

# Unlabeled Compression Schemes for Maximum Classes

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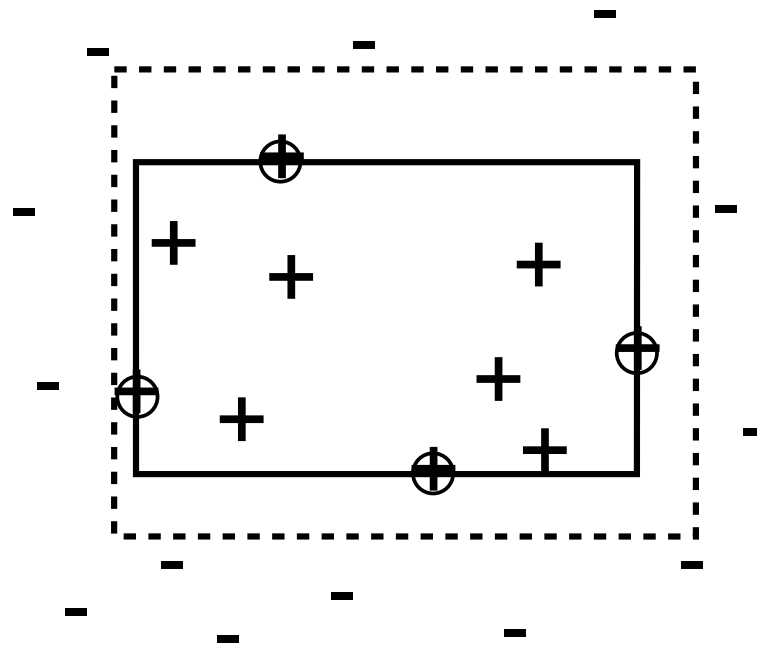
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*some work done while authors were visiting National ICT Australia*

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## Compression Scheme

- Sample consistent with some axis-parallel rectangle
- **Compress to:** leftmost, rightmost, uppermost and lowermost positive points (circled)
- **Reconstruct** all labels based on the smallest rectangle containing the compression set (solid line)



## Compression Schemes into 2 functions

- **Compression function** maps samples into subsamples
- **Reconstruction function** maps compression sets into hypotheses consistent with the original sample
- Variations: labeled, unlabeled, lossless, lossy, additional bits, etc.

## Why Study Compression Schemes?

- Size of compression scheme is alternate measure of complexity
- Inspires good practical algorithms
- Simple proofs of sample size and generalization bounds ([LW86], [FW95],[Lang05])
- Sample size bound for size  $k$  compression scheme:

$$m(\epsilon, \delta) = \Omega\left(\frac{k}{\epsilon} \log \frac{1}{\epsilon} + \frac{\log \frac{1}{\delta}}{\epsilon}\right)$$

## Why Study Compression Schemes?

- Size of compression scheme is alternate measure of complexity
- Inspires good practical algorithms
- Simple proofs of sample size and generalization bounds ([LW86], [FW95],[Lang05])
- Sample size bound for **class of VC dimension  $d$** :

$$m(\epsilon, \delta) = \Omega\left(\frac{d}{\epsilon} \log \frac{1}{\epsilon} + \frac{\log \frac{1}{\delta}}{\epsilon}\right)$$

## Conjecture

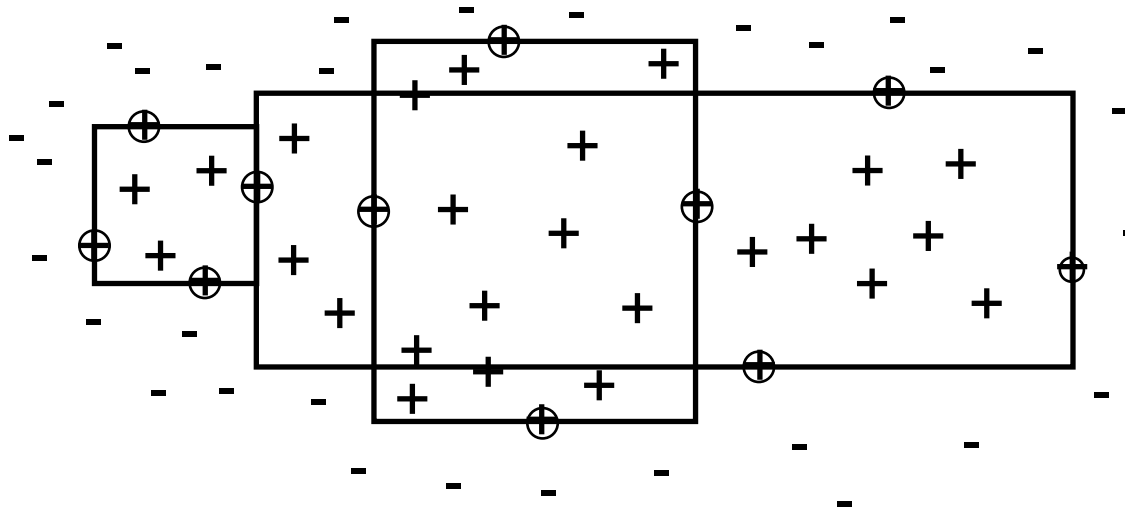
- VC dimension of rectangles is 4
- We used size  $\leq 4$  compression sets
- One of the most tantalizing open problems in learning theory:

For any concept class with VC dimension  $d$  there always is a compression scheme that keeps at most  $d$  points

[FW95]

## Which Practical Algorithms?

- Cover positive points with rectangles



- Compresses to subsample and small number of bits [MST02]
- SVMs: Compression set is set of essential support vectors

[vLBS04]

## Maximum Classes

- Sauer's Lemma provides an upper bound on size of a concept class with VCdim  $d$  and  $n$  instances:

$$|C| \leq \sum_{i=0}^d \binom{n}{i} = \binom{n}{\leq d}$$

- Classes are **maximum** when  $\leq$  becomes  $=$
- Example: class of all subsets of size up to  $d$
- Our results are currently only for such classes



## What is known?

- Compression scheme for **maximum** concept classes that compresses to **labeled** sets of points of size  $= d$  [FW95]

Here:

- We compress maximum classes to **unlabeled** sets of points of size  $\leq d$
- New scheme is tight and new combinatorics
- Connection to the 1-inclusion graph algorithm

## Our Scheme

- Each concept represented by subset of size  $\leq d$

	$x_1$	$x_2$	$x_3$	$x_4$	Representative $r(c)$
$c_1$	0	0	0	0	$\emptyset$
$c_2$	0	0	<u>1</u>	0	$\{x_3\}$
$c_3$	0	0	1	<u>1</u>	$\{x_4\}$
$c_4$	0	<u>1</u>	0	0	$\{x_2\}$
$c_5$	0	1	<u>0</u>	<u>1</u>	$\{x_3, x_4\}$
$c_6$	0	<u>1</u>	<u>1</u>	0	$\{x_2, x_3\}$
$c_7$	0	<u>1</u>	1	<u>1</u>	$\{x_2, x_4\}$
$c_8$	<u>1</u>	0	0	0	$\{x_1\}$
$c_9$	<u>1</u>	0	<u>1</u>	0	$\{x_1, x_3\}$
$c_{10}$	<u>1</u>	0	1	<u>1</u>	$\{x_1, x_4\}$
$c_{11}$	<u>1</u>	<u>1</u>	0	0	$\{x_1, x_2\}$

## Compressing and Reconstructing

- Sample  $(\mathbf{x}_3, \mathbf{1}), (\mathbf{x}_4, \mathbf{0})$

	$x_1$	$x_2$	$x_3$	$x_4$
$c_1$	0	0	0	0
$c_2$	0	0	<u>1</u>	0
$c_3$	0	0	1	<u>1</u>
$c_4$	0	<u>1</u>	0	0
$c_5$	0	1	<u>0</u>	<u>1</u>
$c_6$	0	<u>1</u>	<u>1</u>	0
$c_7$	0	<u>1</u>	1	<u>1</u>
$c_8$	<u>1</u>	0	0	0
$c_9$	<u>1</u>	0	<u>1</u>	0
$c_{10}$	<u>1</u>	0	1	<u>1</u>
$c_{11}$	<u>1</u>	<u>1</u>	0	0

## Compressing and Reconstructing

- Sample  $(\mathbf{x}_3, \mathbf{1})$ ,  $(\mathbf{x}_4, \mathbf{0})$
- Many consistent concepts

	$x_1$	$x_2$	$x_3$	$x_4$
$c_1$	0	0	0	0
$c_2$	0	0	<u>1</u>	0
$c_3$	0	0	1	<u>1</u>
$c_4$	0	<u>1</u>	0	0
$c_5$	0	1	<u>0</u>	<u>1</u>
$c_6$	0	<u>1</u>	<u>1</u>	0
$c_7$	0	<u>1</u>	1	<u>1</u>
$c_8$	<u>1</u>	0	0	0
$c_9$	<u>1</u>	0	<u>1</u>	0
$c_{10}$	<u>1</u>	0	1	<u>1</u>
$c_{11}$	<u>1</u>	<u>1</u>	0	0

## Compressing and Reconstructing

- Sample  $(\mathbf{x}_3, \mathbf{1}), (\mathbf{x}_4, \mathbf{0})$
- Many consistent concepts
- Exactly one has its representation set completely inside the sample

	$x_1$	$x_2$	$x_3$	$x_4$
$c_1$	0	0	0	0
$c_2$	0	0	<u>1</u>	0
$c_3$	0	0	1	<u>1</u>
$c_4$	0	<u>1</u>	0	0
$c_5$	0	1	<u>0</u>	<u>1</u>
$c_6$	0	<u>1</u>	<u>1</u>	0
$c_7$	0	<u>1</u>	1	<u>1</u>
$c_8$	<u>1</u>	0	0	0
$c_9$	<u>1</u>	0	<u>1</u>	0
$c_{10}$	<u>1</u>	0	1	<u>1</u>
$c_{11}$	<u>1</u>	<u>1</u>	0	0

## Compressing and Reconstructing

- Sample  $(\mathbf{x}_3, \mathbf{1}), (\mathbf{x}_4, \mathbf{0})$
- Many consistent concepts
- Exactly one has its representation set completely inside the sample
- **Compress** to this representation set -  $\{x_3\}$
- **Reconstruct** based on represented concept

	$x_1$	$x_2$	$x_3$	$x_4$
$c_1$	0	0	0	0
$c_2$	0	0	<u>1</u>	0
$c_3$	0	0	1	<u>1</u>
$c_4$	0	<u>1</u>	0	0
$c_5$	0	1	<u>0</u>	<u>1</u>
$c_6$	0	<u>1</u>	<u>1</u>	0
$c_7$	0	<u>1</u>	1	<u>1</u>
$c_8$	<u>1</u>	0	0	0
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$c_{10}$	<u>1</u>	0	1	<u>1</u>
$c_{11}$	<u>1</u>	<u>1</u>	0	0

## Condition on Representatives

Two different concepts  $c, c'$  **clash** wrt  $r$  if

$$c \mid r(c) \cup r(c') = c' \mid r(c) \cup r(c')$$

1001 and 1101 **clash** since 01 = 01

0001 and 1001 **don't clash** since 001  $\neq$  101

$r$  must have two properties:

1.  $r$  is a bijection between  $C$  and sets of points of size at most  $d$
2. no two concepts clash

## Central Lemma

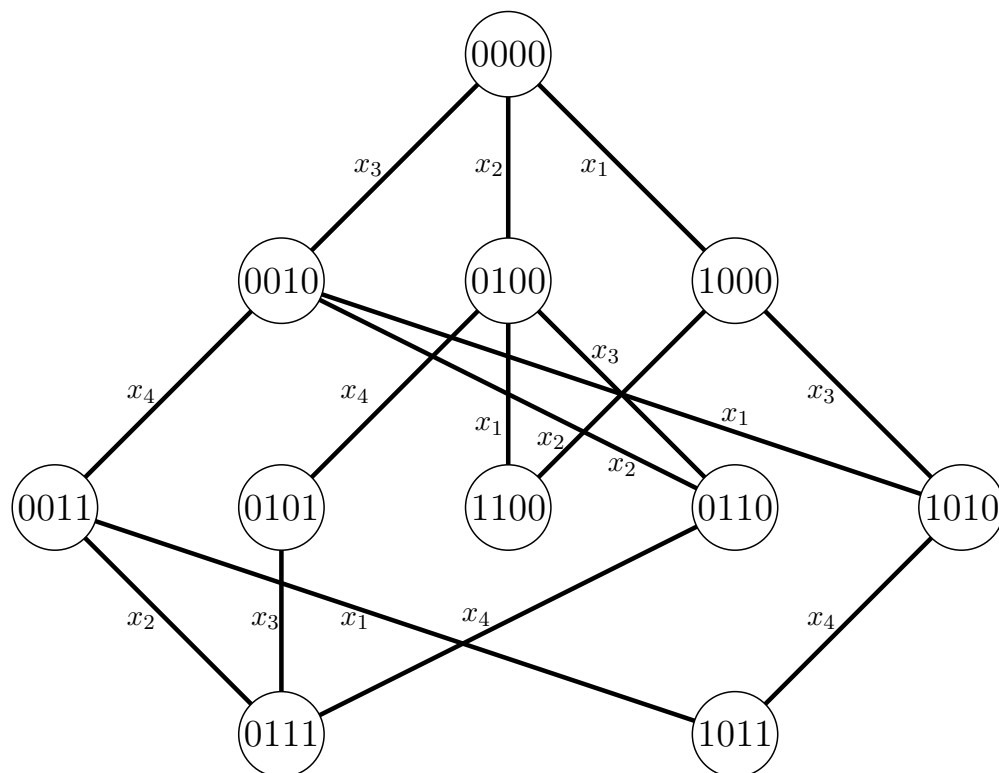
The following two statements are equivalent:

1. No two concepts clash wrt  $r$
2. For all samples  $s$  from  $C$ , there is at most one concept  $c \in C$  that is consistent with  $s$  and  $r(c)$  contains only points from  $s$



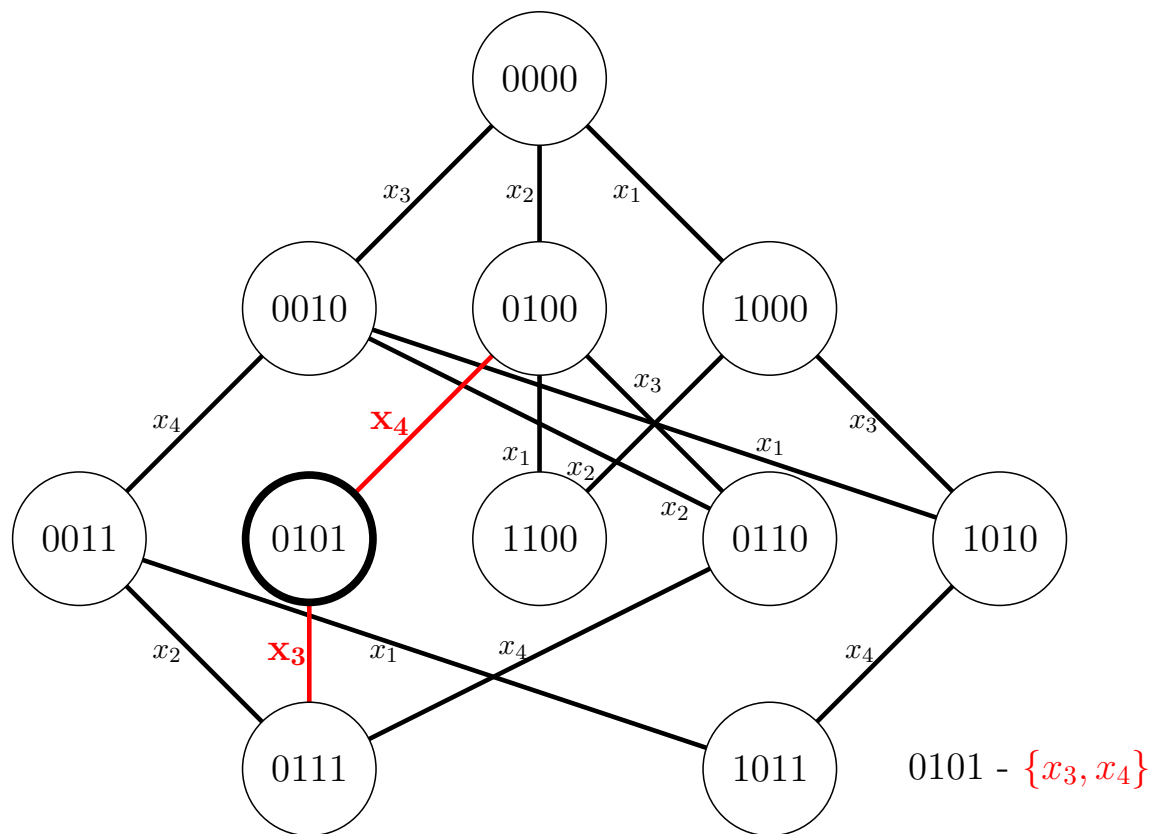
## One-inclusion Graph

- Nodes are concepts
- Edge between two concepts differing on one instance



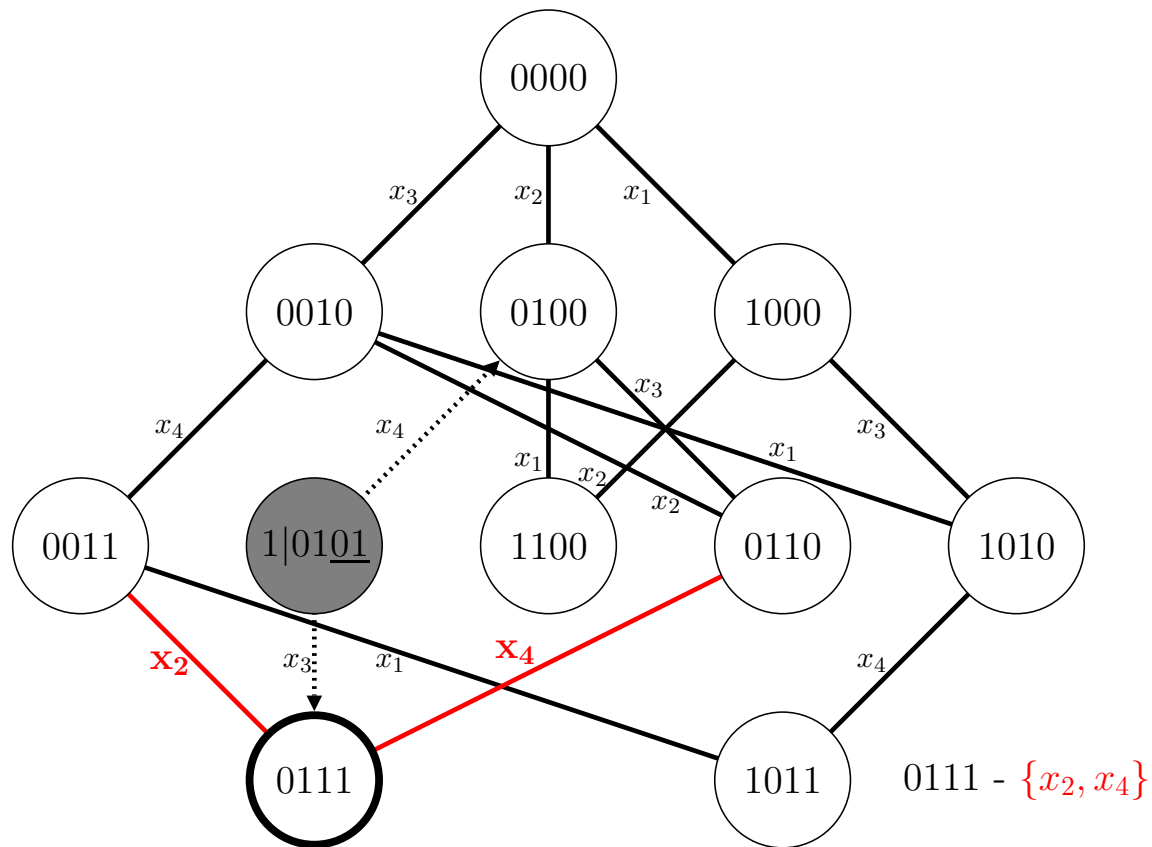
## How to Find Representations

- Peel away any lowest degree vertex
- Labels of incident edges become representation sets



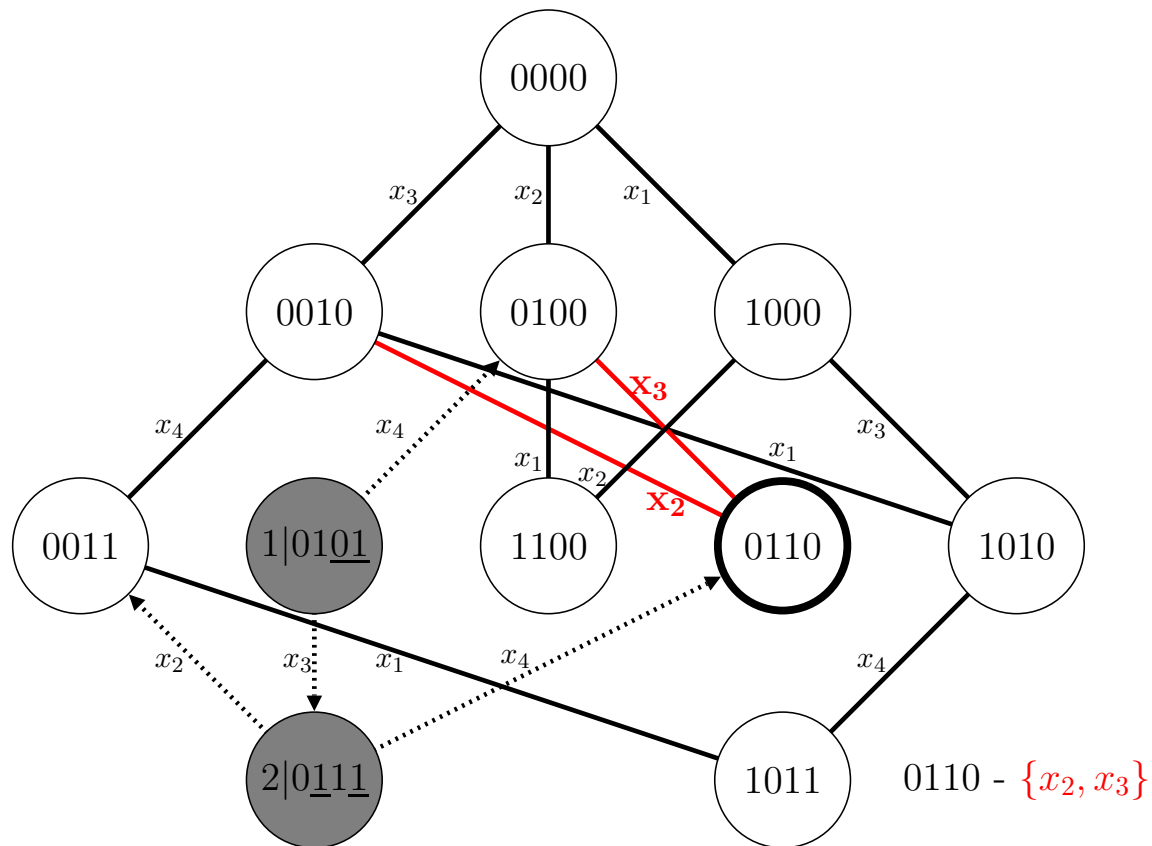
## How to Find Representations

- Now peel away next lowest degree vertex
- Labels of incident edges become representation sets



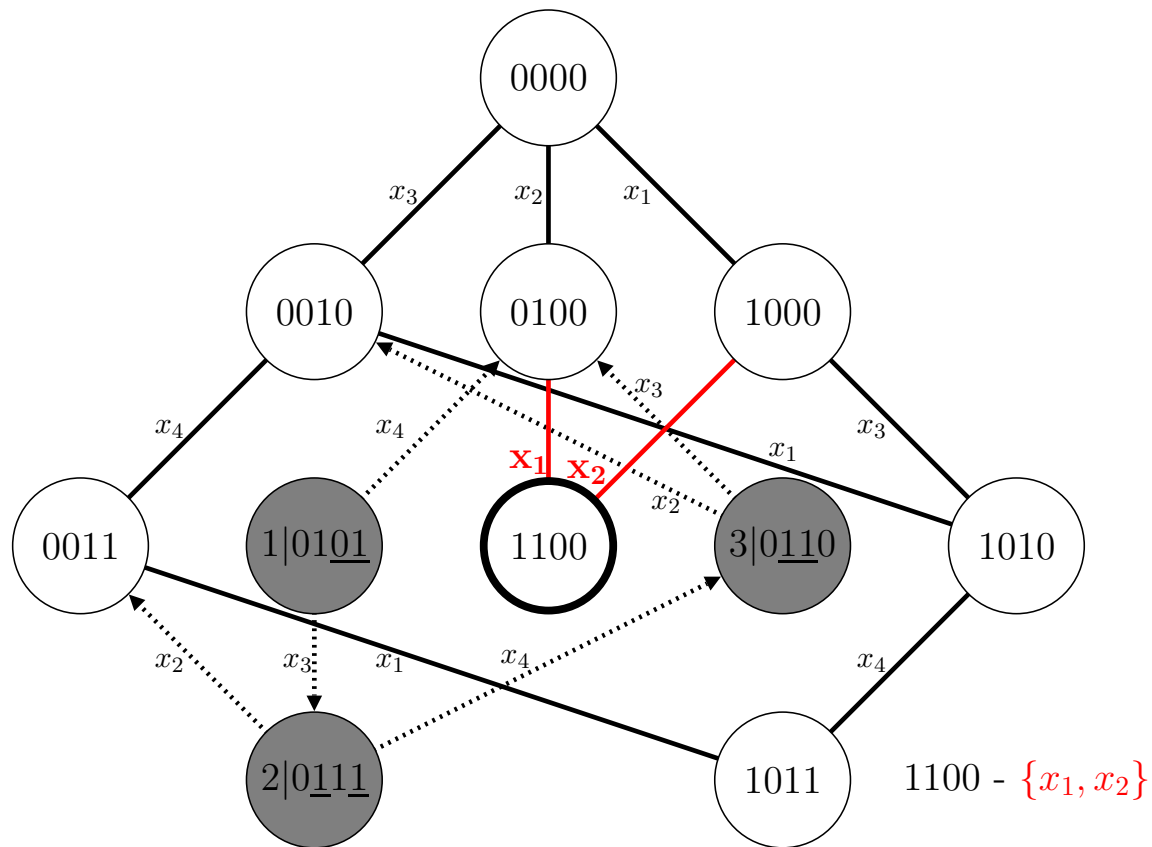
## How to Find Representations

- Now peel away next lowest degree vertex
- Labels of incident edges become representation sets



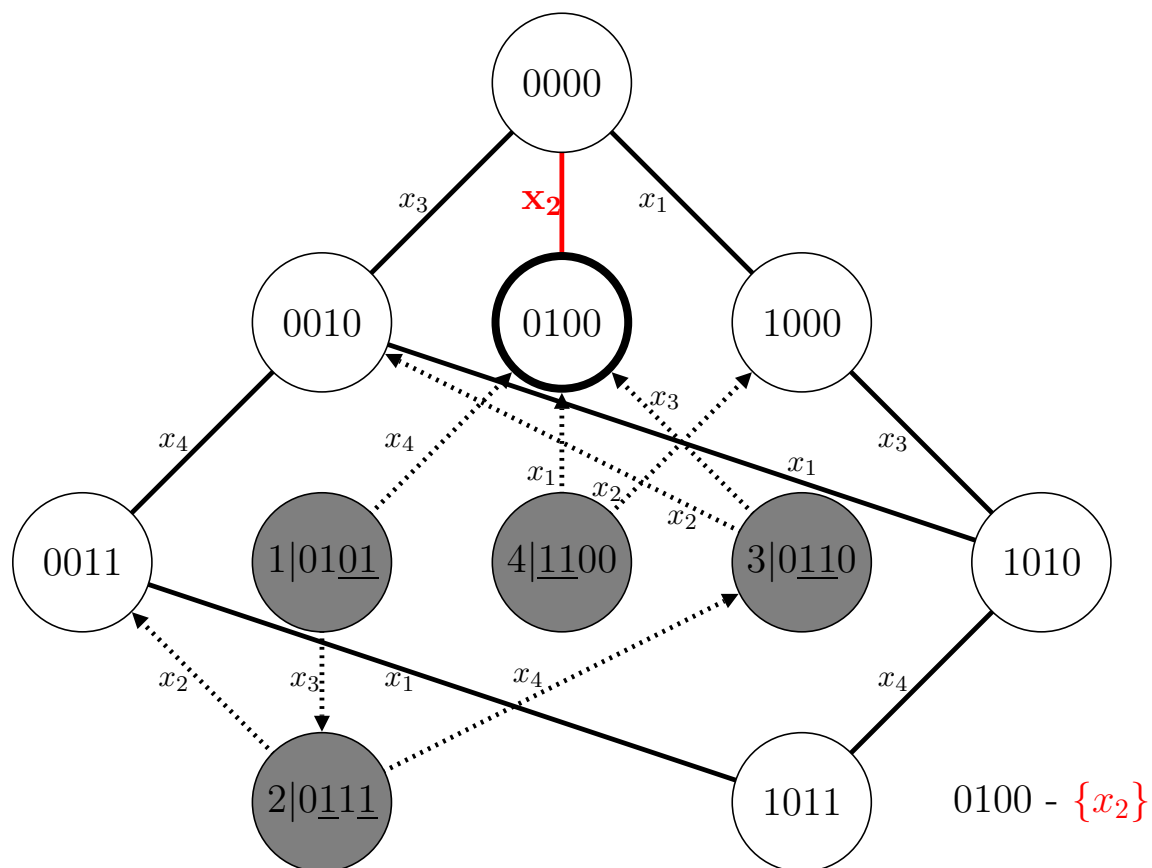
## How to Find Representations

- Now peel away next lowest degree vertex
- Labels of incident edges become representation sets



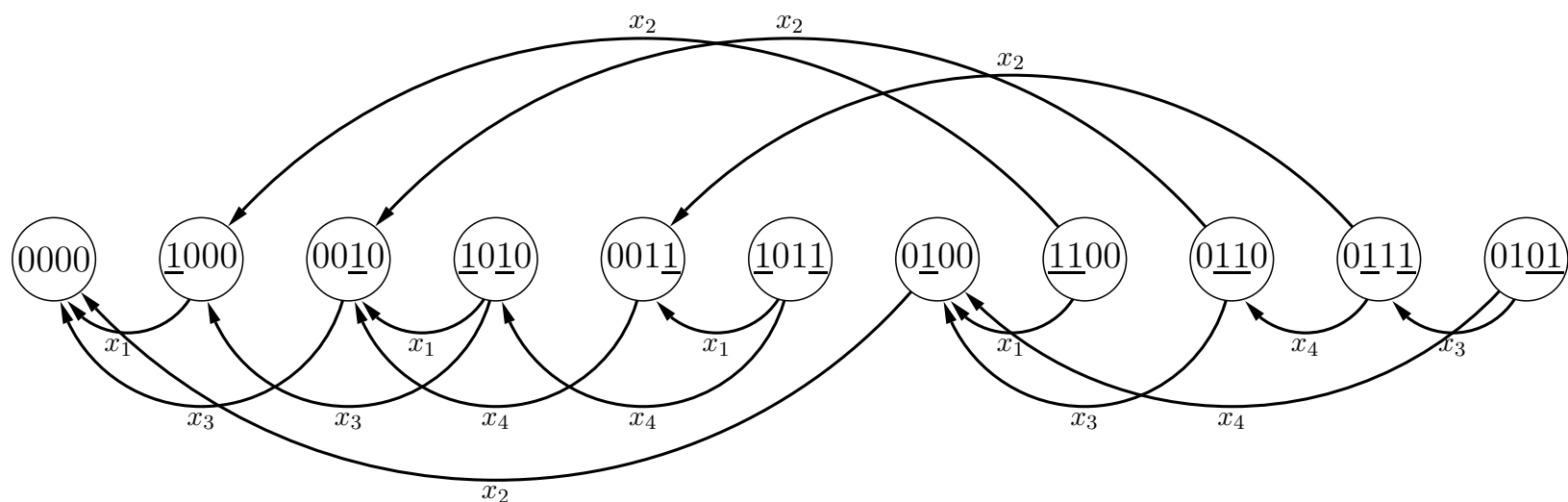
## How to Find Representations

- Now peel away next lowest degree vertex
- Labels of incident edges become representation sets



## The Good and the Bad

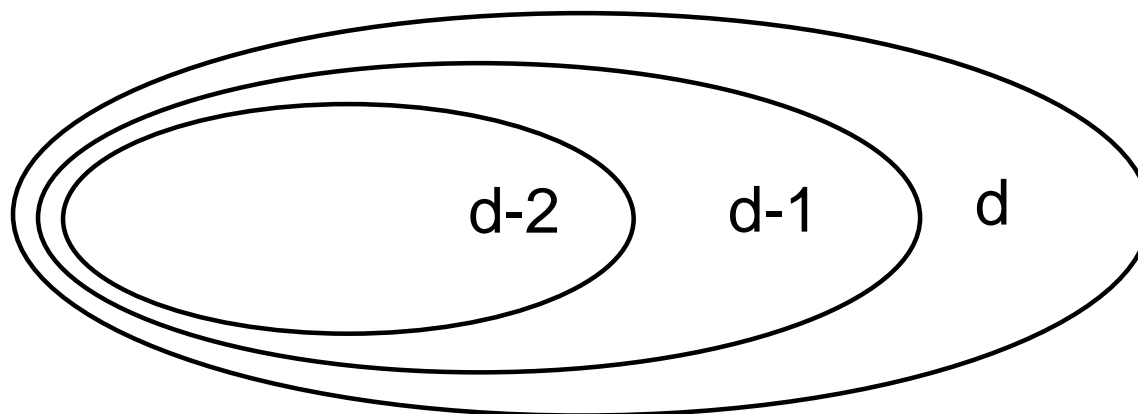
- :-) Algorithm implies a  $d$ -orientation of one-inclusion graph
- :-) Also provides topological order



:-( No proof of correctness for peeling algorithm

## Alternate Recursive Algorithm

- :-) Has correctness proof
- :-) Additional property: for  $k \leq d$ , the concepts that are represented by sets of size up to  $k$  form a maximum class of VC dimension  $k$ .





## Recursive Compression Scheme Algorithm

Goes beyond the scope of this talk! :-)

## Any Unlabeled Scheme Implies $d$ -orientation

$$\begin{array}{ccc} c & \xrightarrow{x} & c' \\ r(c) & & r(c') \end{array}$$

If  $x \in r(c)$ , then  $c \xrightarrow{x} c'$

If  $x \in r(c')$ , then  $c \xleftarrow{x} c'$

No other cases

Provides  $d$ -orientation of the one-inclusion graph

## One-inclusion Graph Algorithm [HLW94]

- Given  $\underbrace{(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_t, y_t)}_{\text{training}}, \underbrace{\mathbf{x}_{t+1}}_{\text{test}}$

Build one-inclusion graph for  $x_1, \dots, x_{t+1}$

- $d$ -orient graph and predict with orientation
- Optimal

## Wrap Up

- Min-degree conjecture: min-degree of one-inclusion graph for concept class with VCdim  $d$  is  $\leq d$
- New **tight** compression scheme for **maximum classes**
- Intricate combinatorics
- Money: Generalizing to **maximal classes**
- Acknowledgements: Sally Floyd and Sanjoy Dasgupta for helpful discussions

## Restriction, Reduction and the Tail

- Restriction  $C - x$  - throw away the  $x$  instance from all concepts
- Reduction  $C^x$  - contains those concepts that differ only on  $x$
- $Tail_x(C)$  - concepts that don't have an  $x$  edge
- $C - x$  is maximum with VCdim  $d$ ,  $C^x$  is maximum with VCdim  $d - 1$
- $C - x = C^x \dot{\cup} (Tail_x(C) - x)$

## Restriction, Reduction and the Tail

	$x_1$	$x_2$	$x_3$	$x_4$						
$c_1$	0	0	0	0						
$c_2$	0	0	1	0	$x_2$	$x_3$	$x_4$			
$c_3$	0	0	1	1	0	0	0			
$c_4$	0	1	0	0	0	1	0	$x_2$	$x_3$	$x_4$
$c_5$	0	1	0	1	0	1	1	0	0	0
$c_6$	0	1	1	0	1	0	0	0	1	0
$c_7$	0	1	1	1	1	0	1	0	1	1
$c_8$	1	0	0	0	1	1	0	1	0	0
$c_9$	1	0	1	0	1	1	1			
$c_{10}$	1	0	1	1						
$c_{11}$	1	1	0	0						
		$C$				$C - x_1$			$C^{x_1}$	

## Forbidden Patterns and Tail Matching

- A forbidden labeling pattern for a set of instances is the one that is not consistent with any concept in class  $C$
- Every tail concept contains some forbidden pattern of size  $d$  for  $C^x$
- Total number of forbidden patterns equal to tail size
- Algorithm idea - assign representatives to the tail that correspond to  $C^x$  forbidden sets. Then clashes with  $C^x$  are automatically prevented
- A matching problem - match tail concepts to forbidden sets