

# Exact Max 2-SAT: Easier and Faster

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# MAX 2-SAT

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- **Input:** A 2-CNF formula  $F$  with weights on clauses.
- **Good assignment** is one that maximizes the sum of weights of satisfied clauses.
- **Optimization Problem:** Find a good assignment.
- **Counting Problem:** Count the number of such good assignments.

# An Example

$$\text{Let } F = (x_1 \vee x_2) \wedge (\neg x_1 \vee \neg x_2) \wedge (x_1 \vee \neg x_2) \wedge (\neg x_1).$$

$x_1$	$x_2$	#-clauses satisfied
0	0	3
0	1	3
1	0	3
1	1	2

good assignments

# Status of Max 2-SAT

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- NP-hard.
- Best approximation ratio known = 0.940.
- APX-hard with inapproximability ratio  $21/22$  (under  $P \neq NP$ ).
- Better hardness results under Unique Game Conjecture.
- Counting version is #P-complete.

# Some Known Results

Authors	Time	Comments
Kojevnikov, Kulikov 2006	$O(2^{m/5.5})$	$m = \#$ -clauses.
Scott, Sorkin 2006	$O(2^{19m/100})$	holds for binary-CSP
Williams 2004	$O(2^{wn/3})$	$n = \#$ -variables, exponential space

**Summary:** For polynomial space algorithms with complexity measure  $n$ , not much is known.

# Our Contributions - I

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- Obtain a worst case bound of  
 $O(2^{((d(F)-2)/(d(F)-1))n})$

$d(F)$  = average number of clauses that a variable participates.

- The algorithm uses only polynomial space.
- Same upper bound for both counting and optimization problems.

# Our Contributions - II

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- We obtain an  $O(2^{cn})$  upper bound if the underlying **constraint graph** has a small **separator decomposition**.
- Here  $c$  is some constant  $< 1$  (i.e., independent of  $n$ ).

# Our Contributions – III

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- We introduce a new notion for **gadget** reductions.
- This notion allows us to obtain same upper bound for problems like
  - Max k-SAT (k constant),
  - Max Cut,
  - Max k-Lin-2 (k constant).



# General Idea

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- The algorithm uses a **DPLL**-like recursive decomposition technique.
- The idea is to chose a variable  $v$  and to recursively assign  $v$  to true and false.  
(a.k.a. we **branch on**  $v$ )
- The aim is to minimize the number of such branchings.

# Some Definitions

- **Constraint graph:**  $G(F) = (\text{Var}(F), E)$  where  
 $\text{Var}(F)$  = set of variables of  $F$ ,  
 $E = \{(u, v) \mid u, v \text{ appear in the same clause of } F\}$ .

- **Problem 3-SAT:**

**Input:** 3-CNF formula with weight  $w(l)$  on a literal  $l$ .

**Good assignment:** An assignment  $M$  satisfying all the clauses such that

$$W(M) = \sum_{(l \text{ satisfied by } M)} w(l) \text{ is maximized.}$$

# Worst case bounds

- Step 1: Parsimonious reduction from Max 2-SAT to 3-SAT.

Clause weighted

Literal weighted

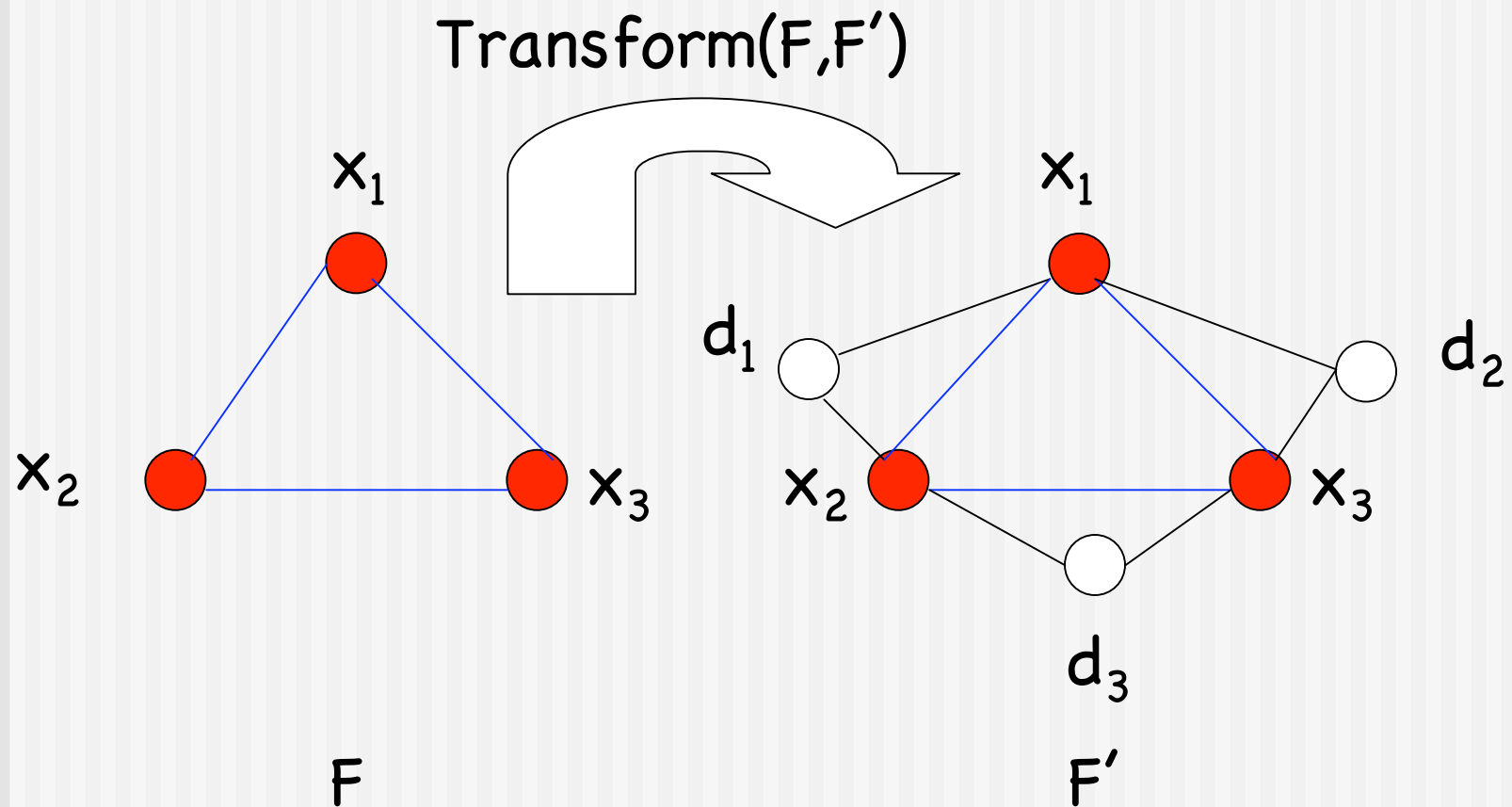
- Step 2: Solve the 3-SAT instance.

# Parsimonious Reduction

Function Transform( $F, F'$ )

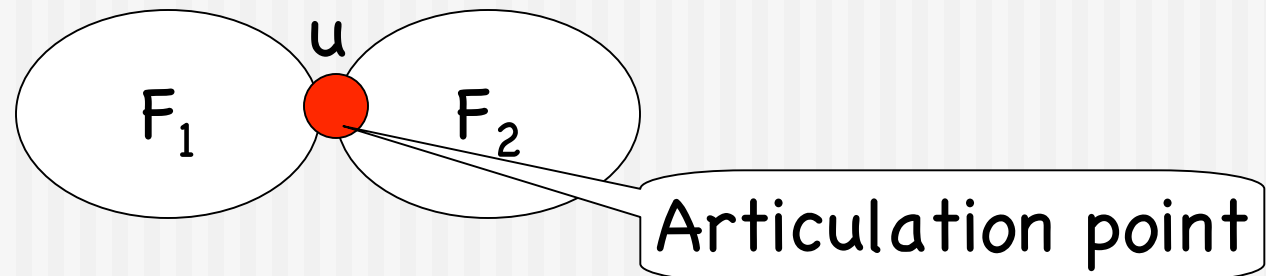
- 1) For each clause  $C = (x_i \vee x_j)$  in  $F$  add a clause  $(x_i \vee x_j \vee d_C)$  to  $F'$ .
- 2) Assign weights to literals in  $F'$  as:
  - 0 to any literal from  $\{x_1, \dots, x_n, \neg x_1, \dots, \neg x_n\}$ .
  - $w(C)$  (weight of clause  $C$ ) to literal  $\neg d_C$ .
  - 0 to literal  $d_C$ .

# Local Effects of Reduction



# An Useful Trick

Let  $F = F_1 \wedge F_2$  and  $F_1, F_2$  have exactly one common variable (say  $u$ ) then one can work with  $F_1$  (or  $F_2$ ) and use the result to update weight of  $u$ .



**Advantage:** One can solve  $F_1$  and  $F_2$  separately.

First Noted by Dahllöf et al 2005.

# Algorithm Local-2-SAT

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If there exists an unassigned variable, then

a) pick a variable  $v$  with lowest degree in the graph induced by unassigned variables.

b) branch on **all but one** of  $v$ 's neighbors simultaneously.

Trick from the previous slide saves one branching.

# Upper Bound on Running Time

- **Theorem 1:** Algorithm Local-2-SAT runs in  $O(2^{((\Delta(F)-2)/(\Delta(F)-1))n})$  time, where  $\Delta(F)$  is the maximum degree in  $G(F)$ .

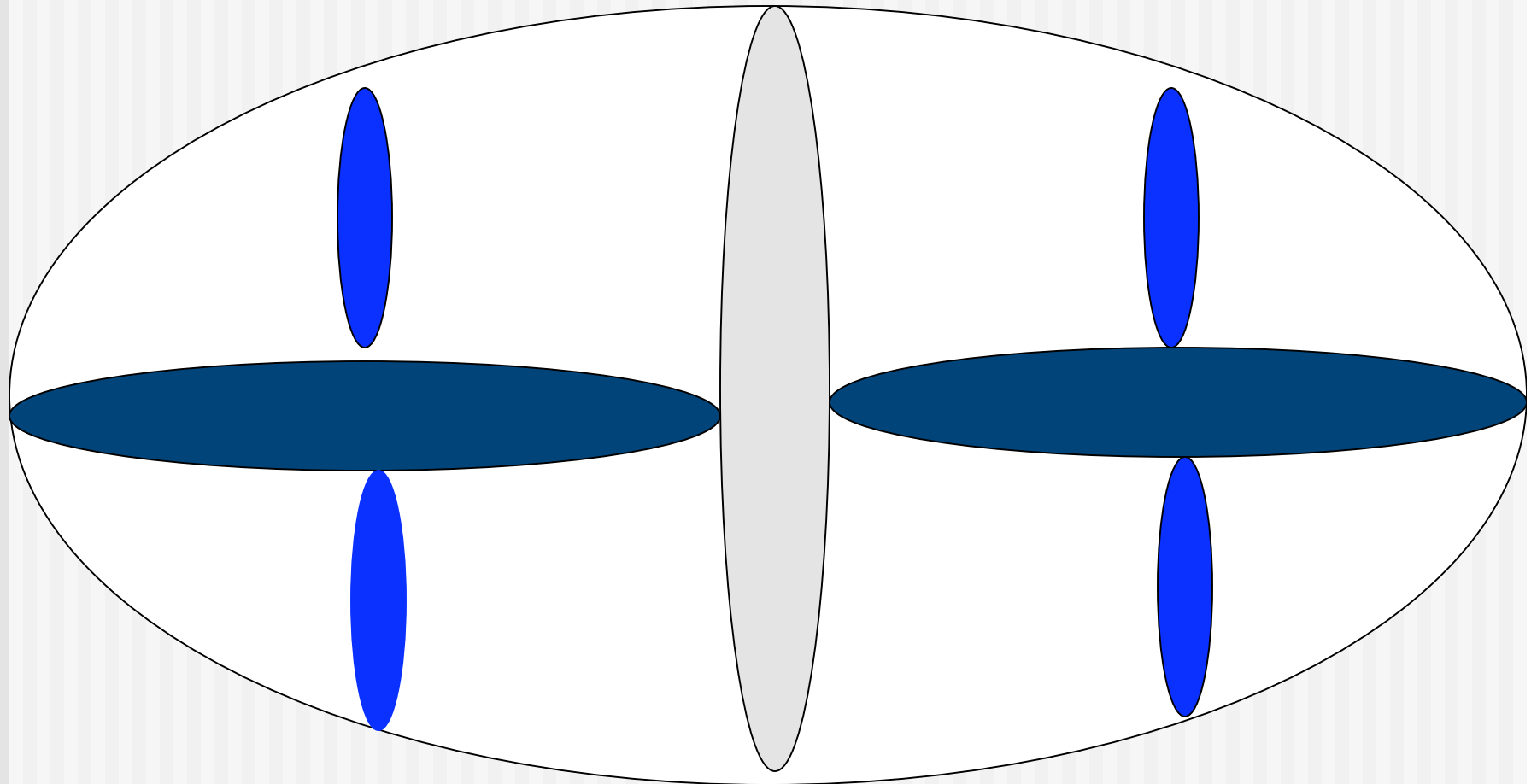
By a more careful analysis.

- **Theorem 2:** Algorithm Local-2-SAT runs in time  $O(2^{((d(F)-2)/(d(F)-1))n})$ , where  $d(F)$  is the average degree in  $G(F)$ .



# Separator Decomposition

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# Algorithm Global-2-SAT

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- 1) Recursively find a separator in the graph.
- 2) Branch on these vertices simultaneously.

# Global-2-SAT for Separable Graphs

Theorem 3: If  $G(F)$  has a small separator decomposition (i.e., every sub-graph of size  $k$  has a separator of size  $\eta k^u$  with  $0 < u < 1$ ), then Global-2-SAT runs in

$O(2^{n^u \eta / (1 - \rho^u)})$  time.

A constant  $< 1$  arising out of splitting ratio.

# Global-2-SAT worst case bounds

- For many classes of graphs no small separators exist.
- For these graphs we use BFS to obtain a separator.

Theorem 4: Algorithm Global-2-SAT runs in  $O(2^{((\Delta(F)-2)/(\Delta(F)-1))n+(\Delta(F)+1)\log n})$  time.

# Gadgets

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- Gadgets ( $\alpha$ -gadgets) introduced by Trevisan et al. defines a reduction from a constraint function to a constraint family.
- We parameterize gadgets by two parameters  $\alpha, \beta$ .
- **Advantage:** Allows compositions of gadgets.

# Definition of $(\alpha, \beta)$ -gadgets

A  $(\alpha, \beta)$ -gadget for  $\alpha, \beta \in \mathbb{R}^+$ , reduces a constraint function  $f: \{0,1\}^n \rightarrow \{0,1\}$  to a constraint family  $H$  such that,

a) the result is a finite collection of constraints  $\{C_1, \dots, C_\beta\}$  from  $H$  over input variables  $x_1, \dots, x_n$  and auxiliary variables  $y_1, \dots, y_m$ .

## Definition Contd...

b) The weights  $\{w_1, \dots, w_{\beta'}\}$  are assigned such that

$$w_1 + w_2 + \dots + w_{\beta'} = \beta.$$

and for Boolean assignments  $A$  to  $x_1, \dots, x_n$  and  $B$  to  $y_1, \dots, y_m$ :

$$(\forall A: f(A) = 1) \max_B (\sum_i w_i C_i(A, B)) = \alpha,$$

$$(\forall B: f(A) = 0) \max_B (\sum_i w_i C_i(A, B)) = \alpha - 1.$$

# Use of Gadgets

$P$   $\xrightarrow{(\alpha, \beta)}$  Max 2-SAT  
(Opt problem) (instance  $F$ )

Sum of constraint weights in  $P$

Max 2-SAT on  $F$  has optimum value  $\alpha W$ .

Any solution value  $S$  for  $F$  corresponds to solution value  $S - (\alpha - 1)W$  in  $P$ .

Parameter  $\beta$  helps us to chain these reductions.



# Results with Gadgets

$$\begin{array}{ccc}
 f \in H_1 & \xrightarrow{(\alpha_1, \beta_1)} & H_2 \\
 g \in H_2 & \xrightarrow{(\alpha_2, \beta_2)} & H_3
 \end{array}
 \left. \vphantom{\begin{array}{ccc} f \in H_1 & \xrightarrow{(\alpha_1, \beta_1)} & H_2 \\ g \in H_2 & \xrightarrow{(\alpha_2, \beta_2)} & H_3 \end{array}} \right\} \longrightarrow f \in H_1 \xrightarrow{(\beta_1(\alpha_2-1) + \alpha_1, \beta_1\beta_2)} H_3$$

$$\text{Max Cut} \xrightarrow{(2,2)} \text{Max 2-SAT}$$

$$\text{Max } k\text{-SAT} \xrightarrow{(3.5(k-2), 4(k-2))} \text{Max 2-SAT}$$

**Final result:** Same upper bound for these problems.

# Some Open Problems

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- Is there an  $O(2^{cn})$  time algorithm for Max 2-SAT?
- Easier problem: Exponential time algorithm for  $(1-\varepsilon)$  approximation?

Thank you

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