Confidentiality Protection and Utility for Contingency Table Data

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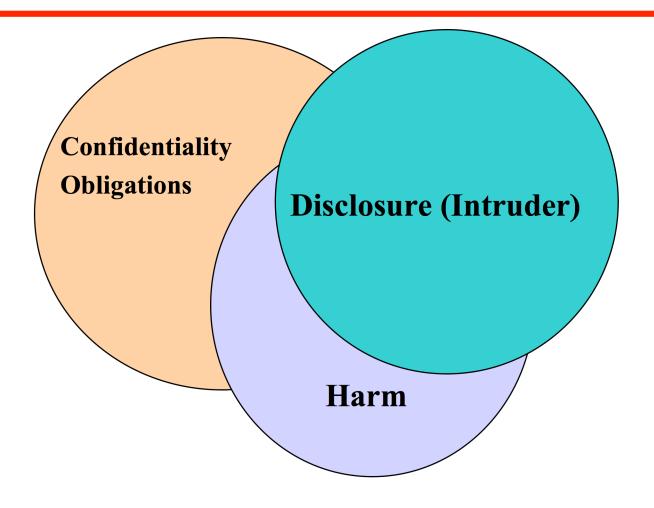
(Joint work with A. Dobra, A. Rinaldo, and Y. Zhou)

Outline

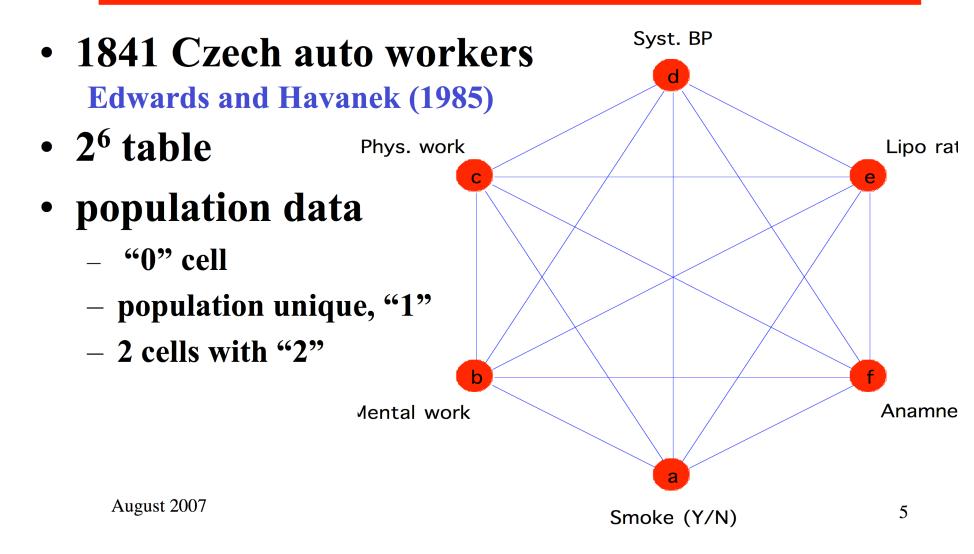
- Privacy and confidentiality
 - Focus individual data (not establishment data)
- Three examples and two problems:
 - 1. Bounds for cell counts in contingency tables given marginals.
 - 2. Maximum likelihood estimation for log-linear models.
 - How are they interrelated?
 - What are the mathematical tools? (No details!)
 - Scaling up computations for large sparse tables.



Issues and Linkages

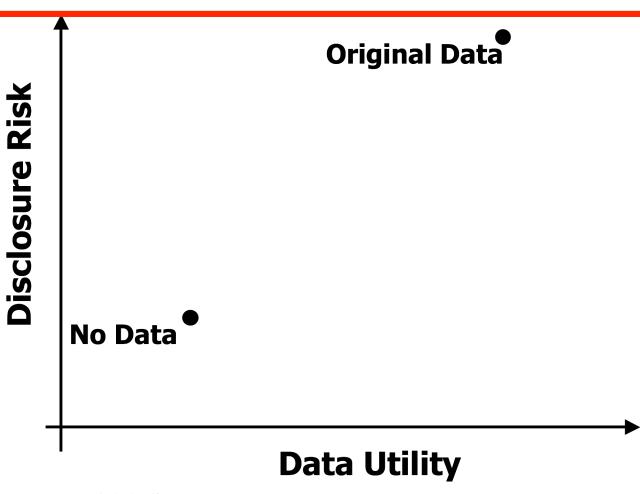


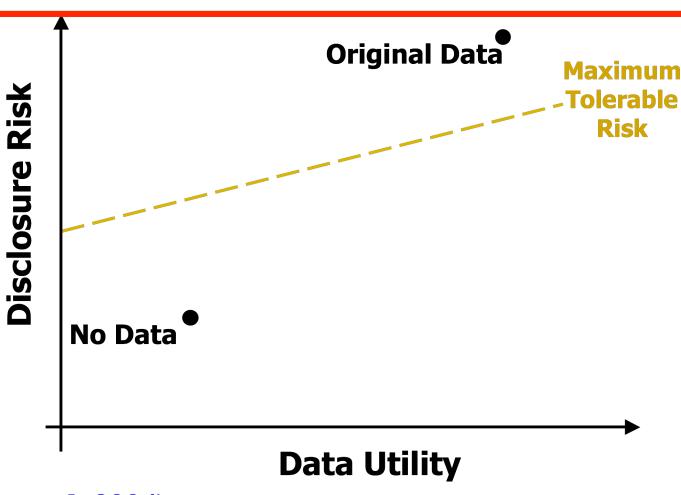
Ex. 1: Risk Factors for Coronary Heart Disease

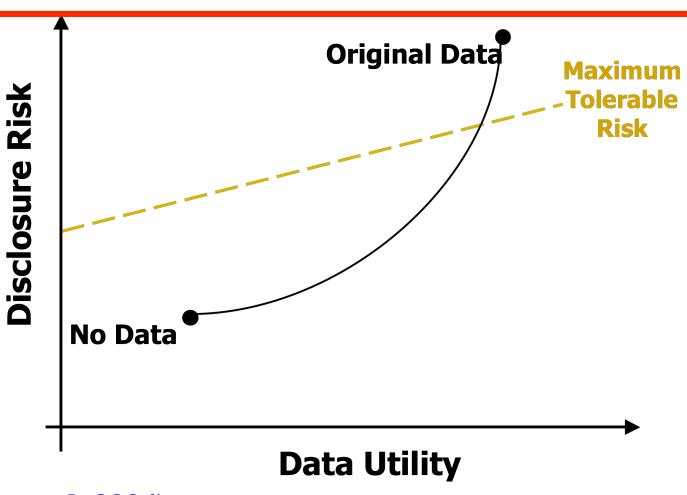


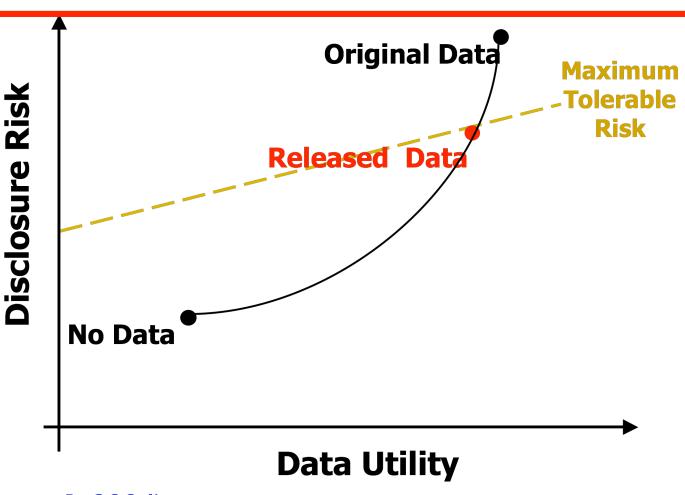
Ex. 1: The Data

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









Disclosure Limitation for Sparse Count Data

- Uniqueness in population table ⇔ 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:
 - Other types of sensible summary statistics?
- Risk concerned with small cell counts.
 - Assess using bounds given marginal totals.

Ex. 2: Genetics Linkage

- Data come from a barley milkdew experiment.
 - Edwards (1992). *CDSA*.
- 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		D
			1		6	2	-	1		2	\mathbf{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	В	С									•

Ex. 3: Australia Census Data

• 10-dimensional highly sparse contingency table extracted from 1981 Australian population census (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-Way Fréchet Bounds

• For 2×2 tables of counts $\{x_{ij}\}$ given the marginal totals $\{x_{1+},x_{2+}\}$ and $\{x_{+1},x_{+2}\}$:

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

 Interested in multi-way generalizations involving higher-order, overlapping margins.

Multi-way Bounds

For decomposable log-linear models:

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.

2³ Table Given 2×2 Margins

<i>x</i> ₁₁₁	<i>x</i> ₁₂₁	x_{1+1}	_		<i>x</i> ₁₂₂	
x_{211}	x_{221}	x_{2+1}	_	x_{212}	x_{222}	x_{2+2}
x_{+11}	x_{+21}	x_{++1}		<i>x</i> ₊₁₂	<i>x</i> ₊₂₂	x_{++2}
		<i>x</i> ₁₁₊	x_{12+}^{-}			
		<i>x</i> ₂₁₊	x_{22+}			

•Obvious upper and lower bounds for x_{111} •Extra upper bound: $x_{111} + x_{222}$

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Role of Log-linear Models?

• For 2×2 case, lower bound is evocative of MLE for estimated expected value under independence:

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

- Bounds correspond to log-linearized version.
- Margins are Minimal Sufficient Statistics (MSS).
- In 3-way table of counts, $\{x_{ijk}\}$, we model logarithms of expectations $\{E(x_{ijk})=m_{ijk}\}$:

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

• MSS are margins corresponding to highest order u-terms: $\{x_{ii+}\}$, $\{x_{i+k}\}$, $\{x_{+ik}\}$.

Log-linear Models (cont.)

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

$$\hat{m}_{ij+} = x_{ij+}$$
 for $i = 1, 2, ..., I, j = 1, 2, ..., J,$

$$\hat{m}_{+jk} = x_{+jk}$$
 for $j = 1, 2, ..., J, k = 1, 2, ..., K,$

$$\hat{m}_{i+k} = x_{i+k}$$
 for $i = 1, 2, ..., I, k = 1, 2, ..., K.$

Existence of MLEs for 2×2×2 Table

Delta must be zero and MLE doesn't exist.

Two Other Three-Way Examples with [12][13][23]

• 3³ table where MLE exists

3	0	0
0	4	0
0	0	4

0	0	1
5	0	0
0	2	0

0	1	0
0	0	5
3	0	0

• 4³ table where MLE does not exist

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

4	0	0	2
5	0	15	2
5	6	5	2
1	0	0	0

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

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

Existence of MLEs

- Linked to pattern of zeros.
- Discoverable by defining basis for models and using algebraic and polyhedral geometry.
- Examples discovered using algebraic software: *Polymake*.
- General theorems in Haberman (1974) and "constructively" in Rinaldo (2005):
 - Currently being implemented in C++ and R.

Two Faces of Algebraic Statistics

- 1. Conditional Inference: study and characterization of portions the sample space and, in particular, of all datasets having the observed margins ("exact distribution").
- 2. Representation of a Statistical Model: alternative, more powerful, description of the parameter space.

Its All About Geometry

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



Polytope



Polyhedral Cone

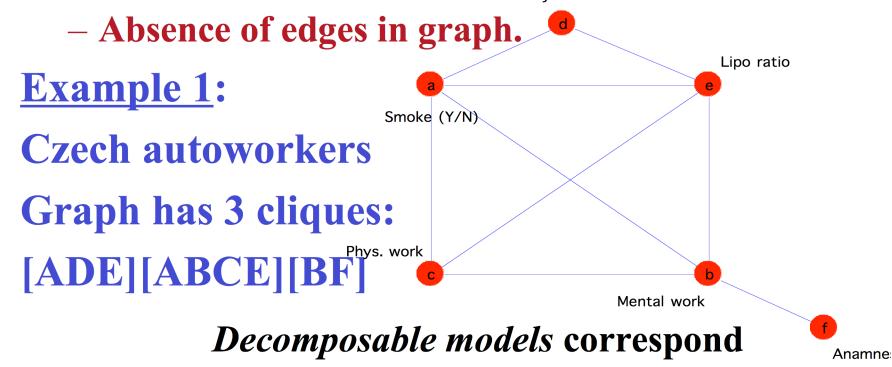
• Algebraic Geometry: a statistical model is specified by a polynomial map. The set of probability distributions is a hyper-surface of points satisfying polynomial equations.

Algebraic

Algebraic (Toric) Variety

Graphical & Decomposable Log-linear Models

• Graphical models: defined by simultaneous conditional independence relationships



to triangulated graphs.

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Multi-way Bounds

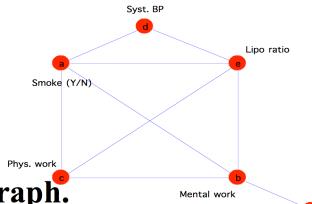
For decomposable log-linear models:

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.

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]

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

Example 1: What to Release?

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- 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].

Example 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].
- Can actually show that release of everything else is "safe": i.e., we can release [ACDE][ABCDF][ABCEF][BCDEF][ABDEF]

Ex. 2: Genetic Linkage Data

			1				2				D
			1		6	2		1		2	
			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	
Α	В	С									

Aug

Ex. 2: Existence of MLEs?

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

			1				2				D
			1		6	2		1		2	
			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	
Δ	В	\mathbf{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			D		
			1	1		2 1			2	E	
			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]	
A	В	С									

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:
 - Three examples of contingency tables
- Confidentiality & bounds for cell entries
- Existence of MLEs for contingency tables
- Role of computational algebraic geometry
- Exploring linkages between bounds and MLEs
- Undone: Scaling up computations

The End

Based in part on paper:

A. Dobra, S.E. Fienberg, A. Rinaldo, and Y. Zhou: "Confidentiality Protection and Utility for Contingency Table Data: Algorithms and Links to Statistical Theory."

 Many related papers available for downloading at http://www.niss.org
 www.stat.cmu.edu/~fienberg/DLindex.html

References

- Dobra, A. and Fienberg, S. E. (2000). Bounds for cell entries in contingency tables given marginal totals and decomposable graphs. *PNAS*, 97, 11885–11892.
- Dobra, A. & Fienberg, S. E. (2003). In Foundations of Statistical Inference: Proceedings of Shoresh Conference 2000 (Y. Haitovsky, H.R. Lerche, and Y. Ritov, eds.) 3–16.
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- Fienberg, S. E. & Rinaldo, A. (2007). Three centuries of categorical data analysis: Log-linear models and maximum likelihood estimation. *JSPI*, 137, 3430-3445.
- Rinaldo, A. (2006). On maximum likelihood estimation for log-linear models. Submitted for publication.

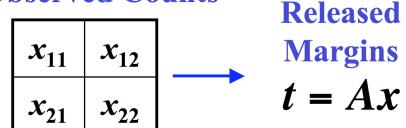
Bounds for k-way Table Entries

- LP and IP approaches are NP-hard.
- Develop efficient methods for several special cases, exploiting linkage to statistical theory where possible:
 - Released margins corresponding to decomposable models have explicit formulae.
 - Margins corresponding to reducible graphs can be broken up into smaller problems.
 - Simple result for 2^k tables with release of all (k-1)-dimensional margins fixed.
- Generalized Shuttle algorithm (Dobra, 2001) for residual cases.

2×2 Table: The Data

Design Matrix





$$t_1 = x_{1+}$$
 $t_2 = x_{2+}$
 $t_3 = x_{+1}$
 $t_4 = x_{+2}$

<i>x</i> ₁₁	x_{12}	x_{21}	x_{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*:

$$\{x \in \mathbf{R}^4_{\ge 0}, Ax = t\}$$

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:

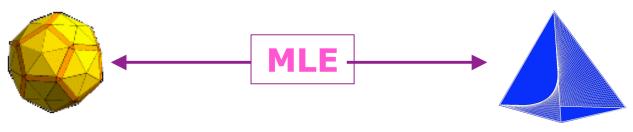
p_{11}	p_{12}
p_{21}	p_{22}

$$\log(p_{11}, p_{12}, p_{21}, p_{22}) = A'\theta = (\theta_1 + \theta_3, \theta_1 + \theta_4, \theta_2 + \theta_3, \theta_2 + \theta_4)$$

• The set of all probability distributions for the 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 Variet

Design Matrix A



Sample Space

Parameter Space

A identifies the fiber:

the set of all tables having the same margins.

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

Leads to the generalized hypergeometric distribution.

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 $u \in kernel(A)$.

Warning: Bounds and Gaps

- Bounds may not not be sufficient to understand degree of protection for confidentiality.
 - Gaps in range of values for specific cells are possible!
- Consider possible 6×4×3 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