in z \oplus S] \\ & = \Sigma_z \ \Pi_i \ (|S^c|/2^m) \ < \Sigma_z \ \Pi_i \ 2^{-n} = 2^m.(2^{-n})^k = 1 \end{array}$
  - So (with  $|S|>(1-2^{-n})2^m$  and k=m/n), ∃P, P(S) =  $\{0,1\}^m$





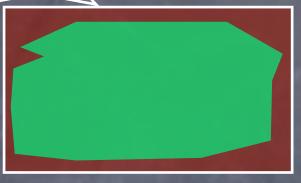
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For each x∈L, ∃P (of size k=m/n) s.t. P(Yes<sub>x</sub>)={0,1}<sup>m</sup>



 $x \in L: |Yes_x| > (1-2^{-n})2^m$ 

x∉L: |Yes<sub>x</sub>|<2<sup>-n</sup>2<sup>m</sup>





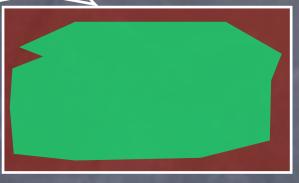
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- For each  $x \notin L$ ,  $P(Yes_x) \subseteq \{0,1\}^m$



 $x \in L: |Yes_x| > (1-2^{-n})2^m$ 

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 $x \in L: |Yes_x| > (1-2^{-n})2^m$ 

 $x \notin L$ :  $|Yes_x| < 2^{-n}2^m$ 





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- For each x∉L, P(Yes<sub>x</sub>) ⊆ {0,1}<sup>m</sup>
  - P(Yes<sub>x</sub>) | ≤ k| Yes<sub>x</sub> | = (m/n)  $2^{-n}2^m < 2^m$
- □ L = { x | ∃P  $\forall$ z for some r∈P<sup>-1</sup>(z) M(x,r)=yes }

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  - Is indeed BPP-Hard

- Not known!
  - $\bullet$  L = { (M,x,1<sup>†</sup>) | M(x)=yes in time t with probability > 2/3} ?
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  - But in BPP?

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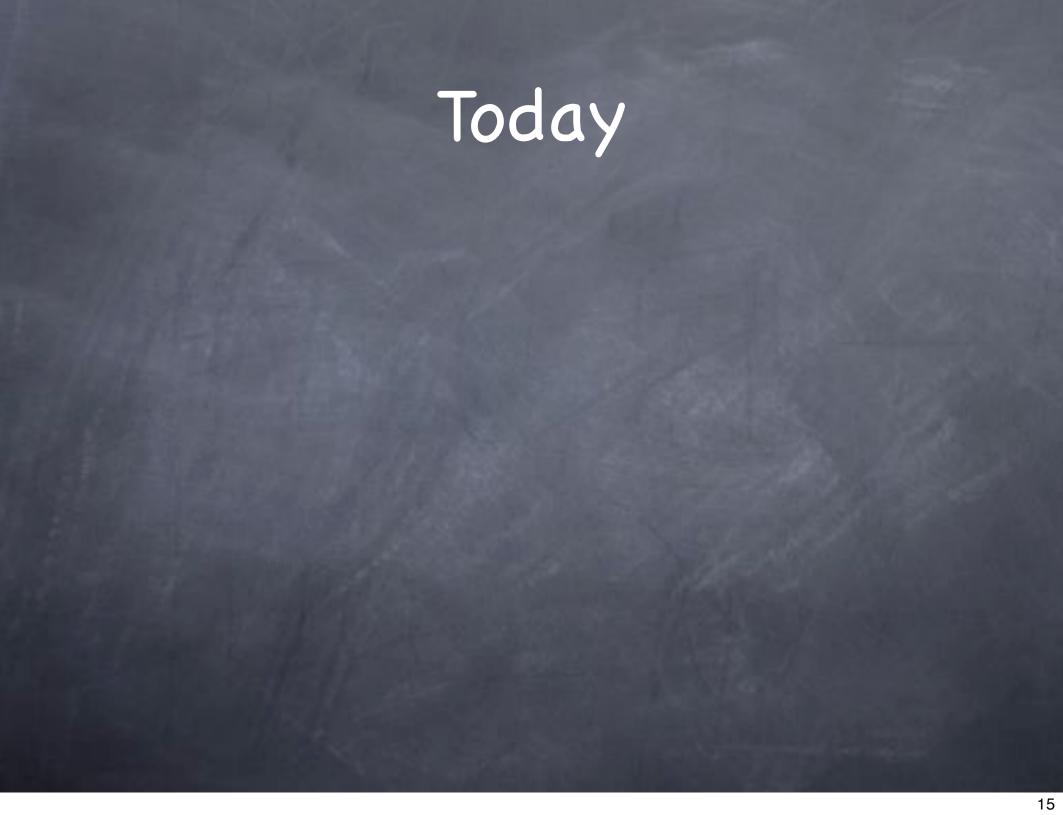
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  - Is indeed BPP-Hard
  - But in BPP?
    - Just run M(x) for t steps and accept if it accepts?
      - If (M,x,1<sup>†</sup>) in L, we will indeed accept with prob. > 2/3
      - But M may not have a bounded gap. Then, if  $(M,x,1^{\dagger})$  not in L, we may accept with prob. very close to 2/3.

BPTIME(n) 
 □ BPTIME( $n^{100}$ )?

- BPTIME(n) 
   □ BPTIME( $n^{100}$ )?
- Not known!

- BPTIME(n)  $\subseteq$  BPTIME(n<sup>100</sup>)?
- Not known!
  - But is true for BPTIME(T)/1



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  - Basic randomized algorithmic techniques

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