

Secant Varieties and Statistical Models



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January 8, 2008

Joint Mathematics
Meetings

Joint work with

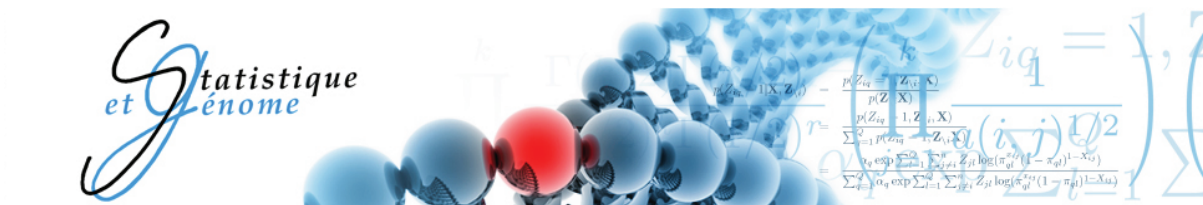
J. Rhodes

Mathematics and Statistics



C. Matias

CNRS, Laboratoire



Background:

“An application of classical invariant theory to identifiability in non-parametric mixtures”

R. Elmore, P. Hall, and A. Neeman, Annales de L’institut Fourier, (2005) **55**(1), 1–28.

secant varieties \longleftrightarrow identifiability of statistical parameters

Example

For a population, 3 observed variables X, Y, Z .

1. height < 6 ft ($Y = 1$, $N = 2$)
2. systolic blood pressure < 120 ($Y = 1$, $N = 2$)
3. eye color ($Br = 1$, $Bl = 2$, $Gr = 3$)

In addition,

one hidden variable W , with $r = 2$ states: (ethnic group)

This can be formulated as a *conditional independence* model, with 9 parameters:

- sub-pop proportions for ethnic groups:

$$\pi_1 = \text{Prob}(W = 1),$$

$$\pi_2 = 1 - \pi_1 = \text{Prob}(W = 2)$$

- probabilities of observations for sub-pop i :

$$\begin{cases} x_{ij} = \text{Prob}(X = j \mid W = i), \ j = 1, 2 \\ y_{ij} = \text{Prob}(Y = j \mid W = i), \ j = 1, 2 \\ z_{ij} = \text{Prob}(Z = j \mid W = i), \ j = 1, 2, 3 \end{cases}$$

Joint distribution is given by the 12 quantities:

p_{ijk} = Proportion of population with $X = i$, $Y = j$, $Z = k$

which the model predicts to be

$$p_{ijk} = \pi_1 x_{1i} y_{1j} z_{1k} + \pi_2 x_{2i} y_{2j} z_{2k}$$

Identifiability —

Is it possible to identify the parameters from these twelve quantities?

Identifiability is required for statistical consistency of inference methods such as Maximum likelihood.

A more geometric viewpoint:

In $\mathbb{P}^1, \mathbb{P}^2$, consider:

$$\left\{ \begin{array}{l} \mathbf{x}_1 = (x_{11} \ x_{12}) \\ \mathbf{y}_1 = (y_{11} \ y_{12}) \\ \mathbf{z}_1 = (z_{11} \ z_{12} \ z_{13}) \end{array} \right. \quad \left\{ \begin{array}{l} \mathbf{x}_2 = (x_{21} \ x_{22}) \\ \mathbf{y}_2 = (y_{21} \ y_{22}) \\ \mathbf{z}_2 = (z_{21} \ z_{22} \ z_{23}) \end{array} \right.$$

The $2 \times 2 \times 3$ tensors

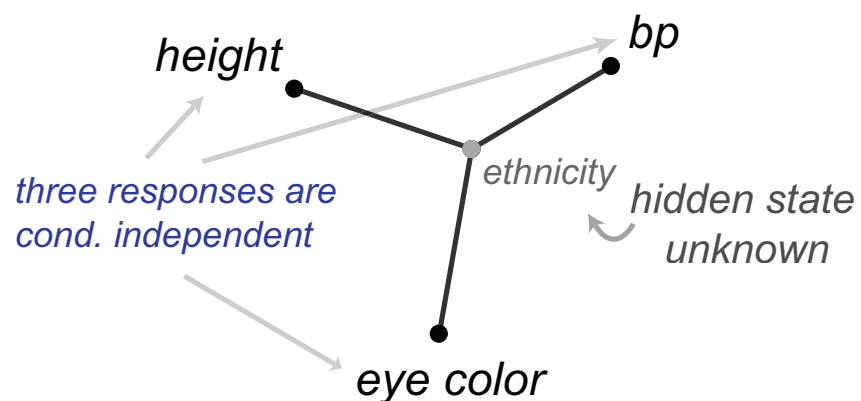
$$\mathbf{x}_1 \otimes \mathbf{y}_1 \otimes \mathbf{z}_1, \quad \mathbf{x}_2 \otimes \mathbf{y}_2 \otimes \mathbf{z}_2$$

give the distributions for sub-pops 1, 2. Thus

$$\pi_1 \mathbf{x}_1 \otimes \mathbf{y}_1 \otimes \mathbf{z}_1 + \pi_2 \mathbf{x}_2 \otimes \mathbf{y}_2 \otimes \mathbf{z}_2$$

is the parameterized distribution for the population as a whole.

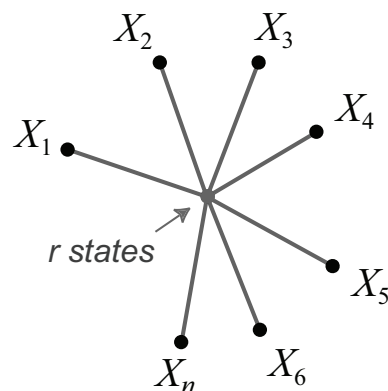
Tensor products describe independence, secants describe conditional independence



The distribution lies in

$$\text{Sec}(\mathbb{P}^1 \times \mathbb{P}^1 \times \mathbb{P}^2).$$

More generally:



- r state hidden variable \rightsquigarrow higher secant
- n observed variables X_j , $j = 1, \dots, n$, with s_j states
 $\rightsquigarrow n$ projective spaces \mathbb{P}^{s_j-1}

$\mathcal{M}(r; s_1, \dots, s_n)$ denotes the statistical model corresponding to
 $V = \text{Sec}^r(\mathbb{P}^{s_1-1} \times \dots \times \mathbb{P}^{s_n-1})$.

Note the particular parameterization is meaningful for statistics.

Questions:

- When is the dimension of V as '*expected*'?

Much recent work, including

Catalisano, Geramita, Gimigliano

Abo, Ottaviani, Peterson

- What are generators for the ideals of V ?

Garcia, Stillman, Sturmfels

Landsberg, Manivel, Weyman

Allman, Rhodes

- Identifiability of parameters,
J. Kruskal,
J. Chang,
Elmore, Hall, Neeman

Note: Understanding dimension =

understanding if parameterization is generically finite

This is *not* enough for statistical identifiability.

Label swapping for hidden variable \Leftrightarrow at least a $r!$ -to-one map

Want to understand

- structure of generic fiber
- characterize exceptional points, and their fibers

EHN thm — n binary observed variables:

$$V = \text{Sec}^r(\underbrace{\mathbb{P}^1 \times \cdots \times \mathbb{P}^1}_n)$$

Modify parameterization Φ' , to account for $r!$ -to-1-ness
(symmetrize parameter space)

Theorem (Elmore, Hall, Neeman): For each $r \geq 2$ there exists a constant $C(r)$ depending only on r , so that if $n > C(r)$ then the map Φ' is birational onto its image.

Moreover,

$$\underbrace{c_1 \ln r}_{\text{parameter count}} \leq C(r) \leq \underbrace{c_2 r \ln r}_{\text{EHN bound}}$$

Statistical interpretation:

$$\begin{array}{ccc} & \Phi' & \\ \text{Parameters} & \longrightarrow & \text{Sec}^r(\underbrace{\mathbb{P}^1 \times \dots \times \mathbb{P}^1}_n) \end{array}$$

$$\text{Stochastic Parameters} \longrightarrow \text{Joint Distributions}$$

For r sub-populations, if the number n of observed binary variables is ‘large,’ then parameters are (generically) identifiable up to label swapping.

‘Large’ means $n > c_2 r \ln r$.

(Bound here is poor.)

Desirable extensions:

- required number of observed variables should be reduced
- consider observed variables with more than 2 states:

$$\mathcal{M}(r; s_1, \dots, s_n) \longleftrightarrow \text{Sec}^r(\mathbb{P}^{s_1-1} \times \dots \times \mathbb{P}^{s_n-1})$$

- allow application to identifiability of many statistical models with hidden variables:
 - multivariate Bernoulli mixture distributions
 - hidden Markov models
 - random graph models, etc.

Basic tool:

Kruskal's Theorem (1977)

Consider the model $\mathcal{M}(r; s_1, s_2, s_3)$ with 3 observed variables.

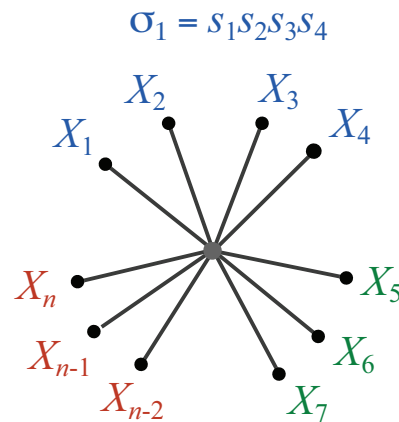
Let $\pi = (\pi_1 \dots \pi_r)$ be the sub-pop proportions, and M_j the $r \times s_j$ Markov matrix whose rows describe the j th observed variable for each sub-pop.

Define $I_j = \max\{k \mid \text{every set of } k \text{ rows of } M_j \text{ is independent}\}$.

Theorem: If all entries of π are non-zero and

$$I_1 + I_2 + I_3 \geq 2r + 2,$$

then from the model's probability distribution π , M_1 , M_2 , M_3 are uniquely determined, up to some permutation.



Theorem (A–, Matias, Rhodes)

Consider the model $\mathcal{M}(r; s_1, s_2, \dots, s_n)$ where $n \geq 3$. Suppose there exists a tripartition of the set $S = \{1, 2, 3, \dots, n\}$ into three subsets S_1, S_2, S_3 , such that if $\sigma_i = \prod_{j \in S_i} s_j$ then

$$\min(r, \sigma_1) + \min(r, \sigma_2) + \min(r, \sigma_3) \geq 2r + 2.$$

Then the model is generically identifiable, up to label swapping.

Cor. The r -class, n -binary-feature model $\mathcal{M}(r; 2, 2, \dots, 2)$ is generically identifiable, up to label swapping, provided

$$n > 2\lceil \log_2 r \rceil,$$

i.e. $C(r) = \Theta(\ln r)$.

Cor. (in progress...) Applications to identifiability of hidden Markov models, random graph models etc.