

# **Statistical Issues Associated With Multi-way Contingency Tables & Links to Algebraic Geometry**

**Stephen E. Fienberg**

**Cylab, Department of Statistics, &**

**Machine Learning Department**

**Carnegie Mellon University**

**&**

**IMA**

**(Joint work with A. Dobra, A. Rinaldo, & Y. Zhou)**

# Preliminaries

- I am an “A” at IMA for *Applications of Algebraic Geometry*.
- This talk:
  - Continuation from last week’s seminar by Serkan Hosten.
    - I won’t provide a notational translation table but I will overlap and give links.
  - Introduction to a number of statistical problems for the analysis of categorical data.

# Overview

**Three data examples and two statistical problems:**

- 1. Bounds for cell counts in contingency tables given marginals.**
- 2. Maximum likelihood estimation for log-linear models and large sparse contingency tables.**

**How are they interrelated?**

**Where do algebraic and other geometry tools fit in?**

**Scaling up computations to deal with large sparse tables.**

# Ex. 1: Risk Factors for Coronary Heart Disease

- 1841 Czech auto workers

Edwards and Havanek (1985)

*Biometrika*

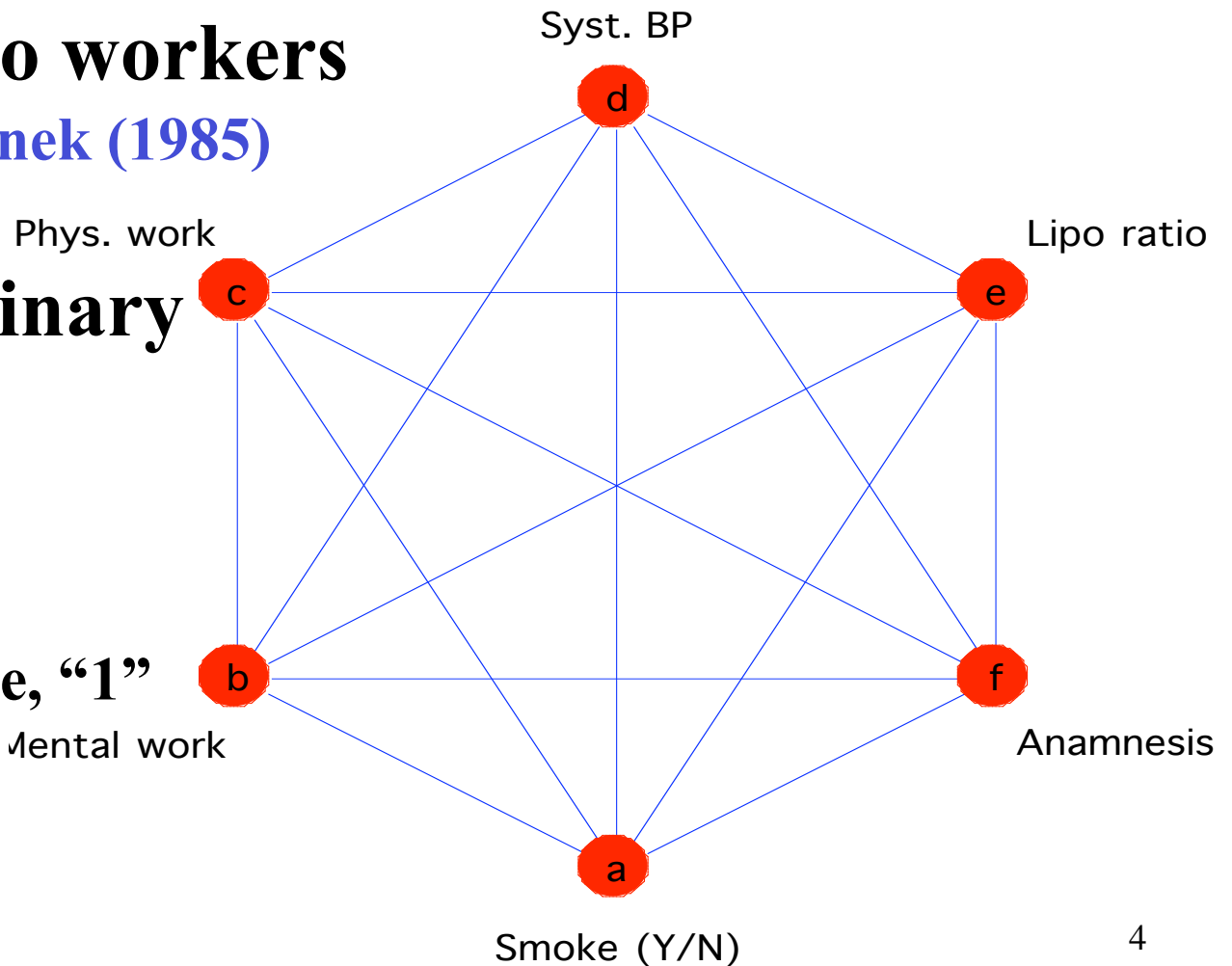
- Selection of 6 binary variables

- $2^6$  table

- “0” cell

- population unique, “1”

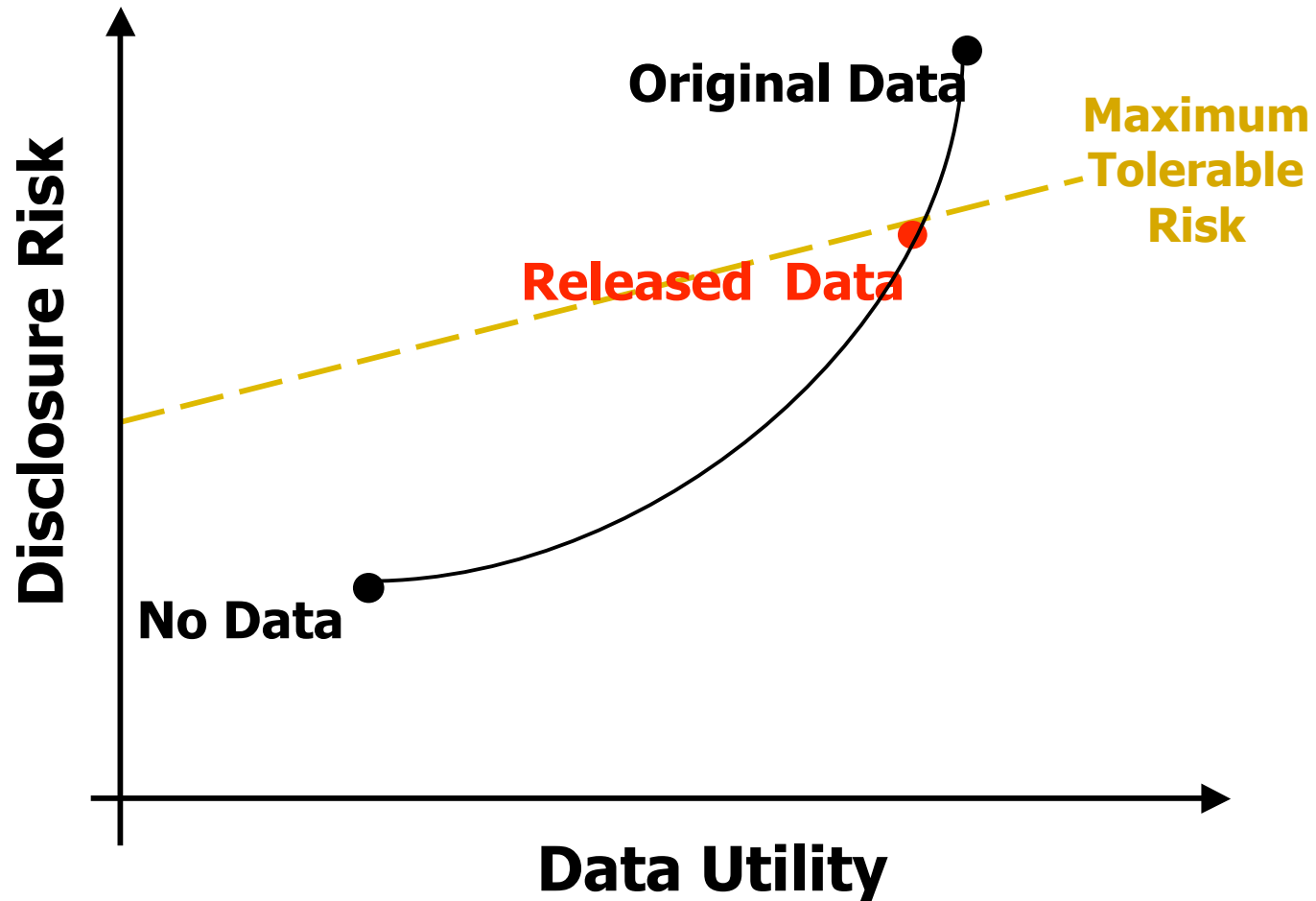
- 2 cells with “2”



# Ex. 1: The Data

F	E	D	C	B	no		yes	
				A	no	yes	no	yes
neg	< 3	< 140	no		44	40	112	67
			yes		129	145	12	23
		no		35	12	80	33	
	≥ 3	< 140	no		109	67	7	9
			yes		23	32	70	66
		no		50	80	7	13	
pos	< 3	< 140	no		24	25	73	57
			yes		51	63	7	16
		no		5	7	21	9	
	≥ 3	< 140	no		9	17	1	4
			yes		4	3	11	8
		no		14	17	5	2	
≥ 140	< 140	no		7	3	14	14	
		yes		9	16	2	3	
	no		4	0	13	11		
		> 140	yes		5	14	4	4

# R-U Confidentiality Map



(Duncan, et al. 2004)

# Disclosure Limitation for Sparse Count Data

- **Uniqueness in population table  $\Leftrightarrow$  cell count of “1”:**
  - Uniqueness allows intruder to match characteristics in table with other data bases **that include same variables** to learn confidential information.
- **Utility typically tied to usefulness of marginal totals for statistical inference.**
- **Risk concerned with small cell counts.**
  - **Assess using bounds for cell counts given marginal totals.**

# Marginals as Data Releases

- Simple summaries corresponding to subsets of variables.
- Traditional mode of reporting for statistical agencies and others.
- **Useful in statistical modeling: Role of log-linear models.**
- *National Institute of Statistical Sciences Project and some of my former students have dealt with other models and other types of releases.*

## Ex. 2: Genetics Linkage

- **Data come from a barley milkdew experiment.**
  - **Edwards (1992). *Comp. Stat. Data Anal.***
  - **37 binary variables (genes) and 81 cases (5% missing data).**
- **Subset of 6 genes that appear closely linked on basis of marginal distributions?**
- **On same chromosome?**

## Ex. 2: The Data

			1		2		1		2		D
			1	2	1	2	1	2	1	2	E
			1	2	1	2	1	2	1	2	F
1	1	1	0	0	0	0	3	0	1	0	
		2	0	1	0	0	0	1	0	0	
	2	1	1	0	1	0	7	1	4	0	
		2	0	0	0	2	1	3	0	11	
2	1	1	16	1	4	0	1	0	0	0	
		2	1	4	1	4	0	0	0	1	
	2	1	0	0	0	0	0	0	0	0	
		2	0	0	0	0	0	0	0	0	
A	B	C									

## Ex. 3: Australian Census Data

- 10-dimensional **highly sparse** contingency table extracted from 1981 Australian population census (based on 10 million people):

Variable	BPL	SEX	AGE	REL	MST	DUR	QAL	INC	FIN	TIS
# Categ.	102	2	11	27	5	62	11	15	16	18

- **892,533,945,600 cells!**

# Collapsed Tables

- **Collapsed 5-way table with 105,600 cells of which 65% are zero**

Variable	BPL	MST	QAL	INC	FIN
# Categ.	8	5	11	15	16

- **Collapsed 6-way table with 48,000 cells of which 41% are zero**

Variable	BPL	SEX	AGE	REL	MST	QAL
# Categ.	8	2	11	5	5	11

# Two Faces of Algebraic Statistics & Contingency Tables

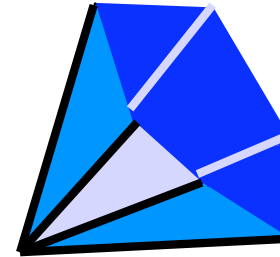
1. **Representation of statistical models for cell probabilities:** Description of **parameter space**.
  - A. Characterizing joint distributions.
  - B. **Log-linear models** including those with “**graphical representation**” via conditional independencies.
2. **Statistical inference:** Studying and characterizing portions of **sample space**:
  - A. **Minimal sufficient statistics** (sufficient data summaries) for models—marginal totals.
  - B. **Maximum likelihood estimation**.
  - C. Distribution over all possible having given marginals (“**exact distribution**”)—**related bounds**.

# Its All About Geometry

- *Polyhedral Geometry*: virtually all data-related quantities can be described by **polyhedra**.

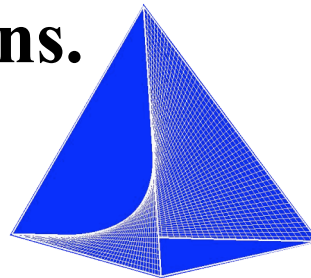


Polytope



Polyhedral  
Cone

- *Algebraic Geometry*: a statistical model is specified by a **polynomial map**. The set of probability distributions is a hyper-surface of points satisfying polynomial equations.



Algebraic  
(Toric)  
Variety

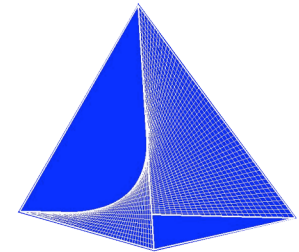
# 2×2 Table: The Model

- We are interested in the distribution of the 4 cells in the table specified by the vector of log probabilities:
- **Model of independence:**  $p_{ij} = p_{i+}p_{+j}$

$p_{11}$	$p_{12}$	$p_{1+}$
$p_{21}$	$p_{22}$	$p_{2+}$
$p_{+1}$	$p_{+2}$	1

$$\log(p_{11}, p_{12}, p_{21}, p_{22}) = A'\theta = (p_{1+}, p_{2+}, p_{+1}, p_{+2})$$

- The set of all probability distributions for model of independence need to satisfy one polynomial equation:  $p_{11}p_{22} - p_{12}p_{21} = 0$ , and belong to surface of independence:



Segre Variety

# 2×2 Table: The Data

Model of independence:  $p_{ij} = p_{i+}p_{+j}$

Observed Counts

$n_{11}$	$n_{12}$
$n_{21}$	$n_{22}$



MSS  
Margins  
 $t = An$

$$t_1 = n_{1+}$$

$$t_2 = n_{2+}$$

$$t_3 = n_{+1}$$

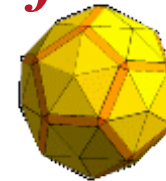
$$t_4 = n_{+2}$$

Design Matrix

$n_{11}$	$n_{12}$	$n_{21}$	$n_{22}$
1	1	0	0
0	0	1	1
1	0	1	0
0	1	0	1

- Set of all tables having margins  $t$  are integer points inside a polytope and form the *fiber*:

$$\{n \in \mathbb{R}_{\geq 0}^4, An = t\}$$



# Design Matrix $A$



**Sample Space**

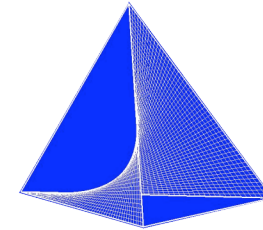
$A$  identifies the fiber: the set of all tables having the same margins:

$$\{x \geq 0, Ax = t\}$$

Leads to the generalized hypergeometric probability distribution.

[Set of all tables are lattice points in the simplex.]

MLE



**Parameter Space**

$A$  specifies the set of polynomial equations that encode the dependence among the variables.

All probability vectors satisfy **binomial** equations:

$$p^{u^+} - p^{u^-} = 0$$

all integer  $u \in \text{kernel}(A)$ .

# Maximum Likelihood Estimation

- Distribution for  $n$  given  $p$ :

$$f(n | p) \propto p_{11}^{n_{11}} p_{12}^{n_{12}} p_{21}^{n_{21}} p_{22}^{n_{22}}$$

- For **model of independence**:  $p_{ij} = p_{i+} p_{+j}$  minimal sufficient statistics for parameters are:

- $t = An = (n_{1+}, n_{2+}, n_{+1}, n_{+2})$

- **Maximum likelihood equations**:

- $p_{i+} = n_{i+}/n$   $i = 1, 2$ ;  $p_{+j} = n_{+j}/n$   $j = 1, 2$ .

- **Solution (MLEs)**:  $\hat{p}_{ij} = n_{i+} n_{+j} / n^2$ .

- **Rescale by total  $n$  to count scale  $np_{ij} = m_{ij}$** :

$$\hat{m}_{ij} = n_{i+} n_{+j} / n.$$

# Two-Way Fréchet Bounds

- For  $2 \times 2$  tables of counts  $\{n_{ij}\}$  given the marginal totals  $\{n_{1+}, n_{2+}\}$  and  $\{n_{+1}, n_{+2}\}$ :

$$\begin{array}{cc|c} n_{11} & n_{12} & n_{1+} \\ n_{21} & n_{22} & n_{2+} \\ \hline n_{+1} & n_{+2} & n \end{array}$$

$$\min(n_{i+}, n_{+j}) \geq n_{ij} \geq \max(n_{i+} + n_{+j} - n, 0)$$

- Link to independence:  $\hat{m}_{ij} = n_{i+}n_{+j}/n$ .
- Interested in multi-way generalizations involving higher-order, overlapping margins.

# Log-linear Models for $2^3$ Tables

- In 3-way table of counts,  $\{n_{ijk}\}$ , we model logarithms of expectations,  $E(n_{ijk})=m_{ijk} > 0$ :

$$\log(m_{ijk}) = u + u_{1(i)} + u_{2(j)} + u_{3(k)} + u_{12(ij)} + u_{13(ik)} + u_{23(jk)}$$

- **MSSs** are margins corresponding to highest order  $u$ -terms:  $\{n_{ij+}\}$ ,  $\{n_{i+k}\}$ ,  $\{n_{+jk}\}$ .
  - MSSs describe *simplicial complex*: [12][13][23].
- Alternative ways to write model:

$$m_{ijk} = \alpha_{ij} \beta_{ik} \gamma_{jk}$$

$$\frac{m_{111} m_{221}}{m_{121} m_{211}} = \frac{m_{112} m_{222}}{m_{122} m_{212}}$$

$$m_{111} m_{221} m_{122} m_{212} - m_{121} m_{211} m_{112} m_{222} = 0$$

# Log-linear Models (cont.)

- Maximum likelihood estimates (MLEs) found by setting MSSs equal to their expectations:

$$\hat{m}_{ij+} = n_{ij+} \quad \text{for } i = 1, 2, j = 1, 2,$$

$$\hat{m}_{+jk} = n_{+jk} \quad \text{for } j = 1, 2, k = 1, 2,$$

$$\hat{m}_{i+k} = n_{i+k} \quad \text{for } i = 1, 2, k = 1, 2.$$

- Set:  $m_{ijk} = n_{ijk} \pm \delta$
- Solve cubic equation for  $\delta$ :

$$m_{111}m_{221}m_{122}m_{212} - m_{121}m_{211}m_{112}m_{222} = 0$$

- When do we get +ve solutions for  $\{m_{ijk}\}$ ?

# Existence of MLEs for 2×2×2 Table

$0 + \delta$	$n_{121} - \delta$	$n_{1+1}$	$n_{112} - \delta$	$n_{122} + \delta$	$n_{1+2}$
$n_{211} - \delta$	$n_{221} + \delta$	$n_{2+1}$	$n_{212} + \delta$	$0 - \delta$	$n_{2+2}$
$n_{+11}$	$n_{+21}$	$n_{++1}$	$n_{+12}$	$n_{+22}$	$n_{++2}$
		$n_{11+}$	$n_{12+}$		
		$n_{21+}$	$n_{22+}$		

**Delta must be zero and MLE doesn't exist.**

# Two Other 3-Way Examples With [12][13][23]

- $3^3$  table where MLE exists

3	0	0	0	0	1	0	1	0
0	4	0	5	0	0	0	0	5
0	0	4	0	2	0	3	0	0

- $4^3$  table where MLE does not exist

0	0	0	4	4	0	0	2	1	5	0	2	1	5	3	2
0	0	1	2	5	0	5	2	5	3	4	2	0	0	2	0
0	1	2	3	5	6	5	2	0	2	0	0	0	2	4	0
5	1	2	3	1	0	0	0	1	2	0	0	1	2	3	0

# MLEs for Log-Linear Models for $k$ -Way Tables

- Log-linear models and algebraic geometry representations generalize.
- Sampling distributions for  $f(n | p)$  are key!
  - ML equations then have similar form.
- Existence of MLEs linked to pattern of zeros:
  - Discoverable by defining basis for models and using algebraic and polyhedral geometry.
  - Examples discovered using *Polymake*.
- General theorem in Haberman (1974) and “constructive” version in Rinaldo (2005).

# Graphical & Decomposable Log-linear Models

- *Graphical log-linear models*: defined by simultaneous conditional independence relationships:

- **Absence of edges in graph.**

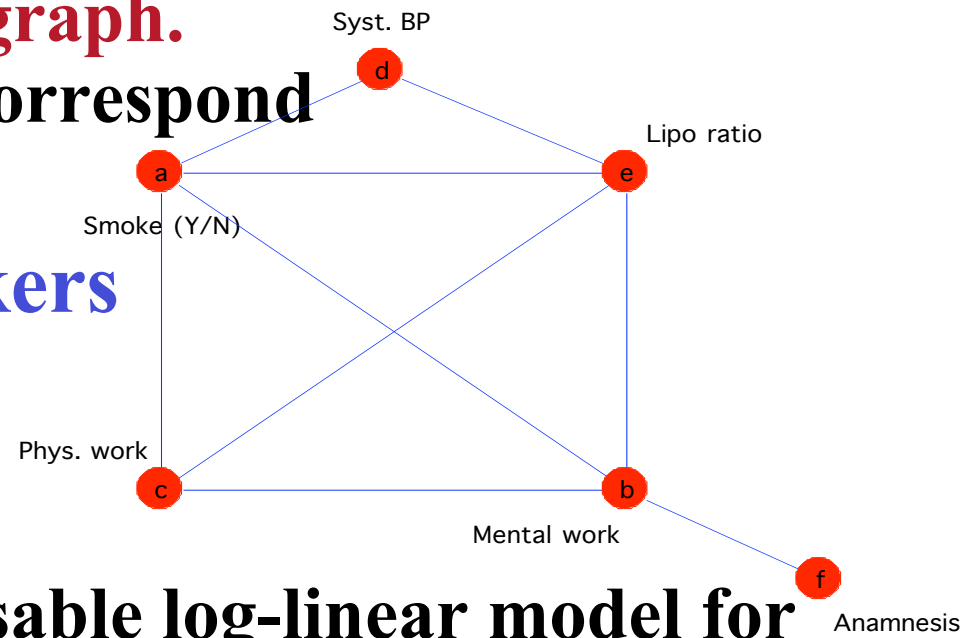
- *Decomposable models* correspond to triangulated graphs.

## Ex. 1: Czech autoworkers

- **Graph has 3 cliques:**

**[ADE][ABCE][BF]**

- “Interesting” decomposable log-linear model for data!



# MLEs for Decomposable Log-linear Models

- For decomposable models, expected cell values are explicit function of margins, corresponding to highest order terms in model (*cliques* in graph):

$$\text{Expected Value} = \frac{\prod \text{MSSs}}{\prod \text{Separators}}$$

– e.g., cond. indep. in 3-way table:  $m_{ijk} = \frac{m_{ij+} m_{i+k}}{m_{i++}}$

- Substitute observed margins for expected in explicit formula to get MLEs.
  - **Hosten: ML degree 1.**

# Bounds for $k$ -way Table Entries Given Set of Marginals

- **Methods for several special cases:**
  - When margins corresponding to decomposable models, bounds have explicit formulae.
  - When margins corresponding to reducible graphs, calculation can be broken up into smaller problems.
  - Simple bounds result for  $2^k$  tables with release of all  $(k-1)$ -dimensional margins fixed.
- **General, less efficient methods for searching over lattice points of convex polytope:**
  - Integer programming; MCMC with Groebner bases; general shuttle algorithm (Dobra, 2001).

# 2<sup>3</sup> Table Given 2×2 Margins

$n_{111}$	$n_{121}$	$n_{1+1}$	$n_{112}$	$n_{122}$	$n_{1+2}$
$n_{211}$	$n_{221}$	$n_{2+1}$	$n_{212}$	$n_{222}$	$n_{2+2}$
$n_{+11}$	$n_{+21}$	$n_{++1}$	$n_{+12}$	$n_{+22}$	$n_{++2}$
	$n_{11+}$	$n_{12+}$			
	$n_{21+}$	$n_{22+}$			

- Obvious upper and lower bounds for  $n_{111}$
- Extra upper bound:  $n_{111} + n_{222}$

# Multi-way Bounds

- For decomposable log-linear models:

$$\text{Expected Value} = \frac{\prod MSSs}{\prod Separators}$$

- ***Theorem***: When released margins correspond to those of decomposable model:
  - *Upper bound*: minimum of values from relevant margins.
  - *Lower bound*: maximum of zero, or sum of values from relevant margins minus separators.
  - Bounds are sharp. [Fienberg and Dobra \(2000\)](#)
  - [Link to Markov bases in Diaconis and Sturmfels \(1998\)](#).

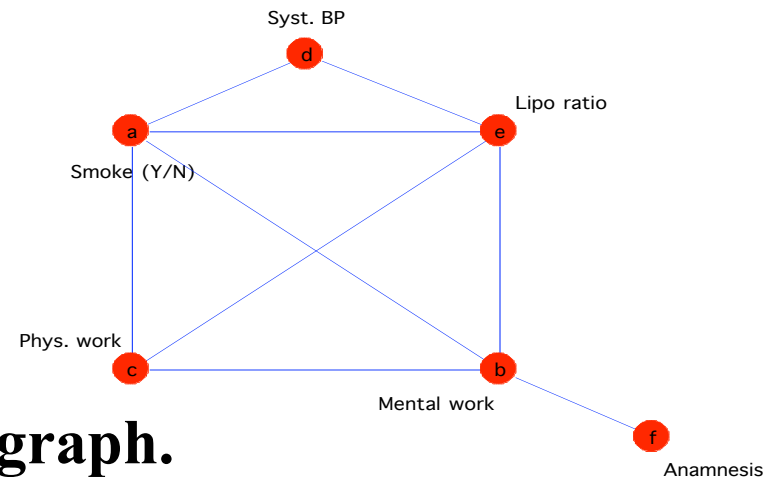
# Ex. 1: Czech Autoworkers

- Released margins:

**[ADE][ABCE][BF]**

- Correspond to decomposable graph.
- Cell containing population unique has bounds  $[0, 25]$ .
- Cells with entry of “2” have bounds:  $[0,20]$  and  $[0,38]$ .
- Lower bounds are all “0”.

- “**Safe**” to release these margins; low risk of disclosure.



# Bounds for [BF][ABCE][ADE]

F	E	D	C	B		yes		
				A	no	no	yes	
neg	< 3	< 140	no		[0,88]	[0,62]	[0,224]	[0,117]
			yes	[0,261]	[0,246]	[0,25]	[0,38]	
			no	[0,88]	[0,62]	[0,224]	[0,117]	
		≥ 3	< 140	yes	[0,261]	[0,151]	[0,25]	[0,38]
				no	[0,58]	[0,60]	[0,170]	[0,148]
				yes	[0,115]	[0,173]	[0,20]	[0,36]
	≥ 140	no	no	[0,58]	[0,60]	[0,170]	[0,148]	
			yes	[0,115]	[0,173]	[0,20]	[0,36]	
			yes	[0,115]	[0,173]	[0,20]	[0,36]	
		< 3	< 140	no	[0,88]	[0,62]	[0,126]	[0,117]
				yes	[0,134]	[0,134]	[0,25]	[0,38]
				no	[0,88]	[0,62]	[0,126]	[0,117]
≥ 3	< 140	yes	[0,134]	[0,134]	[0,25]	[0,38]		
		no	[0,58]	[0,60]	[0,126]	[0,126]		
		yes	[0,115]	[0,134]	[0,20]	[0,36]		
≥ 140	no	no	[0,58]	[0,60]	[0,126]	[0,126]		
		yes	[0,115]	[0,134]	[0,20]	[0,36]		

# Ex. 1: Counting Tables

- **How many tables are there with various sets of given marginals?**
  - For release of only the 15 two-way margins there are 705,884 possible tables, although many of these may correspond to same bounds! [via [4ti2](#)]
  - For [ACDEF][ABDEF][ABCDE][BCDF][ABCF][BCEF] There are only 810 tables.
  - For release of all 5-way margins, there are only 2 tables!
    - Almost identical upper and lower values; they all differ by 1.

## Ex. 1: What to Release?

- Among all 32,000+ decomposable models, the tightest possible bounds for three target cells are: (0,3), (0,6), (0,3).
  - 31 models with these bounds! All involve [ACDEF].
  - Another 30 models have bounds that differ by 5 or less and these involve [ABCDE].
- If treat everything else as safe, i.e., we release [ACDE][ABCDF][ABCEF][BCDEF][ABDEF]
  - Can fit all reasonable models including our “favorite” one: [ADE][ABCE][BF].

# Ex. 2: Genetic Linkage Data

			1		2		1		2		D
			1	2	1	2	1	2	1	2	E
			1	2	1	2	1	2	1	2	F
1	1	1	0	0	0	0	3	0	1	0	
		2	0	1	0	0	0	1	0	0	
	2	1	1	0	1	0	7	1	4	0	
		2	0	0	0	2	1	3	0	11	
2	1	1	16	1	4	0	1	0	0	0	
		2	1	4	1	4	0	0	0	1	
	2	1	0	0	0	0	0	0	0	0	
		2	0	0	0	0	0	0	0	0	
A	B	C									

## Ex. 2: Existence of MLEs?

- When we fit model corresponding to  
**[ACD][ADE][ADF][CE][CF][EF][BCD]**  
**[BDE][BDF]**

			1		2		1		2		D
			1	2	1	2	1	2	1	2	E
			1	2	1	2	1	2	1	2	F
1	1	1	0	0	0	0	+	0	+	0	
		2	0	+	0	0	0	+	0	0	
	2	1	+	0	+	0	+	+	+	0	
		2	0	0	0	+	+	+	0	+	
2	1	1	+	+	+	0	+	0	0	0	
		2	+	+	+	+	0	0	0	+	
	2	1	0	0	0	0	0	0	0	0	
		2	0	0	0	0	0	0	0	0	
A	B	C									

## Ex. 2: Cont.

- For [ACD][ADE][ADF][CE][CF][EF][BCD][BDE][BDF] there are 42 problematic zero cells:
  - Detected by generalized shuttle algorithm for bounds and verified by MLE software.
  - Correspond to zeros in all 255,880 tables.
  - **Extended MLE exists here.**
- For no-2nd-order interaction model there are 15 MSS marginals and no problematic zeros.
  - Based on shuttle algorithm and verified by MLE software.
  - 8,628,046 tables.

# Discovering Non-Existence Using Bounds

- **Replace positive counts by counts of 1.**
- **Run bounds algorithm and/or LP on 0-1 table.**
  - Look for: **upper bound = lower bound = 0.**
  - Fractional LP bounds may not detect non-existence.
- **Compare with methods for detecting non-existence of MLEs.**
  - Is bounds software simpler than MLE software?

# Degenerate MLE

- Fixing all 15 positive 3-way margins produces following bounds using integer programming procedure in “*lp solve*”:

			1		2		1		2		D
			1	2	1	2	1	2	1	2	E
A	B	C	1	2	1	2	1	2	1	2	F
1	1	1	[0, 1]	[0, 0]	[0, 2]	[0, 0]	[1, 4]	[0, 1]	[0, 2]	[0, 1]	
		2	[0, 0]	[0, 2]	[0, 0]	[0, 2]	[0, 1]	[0, 2]	[0, 1]	[0, 1]	
	2	1	[0, 1]	[0, 0]	[0, 2]	[0, 0]	[6, 9]	[0, 1]	[1, 4]	[0, 1]	
		2	[0, 0]	[0, 1]	[0, 0]	[0, 2]	[0, 1]	[1, 4]	[0, 1]	[9, 12]	
2	1	1	[15, 18]	[0, 1]	[0, 4]	[0, 1]	[0, 1]	[0, 0]	[0, 1]	[0, 0]	
		2	[0, 1]	[2, 5]	[1, 2]	[1, 5]	[0, 0]	[0, 1]	[0, 0]	[0, 1]	
	2	1	[0, 1]	[0, 0]	[0, 2]	[0, 1]	[0, 1]	[0, 0]	[0, 1]	[0, 0]	
		2	[0, 0]	[0, 1]	[0, 1]	[0, 2]	[0, 0]	[0, 1]	[0, 0]	[0, 1]	

## Ex. 3: Collapsed Tables

- Collapsed 5-way table with 105,600 cells of which 65% are zero

Variable	BPL	MST	QAL	INC	FIN
# Categ.	8	5	11	15	16

- Collapsed 6-way table with 48,000 cells of which 41% are zero

Variable	BPL	SEX	AGE	REL	MST	QAL
# Categ.	8	2	11	5	5	11

## **Ex. 3: 5-way Table**

- **Table has 105,600 cells; 65% are 0.**
  - We set counts in all positive cells = 1 to simplify the problem.
- **Then we use LP to find upper bounds of cells when all the 2-way margins are fixed.**
  - We can run the LP solver for the table cells in parallel.
  - In our experiment, we used cluster of 64 processors and it took about 4 hours.
  - Upper bounds of the cells are all positive, so there are no structural zeros found for this 5-way table.

## Ex. 3: 6-way Table

- **Table has 48,400 cells and 41% have zero cells.**
  - Use 0-1 representation again.
  - Fixed all 2-way margins.
  - All upper bounds found are positive—MLEs exist.
  - Took about 1 hour on the cluster of 64 processors.
- **Issue: Can we scale to larger models and bigger tables.**

# Summary

- **What do we mean by sparseness:**
  - 3 examples of contingency tables; 2 sparse.
- **Statistical problems involving log-linear models:**
  - **Confidentiality & bounds for cell entries in tables.**
  - **Existence of MLEs for contingency tables.**
- **Role of computational algebraic and polyhedral geometry**
- **Exploring linkages between bounds and MLEs.**
- **Undone: Scaling up computations.**

# The End

- **Many related papers available for downloading at**
  - [www.niss.org](http://www.niss.org)
  - [www.stat.cmu.edu/~fienberg/DLindex.html](http://www.stat.cmu.edu/~fienberg/DLindex.html)
  - [www.stat.washington.edu/adobra/html/research.html](http://www.stat.washington.edu/adobra/html/research.html)
  - [www.stat.cmu.edu/~arinaldo](http://www.stat.cmu.edu/~arinaldo)

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# *Warning:* Bounds and Gaps

- **Bounds may not be sufficient to understand degree of protection for confidentiality.**
  - Gaps in range of values for specific cells are possible!
- **Consider possible  $6 \times 4 \times 3$  tables:**
  - Specify values for (1,1,1) cell: 0 and 2 (with gap at 1).
  - Can construct margins for which gaps are realized:

2	1	1	0
1	0	0	1
2	2	0	0
0	0	2	2
2	0	2	0
0	2	0	2

2	2	0
1	1	0
2	0	2
3	0	1
0	2	0
0	1	3

2	3	2
2	1	2
2	1	2
2	1	2

deLoera & Ohn (2006)  
*J. Symb. Comp.*