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**COE 561**  
**Digital System Design &  
Synthesis**  
**Logic Synthesis Background**

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[Adapted from slides of Prof. G. De Micheli: Synthesis & Optimization of Digital Circuits]

# Outline

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- **Boolean Algebra**
- **Boolean Functions**
- **Basic Definitions**
- **Representations of Boolean Functions**
- **Binary Decision Diagrams (BDDs)**
  - Ordered BDDs (OBDDs)
  - Reduced Ordered BDDs (ROBDDs)
- **If-then-else (ITE) DAGS**
- **Satisfiability and Minimum Cover Problems**
- **Branch and Bound Algorithm**

# Boolean Algebra

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## ■ Boolean algebra

- Quintuple  $(B, +, \cdot, 0, 1)$
- Satisfies *commutative* and *distributive* laws
- **Identity** elements are 0 and 1.
- Each element has a **complement**:  $a + a' = 1$  ;  $a \cdot a' = 0$
- Binary Boolean algebra  $B = \{0, 1\}$

## ■ Some properties of Boolean algebraic systems

<b>Associativity</b>	$a + (b + c) = (a + b) + c$	$a(bc) = (ab)c$
<b>Idempotence</b>	$a + a = a$	$a \cdot a = a$
<b>Absorption</b>	$a + (ab) = a$	$a(a + b) = a$
<b>De Morgan</b>	$(a + b)' = a' \cdot b'$	$(a \cdot b)' = a' + b'$
<b>Involution</b>	$(a')' = a$	

# Boolean Functions

## ■ Boolean function

- Single output:

$$f : B^n \rightarrow B$$

- Multiple output:

$$f : B^n \rightarrow B^m$$

- Incompletely specified

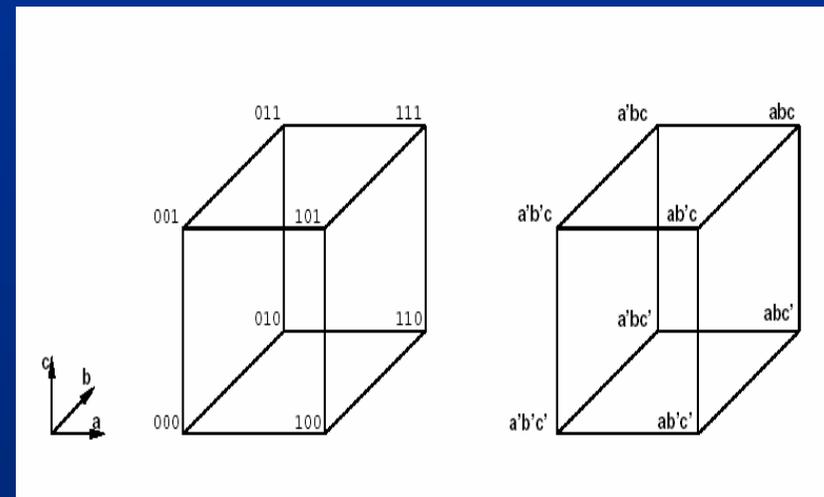
- don't care symbol \*

$$f : B^n \rightarrow \{0,1,*\}^m$$

## ■ Don't care conditions

- We don't care about the value of the function.
- Related to the environment:
  - Input patterns that never occur.
  - Input patterns such that some output is never observed.
- Very important for synthesis and optimization.

## 3-dimensional Boolean Space



# Definitions ...

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## ■ Scalar function

- **ON-Set**: subset of the domain such that  $f$  is **true**.
- **Off-Set**: subset of the domain such that  $f$  is **false**.
- **Don't care Set**: subset of the domain such that  $f$  is a **don't care**.

## ■ Multiple-output function

- Defined for each component.

## ■ Boolean **literal**: variable or its complement.

## ■ **Product** or **cube**: product of literals.

## ■ **Implicant**: product implying a value of a function (usually TRUE).

- Hypercube in the Boolean space.

## ■ **Minterm**: product of all input variables implying a value of a function (usually TRUE).

- Vertex in the Boolean space.

## ... Definitions ...

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- Let  $f(x_1, x_2, \dots, x_n)$  be a Boolean function of  $n$  variables.
- The set  $(x_1, x_2, \dots, x_n)$  is called the **support** of the function.
- The **cofactor** of  $f(x_1, x_2, \dots, x_i, \dots, x_n)$  with respect to variable  $x_i$  is  $f_{x_i} = f(x_1, x_2, \dots, x_i=1, \dots, x_n)$
- The **cofactor** of  $f(x_1, x_2, \dots, x_i, \dots, x_n)$  with respect to variable  $x_i'$  is  $f_{x_i'} = f(x_1, x_2, \dots, x_i=0, \dots, x_n)$
- **Theorem: Shannon's Expansion**

$$\begin{aligned} \text{Let } f : B^n \rightarrow B. \text{ Then } f(x_1, x_2, \dots, x_i, \dots, x_n) &= x_i \cdot f_{x_i} + x_i' \cdot f_{x_i'} \\ &= (x_i + f_{x_i'}) \cdot (x_i' + f_{x_i}) \quad \forall i = 1, 2, \dots, n \end{aligned}$$

- Any function can be expressed as **sum of products** (**product of sums**) of  $n$  literals, **minterms** (**maxterms**), by recursive expansion.

# ... Definitions ...

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## ■ Example: $f = ab + ac + bc$

- $f_a = b + c$
- $f_{a'} = bc$
- $F = a f_a + a' f_{a'} = a(b + c) + a'(bc)$

## ■ A Boolean function can be interpreted as the set of its minterms.

## ■ Operations and relations on Boolean functions can be viewed as operations on their minterm sets

- **Sum** of two functions is the **Union** ( $\cup$ ) of their minterm sets
- **Product** of two functions is the **Intersection** ( $\cap$ ) of their minterm sets
- **Implication** between two functions corresponds to **containment** ( $\subseteq$ ) of their minterm sets
  - $f_1 \rightarrow f_2 \equiv f_1 \subseteq f_2 \equiv f_1' + f_2 = 1$

## ... Definitions ...

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- A function  $f(x_1, x_2, \dots, x_i, \dots, x_n)$  is **positive (negative) Unate** with respect to variable  $x_i$  if  $f_{x_i} \supseteq f_{x_i'}$  ( $f_{x_i} \subseteq f_{x_i'}$ ).
- A function is (positive/negative) **Unate** if it is (positive/negative) unate in all support variables, otherwise it is **Binate** (or mixed).
- **Example:  $f = a + b + c'$** 
  - $f$  is positive unate with respect to variable  $a$ 
    - $f_{a=1} \supseteq f_{a'=b+c'}$
    - Minterms of  $f_a = \{bc, b'c, bc', b'c'\} \supseteq$  minterms of  $f_{a'} = \{bc, bc', b'c'\}$
  - $f$  is positive unate with respect to variable  $b$
  - $f$  is negative unate with respect to variable  $c$
  - Thus,  $f$  is binate.

## ... Definitions

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- The **Boolean Difference** of a function  $f(x_1, x_2, \dots, x_i, \dots, x_n)$  with respect to variable  $x_i$  is  $\partial f / \partial x_i = f_{x_i} \oplus f_{x_i'}$ 
  - Indicates whether  $f$  is sensitive to changes in  $x_i$
- The **Consensus** of a function  $f(x_1, x_2, \dots, x_i, \dots, x_n)$  with respect to variable  $x_i$  is  $f_{x_i} \cdot f_{x_i'}$ 
  - Represents the component that is independent of  $x_i$
- The **Smoothing** of a function  $f(x_1, x_2, \dots, x_i, \dots, x_n)$  with respect to variable  $x_i$  is  $f_{x_i} + f_{x_i'}$ 
  - Corresponds to dropping the variable from the function
- **Example:  $f = ab + ac + bc$** 
  - $f_a = b+c$       $f_{a'} = bc$
  - Boolean difference =  $f_a \oplus f_{a'} = (b+c) \oplus bc = b'c + bc'$
  - Consensus =  $f_a \cdot f_{a'} = (b+c) \cdot bc = bc$
  - Smoothing =  $f_a + f_{a'} = (b+c) + bc = b+c$

# Boolean Expansion Based on Orthonormal Basis ...

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- Let  $\phi_i$ ,  $i=1,2, \dots,k$  be a set of Boolean functions such that  $\sum_{i=1 \text{ to } k} \phi_i = 1$  and  $\phi_i \cdot \phi_j = 0$  for  $\forall i \neq j \in \{1,2,\dots,k\}$ .

- An **Orthonormal Expansion** of a function  $f$  is

$$f = \sum_{i=1 \text{ to } k} f_{\phi_i} \cdot \phi_i$$

- $f_{\phi_i}$  is called the **generalized cofactor** of  $f$  w.r.t.  $\phi_i \forall i$ .

- The **generalized cofactor** may not be unique

- $f \cdot \phi_i \subseteq f_{\phi_i} \subseteq f + \phi_i$

- **Example:**  $f = ab+ac+bc$ ;  $\phi_1 = ab$ ;  $\phi_2 = a'+b'$ ;

- $ab \subseteq f_{\phi_1} \subseteq 1$ ; **let**  $f_{\phi_1} = 1$

- $a'bc+ab'c \subseteq f_{\phi_2} \subseteq ab+bc+ac$ ; **let**  $f_{\phi_2} = a'bc+ab'c$

- $f = \phi_1 f_{\phi_1} + \phi_2 f_{\phi_2} = ab(1) + (a'+b')(a'bc+ab'c) = ab+bc+ac$

# ... Boolean Expansion Based on Orthonormal Basis ...

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## ■ Theorem

- Let  $f, g$ , be two Boolean functions expanded with the same orthonormal basis  $\phi_i, i=1,2, \dots,k$
- Let  $\otimes$  be a binary operator on two Boolean functions

$$f \otimes g = \sum_{i=1}^k \Phi_i \cdot (f_{\phi_i} \otimes g_{\phi_i})$$

## ■ Corollary

- Let  $f, g$ , be two Boolean functions with support variables  $\{x_i, i=1,2, \dots,n\}$ .
- Let  $\otimes$  be a binary operator on two Boolean functions

$$f \otimes g = x_i \cdot (f_{x_i} \otimes g_{x_i}) + x_i' \cdot (f_{x_i'} \otimes g_{x_i'})$$

# ... Boolean Expansion Based on Orthonormal Basis

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## ■ Example:

- Let  $f = ab + c$ ;  $g = a'c + b$ ; Compute  $f \oplus g$
- Let  $\phi_1 = a'b'$ ;  $\phi_2 = a'b$ ;  $\phi_3 = ab'$ ;  $\phi_4 = ab$ ;
- $f_{\phi_1} = c$ ;  $f_{\phi_2} = c$ ;  $f_{\phi_3} = c$ ;  $f_{\phi_4} = 1$ ;
- $g_{\phi_1} = c$ ;  $g_{\phi_2} = 1$ ;  $g_{\phi_3} = 0$ ;  $g_{\phi_4} = 1$ ;
- $f = a'b' (c \oplus c) + a'b (c \oplus 1) + ab' (c \oplus 0) + ab (1 \oplus 1)$   
 $= a'bc' + ab'c$
- $F = (ab+c) \oplus (a'c+b) = (ab+c)(a+c')b' + (a'+b')c'(a'c+b)$   
 $= (ab+ac)b' + (a'c+a'b)c' = ab'c + a'bc'$

# Representations of Boolean Functions

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- There are three different ways of representing Boolean functions:
  - Tabular forms
    - Personality matrix
    - Truth table
    - Implicant table
  - Logic expressions
    - Expressions of literals linked by the + and . Operators
    - Expressions can be nested by parenthesis
    - Two-level: sum of products or products of sum
    - Multilevel: factored form
  - Binary decisions diagrams
    - Represents a set of binary-valued decisions, culminating in an overall decision that can be either TRUE or FALSE

# Tabular Representations

- **Truth table**

- List of all minterms of a function.

- **Implicant table or cover**

- List of implicants of a function sufficient to define a function.

- **Implicant tables are smaller in size.**

- **Example:  $x = ab+a'c$ ;  $y = ab+bc+ac$**

*Truth  
Table*

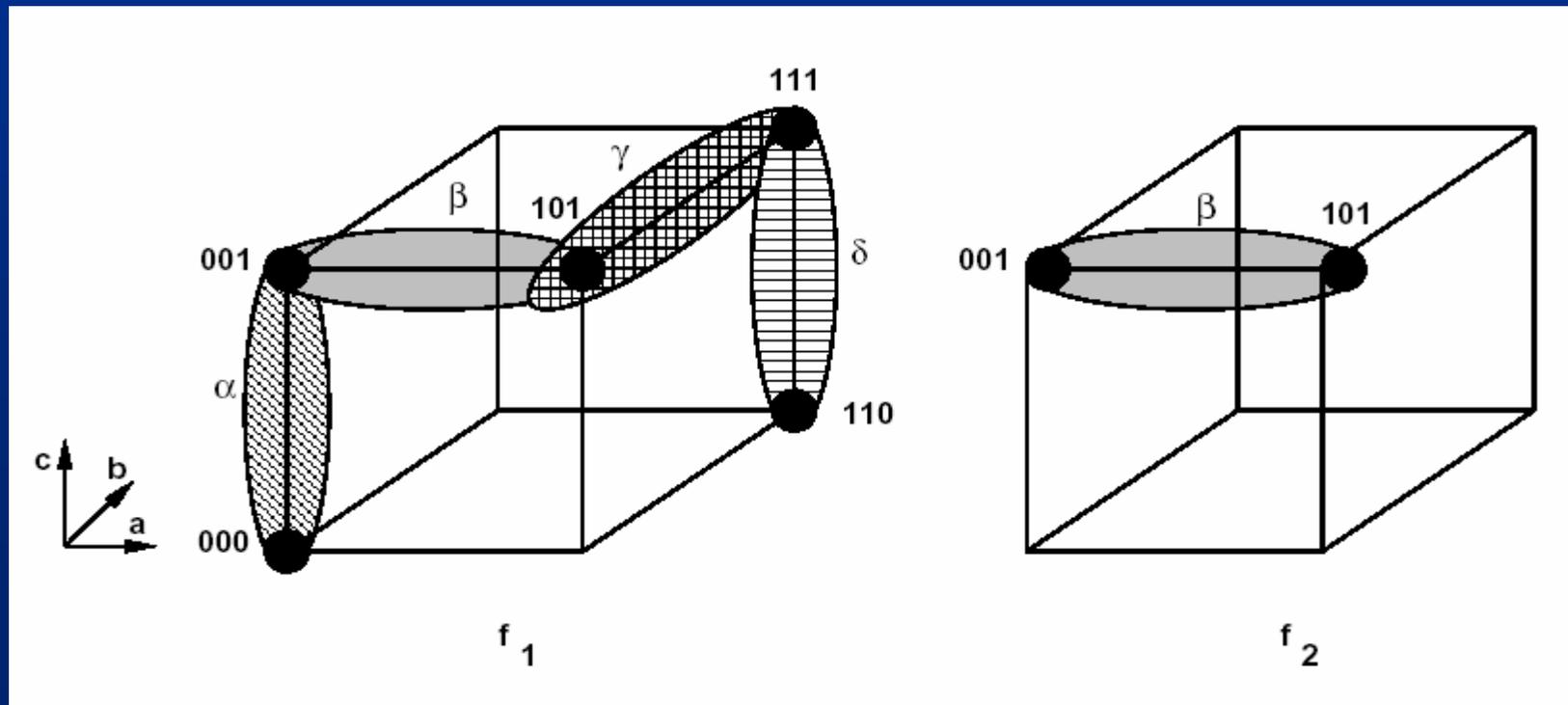
abc	xy
000	00
001	10
010	00
011	11
100	00
101	01
110	11
111	11

*Implicant  
Table*

abc	xy
001	10
*11	11
101	01
11*	11

# Cubical Representation of Minterms and Implicants

- $f_1 = a'b'c' + a'b'c + ab'c + abc + abc' = a'b' + b'c + ac + ab$
- $f_2 = a'b'c + ab'c = b'c$



# Binary Decision Diagrams ...

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- **Binary decision diagrams (BDDs)** can be represented by trees or rooted DAGs, where decisions are associated with vertices.
- **Ordered binary decision diagrams (OBDDs)** assume an ordering on the decision variables.
  - Can be transformed into canonical forms, reduced ordered binary decision diagrams (ROBDDs)
  - Operations on ROBDDs can be made in polynomial time of their size i.e. vertex set cardinality
  - Size of ROBDDs depends on **ordering of variables**
    - Adder functions are very sensitive to variable ordering
      - Exponential size in worst case
      - Linear size in best case
    - Arithmetic multiplication has exponential size regardless of variable order.

# ... Binary Decision Diagrams ...

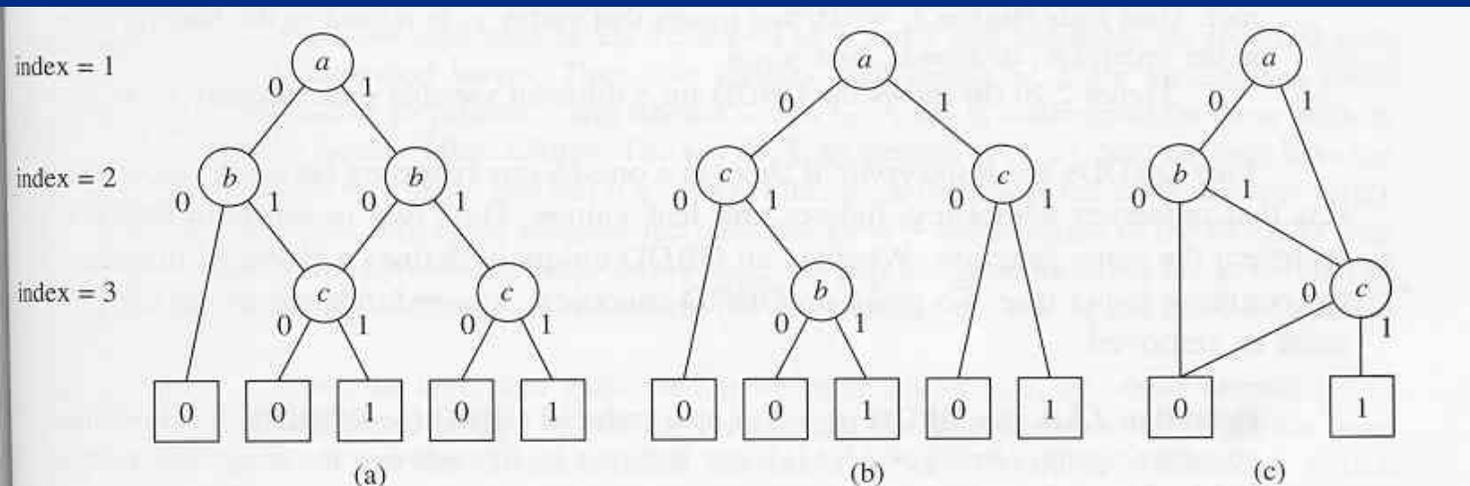
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- An OBDD is a rooted DAG with vertex set  $V$ . Each non-leaf vertex has as attributes
  - a pointer  $\text{index}(v) \in \{1, 2, \dots, n\}$  to an input variable  $\{x_1, x_2, \dots, x_i, \dots, x_n\}$ .
  - Two children  $\text{low}(v)$  and  $\text{high}(v) \in V$ .
- A leaf vertex  $v$  has as an attribute a value  $\text{value}(v) \in B$ .
- For any vertex pair  $\{v, \text{low}(v)\}$  (and  $\{v, \text{high}(v)\}$ ) such that no vertex is a leaf,  $\text{index}(v) < \text{index}(\text{low}(v))$  ( $\text{index}(v) < \text{index}(\text{high}(v))$ )
- An OBDD with root  $v$  denotes a function  $f^v$  such that
  - If  $v$  is a leaf with  $\text{value}(v)=1$ , then  $f^v=1$
  - If  $v$  is a leaf with  $\text{value}(v)=0$ , then  $f^v=0$
  - If  $v$  is not a leaf and  $\text{index}(v)=i$ , then  $f^v = x_i \cdot f^{\text{low}(v)} + \bar{x}_i \cdot f^{\text{high}(v)}$

# ... Binary Decision Diagrams

## ■ Example: $f=(a+b)c$

- Vertices  $\{v_1, v_2, v_3, v_4, v_5\}$  (Fig. 2.20 (c) )
- Variable  $x_1=a$ ,  $x_2=b$ ,  $x_3=c$ ;
- $v_1$  is the root;  $\text{index}(v_1)=1$  meaning that  $v_1$  is related to first variable in the order i.e.  $x_1=a$



**FIGURE 2.20**

Binary decision diagrams for  $f = (a + b)c$ : (a) OBDD for the variable order  $(a, b, c)$ , (b) OBDD for the variable order  $(a, c, b)$ , (c) ROBDD for the variable order  $(a, b, c)$ .

# Reduced Binary Decision Diagrams ...

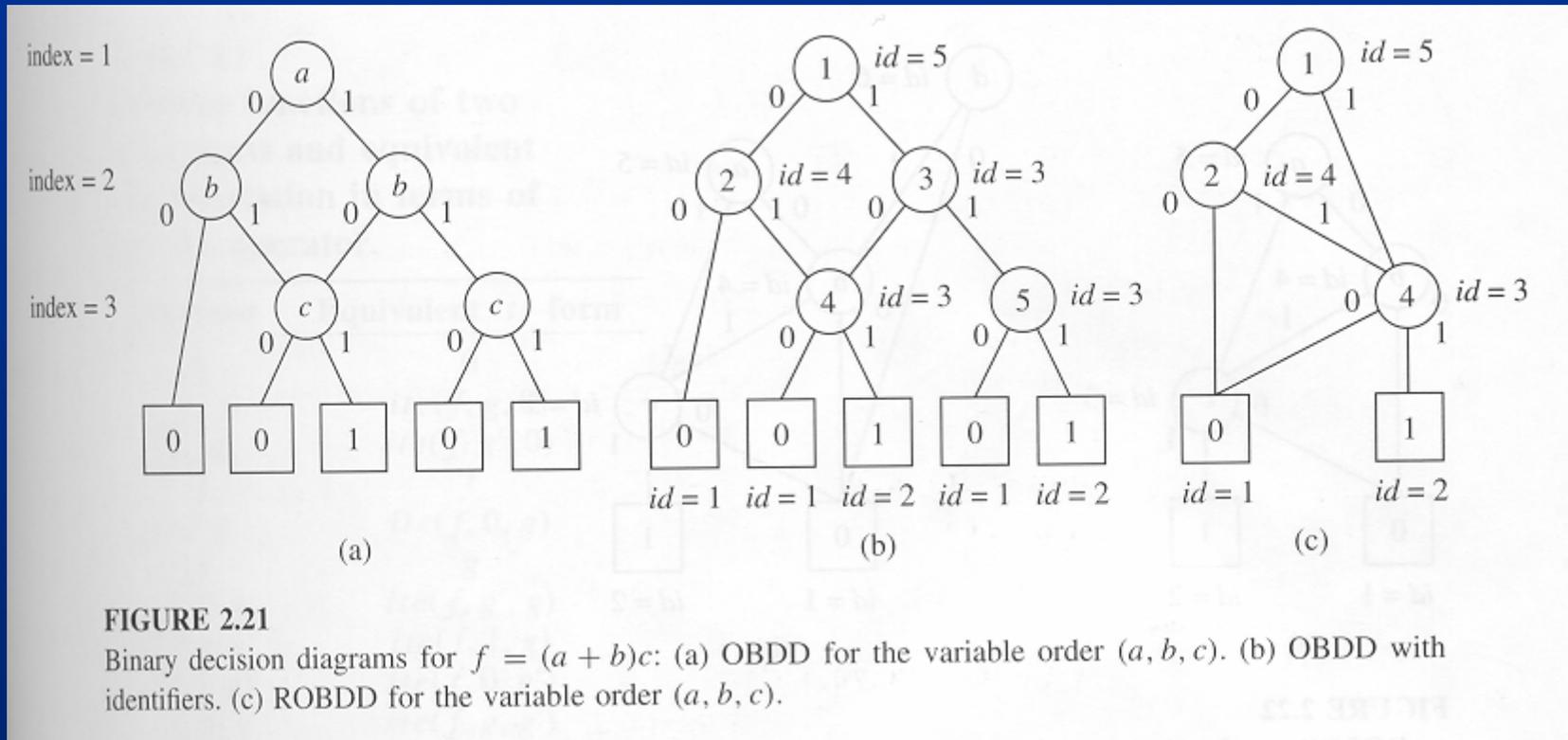
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- Two OBDDs are **isomorphic** if there is a one-to-one mapping between the vertex set that preserves adjacency, indices and leaf values.
- Two isomorphic OBDDs represent the same function.
- An OBDD is said to be **reduced OBDD (ROBDD)** if
  - It contains no vertex  $v$  with  $\text{low}(v)=\text{high}(v)$
  - Not any pair  $\{u,v\}$  such that the subgraphs rooted in  $u$  and in  $v$  are isomorphic.
- **ROBDDs are canonical**
  - All equivalent functions will result in the same ROBDD.

# ... Reduced Binary Decision Diagrams ...

```
REDUCE(OBDD){
  Set  $id(v) = 1$  to all leaves  $v \in V$  with  $value(v) = 0$ ;
  Set  $id(v) = 2$  to all leaves  $v \in V$  with  $value(v) = 1$ ;
  Initialize ROBDD with two leaves with  $id = 1$  and  $id = 2$  respectively;
   $nextid = 2$ ; /* nextid is the next available identifier value */
  for ( $i = n$  to 1 with  $i = i - 1$ ){
     $V(i) = \{v \in V : index(v) = i\}$ ;
    foreach ( $v \in V(i)$ ){ /* consider vertices at level  $i$  */
      if ( $id(low(v)) = id(high(v))$ ){
         $id(v) = id(low(v))$ ; /* redundant vertex */
        Drop  $v$  from  $V(i)$ ;
      }
      else
         $key(v) = id(low(v)), id(high(v))$ ;
        /* define  $key(v)$  as the identifier pair of  $v$ 's children */
    }
     $oldkey = 0, 0$ ; /* initial key that cannot be matched by any vertex */
    foreach  $v \in V(i)$  sorted by  $key(v)$  {
      if ( $key(v) = oldkey$ ) /* graph rooted at  $v$  is redundant */
         $id(v) = nextid$ 
      else { /* nonredundant vertex to receive new identifier value */
         $nextid = nextid + 1$ ;
         $id(v) = nextid$ ;
         $oldkey = key(v)$ ;
        Add  $v$  to ROBDD with edges to vertices in ROBDD
          whose  $id$  equal those of  $low(v)$  and  $high(v)$ ;
      }
    }
  }
}
```

# Reduced Binary Decision Diagrams ...



# If-then-else (ITE) DAGs ...

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- ROBDD construction and manipulation can be done with the *ite* operator.
- Given three scalar Boolean functions  $f$ ,  $g$  and  $h$ 
  - $\text{ite}(f, g, h) = f \cdot g + f' \cdot h$
- Let  $z = \text{ite}(f, g, h)$  and let  $x$  be the top variable of functions  $f$ ,  $g$  and  $h$ .
- The function  $z$  is associated with the vertex whose variable is  $x$  and whose children implement  $\text{ite}(f_x, g_x, h_x)$  and  $\text{ite}(f_{x'}, g_{x'}, h_{x'})$ .
  - $z = x z_x + x' z_{x'}$
  - $= x (f g + f' h)_x + x' (f g + f' h)_{x'}$
  - $= x (f_x g_x + f'_{x'} h_{x'}) + x' (f_{x'} g_{x'} + f'_{x'} h_{x'})$
  - $= \text{ite}(x, \text{ite}(f_x, g_x, h_x), \text{ite}(f_{x'}, g_{x'}, h_{x'}))$

# ... If-then-else (ITE) DAGs

- Terminal cases of *ite* operator
  - $\text{ite}(f, 1, 0) = f$ ,  $\text{ite}(1, g, h) = g$ ,  
 $\text{ite}(0, g, h) = h$ ,  $\text{ite}(f, g, g) = g$   
 and  $\text{ite}(f, 0, 1) = f'$ .
- All Boolean functions of two arguments can be represented in terms of *ite* operator.

Operator	Equivalent <i>ite</i> form
0	0
$f \cdot g$	$\text{ite}(f, g, 0)$
$f \cdot g'$	$\text{ite}(f, g', 0)$
$f$	$f$
$f'g$	$\text{ite}(f, 0, g)$
$g$	$g$
$f \oplus g$	$\text{ite}(f, g', g)$
$f + g$	$\text{ite}(f, 1, g)$
$(f + g)'$	$\text{ite}(f, 0, g')$
$f \oplus g$	$\text{ite}(f, g, g')$
$g'$	$\text{ite}(g, 0, 1)$
$f + g'$	$\text{ite}(f, 1, g')$
$f'$	$\text{ite}(f, 0, 1)$
$f' + g$	$\text{ite}(f, g, 1)$
$(f \cdot g)'$	$\text{ite}(f, g', 1)$
1	1

# ITE Algorithm ...

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```
ITE(f, g, h){
  If (terminal case)
    return (r = trivial result)
  else {
    if (computed table has entry {(f,g,h), r})
      return (r from computed table)
    else {
      x top variable of f, g, h
      t = ITE(fx, gx, hx)
      e = ITE(fx', gx', hx')
      if ( t == e) return (t)
      r = find_or_add_unique_table(x, t, e)
      Update computed table with {(f,g,h), r}
      return (r)
    }
  }
}
```

# ... ITE Algorithm

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## ■ Uses two tables

- **Unique table**: stores ROBDD information in a strong canonical form
  - Equivalence check is just a test on the equality of the identifiers
  - Contains a key for a vertex of an ROBDD
  - Key is a triple of variable, identifiers of left and right children
- **Computed table**: to improve the performance of the algorithm
  - Mapping between any triple  $(f, g, h)$  and vertex implementing  $\text{ite}(f, g, h)$ .

# Applications of ITE DAGs

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## ■ Implication of two functions is Tautology

- $f \rightarrow g \equiv f' + g = 1$
- Check if  $\text{ite}(f, g, 1)$  has identifier equal to that of leaf value 1
- Alternatively, a function associated with a vertex is tautology if both of its children are tautology

## ■ Functional composition

- Replacing a variable by another expression
- $f_{x=g} = f_x g + f_{x'} g' = \text{ite}(g, f_x, f_{x'})$

## ■ Consensus

- $f_x \cdot f_{x'} \equiv \text{ite}(f_x, f_{x'}, 0)$

## ■ Smoothing

- $f_x + f_{x'} \equiv \text{ite}(f_x, 1, f_{x'})$

# Satisfiability ...

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- Many synthesis and optimization problems can be reduced to a fundamental one: **satisfiability**.
- A Boolean function is **satisfiable** if there exists an assignment of Boolean values to the variables that makes the function **TRUE**.
- Most common formulation requires the function to be expressed in **a product of sum form**
  - Sum terms are called clauses
  - Assignment must make all clauses true
- **Satisfiability problem is Intractable**
  - **3-satisfiability** (i.e. clauses with max. 3 literals) is intractable
  - **2-satisfiability** can be solved in polynomial time

# ... Satisfiability

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## ■ Example

- $F=(a+b+c')(a+b'+c')(a+b'+c)(a'+b+c)(a'+b+c')(a'+b'+c)(a'+b'+c)$
- Find an input assignment that makes  $F=1$

## ■ Solution

- $A=1, B=1, C=0 \Rightarrow$  Fails
- $A=0, B=1, C=0 \Rightarrow$  Fails
- $A=1, B=0, C=1 \Rightarrow$  Fails
- $A=0, B=0, C=1 \Rightarrow$  Fails
- $A=1, B=1, C=1 \Rightarrow$  Fails
- $A=0, B=1, C=1 \Rightarrow$  Fails
- $A=1, B=0, C=0 \Rightarrow$  Fails
- $A=0, B=0, C=0 \Rightarrow$  Success!!

# Satisfiability Formulation as Zero-One Linear Programming (ZOLP) Problem

- Satisfiability problem can be modeled as a ZOLP
- Example: Satisfiability problem
  - $(a+b)(a'+b'+c)$
  - Possible solution:  $a=1; b=1; c=1$
- ZOLP modeling
  - $a + b \geq 1$
  - $(1-a)+(1-b)+c \geq 1$
  - $a, b, c \in B$
- Minimum-cost satisfiability problem
  - Find  $x \in B^n$  that minimizes the cost  $c^T x$  where  $c$  is a weight vector.

# Minimum Covering Problem

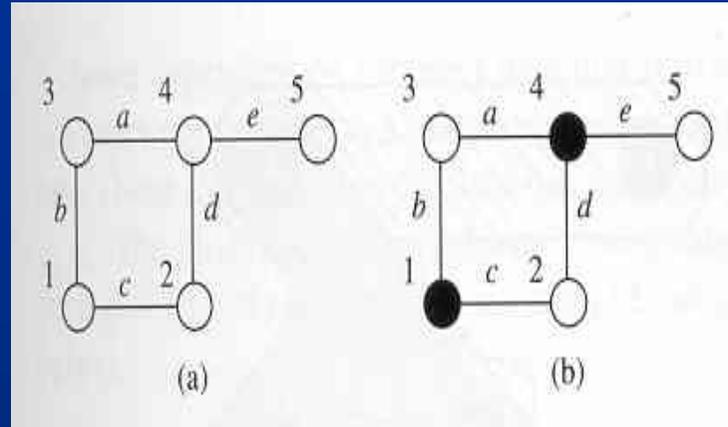
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- Given a collection **C** (called groups) of subsets of a finite set **S**. A **minimum-covering problem** is the search of a minimum number of subsets from **C** that cover **S**.
- Let  $A \in B^{n \times m}$ , where **#rows**= $n=|S|$  and **#columns**= $m=|C|$ 
  - A **cover** corresponds to a subset of columns having at least a 1 entry in all rows of  $A$ .
  - Corresponds to selecting  $x \in B^m$ , such that  $Ax \geq 1$
  - **Minimum-weighted cover** corresponds to selecting  $x \in B^m$ , such that  $Ax \geq 1$  and  $c^T x$  is minimum.
- **Intractable.**
- **Exact method**
  - Branch and bound algorithm.
- **Heuristic methods.**

# Minimum-Vertex Cover Example

*Vertex/edge incidence matrix*

$$A_I = \begin{pmatrix} 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$



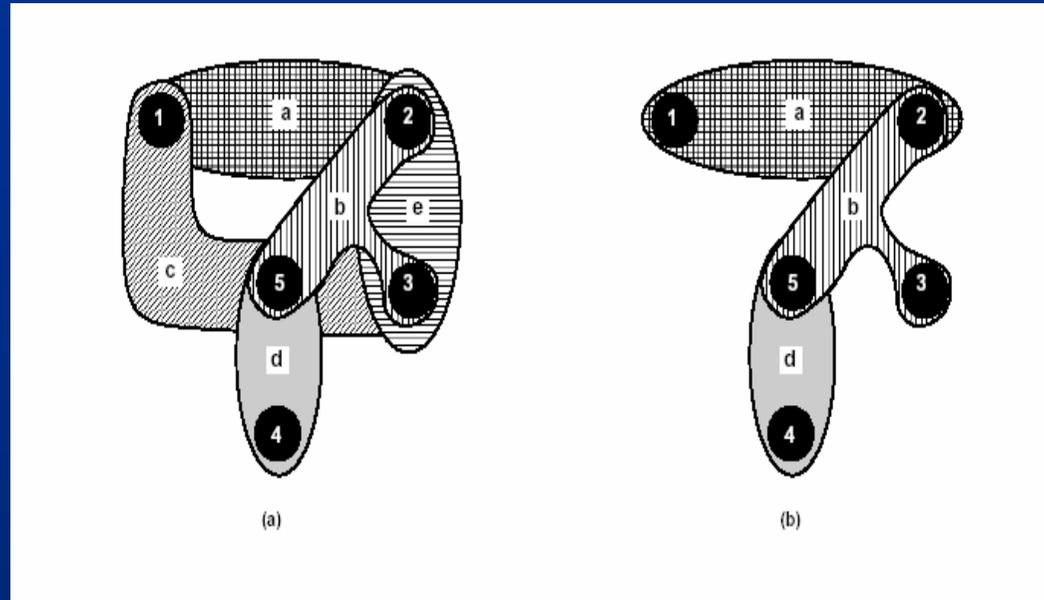
- **Minimum vertex cover**

- Edge set corresponds to S and vertex set to C
- $A = A_I^T$  and  $c = 1$ .
- Possible covers:  $x^1 = [10010]^T$ ,  $x^2 = [01101]^T$ ,  $x^3 = [01111]^T$
- Note that  $Ax \geq 1$  for  $x = x^1, x^2, x^3$
- Vector  $x^1$  is a minimum cover

# Minimum-Edge Cover Example

*Vertex/edge incidence matrix*

$$A_I = \begin{pmatrix} 1 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 \end{pmatrix}$$



- **Minimum edge cover**

- Vertex set corresponds to S and edge set to C
- $A = A_I$  and  $c = 1$ .
- A minimum cover is {a, b, d} or  $x = [11010]^T$
- Let  $c = [1, 2, 1, 1, 1]^T$ ; a minimum cover is {a, c, d},  $x = [10110]^T$

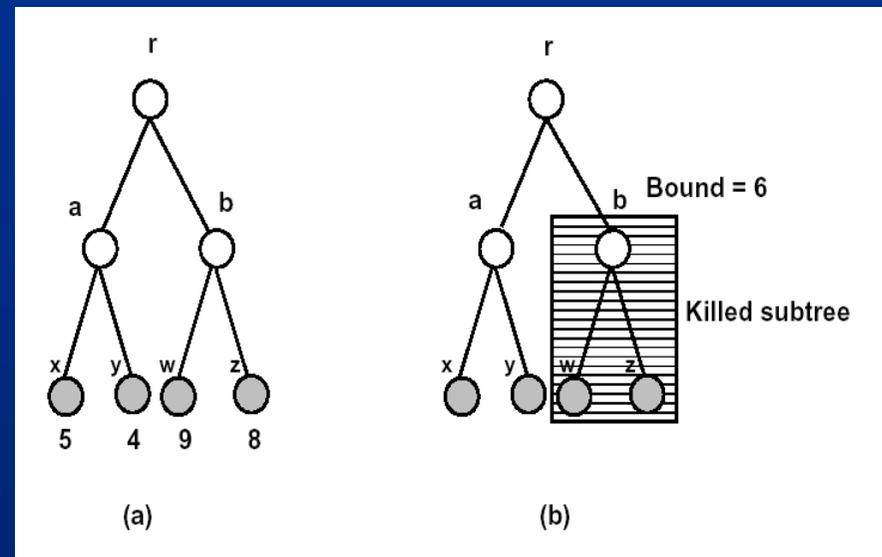
# Covering Problem Formulated as Satisfiability Problem

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- Associate a selection variable with each group (element of C)
- Associate a clause with each element of S
  - Each clause represents those groups that can cover the element
  - Disjunction of variables corresponding to groups
- Note that the product of clauses is a unate expression
  - Unate cover
- Edge-cover example
  - $(x_1+x_3)(x_1+x_2+x_5)(x_2+x_3+x_5)(x_4)(x_2+x_3+x_4)=1$
  - $(x_1+x_3)$  denotes vertex  $v_1$  must be covered by edge  $a$  or  $c$
  - $x=[11010]^T$  satisfies the product of sums expression

# Branch and Bound Algorithm ...

- Tree search of the solution space
  - Potentially exponential search.
- For each branch, a lower bound is computed for all solutions in subtree.
- Use bounding function
  - If the lower bound on the solution cost that can be derived from a set of future choices exceeds the cost of the best solution seen so far
    - **Kill the search.**
- Good pruning may reduce run-time.



# ... Branch and Bound Algorithm

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## BRANCH AND BOUND {

Current best = anything; Current cost =  $\infty$  ; S = s0;

while (S  $\neq$  0) do {

    Select an element  $s \in S$ ; Remove s from S ;

    Make a branching decision based on s yielding sequences  $\{s_i, i = 1, 2, \dots, m\}$ ;

    for ( i = 1 to m) {

        Compute the **lower bound**  $b_i$  of  $s_i$ ;

        if ( $b_i \geq$  Current cost) Kill  $s_i$ ;

        else {

            if ( $s_i$  is a complete solution )&(cost of  $s_i <$  Current cost) {

                Current best =  $s_i$ ; Current cost = cost of  $s_i$  ;

            } else if ( $s_i$  is not a complete solution ) Add  $s_i$  to set S;

        }

    }

}

}

- S denotes a solution or group of solutions with a subset of decisions made
- s0 denotes the sequence of zero length corresp. to initial state with no decisions made

# Covering Reduction Strategies ...

---

## ■ Partitioning

- If  $A$  is block diagonal
  - Solve covering problem for corresponding blocks.

## ■ Essentials

- Column incident to one (or more) rows with single 1
  - Select column,
  - Remove covered row(s) from table.

## ■ Column dominance

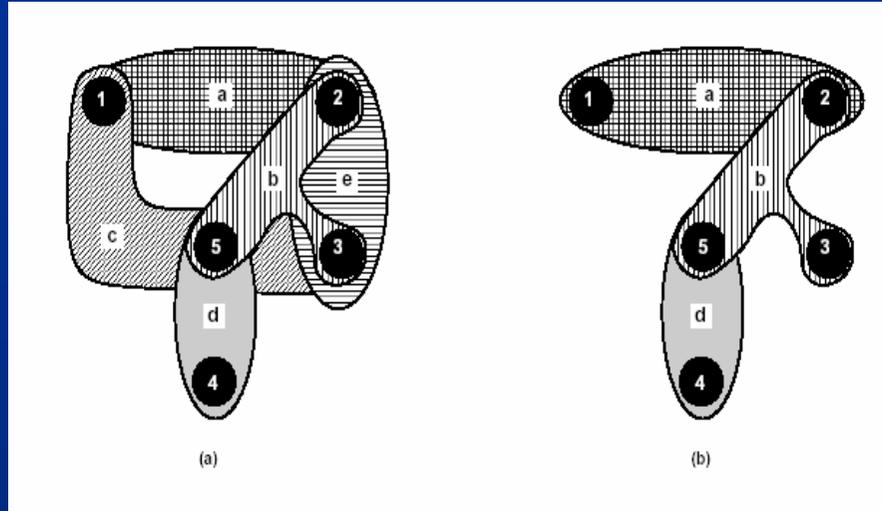
- If  $a_{ki} \geq a_{kj} \forall k$ : remove column  $j$ .
- Dominating column covers more rows.

## ■ Row dominance

- If  $a_{ik} \geq a_{jk} \forall k$ : remove row  $i$ .
- A cover for the dominated rows is a cover for the set.

# ... Covering Reduction Strategies

$$A = \begin{pmatrix} 1 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 \end{pmatrix}$$



- Fourth column is essential.
- Fifth column is dominated by second column.
- Fifth row dominates fourth row.

**Reduced matrix**  $A = \begin{pmatrix} 1 & 0 & 1 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{pmatrix}$

# Branch and Bound Exact Covering Algorithm

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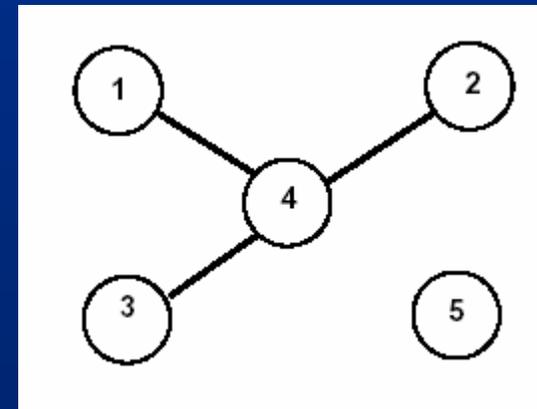
```
EXACT_COVER(A, x, b) {  
    Reduce matrix A and update corresponding x;  
    if (Current estimate  $\geq$  |b|) return(b);  
    if ( A has no rows ) return (x);  
    Select a branching column c;  
     $x_c = 1$  ;  
     $A^{\sim} = A$  after deleting c and rows incident to it;  
     $x^{\sim} =$  EXACT_COVER( $A^{\sim}$  , x, b);  
    if (  $|x^{\sim}| < |b|$ )    b =  $x^{\sim}$  ;  
     $x_c = 0$  ;  
     $A^{\sim} = A$  after deleting c ;  
     $x^{\sim} =$  EXACT_COVER( $A^{\sim}$  , x, b);  
    if (  $|x^{\sim}| < |b|$ )    b =  $x^{\sim}$  ;  
    return (b);  
}
```

*x contains current solution  
initially set to 0;  
b contains best solution  
initially set to 1;*

# Bounding function ...

- Estimate **lower bound** on the covers derived from the current  $x$ .
- The sum of 1's in  $x$ , plus **bound** on cover for local  $A$ 
  - **Independent set of rows**: no 1 in same column.
  - Build graph denoting pairwise independence.
  - Find clique number (i.e. largest clique)
  - Approximation (lower) is acceptable.

$$A_I = \begin{pmatrix} 1 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 \end{pmatrix}$$



- Row 4 independent from 1, 2, 3
- Clique number is 2; Bound is 2

# ... Bounding function

- There are no independent rows.
- Clique number is 1 (1 vertex).
- Bound is 1 + 1 (already selected essential).
- Choose first column  $x_1$ 
  - Recur with  $A^{\sim} = [11]$ .
  - Delete one dominated column.
  - Take other col. (essential); assume it  $x_2$
- New cost is 3;  $x=[11010]^T$  and  $b=[11010]^T$
- Exclude first column  $x_1$ 
  - Both columns are essential
  - $x=[01110]^T$ ; cost is 3 (discarded)
- Returned solution is  $x=[11010]^T$

$$A = \begin{pmatrix} 1 & 0 & 1 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{pmatrix}$$

$$A^{\sim} = \begin{pmatrix} 0 & 1 \\ 1 & 0 \\ 1 & 1 \end{pmatrix}$$