





# PORT SECURITY, ANTHRAX, AND DRUG SAFETY: A DIMACS MEDLEY

David Madigan
Columbia University

## Back in 2001...

Sure Fred. Somebody should make the drug safety people talk to the disease surveillance people but I'm too busy to organize it

Hi David, lets brainstorm on the new special focus on computational epidemiology

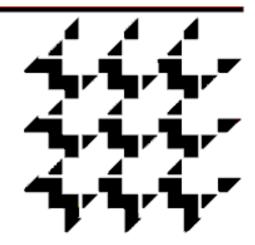
Interesting...

time passes...

arms twisted...

# DIMACS

Center for Discrete Mathematics & Theoretical Computer Science Founded as a National Science Foundation Science and Technology Center



DIMACS Working Group on Adverse Event/Disease Reporting, Surveillance, and Analysis

October 16 - 18, 2002 DIMACS Center, CoRE Building, Rutgers University

#### Organizers:

Donald Hoover, Rutgers, Statistics, <a href="mailto:drhoover@stat.rutgers.edu">drhoover@stat.rutgers.edu</a>
David Madigan, Rutgers, Statistics, <a href="mailto:madigan@stat.rutgers.edu">madigan@stat.rutgers.edu</a>
Henry Rolka, (CDC), <a href="mailto:hrr2@cdc.gov">hrr2@cdc.gov</a>





## Carnegie Mellon



**U.S. Food and Drug Administration**Protecting and Promoting *Your* Health



Los Alamos











NEW YORK CITY DEPARTMENT of HEALTH and MENTAL HYGIENE















HARVARD UNIVERSITY

# Drug Safety + Disease Surveillance



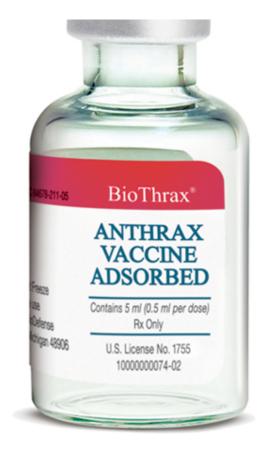
Signal detection methods project

Food and Drug Administration Amendments Act (FDAAA) of 2007



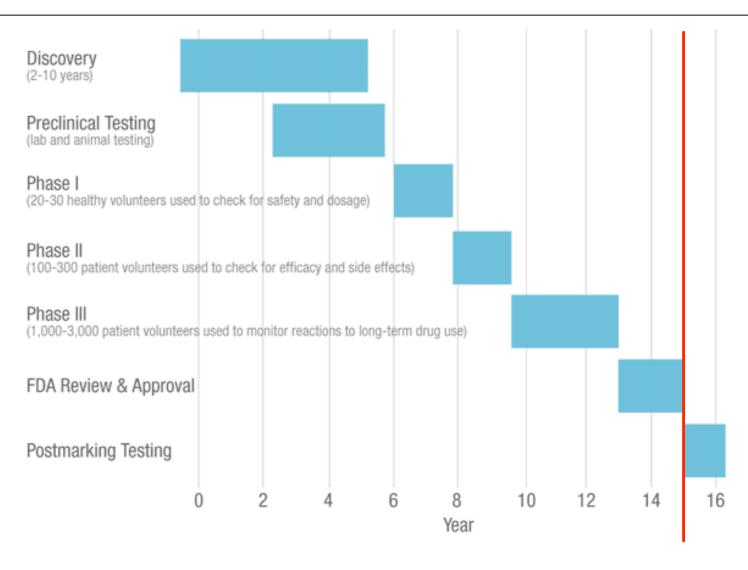


**Observational Medical Outcomes Partnership** 



Welcome to the 2009/2010 OMOP Cup!

# Safety in Lifecycle of a Drug/Biologic product



# Drug Safety Post-Approval

Low quality data

 Extensive use of "data mining" U.S. Department of Health and Human Services

Form Approved: OMB No. 0910-0291, Expires: 10/31/08 See OMB statement on reverse.

#### MEDWATCH

For VOLUNTARY reporting of adverse events, product problems and product use errors

FDA USE ONLY
Triage unit
sequence #

Adverse Event Reporting Program	n Page	_ of		
A. PATIENT INFORMATION		D. SUSPECT PRODU		
Patient Identifier 2. Age at Time of Eve Date of Birth:	mt, or 3. Sex 4. Weight	1. Name, Strength, Manufact	urer (from product lab	al)
In confidence	Male or kg	#1		
B. ADVERSE EVENT, PRODUCT		#2 2. Dose or Amount		
Check all that apply:			Frequenc	y Route
Product Use Error Problem with	blem (e.g., defects/melfunctions) h Different Manufacturer of Same Medicine	#1	$\dashv\vdash$	
Outcomes Attributed to Adverse Event (Check all that apply)		3. Dates of Use (If unknown,	nive divisation) from to	or 5. Event Abated After Use
Death:	Disability or Permanent Damage	best estimate)	gree summers, monero (	Stopped or Dose Reduced?
(mm/dd/yyyy) Life-threatening	Congenital Anomaly/Birth Defect	#1		#1 Yes No Does
Hospitalization - initial or prolonged	Other Serious (Important Medical Events)	A2		A2 Yes No Does
Required Intervention to Prevent Perm	anent Impairment/Damage (Devices)	4. Diagnosis or Reason for U	lse (Indication)	8. Event Reappeared After
Date of Event (mm/dd/)5599)	4. Date of this Report (mm/dd/yyyy)	#1		Reintroduction?
		#2		#1 Yes No Apply
. Describe Event, Problem or Product Use	Error	6. Lot # 7.	Expiration Date	#2 Yes No Doesr
		A1 A	1	9. NDC # or Unique ID
		#2 A	2	
		E. SUSPECT MEDICA 1. Brand Name	L DEVICE	
		2. Common Device Name		
		3. Manufacturer Name, City a	and State	
		4. Model #	Lot #	5. Operator of Device
		Catalog # Expiration Date (mm/35/2007)		(mm/dd/yyyy) Health Professiona
		Serial #	Other #	Other:
		6. If Implanted, Give Date (m	m/dalyyyy) 7. If I	Explanted, Give Date (mm/dd/yyyy)
		8. Is this a Single-use Device Yes No	that was Reprocess	ed and Reused on a Patient?
		9. If Yes to Item No. 8, Enter	Name and Address o	f Reprocessor
. Relevant Tests/Laboratory Data, Includir	no Dotos			
. Nelevant Tests/Laboratory Data, Inciden	ng Danies			
		F. OTHER (CONCOM	ITANT) MEDICAI	L PRODUCTS
		Product names and therapy	dates (exclude treatm	sent of event)
Andrew Reference Little Control of the Control of t				
<ol> <li>Other Relevant History, Including Preexi race, pregnancy, smoking and alcohol use,</li> </ol>	liver/kidney problems, etc.)	G. REPORTER (See	confidentiality s	ection on back)
		1. Name and Address		
		Phone #	E-ma	ail
C. PRODUCT AVAILABILITY		2. Health Professional? 3. C	Decupation	4. Also Reported to:
roduct Available for Evaluation? (Do not a	end product to FDA)	Yes No		Manufacturer
Yes No Returned to N		5. If you do NOT want your is		User Facility
eo _ No _ Heatimed to k	(mm/dd/yyyy)	to the manufacturer, place		☐ Distributos/Importer

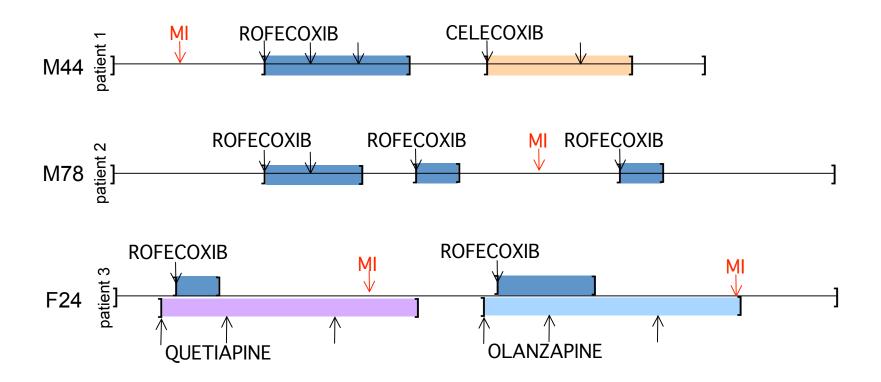
# Problems with Spontaneous Reports

- Under-reporting
- Duplicate reports
- No temporal information
- No denominator

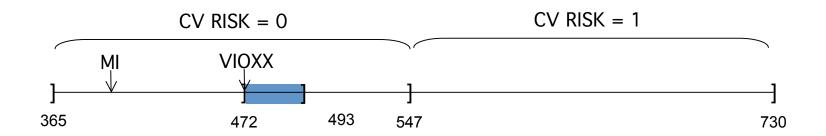
## Newer Data Sources for PV



# Longitudinal Claims Data



### Self Controlled Case Series



- assume diagnoses arise according to a non-homogeneous Poisson process
  - $e^{!_i}$  baseline incidence for subject i
  - $e^{!_{\, 1}}$  relative incidence associated with CV risk group 1
  - $e^{!_1}$  relative incidence associated with Vioxx risk level 1
- $l_1 = 107e^{-1}$  Poisson rate for subject 1, period 1

overall Poisson rate for subject 1:

$$\Lambda = 107e^{\phi_1} + 21e^{\phi_1}e^{\beta_1} + 54e^{\phi_1} + 183e^{\phi_1}e^{\alpha_1}$$

cohort study contribution to the likelihood:

$$(\lambda_1 e^{-\lambda_1}) \times e^{-\lambda_2} \times e^{-\lambda_3} \times e^{-\lambda_4} = \lambda_1 e^{-\Lambda}$$

conditional likelihood:

$$\frac{\lambda_1 e^{-\Lambda}}{\Lambda e^{-\Lambda}} = \frac{\lambda_1}{\Lambda}$$

$$= \frac{107 e^{\phi_1}}{107 e^{\phi_1} + 21 e^{\phi_1} e^{\beta_1} + 54 e^{\phi_1} + 183 e^{\phi_1} e^{\alpha_1}}$$

$$= \frac{107}{107 + 21 e^{\beta_1} + 54 + 183 e^{\alpha_1}}.$$

## Self-Controlled Case Series Method

Farrington et al.

equivalent multinomial likelihood:

$$l(\alpha_1, \beta_1) = \left(\frac{107}{107 + 21e^{\beta_1} + 54 + 183e^{\alpha_1}}\right)^1 \times \left(\frac{21e^{\beta_1}}{107 + 21e^{\beta_1} + 54 + 183e^{\alpha_1}}\right)^0 \times \left(\frac{54}{107 + 21e^{\beta_1} + 54 + 183e^{\alpha_1}}\right)^0 \times \left(\frac{183e^{\alpha_1}}{107 + 21e^{\beta_1} + 54 + 183e^{\alpha_1}}\right)^0$$

regularization => Bayesian approach

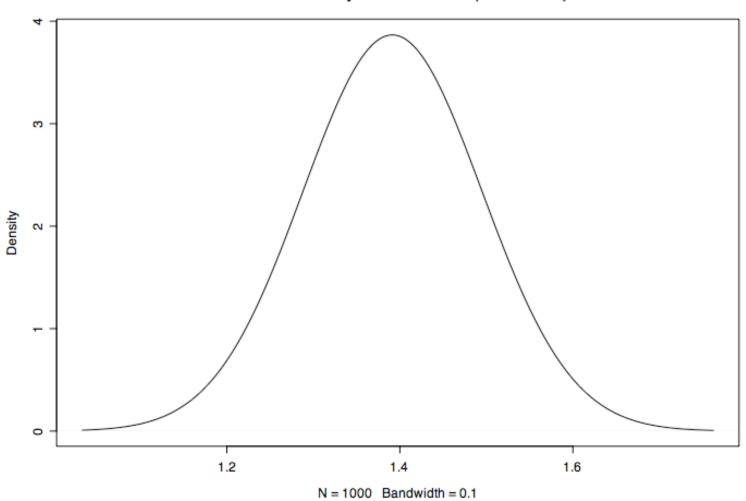
scale to full database?

# Vioxx & MI: SCCS RRs i3 claims database

- Bayesian analysis N(0,10) prior + MCMC
- Overall: 1.38 (n=11,581)
- Male: 1.41 Female: 1.36
- Age >= 80: 1.48
- Male + Age >= 80: 1.68

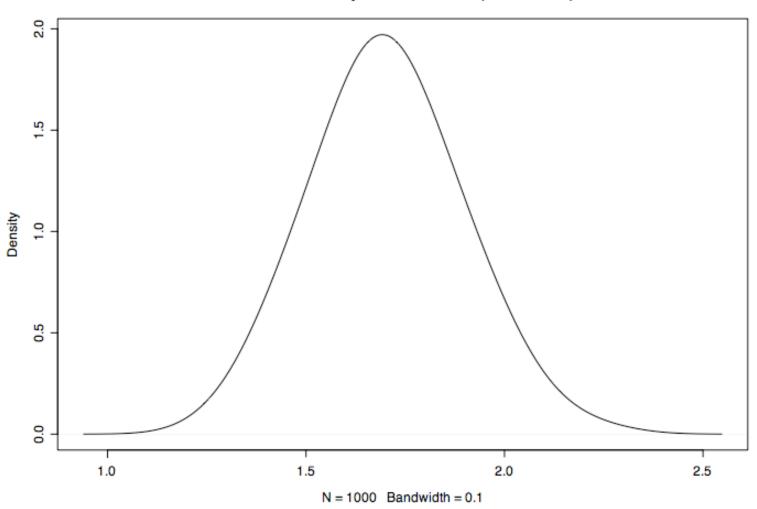
## overall (n=11,581)

#### Posterior Density of Vioxx-MI RR (1000 draws)

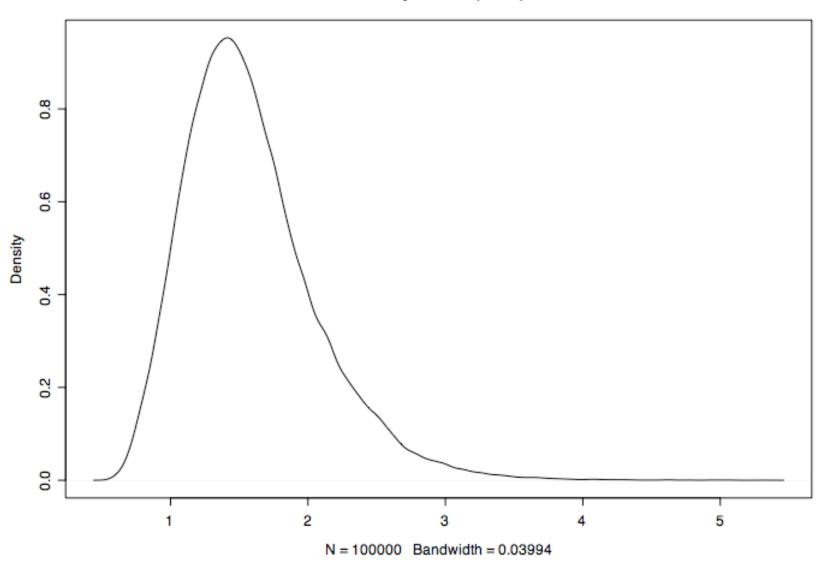


### males 80 and over (n=440)

#### Posterior Density of Vioxx-MI RR (1000 draws)

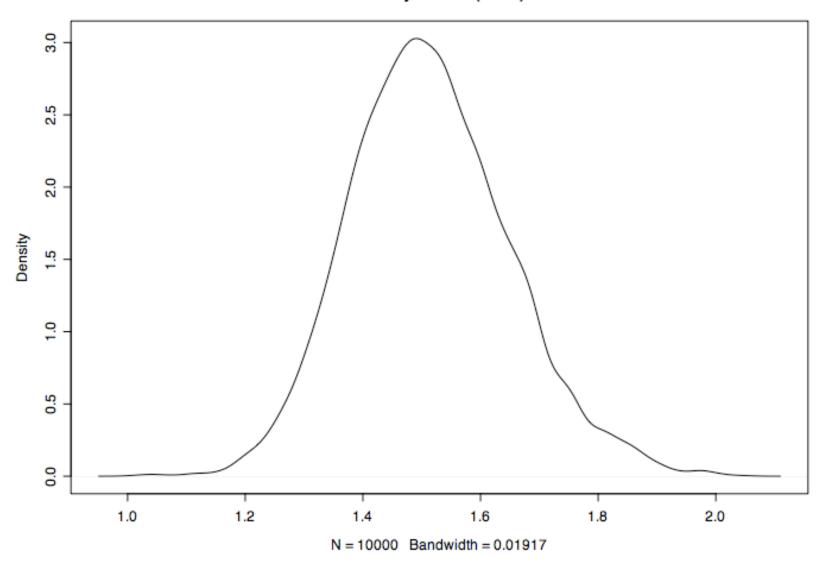


#### density.default(x = b)



June 30, 2000 RR=1.53 Pr(RR>1)=0.92

#### density.default(x = b)



Dec 31, 2000 RR=1.51 Pr(RR>1)=1.0

## The New York Times

### Diabetes Drug Tied to New Deaths

By BLOOMBERG NEWS Published: August 26, 2008

The <u>diabetes</u> drug Byetta, marketed by <u>Eli Lilly & Company</u> and <u>Amylin Pharmaceuticals</u>, was linked to four more deaths in patients with <u>pancreatitis</u>, adding to two deaths announced by federal regulators last week.

#### Add to Portfolio



Go to your Portfolio »

No definite relationship between
Byetta and the deaths has been proved,
and the Food and Drug Administration
was aware of the additional deaths

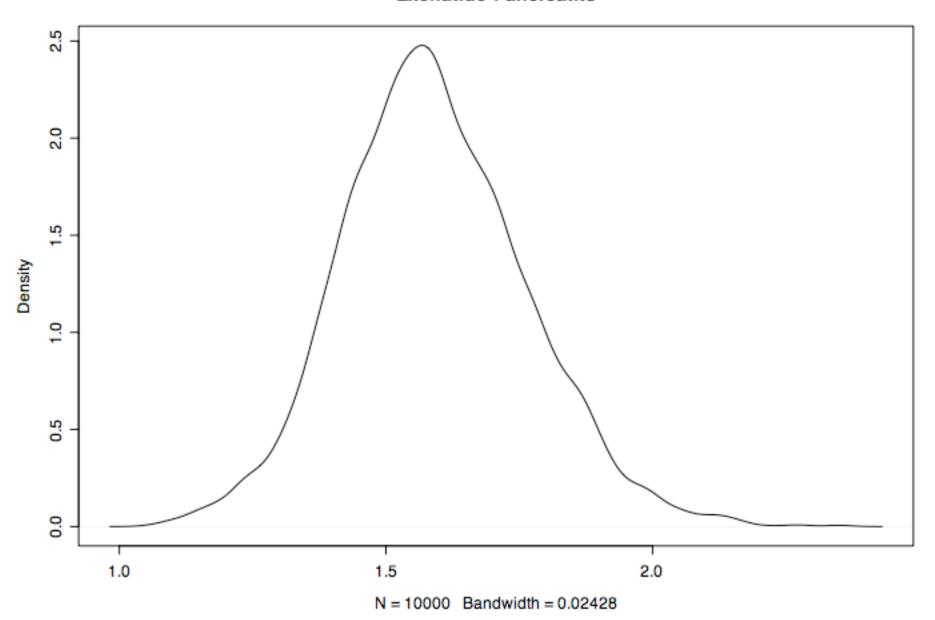
when it made its announcement last week, Amylin's chief executive, Dan Bradbury, said on Tuesday. The company is

talking with the F.D.A. about adding warnings on the drug's prescribing information.

Byetta is Amylin's leading product.



#### **Exenatide-Pancreatits**



## Back in 2004...

Sounds interesting Fred but I'm too busy with the drug safety stuff

Hi David, you might be interested in some of the port security work we are doing

Let me tell you more...

time passes...

arms twisted...

# Port of Entry Inspection Algorithms

Aim: Develop decision support algorithms that will help us to "optimally" intercept illicit materials and weapons subject to limits on delays, manpower, and equipment

Find inspection schemes that minimize total cost including cost of false positives and false negatives



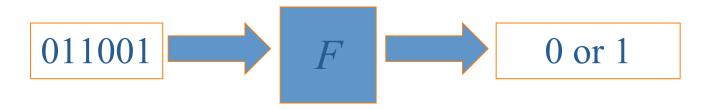
Mobile VACIS: truckmounted gamma ray imaging system

# Sequential Decision Making Problem

- Containers arriving are classified into categories
- Simple case: 0 = "ok", 1 = "suspicious"
- Containers have attributes, either in state 0 or 1
- Sample attributes:
  - Does the ship's manifest set off an alarm?
  - Is the neutron or Gamma emission count above certain threshold?
  - Does a radiograph image return a positive result?
  - Does an induced fission test return a positive result?
- Inspection scheme:
  - specifies which inspections are to be made based on previous observations
- Different "sensors" detect presence or absence of various attributes

# Sequential Decision Making Problem

- Simplest Case: Attributes are in state 0 or 1
- Then: Container is a binary string like 011001
- •So: Classification is a *decision function* F that assigns each binary string to a category.



If attributes 2, 3, and 6 are present, assign container to category F(011001).

# Sequential Decision Making Problem

•If there are two categories, 0 and 1, decision function F is a *Boolean function*.

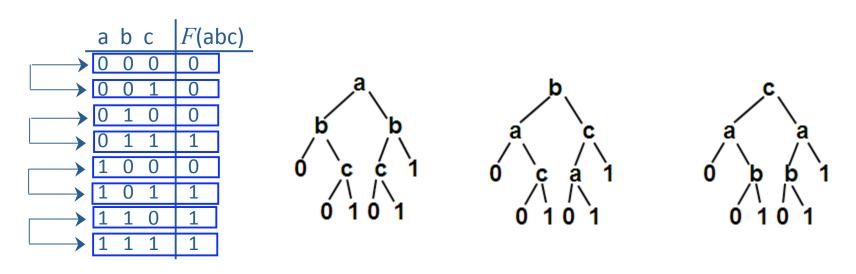
•Example:

a	b	С	F(abc)
0	0	0	0
0	0	1	0
0	1	0	0
0	1	1	1
1	0	0	0
1	0	1	1
1	1	0	1
1	1	1	1

•This function classifies a container as positive iff it has at least two of the attributes.

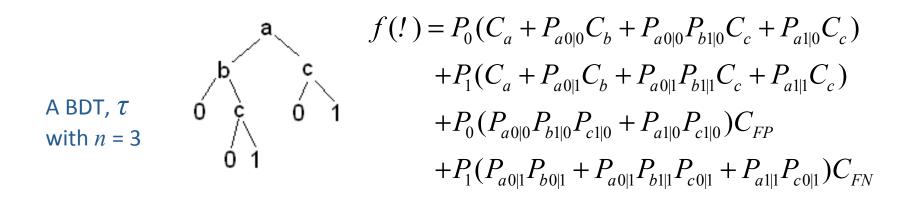
# **Binary Decision Tree Approach**

- Binary Decision Tree:
  - Nodes are sensors or categories (0 or 1)
  - -Two arcs exit from each sensor node, labeled left and right.
  - —Take the right arc when sensor says the attribute is present, left arc otherwise



## Cost of a BDT

- Cost of a BDT comprises of:
  - Cost of utilization of the tree and
  - Cost of misclassification



 $P_1$  is prior probability of occurrence of a bad container

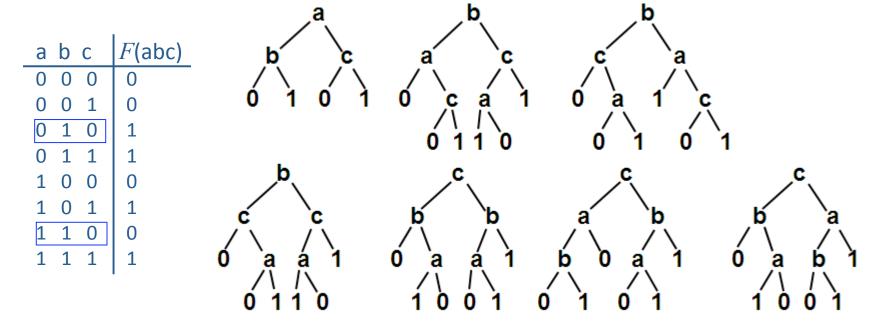
 $P_{i|j}$  is the conditional probability that given the container was in state j, it was classified as i

# **Revisiting Monotonicity**

### Monotonic Decision Trees

 A binary decision tree will be called monotonic if all the left leafs are class "0" and all the right leafs are class "1".

## Example:



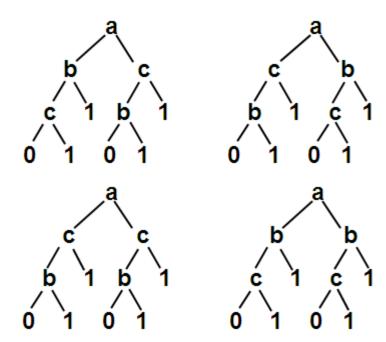
# **Revisiting Completeness**

## Complete Decision Trees

 A binary decision tree will be called complete if every sensor occurs at least once in the tree and at any non-leaf node in the tree, its left and right sub-trees are not identical.

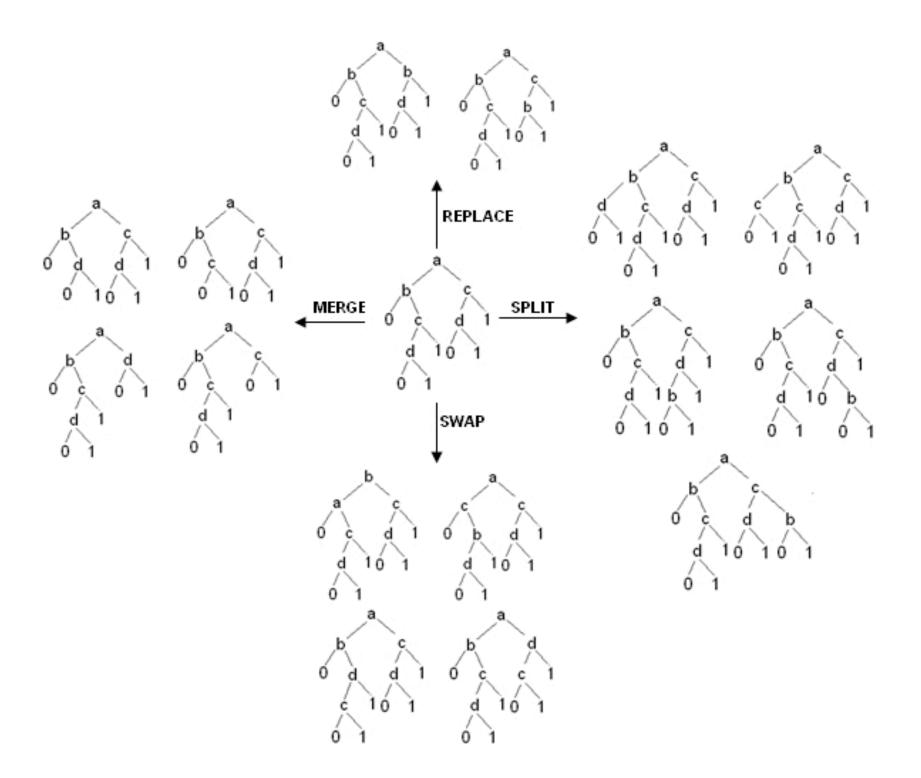
## Example:

а	b	С	<i>F</i> (	abc)
0	0	0	0	
0	0	1	1	
0	1	0	1	
0	1	1	1	
1	0	0	0	
1	0	1	1	
1	1	0	1	
1	1	1	1	



# The CM Tree Space

No. of attributes	Distinct BDTs	Trees From CM Boolean Functions	Complete and Monotonic BDTs
2	74	4	4
3	16,430	60	114
4	1,079,779,602	11,808	66,000



## Tree Space Traversal

## Greedy Search

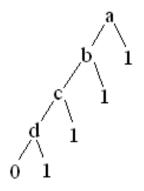
- 1. Randomly start at any tree in the CM tree space
- 2. Find its neighboring trees using neighborhood operations
- 3. Move to the neighbor with the lowest cost
- 4. Iterate till the solution converges
- The CM Tree space has a lot of local minima. For example: 9 in the space of 114 trees for 3 sensors and 193 in the space of 66,000 trees for 4 sensors.

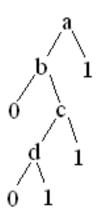
## Proposed Solutions

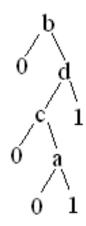
- Stochastic Search Method with Simulated Annealing
- Genetic Algorithms based Search Method

# Tree Space Irreducibility

- We have proved that the CM tree space is irreducible under the neighborhood operations
- Simple Tree:
  - A simple tree is defined as a CM tree in which every sensor occurs exactly once in such a way that there is exactly one path in the tree with all sensors in it.







## Results

- Significant computational savings over previous methods
- Have run experiments with up to 10 sensors
- Genetic algorithms especially useful for larger scale problems

## **Current Work**

- Tree equivalence
- Tree reduction and irreducible trees
- Canonical form representation of the equivalence class of trees
- Revisiting completeness and monotonicity

Thank You!