Study of diagonal-effect models as toric and mixture models

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Summary

- Toric models, Markov bases, and invariants
- Diagonal-effect models in torc form
- Diagonal-effect models in mixture form
- Concluding remarks

This work is joint with Cristiano Bocci (University of Siena, Italy) and Enrico Carlini (Politecnico di Torino, Italy).

Statistical models for contingency tables

A probability distribution for an $I \times J$ contingency table is a non-negative normalized matrix $P = (p_{i,j})$, i.e., is a point of the closed simplex

$$\Delta = \left\{ \boldsymbol{P} = (\boldsymbol{p}_{i,j}) \; : \; \boldsymbol{p}_{i,j} \geq \boldsymbol{0} \; , \; \sum_{i,j} \boldsymbol{p}_{i,j} = \boldsymbol{1} \right\}$$

Definition

A statistical model is a subset of Δ .

Toric models

In a toric model, the raw probabilities of the cells are defined (apart from normalization) in parametric form as power products:

$$p_{i,j} = \prod_{h=1}^{s} \zeta_h^{A_{(i,j),h}}$$

where ζ_1, \ldots, ζ_s are non-negative real parameters.

The structure of the toric model is encoded in an $IJ \times s$ non-negative integer matrix A.

Given an observed contingency table f (table of counts), it is easy to see that $A^t f$ is the sufficient statistic.

Invariants

Eliminating the ζ parameters from the system:

$$\mathbf{p}_{i,j} = \prod_{h=1}^{s} \zeta_h^{\mathbf{A}_{(i,j),h}}$$

one obtains the toric ideal

$$\mathcal{I}_A \subset \mathbb{R}[\boldsymbol{\rho}] = \mathbb{R}[\boldsymbol{\rho}_{1,1}, \dots, \boldsymbol{\rho}_{I,J}]$$

associated to the statistical model.

The ideal \mathcal{I}_A is generated by pure binomials.

The polynomials in \mathcal{I}_A are the invariants of the model.

Markov bases

A Markov basis for the statistical toric model defined by the matrix A is a finite set of tables $m_1, \ldots, m_\ell \in \mathbb{Z}^{M}$ that allows us to connect any two contingency tables f_1 and f_2 in the same fiber, i.e. such that $A^t(f_1) = A^t(f_2)$, with a path of elements of the fiber.

The path is therefore formed by tables of non-negative counts with constant image under A^t (the sufficient statistic).

Markov bases and invariants

The relation between the Markov basis and the toric ideal \mathcal{I}_A is known.

Theorem

The set of moves $\{m_1, \ldots, m_\ell\}$ is a Markov basis if and only if the set $\{p^{m_1+} - p^{m_1-}, i = 1, \ldots, \ell\}$ generates the ideal \mathcal{I}_A .

Usually this theorem is used in its "if" part to deduce Markov bases from the computation of a system of generators of a toric ideal.

For our study, we will make use of this theorem in its "only if" implication.

The independence model

Given:

• *I* non-negative row parameters $\zeta_1^{(r)}, \ldots, \zeta_J^{(r)}$;

• *J* non-negative column parameters $\zeta_1^{(c)}, \ldots, \zeta_J^{(c)}$; the independence model is parametric form is:

$$\mathcal{M} = \{ p_{i,j} = \zeta_i^{(r)} \zeta_j^{(c)} , \ 1 \leq i \leq I, \ 1 \leq j \leq J \} \cap \Delta$$
.

In implicit form, this translates into:

 $\mathcal{M}' = \{p_{i,j} p_{k,h} - p_{i,h} p_{k,j} = 0 \ , \ 1 \le i < k \le I, \ 1 \le j < h \le J\} \cap \Delta \, .$

Remark

In the open simplex $\Delta_{>0}$, $\mathcal{M} = \mathcal{M}'$.

 $\mathcal M$ and $\mathcal M'$ are in general different on the boundary $\Delta\setminus\Delta_{>0}.$

Diagonal-effect models in toric form

Let us consider $I \times I$ (square) tables.

Definition

The diagonal-effect model \mathcal{M}_1 is defined as the set of probability matrices $P \in \Delta$ such that:

$$\mathcal{D}_{i,j} = \zeta_i^{(r)} \zeta_j^{(c)}$$
 for $i \neq j$

$$p_{i,j} = \zeta_i^{(r)} \zeta_j^{(c)} \zeta_i^{(\gamma)}$$
 for $i = j$

where $\zeta^{(r)}$, $\zeta^{(c)}$ and $\zeta^{(\gamma)}$ are non-negative vectors with length *I*.

Theorem

The invariants of the model \mathcal{M}_1 are the binomials

 $p_{i,j}p_{i',j'}-p_{i,j'}p_{i',j}$

for i, i', j, j' all distinct, and

$$p_{i,i'}p_{i',i''}p_{i'',i} - p_{i,i''}p_{i'',i'}p_{i',i}$$

for *i*, *i*', *i*" all distinct.

Sketch of the proof. In Aoki and Takemura (2005) it is shown that a minimal Markov basis for the model M_1 is formed by:

(a) The basic degree 2 moves:

$$egin{array}{ccc} j & j' \ i & +1 & -1 \ i' & -1 & +1 \end{array}$$

with *i*, *i'*, *j*, *j'* all distinct, for $l \ge 4$;

(b) The degree 3 moves of the form:

	i	i′	i''
i	0	+1	-1
i′	-1	0	+1
i″	+1	-1	0

with *i*, *i'*, *i''* all distinct, for $I \ge 3$.

Thus, it is enough to write such moves in polynomial form.

Diagonal-effect models in mixture form

Definition

The diagonal-effect model \mathcal{M}_2 is defined as the set of probability matrices P such that

 $\boldsymbol{P} = \alpha \boldsymbol{c} \boldsymbol{r}^t + (1 - \alpha) \boldsymbol{D}$

where *r* and *c* are non-negative vectors with length *I* and sum equal to one, $D = \text{diag}(d_1, \ldots, d_l)$ is a non-negative diagonal matrix with sum equal to one, and $\alpha \in [0, 1]$.

Remark

While in the toric definition the normalization is applied once, in the mixture definition the normalization is applied twice.

Some geometry

Theorem

The models \mathcal{M}_1 and \mathcal{M}_2 have the same invariants.

Proof. The proof is based on the properties of the elimination technique.

The non-negativity conditions imply that $\mathcal{M}_1 \neq \mathcal{M}_2$ and

Theorem

Neither $\mathcal{M}_2 \subset \mathcal{M}_1$ nor $\mathcal{M}_1 \subset \mathcal{M}_2$.

We see this with two examples.

First example

$$P = \begin{pmatrix} 0 & \frac{1}{l(l-1)} & \frac{1}{l(l-1)} & \cdots & \frac{1}{l(l-1)} \\ \frac{1}{l(l-1)} & 0 & \frac{1}{l(l-1)} & \cdots & \frac{1}{l(l-1)} \\ \frac{1}{l(l-1)} & \frac{1}{l(l-1)} & 0 & \cdots & \frac{1}{l(l-1)} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \frac{1}{l(l-1)} & \frac{1}{l(l-1)} & \frac{1}{l(l-1)} & \cdots & 0 \end{pmatrix} .$$

 $P \in \mathcal{M}_1$ by constructions, while it does not belong to \mathcal{M}_2 (easy to check).

Second example

$$P = \begin{pmatrix} \frac{1}{7} & 0 & 0 & \dots & 0\\ 0 & \frac{1}{7} & 0 & \dots & 0\\ 0 & 0 & \frac{1}{7} & \dots & 0\\ \vdots & \vdots & \vdots & \vdots & \vdots\\ 0 & 0 & 0 & \dots & \frac{1}{7} \end{pmatrix}$$

.

 $P \in \mathcal{M}_2$, by setting $\alpha = 0$ and $D = \text{diag}(1/I, \dots, 1/I)$, while it does not belong to \mathcal{M}_1 (once again, easy to check).

Other results in the open simplex

Theorem

In the open simplex

$$\Delta_{>0} = \left\{ {m{P} = \left({{m{p}_{i,j}}}
ight) \; : \; {m{p}_{i,j} > 0} \; , \; \sum\limits_{i,j} {{m{p}_{i,j} = 1}}
ight\}$$

the following inclusion holds:

$$\mathcal{M}_2 \subset \mathcal{M}_1$$
 .

With some polynomial manipulations we are also able to characterize the set $\mathcal{M}_1\setminus\mathcal{M}_2.$

Theorem

Let $P \in \mathcal{M}_1 \cap \Delta_{>0}$ be a strictly positive probability table given by the vectors $\zeta^{(r)}$, $\zeta^{(c)}$ and $\zeta^{(\gamma)}$. Define: • $N_T = \sum_{i \neq j} \zeta_i^{(r)} \zeta_j^{(c)} + \sum_{i=j} \zeta_i^{(r)} \zeta_j^{(c)} \zeta_j^{(\gamma)}$ • $N = \sum_{i,i} \zeta_i^{(r)} \zeta_i^{(c)}$. Then $P \in \mathcal{M}_1 \setminus \mathcal{M}_2$ if one of the following situations holds: (i) $N_T < N$; (ii) $N_T = N$ and there exists at least an index *i* such that $\zeta_i^{(\gamma)} \neq \mathbf{1};$ (iii) $N_T > N$ and there exists at least an index *i* such that $C^{(\gamma)} < 1.$

Maximum likelihood estimation

Theorem

For an independent sample of size *n*, the models M_1 and M_2 have the same sufficient statistic.

Nevertheless the MLE can differ. Consider the table

$$\begin{pmatrix} 2 & 1 & 1 & 1 \\ 1 & 2 & 1 & 1 \\ 1 & 1 & 2 & 1 \\ 1 & 1 & 1 & 2 \end{pmatrix}$$

In this case, the normalized observed table belongs to \mathcal{M}_1 and to \mathcal{M}_2 , and thus the MLE is equal to the observed table for both models.

On the other hand, consider the following observed table

$$\begin{pmatrix} 1 & 2 & 2 & 2 \\ 2 & 1 & 2 & 2 \\ 2 & 2 & 1 & 2 \\ 2 & 2 & 1 & 2 \\ 2 & 2 & 2 & 1 \end{pmatrix}$$

After normalization, this table belongs to \mathcal{M}_1 and thus under the toric model, the MLE is again equal to the observed table. However, the table does not belong to \mathcal{M}_2 and (with symmetry arguments), the MLE is the rank-one table

Concluding remarks

- The models M₁ (toric) and M₂ (mixture) have the same invariants, but they are "essentially" different.
- Here "essentially" means: "not only on the boundary".
- Therefore, we also have a different behavior in terms of maximum likelihood estimation.

Thank you!

The complete manuscript is available at http://arxiv.org/abs/0908.0232.

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