# Complexity of Counting

Lecture 21 #P



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  - Computed by a TM running in polynomial time

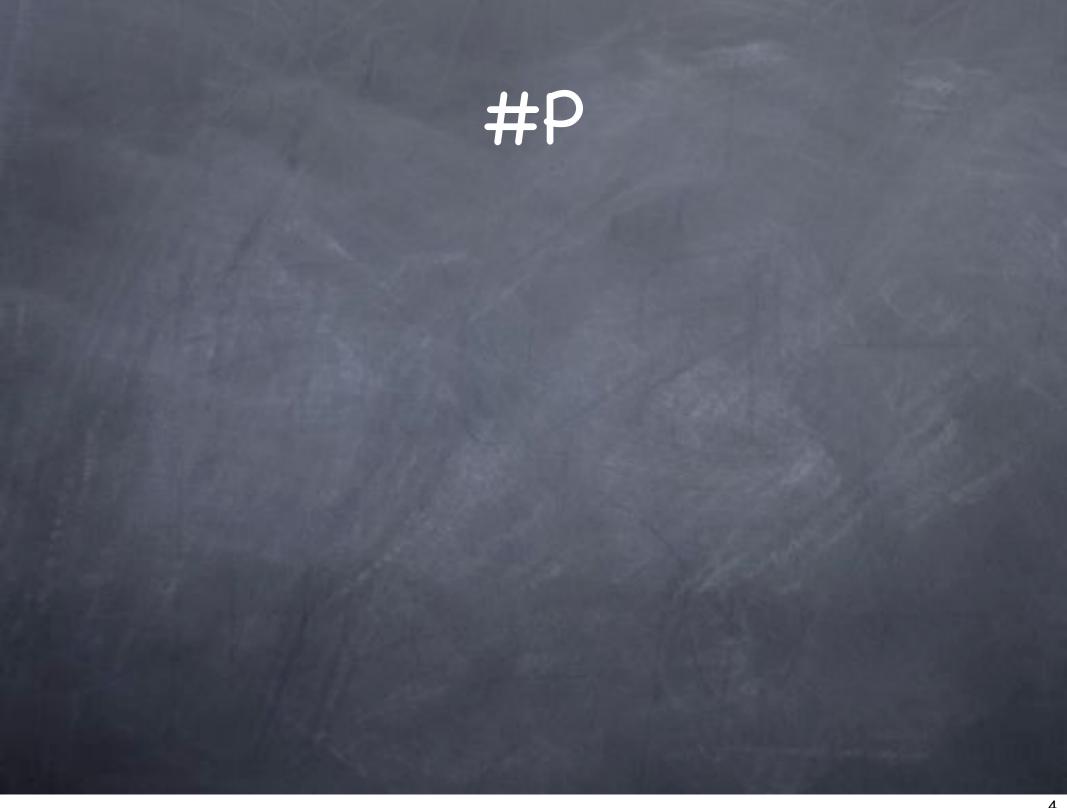
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    - e.g.: Number of satisfying assignments to a boolean formula
    - e.g.: Number of inputs in a language L that are less than x (lexicographically)





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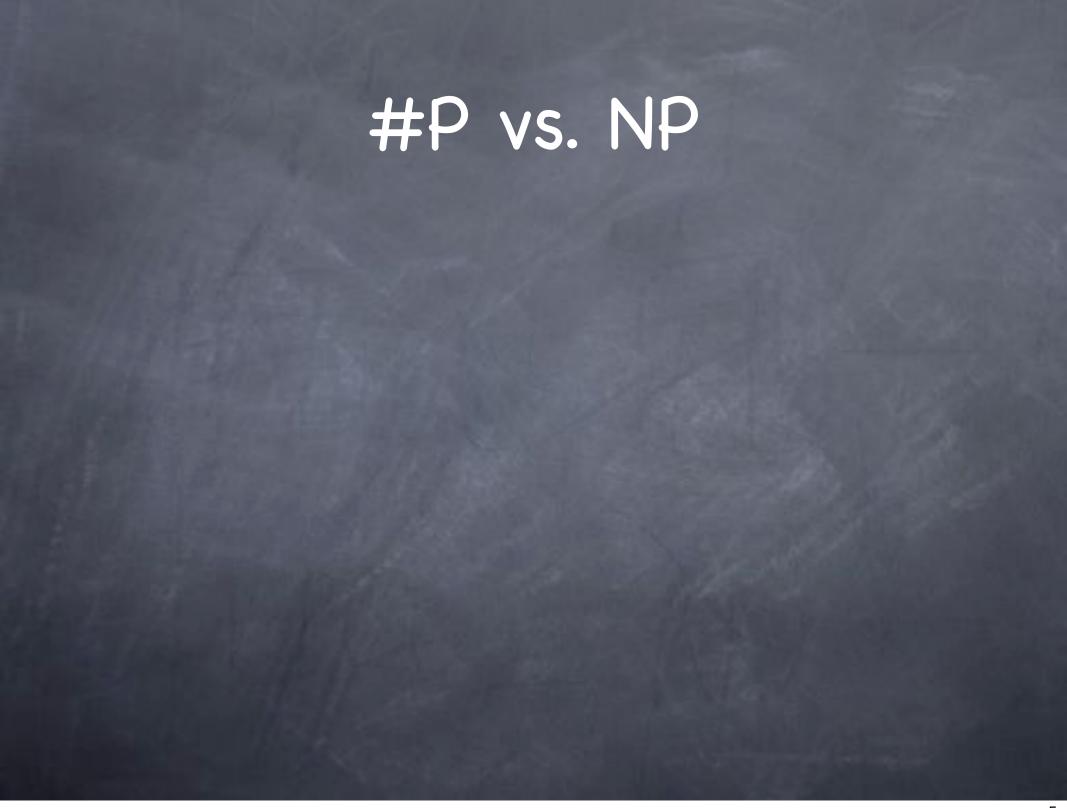
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    - @ e.g.: #SAT(φ) = number of satisfying assignments of φ
- Easy to see: FP ⊆ #P (interpreting numbers as strings suitably)
   [Exercise]



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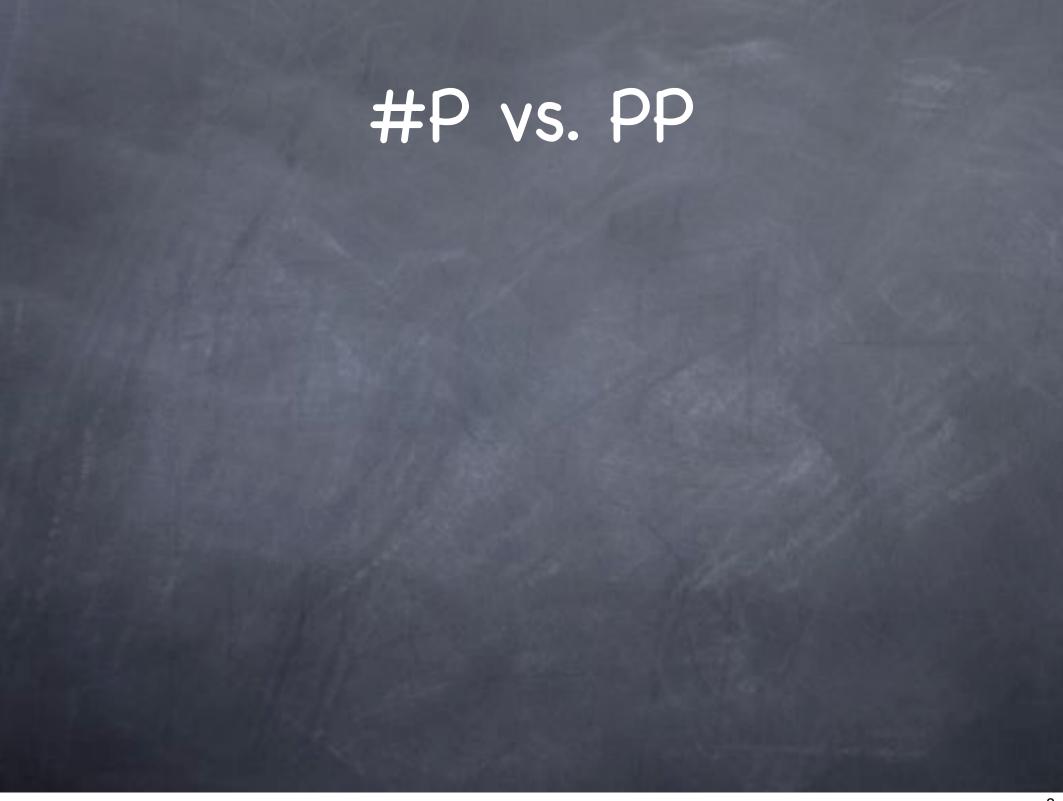
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    - - HAMILTONICITY(G) 
         ⇔ #CYCLES(G) ≥ n<sup>n^2</sup>



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    - #P ⊆ FP<sup>PP</sup> [exercise] (and PP ⊆ P<sup>#P</sup> [why?])
    - So if PP = P, then #P = FP (and vice versa)

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    - Permanent (for binary matrices) is #P-complete

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      - Perm(A) =  $\Sigma_{\sigma}$  W( $\sigma$ ) over all cycle covers  $\sigma$  of directed graph G<sub>A</sub> (with edge-weights from A)

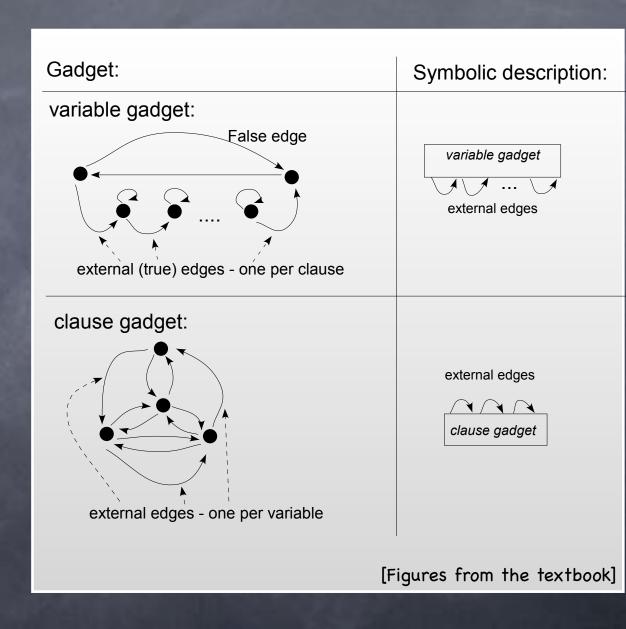
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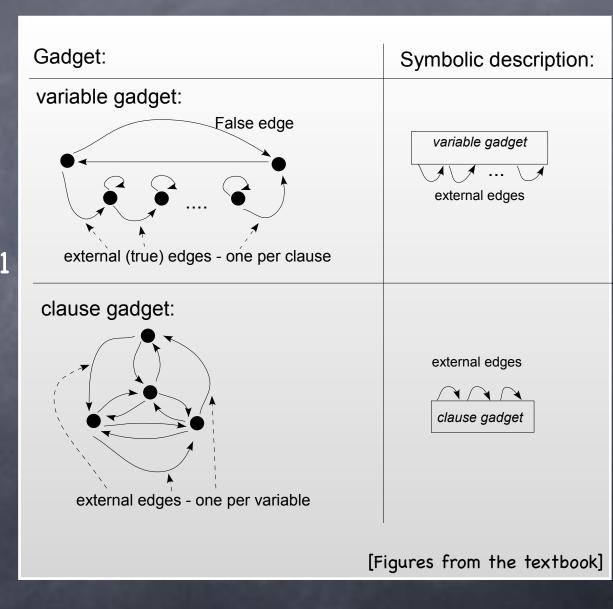
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  - Almost Karp-reduction (need to rescale)

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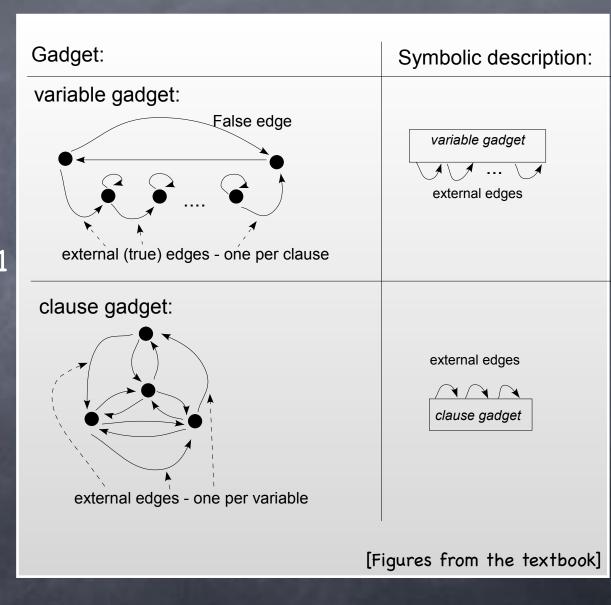
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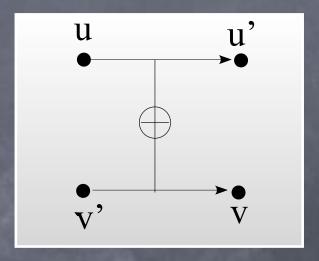


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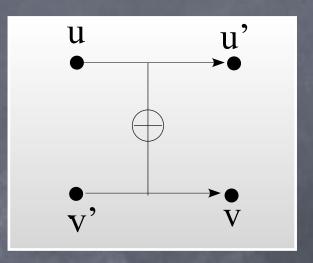


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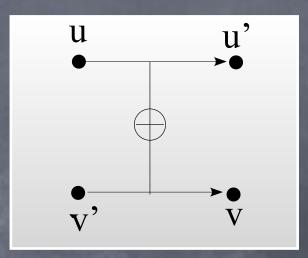
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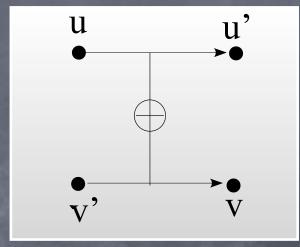


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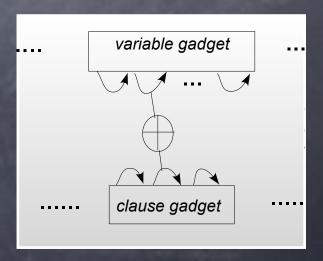


Final graph

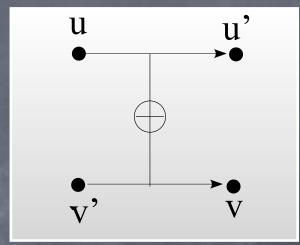
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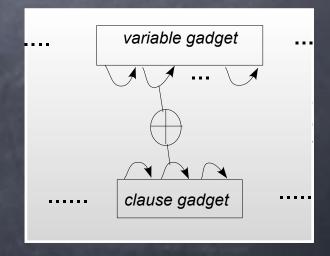


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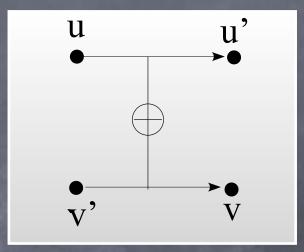


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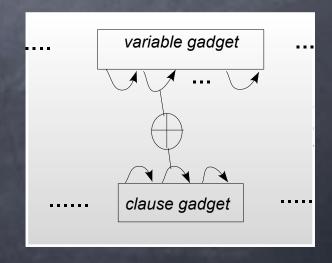


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- Each satisfying assignment gives a cycle cover of weight 4<sup>3m</sup>



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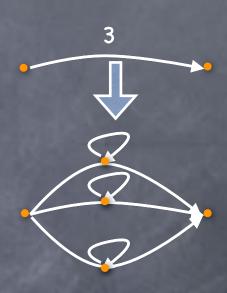


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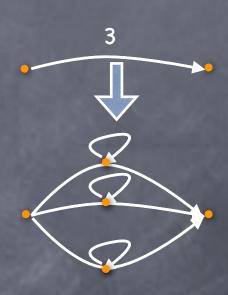
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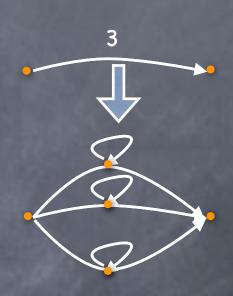
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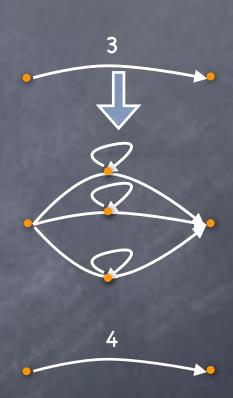
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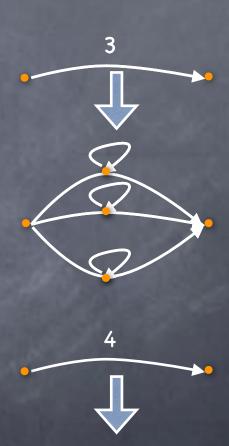
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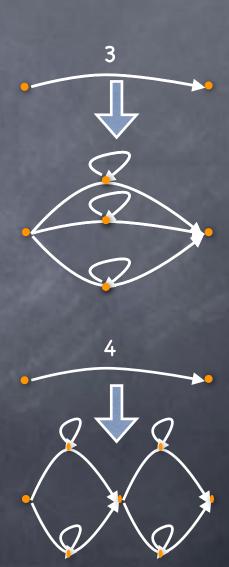
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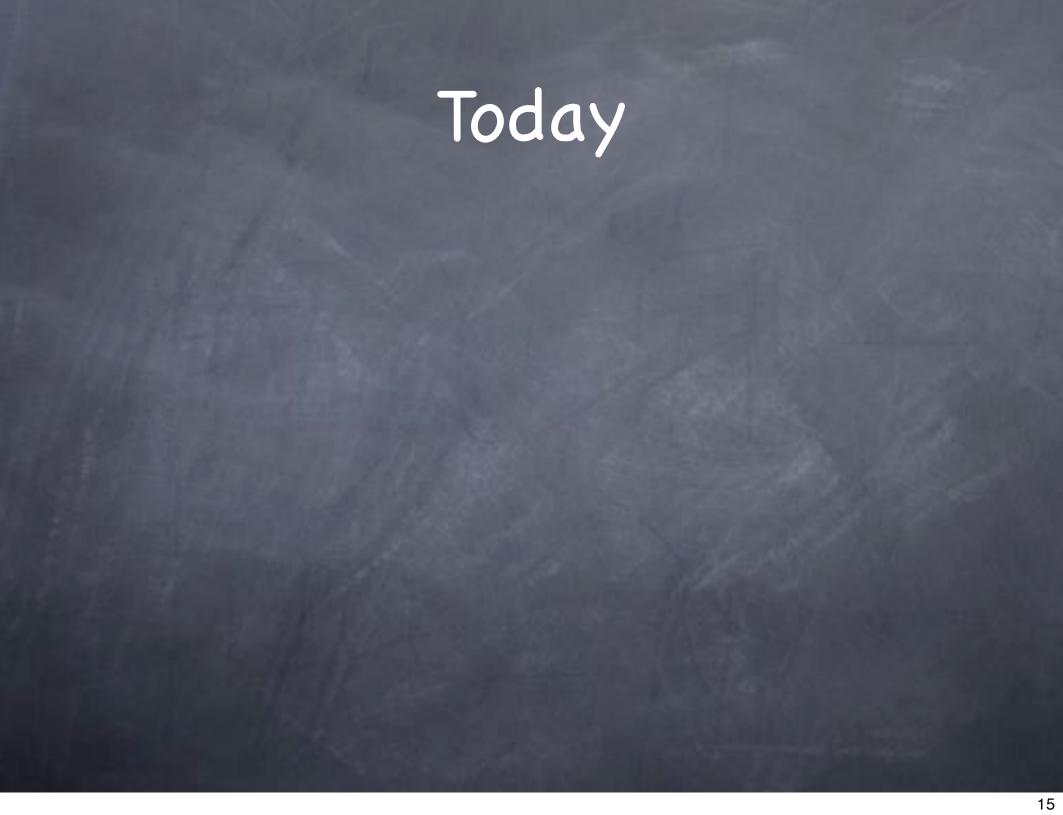


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- Next: Toda's Theorem: PH ⊆ P<sup>#P</sup> = P<sup>PP</sup>