

PCP

Lecture 20 And Hardness of Approximation

Promise Problems

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- Specified by a Yes set and a No set, disjoint

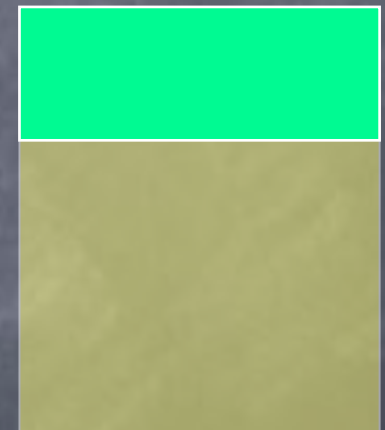
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- Specified by a Yes set and a No set, disjoint
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- For inputs outside the two, don’t care
 - We’re “promised” that such inputs are not given



Gap Problems

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- Non-boolean functions (e.g. optimization problems)

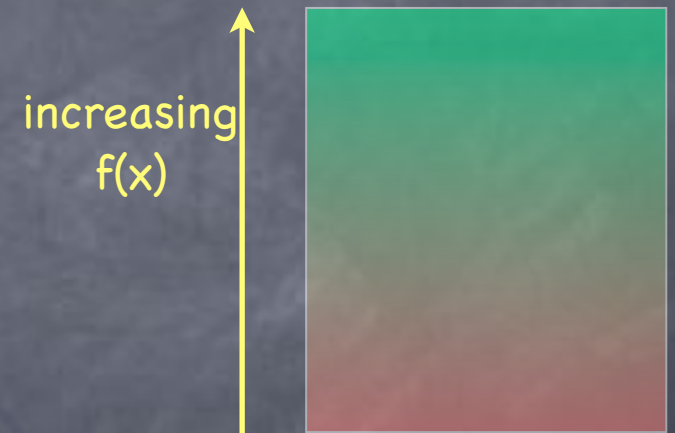
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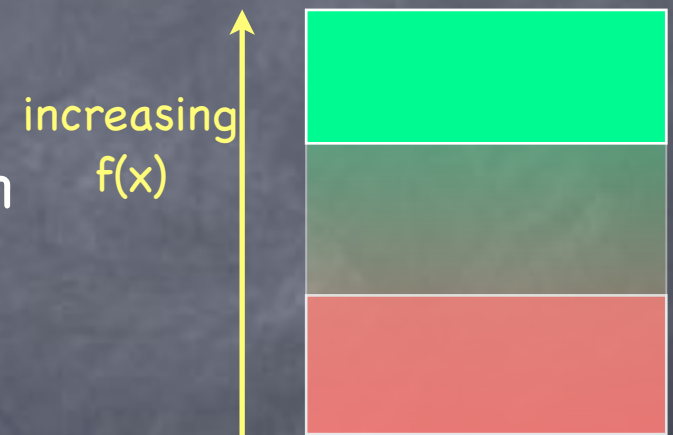
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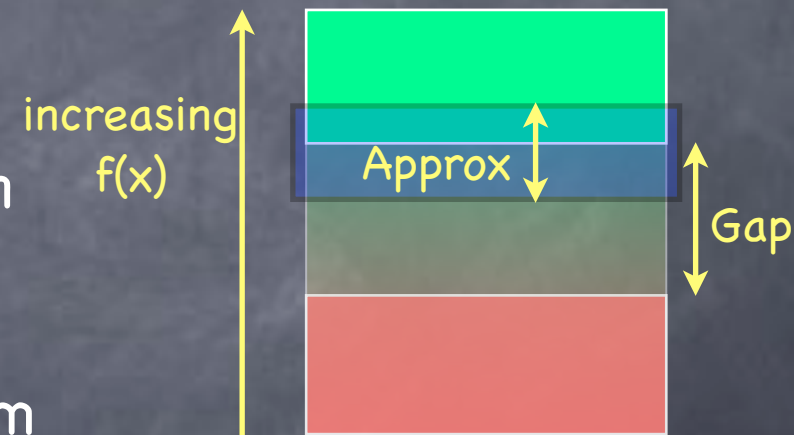
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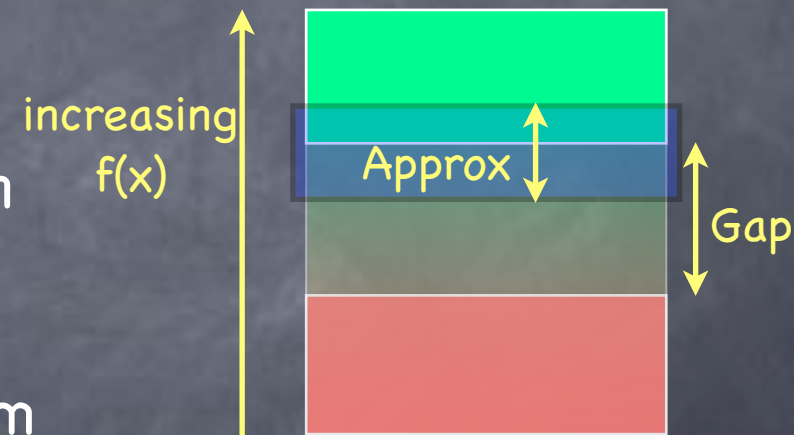
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PCP and CSP

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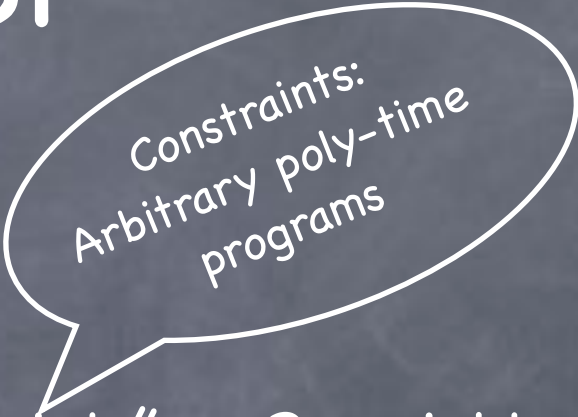
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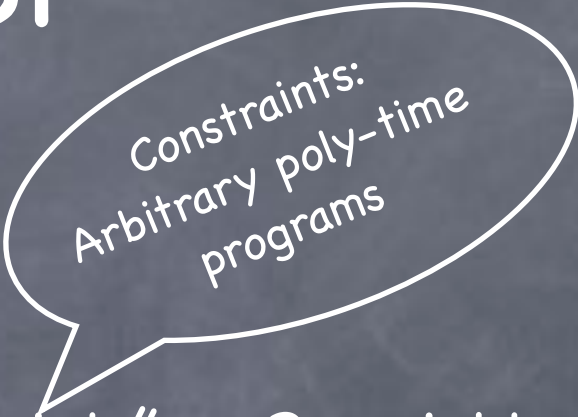
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Arbitrary poly-time
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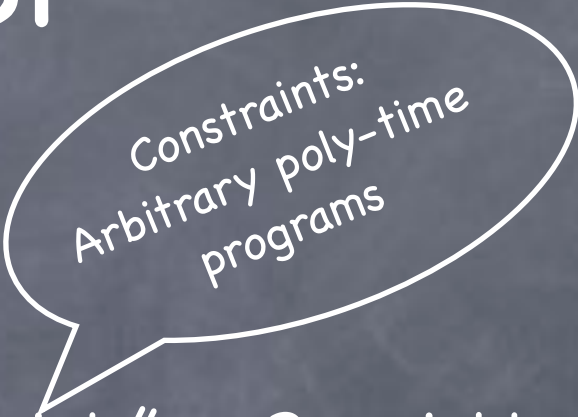
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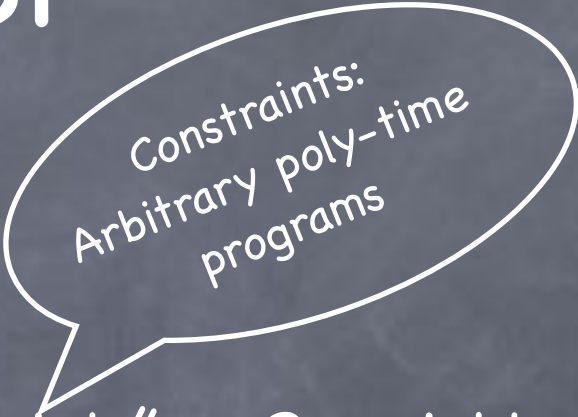
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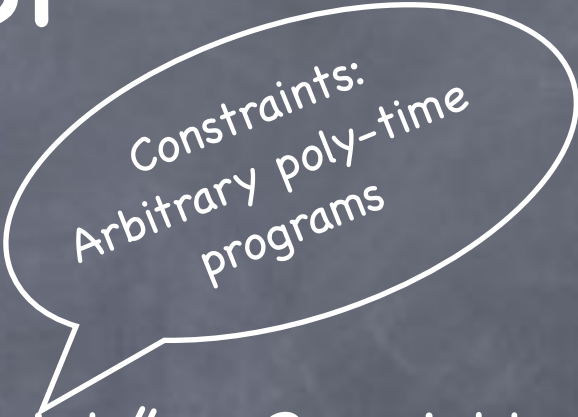
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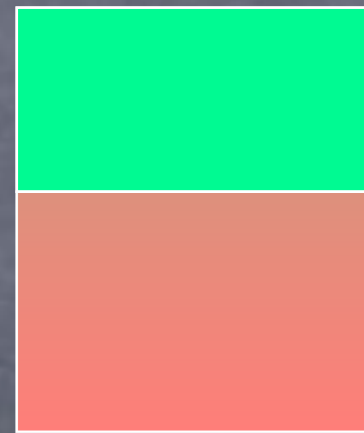
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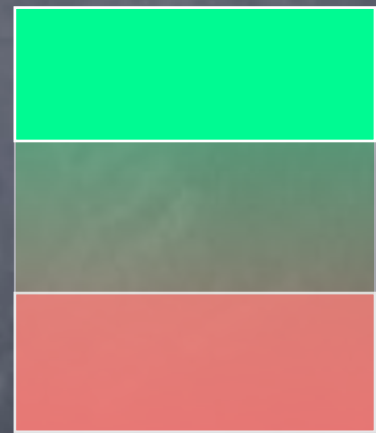
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 - PCP($\log m, q$): q -query (non-adaptive) verifier, tosses at most $\log m$ coins

Decision Problem to Gap Problem



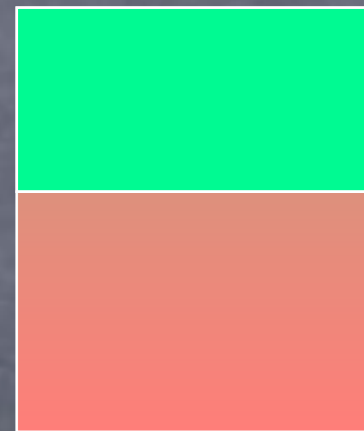
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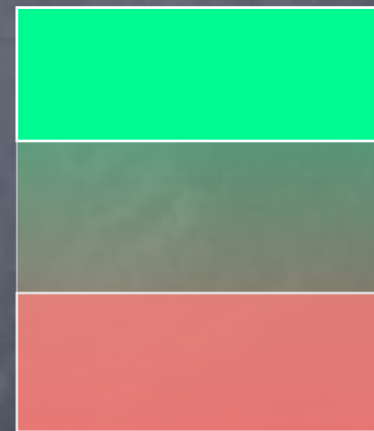
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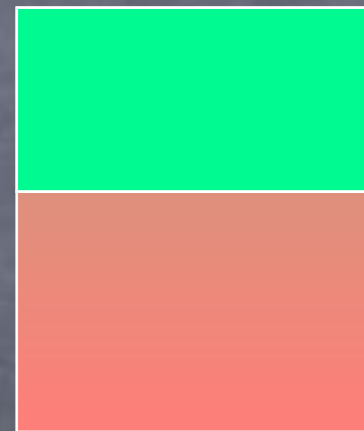
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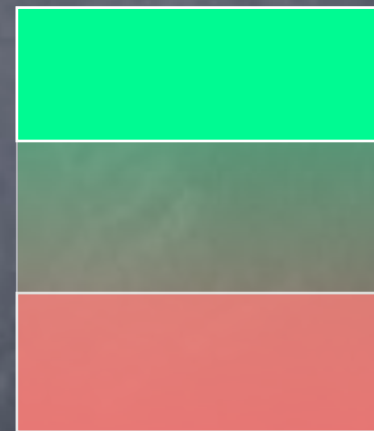
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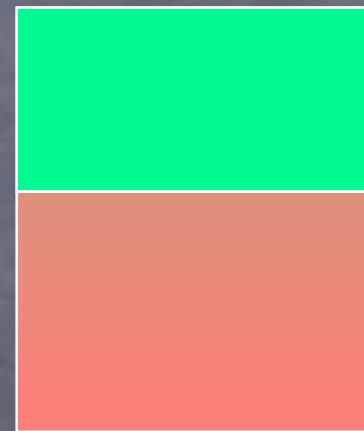
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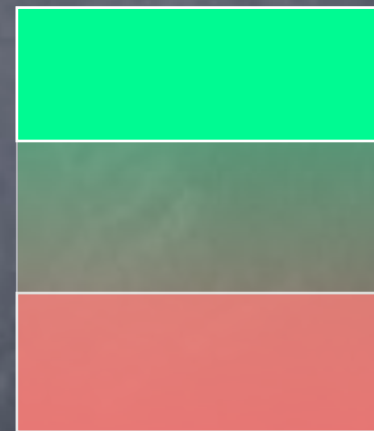
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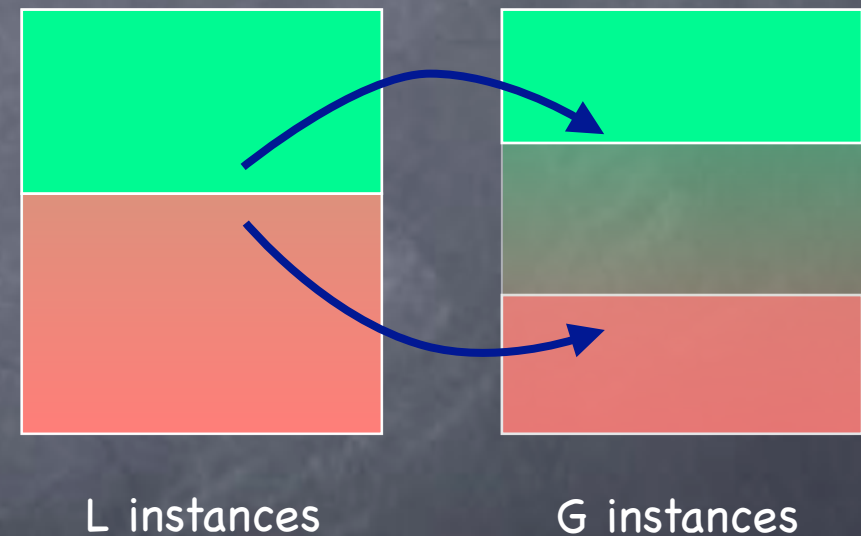
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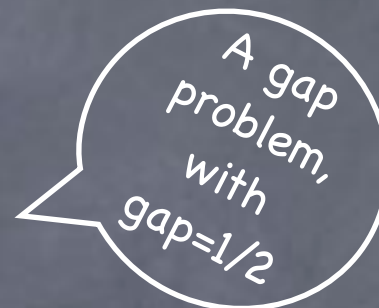
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 - Such that approximation for them imply approximation for Max-qCSPSat

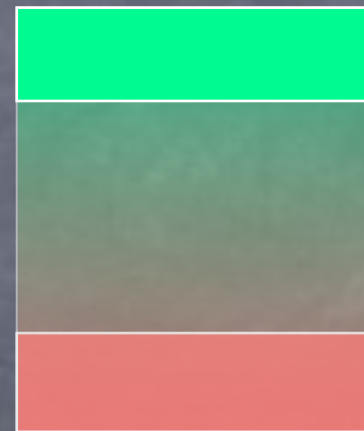
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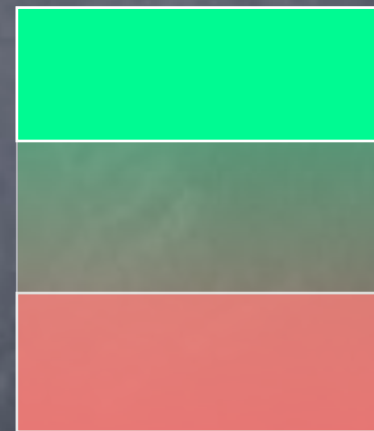
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G_1 instances



G_2 instances

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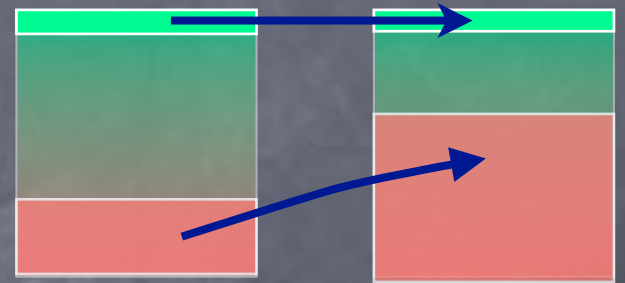


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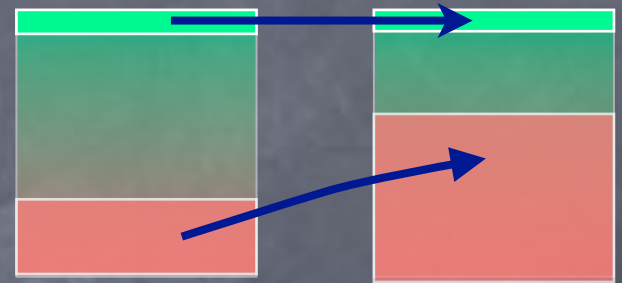


Max-qCSP to Max-3SAT



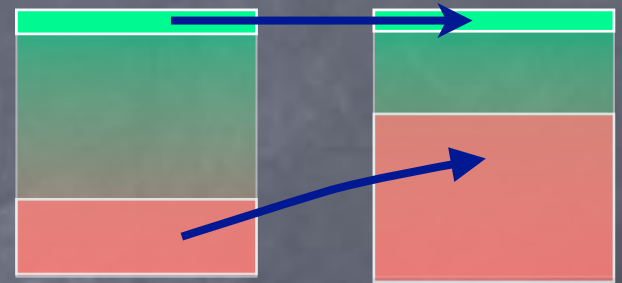
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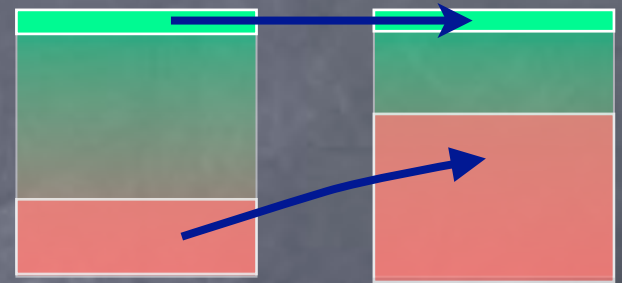
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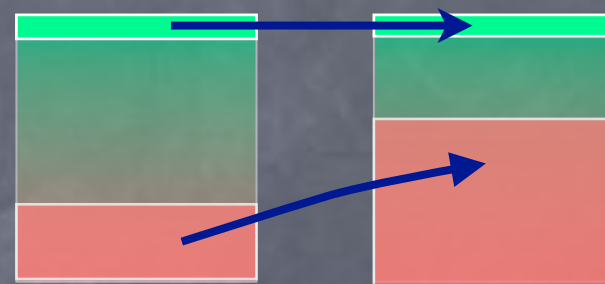
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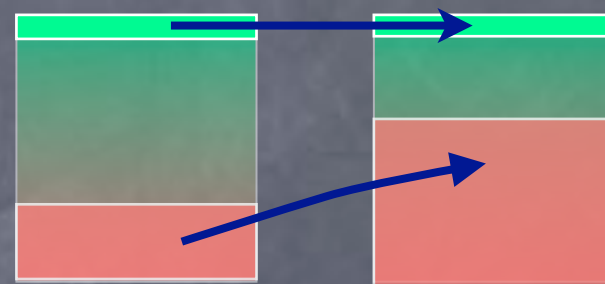
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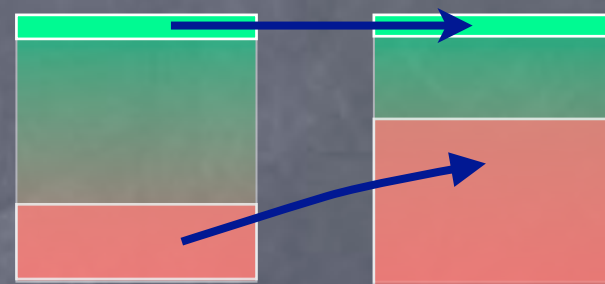


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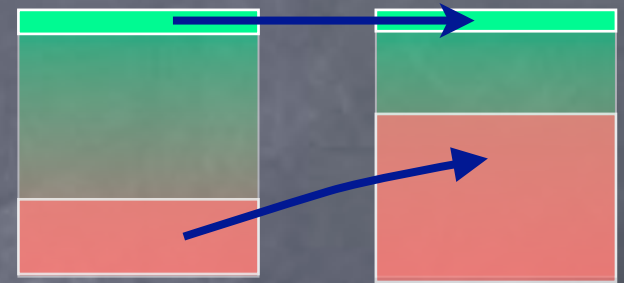
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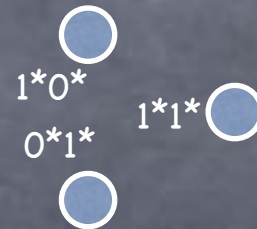
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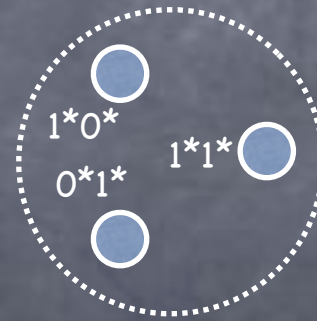
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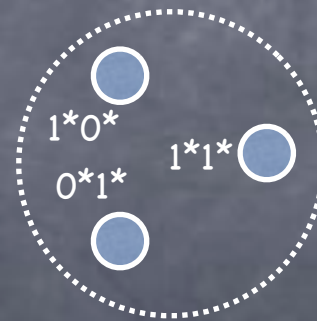
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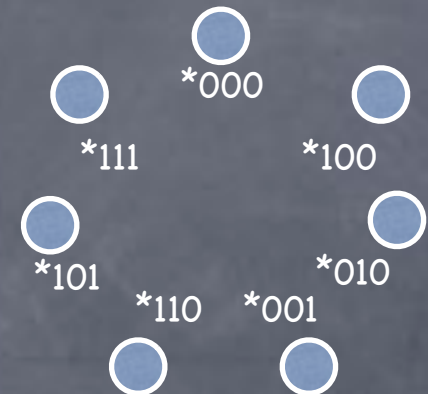
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Max-3SAT to Max-CLIQUE

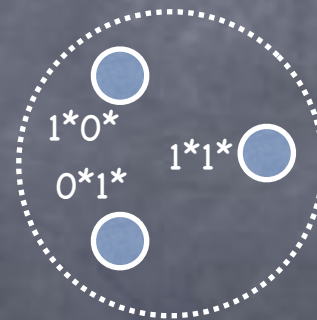
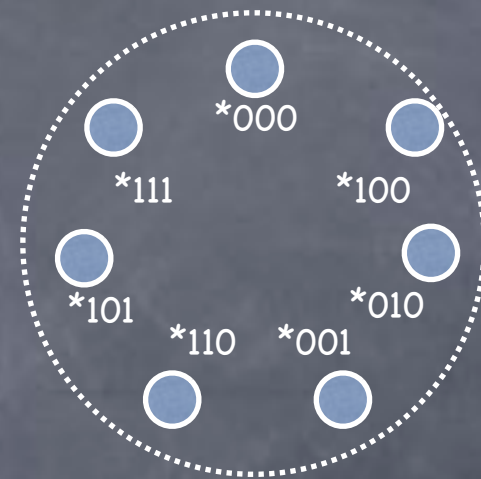
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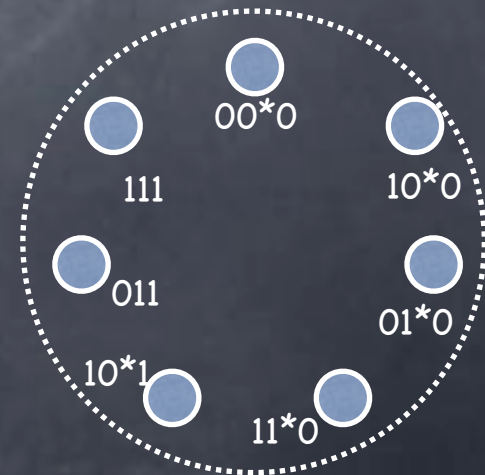
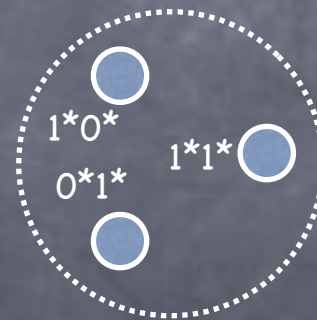
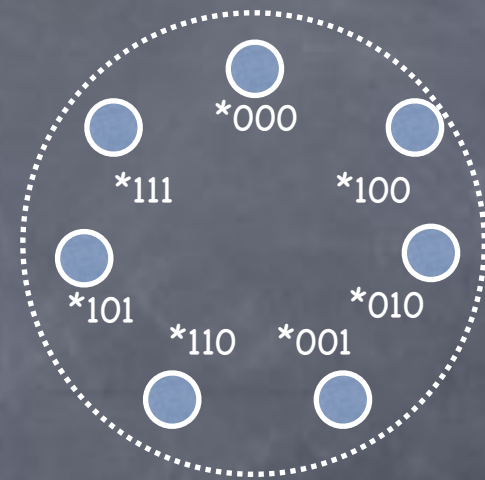
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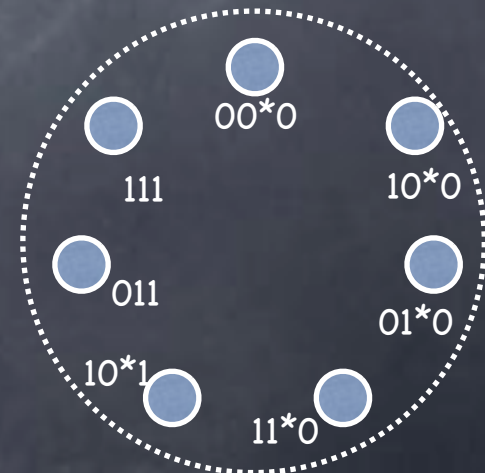
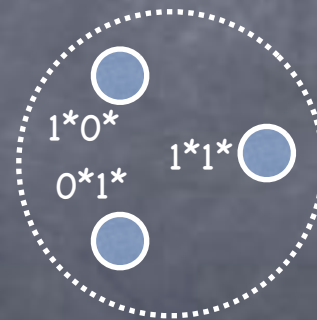
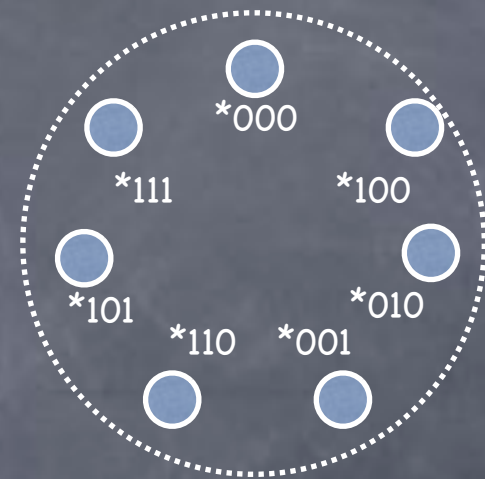
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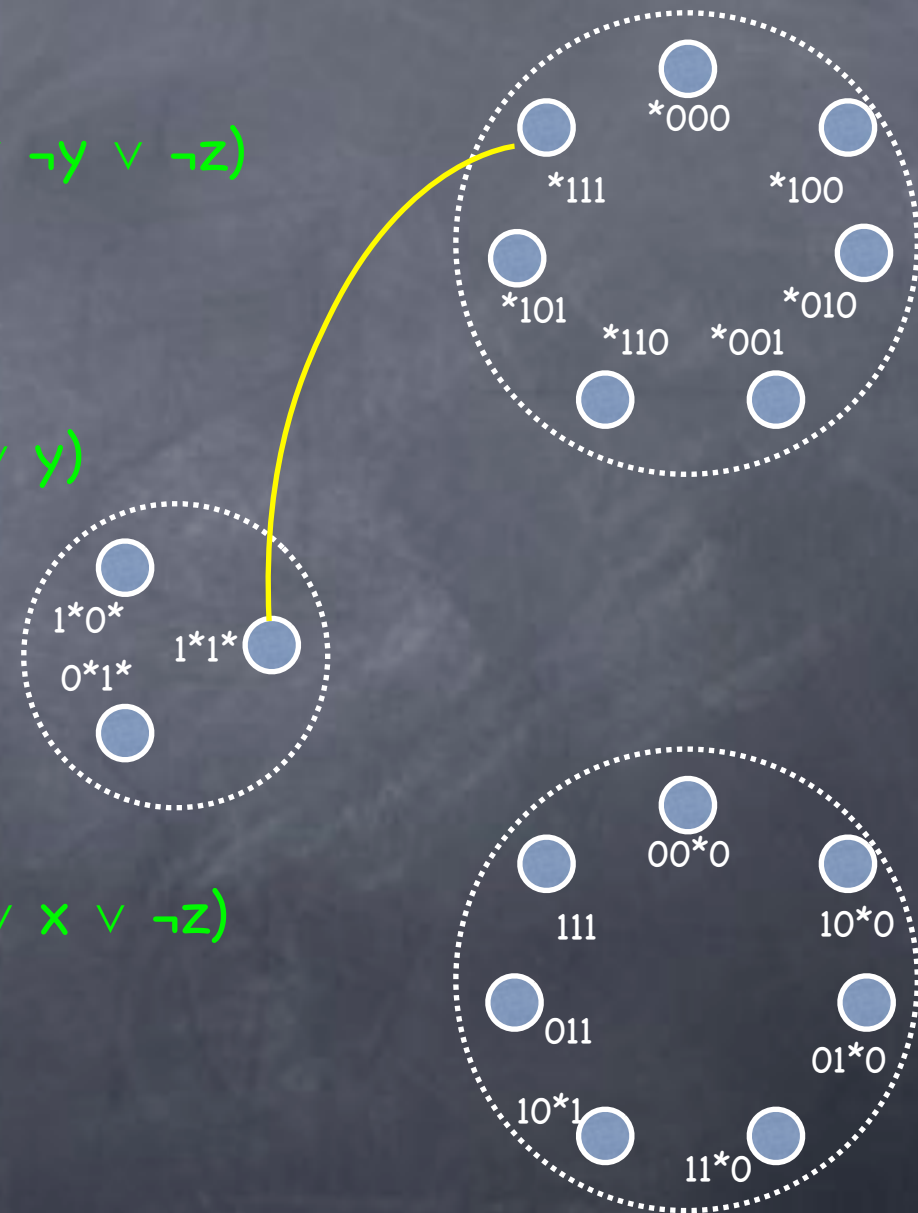
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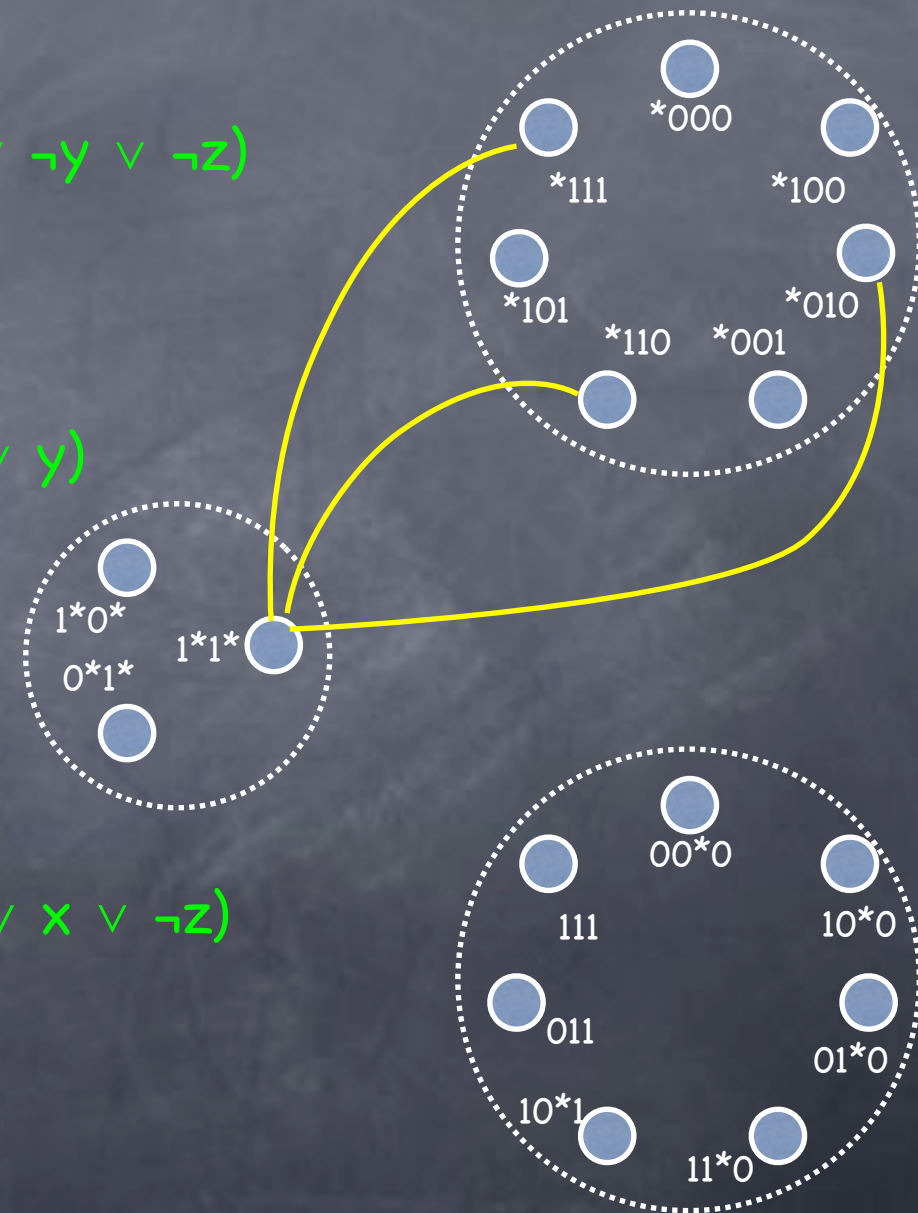
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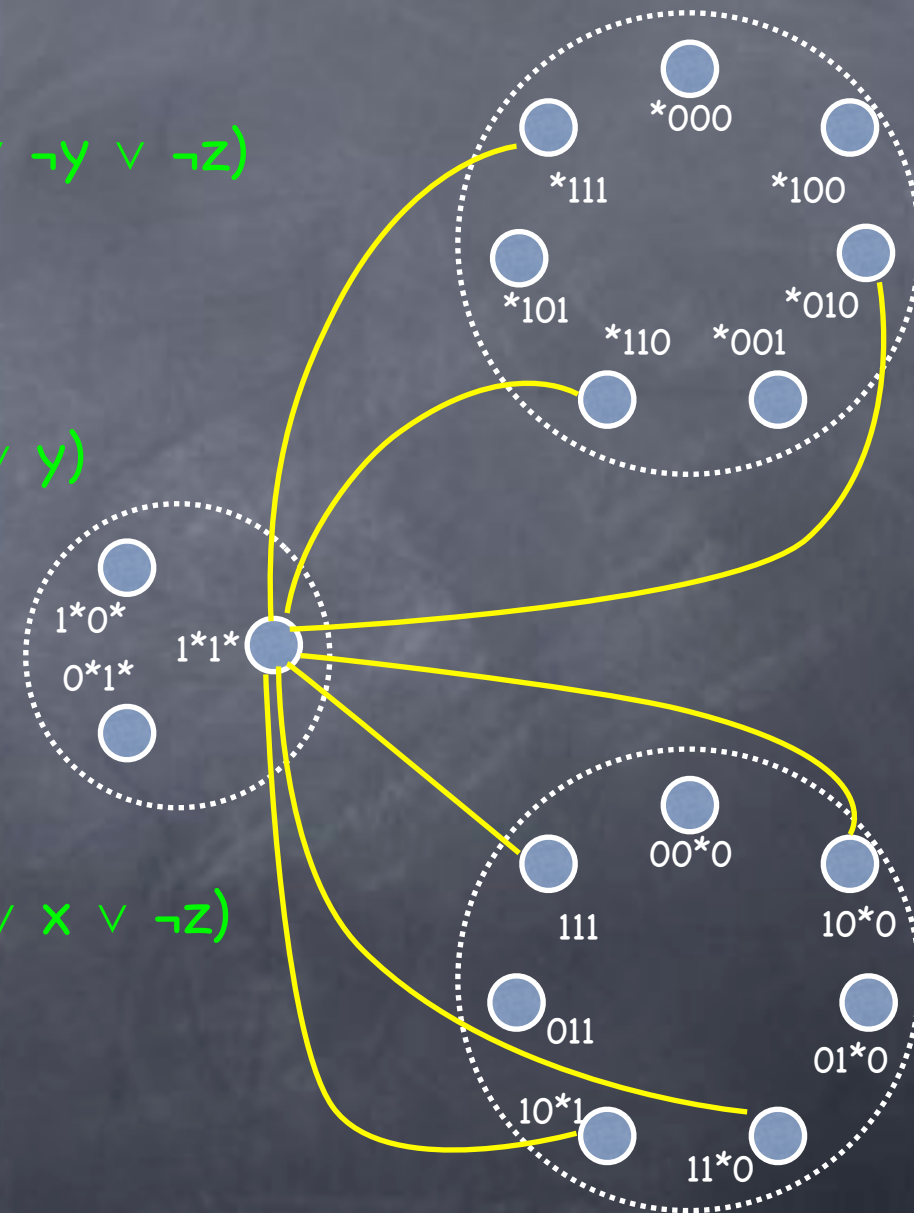
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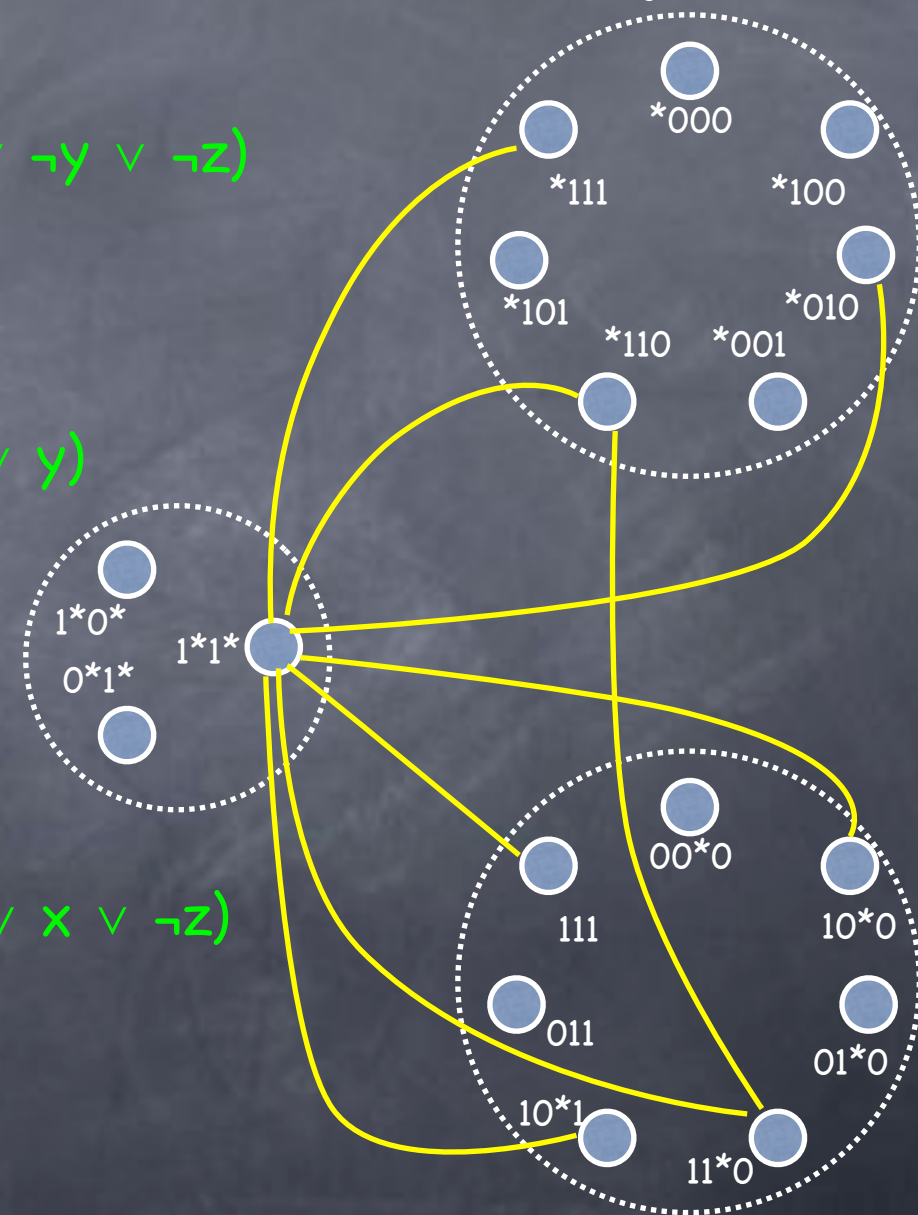
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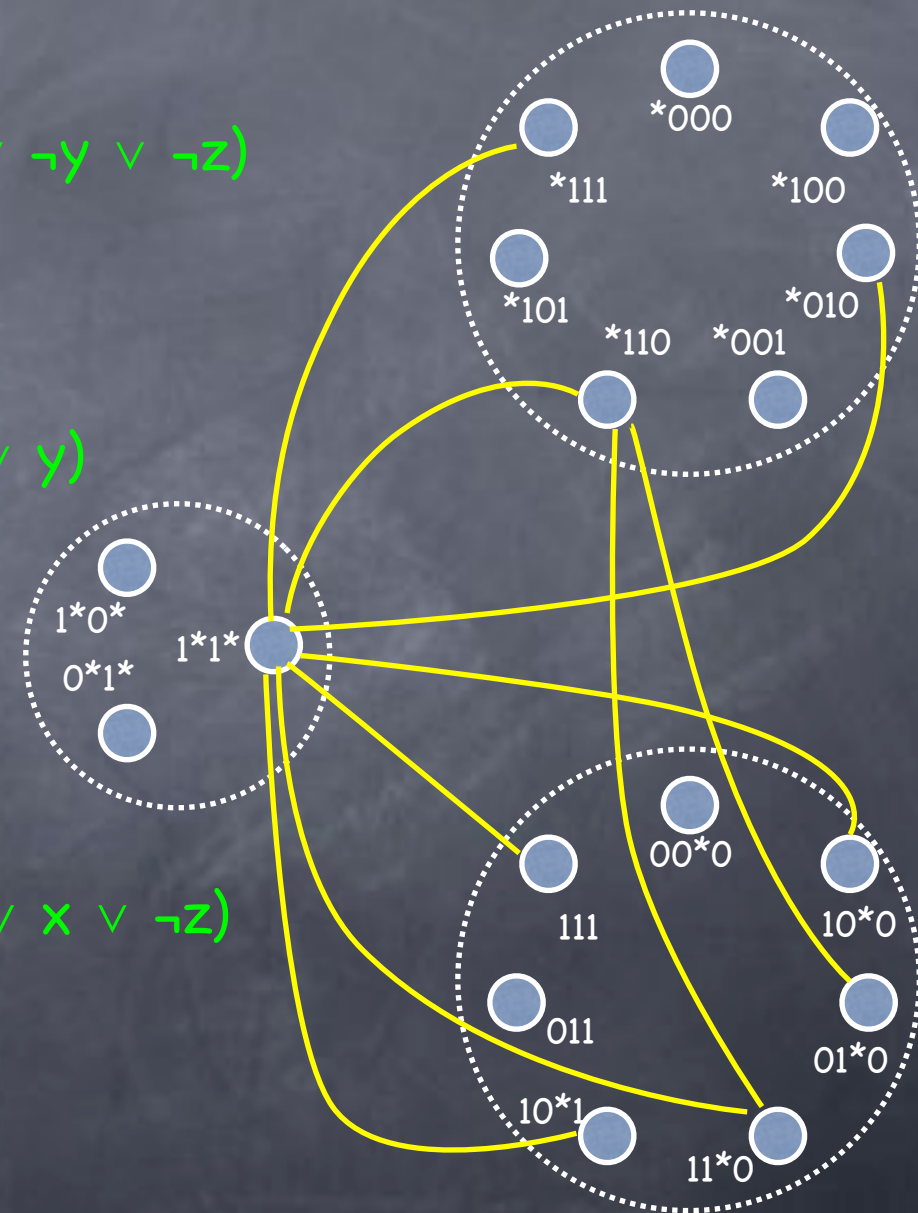
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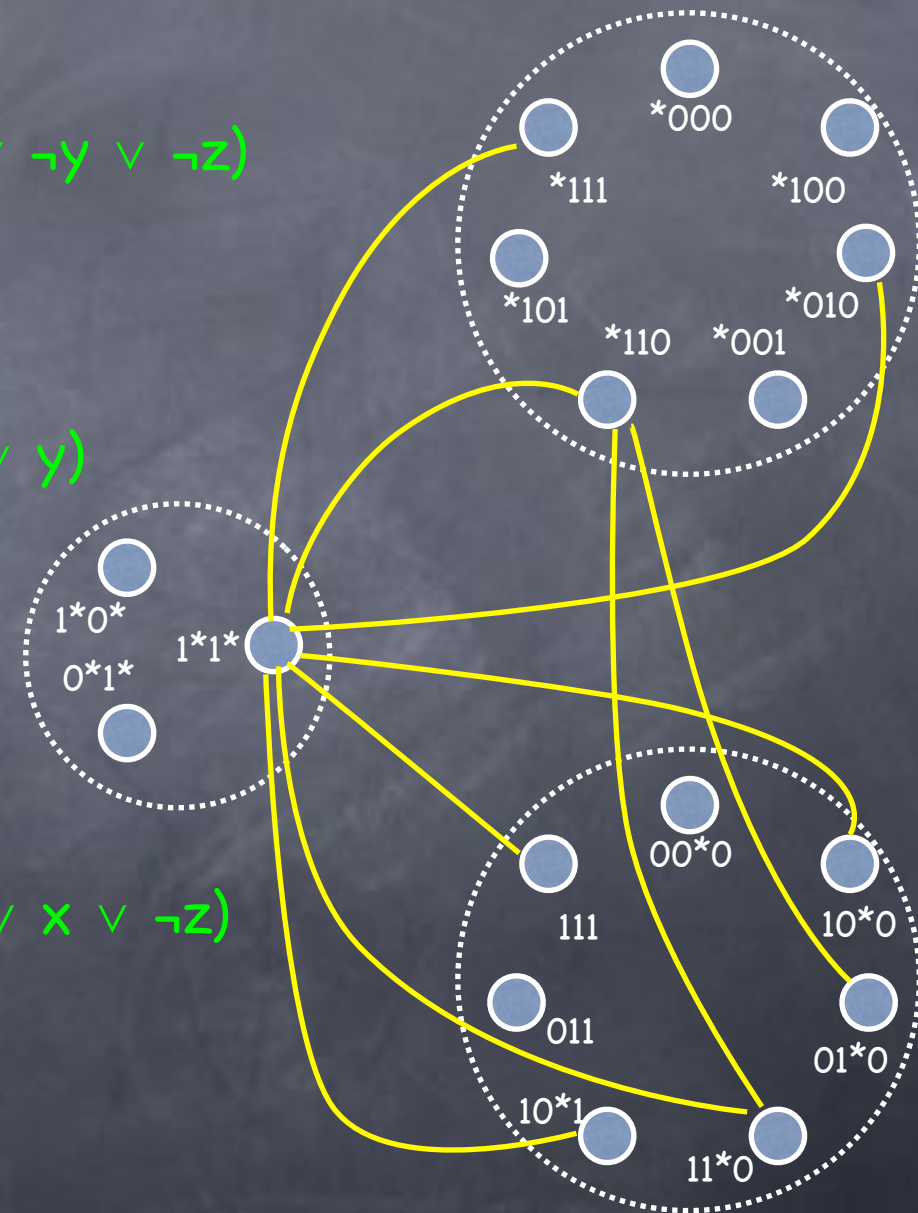
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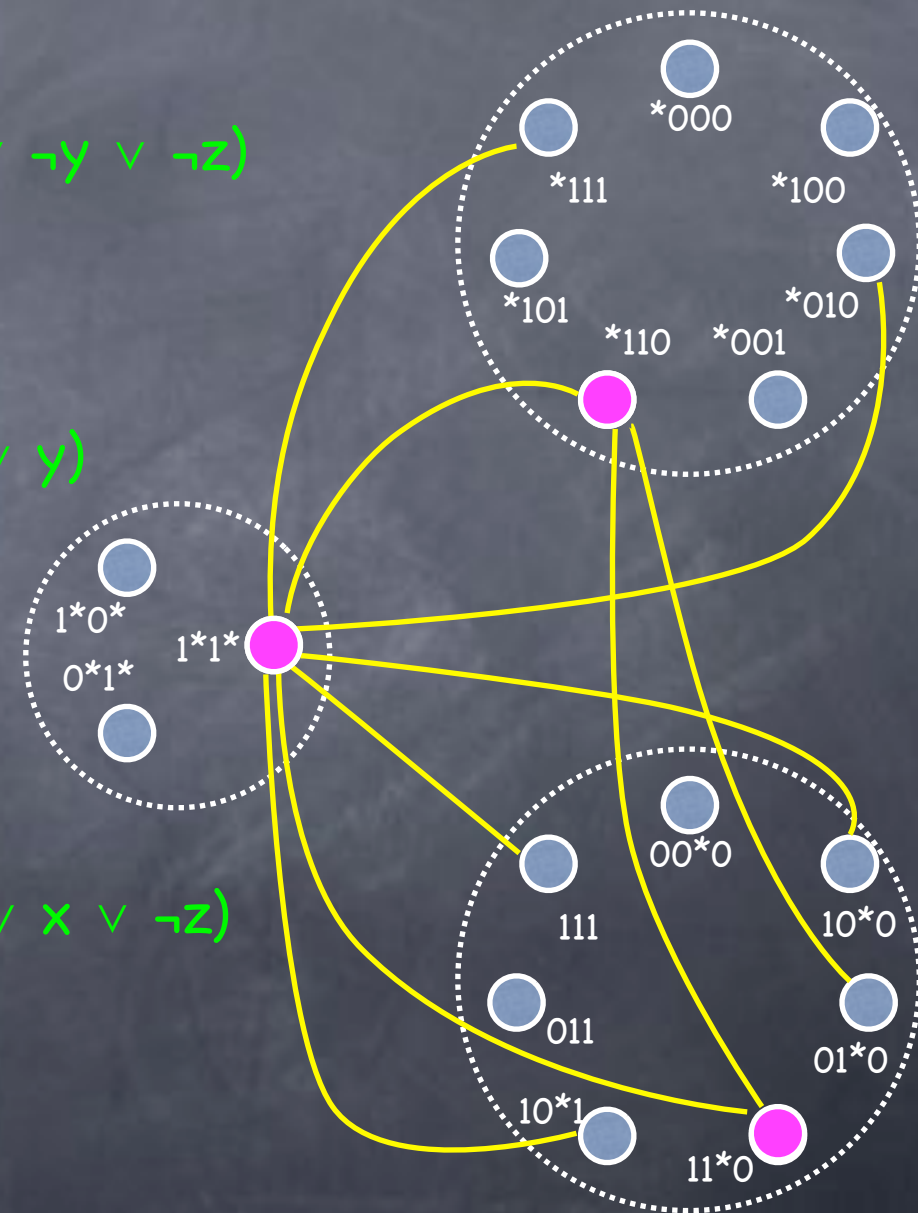
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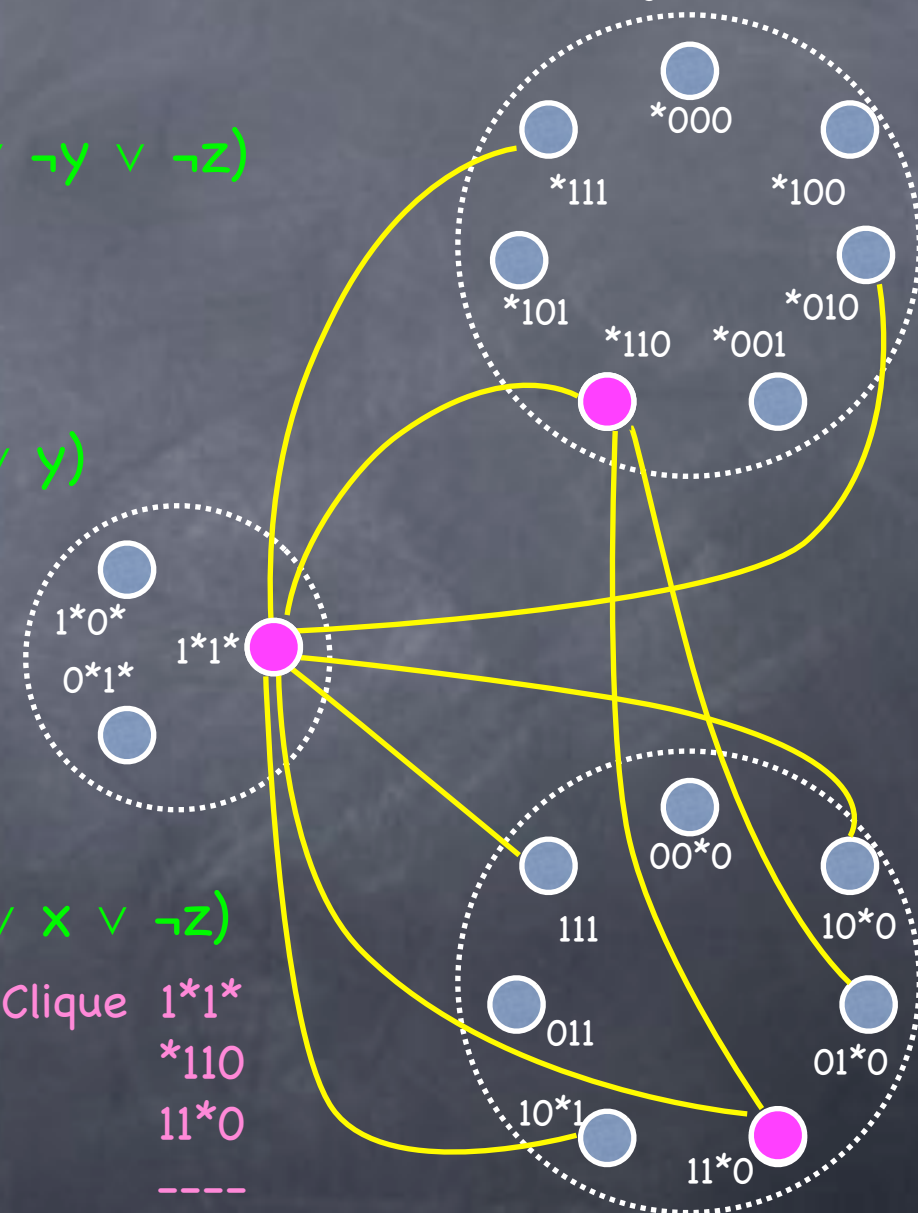
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sat assignment 1110



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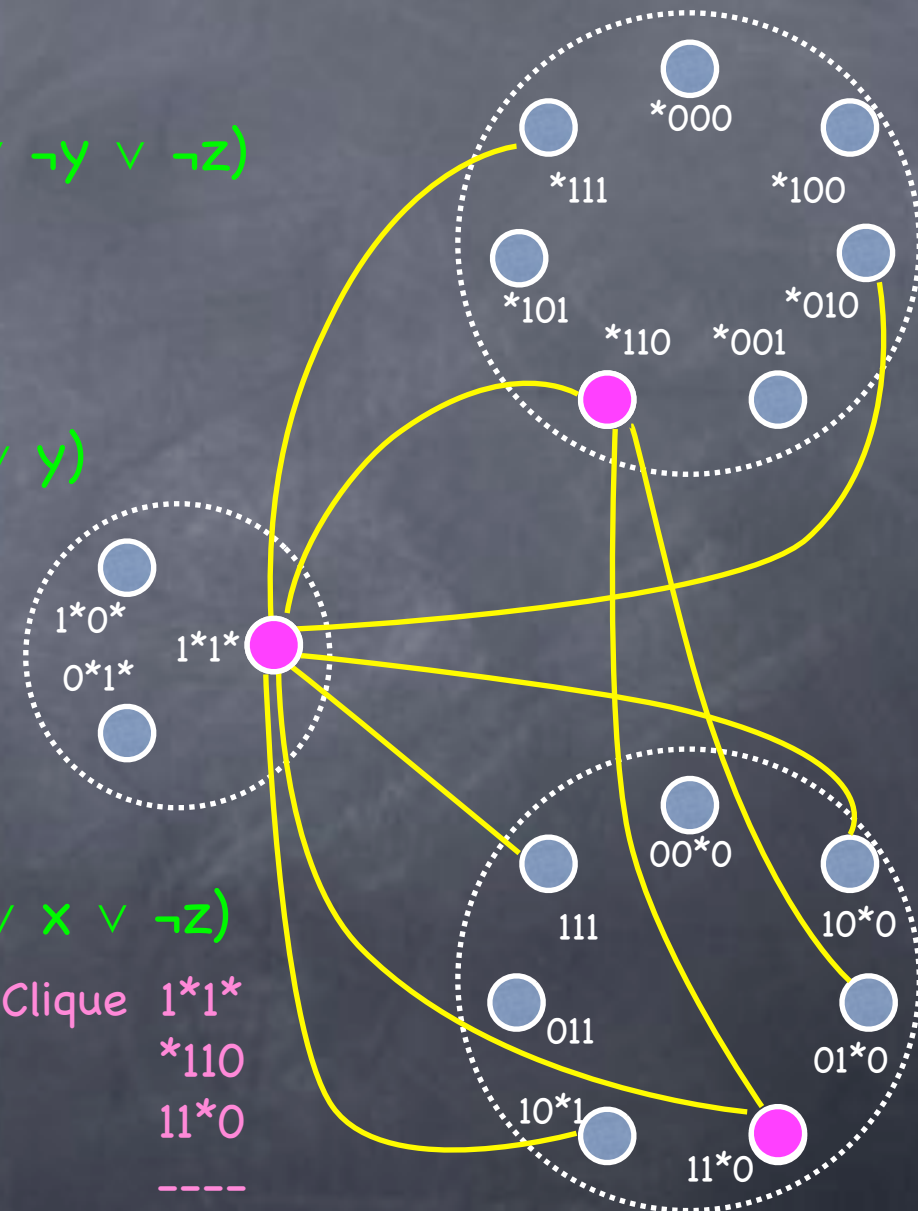
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Summary

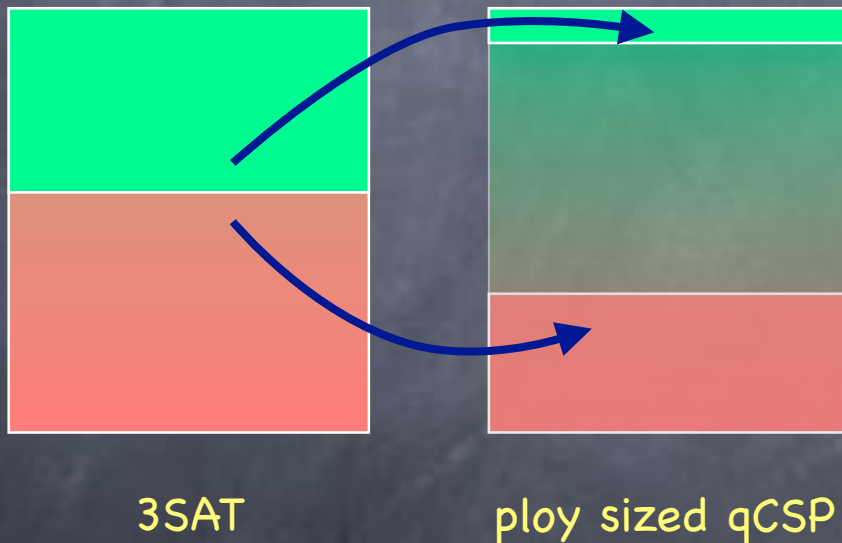
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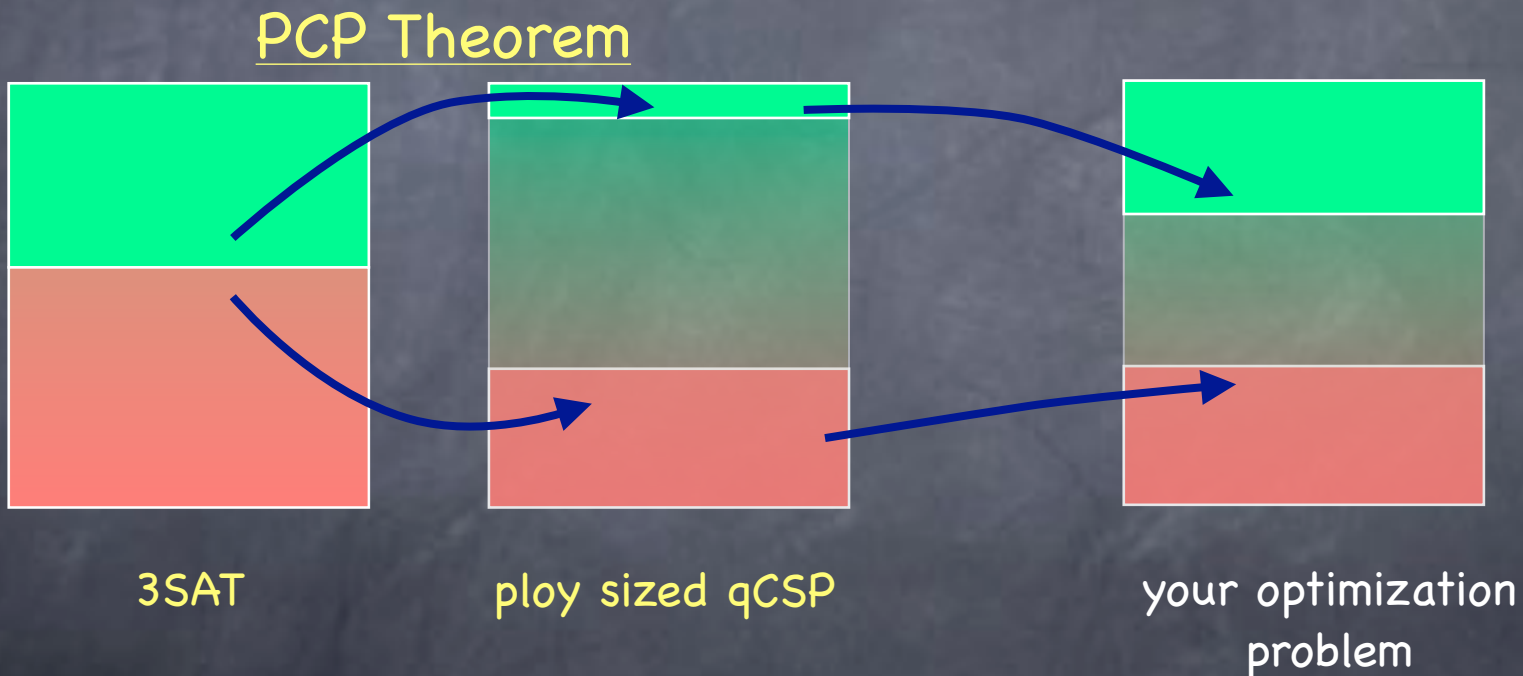
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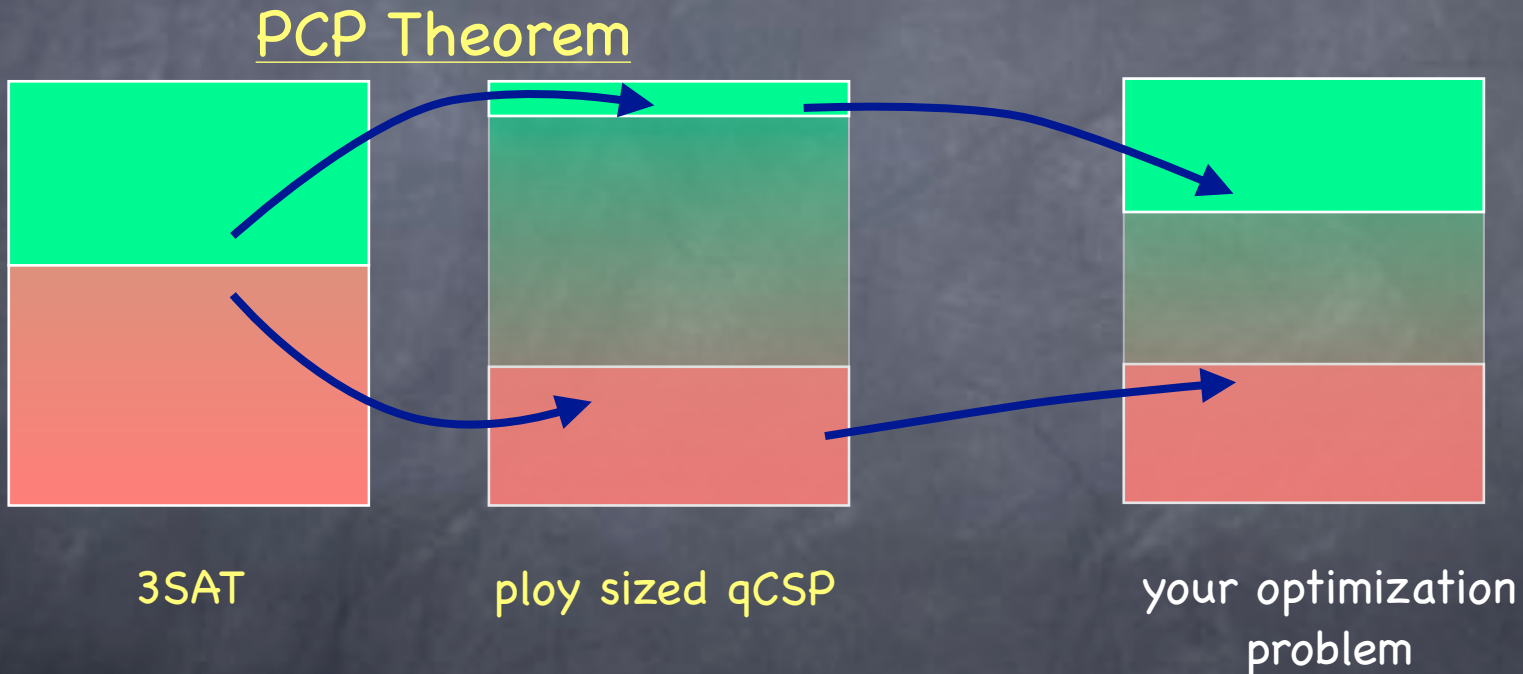
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