

Identification of discrete concentration graph models with one hidden binary variable

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Conditions are presented for different types of identifiability of discrete variable models generated over an undirected graph in which one node represents a binary hidden variable. These models can be seen as extensions of the latent class model to allow for conditional associations between the observable random variables. Since local identification corresponds to full rank of the parametrization map, we establish a necessary and sufficient condition for the rank to be full everywhere in the parameter space. The condition is based on the topology of the undirected graph associated to the model. For non-full rank models, the obtained characterization allows us to find the subset of the parameter space where the identifiability breaks down.

Keywords: conditional independence; contingency tables; finite mixtures; hidden variables; identifiability; latent class; latent structure; log linear models

1. Introduction

Statistical models with latent variables have become important tools in applied studies, as they allow to include the effects of unobservable variables over the observable ones and to correct for the possible distortion induced by heterogeneity in the data. However, it is now widely recognized that when some of the variables are never observed, standard statistical procedures may be problematic, as non-identifiability of the parameters and local maxima in the likelihood function can occur.

In this paper, we focus on local identifiability of undirected graphical models for discrete variables with one binary hidden, or latent, variable. Note that models with a binary latent variable arise in several studies, as those concerning the absence/presence of a particular trait. In a recent paper by Allman *et al.* [1], a weaker form than local identification has been treated and named generic identification in which case a set of non-identifiable parameters may be present which resides in a subset of null measure. To find the explicit expression of such subset is important, since standard statistical procedures may fail if the estimates of the parameters are close to the singular locus; see, for example, [3].

Since, by the inverse function theorem, local identifiability corresponds to full rank of the parametrization map, we establish a necessary and sufficient condition for the rank to be full everywhere in the parameter space. The condition is based on the topology of the undirected graph associated to the model. This contribution is similar to what is done in [4] for linear structural equation models. For non-full rank models, the obtained characterization allows us to find the subset where the identifiability breaks down.

In Section 2, the class of models is presented together with the notion of identification. The main theorem is in Section 3. In Section 4, we present the derivations that lead to the main result. Section 5 contains concluding remarks.

2. Discrete undirected graphical model

Let $G^K = (K, E)$ be an undirected graph with node set $K = \{0, 1, \dots, n\}$ and edge set $E = \{(i, j)\}$ whenever vertices i and j are adjacent in G^K , $0 \leq i < j \leq n$. To each node, v is associated a discrete random variable A_v with finitely many levels. A discrete undirected graphical model is a family of joint distributions of the variables A_v , $v \in K$, satisfying the Markov property with respect to G^K , namely that the joint distribution of the random variables factorizes according to G^K ; see [7], Chapter 3, for definitions and concepts.

Let A_0 be a binary latent variable and $O = \{1, \dots, n\}$ be the set of nodes associated to observable random variables. In the following, let G^B be the (sub)graph $G^B = (B, E_B)$ of G^K induced by $B \subseteq K$. We denote with $\tilde{G}^B = (B, \tilde{E}_B)$ the complementary graph of the (sub)graph G^B , where \tilde{E}_B is the edge set formed by the pairs $(i, j) \notin E_B$ with $i, j \in B$ ($i \neq j$). In Figure 1(b) and (c), the graph G^O and its complementary graph \tilde{G}^O associated to the graph G^K of Figure 1(a) is presented.

Let l_v denote the number of levels of A_v , $v \in K$, and let $l = \prod_{v=1}^n l_v$. Without loss of generality, we assume that the variable A_v takes value in $\{0, \dots, l_v - 1\}$. We consider the multidimensional contingency table obtained by the cross classification of N objects according to A_v . Let X be the $2l \times 1$ vector of entries of the contingency table, stacked in a way that the levels of A_0 are changing slowest.

Data for contingency tables can be collected under various sampling schemes; see [7], Chapter 4. We assume for now that the elements of X are independent Poisson random variables with $E(X) = \mu_X$.

Let $\log \mu_X = Z\beta$, where β is a p -dimensional vector of unknown parameters; Z is a $2l \times p$ design matrix defined in a way that the joint distribution of A_v , $v \in K$, factorizes according to G^K and such that the model is graphical. We assume $\beta \neq 0$ and let Ω be parameter space, $\Omega = (\mathbb{R} \setminus 0)^p$. This implies that for each complete subgraph $G^S = (S, E_S)$, $S \subseteq K$, there is a non-zero interaction term of order $|S|$ among the variables A_v , $v \in S$.

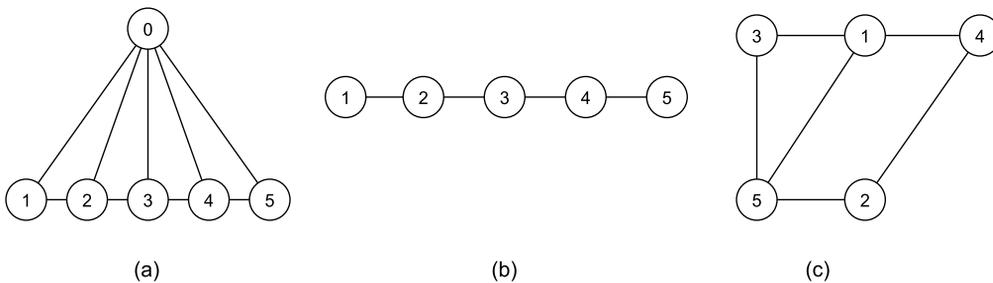


Figure 1. Example of (a) a G^K graph and the corresponding graphs (b) G^O and (c) \tilde{G}^O .

We adopt the corner point parametrization that takes as first level the cell with $A_v = 0$, for all $v \in K$, see, for example, [2]. We denote by Y the $l \times 1$ vector of the counts in the marginal table, obtained by the cross classification of the N objects according to the observed variables only. The vector Y is stacked in a way that $Y = LX$, with $L = (1, 1) \otimes e_l$, where e_l is the identity matrix of dimension l . By construction, the elements of Y are independent Poisson random variables with $\mu_Y = Le^{Z\beta}$.

If we denote with ψ the parametrization map from the natural parameters μ_Y to the new parameters β , global identifiability, also known as strict identifiability, corresponds to injectivity of ψ , while, when ψ is polynomial, local identifiability corresponds to ψ being finite-to-one. As argued in [1], there may be models such that the parametrization mapping is finite-to-one almost everywhere (i.e., everywhere except in a subset of null measure). In this case, we speak of generically identifiable models.

By the inverse function theorem, a model is locally identified if the rank of the transformation from the natural parameters μ_Y to the new parameters β is full everywhere in the parameter space Ω . This is equivalent to the rank of the following derivative matrix

$$D(\beta)^T = \frac{\partial \mu_Y^T}{\partial \beta} = \frac{\partial (Le^{Z\beta})^T}{\partial \beta} = (LRZ)^T \tag{1}$$

being full, where $R = \text{diag}(\mu_X)$. Note that the (i, j) th element of $D(\beta)$ is the partial derivative of the i th component of μ_Y with respect to β_j the j th element of β .

The multinomial case can be addressed in an analogous way to the Poisson, after noting that the rank of the matrix $D(\beta)$ and the rank of its submatrix $D_0(\beta)$ obtained by deleting the last column are the same.

Note that, by setting $t_j = e^{\beta_j}$ for any parameter β_j , the parametrization map turns into a polynomial one. This implies, see, for example, [9], Chapter 1, that if there exists a point in the parameter space of t_j , and therefore in Ω , at which the Jacobian has full rank, then the rank is full almost everywhere. Therefore, either there is no point in the parameter space at which the rank is full, or the rank is not full in a subset of null measure. The object of this paper is (a) to establish a necessary and sufficient condition for the rank of $D(\beta)$ to be full everywhere and (b) to provide expressions of the subset of null measure where identifiability breaks down.

3. Main results

The following definition introduces a graphical notion that is recalled in the main theorem.

Definition 1 (Generalized identifying sequence for a clique). A generalized identifying sequence for a clique C_0 of G^O with $|C_0| > 1$ is a sequence $\{S_s\}_{s=0}^q$ in G^O of complete subgraphs such that:

- (a) for $s \in \{0, \dots, q - 1\}$ and for all $i \in S_s$ there exists a $j \in S_{s+1}$ such that $(i, j) \in \bar{E}$;
- (b) $|S_{s+1}| \leq |S_s|$ for $s \in \{0, \dots, q - 1\}$, $S_0 = C_0$ and $|S_q| = 1$.

Example 1. Consider the model with graphs G^K , G^O and \bar{G}^O as in Figure 1(a)–(c). The clique of G^O are $\{1, 2\}$, $\{2, 3\}$, $\{3, 4\}$, $\{4, 5\}$. For any clique, there is a generalized identifying sequence.

For $C_0 = \{1, 2\}$, $S_1 = \{4\}$ satisfies the assumptions of Definition 1. For $C_0 = \{2, 3\}$, $S_1 = \{5\}$ satisfies the same assumptions. The same holds for $C_0 = \{3, 4\}$ and $C_0 = \{4, 5\}$, since for both $S_1 = \{1\}$ is the required set.

The following theorem characterizes discrete concentration graph models with one unobserved binary node that are locally identified everywhere in the parameter space Ω . The proof is in Appendix B, and uses the results for binary models developed in Section 4.

Theorem 1. *Let β be the vector of parameters of an undirected graphical model G^K over the discrete variables (A_0, A_1, \dots, A_n) , with A_0 latent binary variable. Suppose that $(0, u) \notin E$, for any $u \in T_1 \subseteq (K \setminus \{0\})$, and $(0, u) \in E$, for all $u \in S = K \setminus \{0 \cup T_1\}$. A necessary and sufficient condition for $D(\beta)$ to be full rank everywhere in the parameter space is that:*

- (i) \bar{G}^S contains at least one m -clique C , with $m \geq 3$;
- (ii) for each clique C_0 in G^S with $|C_0| > 1$ there exists a generalized identifying sequence S_s with all $S_s \subseteq S$.

The graphical model over the concentration graph as in Figure 1(a) is locally identified everywhere in the parameter space, as condition (i) and (ii) of Theorem 1 are satisfied. This can be checked by noting that the corresponding \bar{G}^S , $S = O$, contains the 3-clique $\{1, 3, 5\}$ and for each clique C_0 in G^O , $|C_0| > 1$, there is a generalized identifying sequence as shown in Example 1.

Violation of assumption (i) of Theorem 1 implies that G^S either is composed by two and only two complete components that are not connected or is composed by one connected component. In the first case, a graphical model is not even generically identified, i.e. there is no point in the parameter space such that the parametrization map is full-rank. To see this let T_1 be as in Theorem 1 and pose first $T_1 = \emptyset$. Since every clique of G^S corresponds to a saturated model over the distribution of the observable random variables conditionally on the latent one, the model is observationally equivalent to a binary latent class model with two observable random variables X_j^* , $j \in \{1, 2\}$, constructed by clumping the variables in the clique j into a single one. From [5], without further assumptions, the model is then rank deficient everywhere in the parameter space. Extension to $T_1 \neq \emptyset$ follows by noting that the above considerations hold conditionally on the variables in T_1 . The model associated to Figure 2(b) is an example.

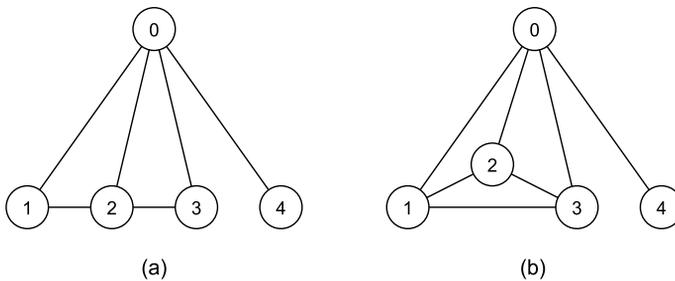


Figure 2. Two examples of G^K graphs corresponding to (a) an identified and (b) a not identified model.

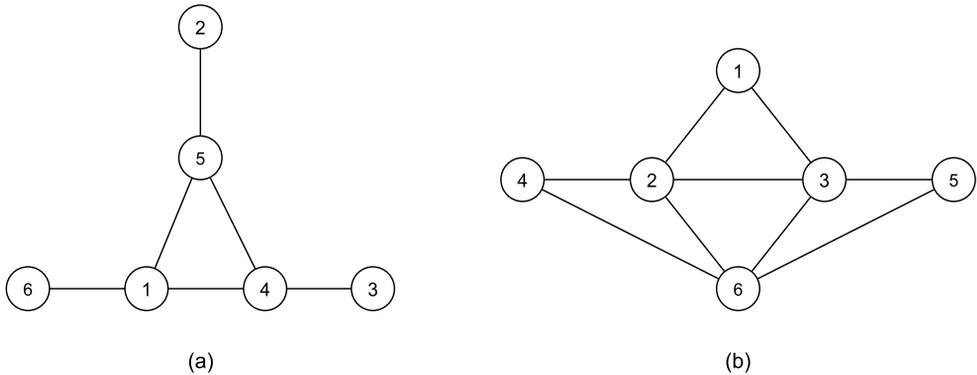


Figure 3. The graphs (a) G^O and (b) \bar{G}^O corresponding to a model with $S = O$ locally identified almost everywhere.

All other instances of violation of the assumptions of Theorem 1 lead to models that are locally identified almost everywhere (see Section 4 and Appendix A). The next example shows an instance of model which is locally identified almost everywhere as condition (ii) of Theorem 1 fails. The subset where identifiability breaks down is also presented. It can be determined throughout the derivations in Section 4.

Example 2. With reference to model associated to the graph in Figure 3, let $S = O$. The \bar{G}^O graph contains at least one 3-clique, for example, $\{1, 2, 3\}$. The clique $C_0 = \{2, 5\}$ has $S_1 = \{6\}$ as generalized identifying sequence, and therefore the corresponding interaction term does not generate non-identifiability in the parameter space. For symmetry also $C_0 = \{1, 6\}$ and $C_0 = \{3, 4\}$. For $C_0 = \{1, 4, 5\}$, however, there is no identifying sequence, since $bd_{\bar{G}^O}(C_0) = \{2, 3, 6\}$ is complete in \bar{G}^O . The subset where identifiability breaks down can be determined from (A.2) in Appendix A, which also makes clear that it is a subspace. For the binary case:

$$\begin{cases} \beta_{\{0,2\}} + \beta_{\{0,2,5\}} = 0, \\ \beta_{\{0,3\}} + \beta_{\{0,3,4\}} = 0, \\ \beta_{\{0,6\}} + \beta_{\{0,1,6\}} = 0. \end{cases}$$

The rank of $D(\beta)$ is equal to 28 everywhere except in the above subspace, where it becomes equal to 27.

When maximum likelihood estimates are close to the subspace where identifiability fails, standard asymptotic results may no longer hold. As an instance, tools for model selection, such as likelihood ratio test, may be inappropriate, see [3]. Notice further that the model with corresponding G^O graph obtained by adding the edge $(2, 6)$ in Figure 3(a) is locally identified everywhere in Ω . Therefore, models obtained by deleting edges between the observed variables of locally identified models may not be locally identified everywhere in the parameter space.

4. Local identification with one binary variable

In this section, we consider graphical models such that all n observed variables are connected to the latent one, that is, $(u, 0) \in E$, for any observed variable $u \in O$. We first focus on binary variables only. The assumption will be relaxed in Theorem 3. Consider $I \subseteq O$, let μ_I be the element of μ_Y associated to the entry of the contingency table having 1 for all variables in I and 0 for the others. Let d_I be the row of the matrix $D(\beta)$ corresponding to the first order partial derivative of μ_I with respect of β . Note that $\beta_v, v \in K$, represents the main effect of the random variable A_v and for each subset $I \subseteq O$ such that $|I| > 1$, β_I is the interaction term between the variables in I . With $\beta_{\{0,I\}}$, we denote the interaction term between the variables in $\{0, I\}$. Moreover, $\beta_\emptyset = \mu$ is the general mean. With reference to the model with concentration graph as in Figure 2(a), let $I = \{1, 2\}$. Then μ_I is the expected value of the ordered entry $(1, 1, 0, 0)$, d_I is the row of $D(\beta)$ corresponding to the partial derivative of μ_I with respect to β and β_I is the term expressing the second order interaction between A_1 and A_2 .

With this notation, to each generic i -row of $D(\beta)$, we can associate the set $I, I \subseteq O$, of the observed variables taking value one in row i . Each generic column j corresponds to the partial derivatives of μ_Y with respect to an element of β , which we denote with β_J . Note that both I and J could be the empty set. It is then easy to see that if $J \not\subseteq I$, the generic ij -element of $D(\beta)$ is 0. If $J \subseteq I$, the ij -element of $D(\beta)$ is equal to $e^{Z_i\beta}$ when $0 \in J$ and to $e^{Z_i\beta} + e^{Z_{i+1}\beta}$ otherwise, where Z_r be the r th row of Z .

Furthermore, let S be a complete subgraph of G^O and $S' \supset S$. For d_S and $d_{S'}$ and β_S and $\beta_{\{0,S\}}$ the 2×2 square sub-matrix of $D(\beta)$ has the following structure:

$$\begin{bmatrix} e^a(1 + e^b) & e^{a+b} \\ e^{a+a'}(1 + e^{b+b'}) & e^{a+a'+b+b'} \end{bmatrix} \tag{2}$$

with

$$a = \mu + \sum_{I \subseteq S} \beta_I, \quad b = \beta_0 + \sum_{I \subseteq S} \beta_{\{0,I\}}, \quad a' = \sum_{\{I \subseteq S', I \not\subseteq S\}} \delta(I)\beta_I$$

and

$$b' = \sum_{\{I \subseteq S', I \not\subseteq S\}} \delta(I)\beta_{\{0,I\}},$$

where $\delta(I) = 1$ if I is complete on G^O and 0 otherwise. Matrix (2) is not full rank if and only if $b' = 0$.

We first consider the binary latent class model, that is, a model such that the joint distribution of the random variables factorizes as follows: $\prod_{v \in O} P(A_v | A_0)P(A_0)$, see [6,8]. From the assumption $\beta \neq 0$, no further independencies than the ones implied by the above factorization are encoded in the binary latent class model.

Note that two models with a relabelling of the latent classes, together with a change of the sign of the $\beta_{\{0,i\}}$, generate the same marginal distribution over the observable variables. This issue is known as “label swapping”.

Proposition 1. *A binary latent class model is strictly identifiable, up to label swapping, if and only if $n \geq 3$.*

Proof. Sufficiency follows (a) for $n = 3$ from [1], Corollary 2; (b) for $n > 3$ from the assumption $\beta \neq 0$. Necessity follows by the fact that if $n < 3$ the model has more parameters than information in the marginal distribution of the observable random variables. \square

We now remove the assumption that the observable random variables are independent conditionally on the latent one to include a more general class of graphical models G^K over the variables $A_v, v \in K$. We first consider graphical models such that $(0, u) \in E$ for all $u \in O$ and the complementary graphs \bar{G}^O are connected and have at least an m -clique C with $m \geq 3$.

Proposition 2. *Let G^K be an undirected graphical model over the binary variables (A_0, A_1, \dots, A_n) with A_0 latent and with $(0, u) \in E$, for all $u \in O$. Assume that in \bar{G}^O there exists an m -clique $C, m \geq 3$. Let $\bar{C} = \{O \setminus C\}$ and M_1 be the sub-matrix of $D(\beta)$ formed by the rows d_i and $d_{\{i,j\}}$, with $i \in \bar{C}$ and j such that $(i, j) \in \bar{E}$, and by the columns β_i and $\beta_{\{0,i\}}$. Then M_1 has rank equal to $2|\bar{C}|$ everywhere in the parameter space if and only if \bar{G}^O is connected.*

Proof. If \bar{G}^O is connected, there exists an ordering (see the algorithm in Appendix A) of the nodes of \bar{C} such that for any $i, 1 \leq i < |\bar{C}|$, the node $j = i + 1$ is such that $(i, j) \in \bar{E}$; for $i = |\bar{C}|, j \in C$. Such ordering generates $|\bar{C}|$ distinct pairs $(i, i + 1)$. Let M_1^* be the sub-matrix of M_1 made up of the rows $d_i, d_{\{i,i+1\}}$. Then M_1^* is a $2|\bar{C}|$ -square lower-block triangular matrix with blocks M^i associated to row $d_i, d_{\{i,i+1\}}$, and columns β_i and $\beta_{\{0,i\}}$. The structure of M^i is as (2) with $a = \mu + \beta_i, b = \beta_0 + \beta_{\{0,i\}}, a' = \beta_j$ and $b' = \beta_{\{0,j\}}$ since by construction $(i, j) \in \bar{E}$. As $\beta_{\{0,j\}} \neq 0$ by assumption, it follows that M_1^* is full rank and so is M_1 .

Conversely, if \bar{G}^O is not connected, then \bar{G}^O has two or more connected components. Let $\bar{G}^1 = (V_1, E_1)$ and $\bar{G}^2 = (V_2, E_2)$ be two of them. Consider any pair of complete sets $I_1 \subseteq V_1$ and $I_2 \subseteq V_2$ (they could be a singleton) in G^O . Note that $(u, j) \in E$ for any $u \in I_1$ and $j \in I_2$. Therefore, $I_1 \cup I_2$ is a complete subset in G^O . Let $S = I_1$ and S' be any (complete) subset of $I_1 \cup I_2$ such that $S \subset S'$. From (2), any matrix formed by the row d_S and a row $d_{S'}$, with S' as above, and by the columns β_S and $\beta_{\{0,S\}}$ is not full-rank for β such that

$$\sum_{\{I \subseteq S', I \not\subseteq S\}} \beta_{\{0,I\}} = 0. \tag{3}$$

Then, the submatrix of M_1 containing the row d_S and all the above rows $d_{S'}$ is not full column rank for the above β , so M_1 is also not full rank. \square

Let t be the maximum order of the non-zero interaction terms among the variables in O . For each order $k, k \in \{2, \dots, t\}$, of interaction between the observable random variables, let s_k be the number of interaction terms of order k . We use $I_{k,r}$ to denote the set of vertices in O having a

non-zero r th interaction term of order k , $r \in \{1, \dots, s_k\}$. Note that, by construction, $|I_{k,r}| > 1$. The following example clarifies the notation.

Example 3. The model with graph G^K as in Figure 2(a) has maximum order $t = 2$ and $s_2 = 2$ with $I_{2,1} = \{1, 2\}$, $I_{2,2} = \{2, 3\}$. The model with graph G^K as in Figure 2(b) has maximum order $t = 3$. For $k = 2$, $s_2 = 3$ with $I_{2,1} = \{1, 2\}$, $I_{2,2} = \{2, 3\}$ and $I_{2,3} = \{1, 3\}$; for $k = 3$, $s_3 = 1$ with $I_{3,1} = \{1, 2, 3\}$. Similarly, the graph G^O as in Figure 3(a) has maximum order $t = 3$. For $k = 2$, $s_k = 6$, with $I_{2,1} = \{1, 4\}$, $I_{2,2} = \{1, 5\}$, $I_{2,3} = \{1, 6\}$, $I_{2,4} = \{2, 5\}$, $I_{2,5} = \{3, 4\}$, $I_{2,6} = \{4, 5\}$; for $k = 3$, $s_k = 1$, with $I_{3,1} = \{1, 4, 5\}$.

The graphical notion of identifying sequence will be used to characterize the subset where identifiability breaks down.

Definition 2 (Identifying sequence for a complete subgraph). An identifying sequence for a complete subgraph $I_{k,r}$ of G^O (with $k \geq 2$) is a sequence $\{I_s\}_{s=0}^{q'+1}$ of complete subgraphs, $q' \geq 0$, of G^O such that $I_0 = I_{k,r}$, $I_s \neq I_{s'}$ (for $s \neq s'$) with $s, s' \in \{0, \dots, q' + 1\}$ and satisfying the following assumptions:

- (a) for all $s \in \{0, \dots, q'\}$ and for all $i \in I_s$ there exists a $j \in I_{s+1}$ such that $(i, j) \notin E$;
- (b) for all $s \in \{0, \dots, q'\}$, $|I_s| = k$ and $|I_{q'+1}| < k$.

An equivalent formulation of condition (a) is that for $s \in \{0, \dots, q'\}$ and for all $i \in I_s$ there exists a $j \in I_{s+1}$ such that i and j are connected in the complementary graph \bar{G}^O .

Remark 1. If there exists a sequence of complete subgraphs satisfying (a), but such that $|I_s| > k$, for some $s \in \{1, \dots, q'\}$, then there exists also a sequence satisfying $|I_s| = k$: as a matter of fact, if for all $i \in I_s$ there exists a node $j \in I_{s+1}$ such that $(i, j) \notin E$, then I_{s+1} can be chosen in a way that $|I_{s+1}|$ cannot be greater than $|I_s|$. Therefore, if a complete subgraph $I_{k,r}$ admits no identifying sequence of complete subgraphs, then either there is no sequence of I_s such that (a) is satisfied or there is no $I_{q'+1}$ such that $|I_{q'+1}| < k$.

Remark 2. For any identifying sequence $\{I_s\}_{s=0}^{q'+1}$ related to a complete subgraph G^O , $I_s \cap I_{s+1} = \emptyset$ holds, as if, by absurd, $i \in I_s \cap I_{s+1}$, then $(i, k) \in E$ for any $k \in I_{s+1}$ (since I_{s+1} is complete in G^O), which contradicts the assumptions.

Given an identifying sequence $\{I_s\}_{s=0}^{q'+1}$, related to a complete set $I_{k,r}$, let $V \subseteq I_{s+1}$ and

$$I_s^V = \bigcap_{j \in V} \{i \in I_s : (i, j) \in E\}$$

be the subset of I_s with nodes connected in G^O to any node j belonging to V . Note that, from Remark 2, for $V = I_{s+1}$, $I_s^V = \emptyset$.

Remark 3. If there is an identifying sequence satisfying (a) but such that $I_s = I_{s'}$ for some $s \neq s', s < s'$, then there is also a shorter identifying sequence, which is constructed by excluding the interactions from $I_{s+1}, \dots, I_{s'}$.

Remark 4. The fact that the assumptions (a)–(b) hold for all complete subgraphs $I_{k,r}$ does not imply that they hold also for the all complete subgraphs $I_{k',v}$ such that $I_{k',v} \supset I_{k,r}$. The graph in Figure 3(a) is an example, as for each complete subgraph of G^O such that $k = 2$ there is an identifying sequence. However, there is no identifying sequence for $I_{3,1} = C_0 = \{1, 4, 5\}$, with $I_{3,1} \supset I_{2,1}, I_{2,2}, I_{2,6}$ (see also Examples 2 and 3).

Obviously, for a complete subgraph there may be more than one identifying sequence. The following result shows the relationship between generalized identifying sequence for cliques and identifying sequence for complete subsets.

Proposition 3. For any complete subgraph $I_{k,r}$ (for any k) of graph G^O there exists an identifying sequence $\{I_s\}_{s=0}^{q'+1}, I_0 = I_{k,r}$, if and only if for each clique C_0 of G^O with $|C_0| > 1$ there exists a generalized identifying sequence $\{S_s\}_{s=0}^q, S_0 = C_0$.

Proof. It is immediate to see that the existence for a complete subgraph in G^O of an identifying sequence implies the condition on the cliques C : it is enough for any clique C to consider the relevant identifying sequence $I_{q'+1}^C$ and then, since $I_{q'+1}^C$ is complete, consider again the relevant identifying sequence for $I_{q'+1}^C$ until the last term has cardinality 1. The proof of the inverse implication is the following. For $S = C_0$, it is trivial. For $S \subset C_0$ consider the following restriction on the sets S_0, \dots, S_q in the generalized identifying sequence for C_0 : let $I_0 = S$ and, for $i \in \{1, \dots, q' + 1\}$, let I_i be the subset of nodes $v \in S_i$ such that there exists $j \in I_{i-1}$ with $(j, v) \in \bar{E}$ and such that the cardinality of I_i is not greater than $|S|$ (see Remark 1). The existence of $I_{q'+1}$ with $|I_{q'+1}| < |S|$ follows from $|S_q| = 1$. □

Lemma 1. Let G^K be an undirected graphical model over the binary variables (A_0, A_1, \dots, A_n) with A_0 latent and with $(0, u) \in E$, for all $u \in O$. Let $I_{k,r}$ be a complete subgraph of G^O with $k \geq 2$ that admits an identifying sequence $\{I_s\}_0^{q'+1}$. Then $D(\beta)$ contains at least one square sub-matrix $M_{k,r}$ of order $2(q + 1)$ formed by the rows d_{I_s} and $d_{\{V, I_s\}}$, $V \subseteq I_{s+1}$, and by the columns associated to β_{I_s} and $\beta_{\{0, I_s\}}$, $s \in \{0, \dots, q\}$, that has full rank everywhere in the parameter space.

Conversely, if $D(\beta)$ is full rank everywhere in the parameter space, then for any clique C_0 of G^O with $|C_0| > 1$ there is at least a generalized identifying sequence.

Proof. See Appendix A. □

Example 4. With reference to Figure 1, let $I = \{1, 2\}$. The square sub-matrix with rows d_I and $d_{\{4, I\}}$, and columns β_I and $\beta_{\{0, I\}}$ is full rank, as the sequence $I_0 = \{1, 2\}, I_1 = \{4\}$ satisfies the assumptions of Lemma 1. Let $I = \{2, 3\}$, the square sub-matrix with rows d_I and $d_{\{5, I\}}$ and columns β_I and $\beta_{\{0, I\}}$ is also full rank, as the sequence $I_0 = \{2, 3\}, I_1 = \{5\}$ satisfies the assumptions of Lemma 1. The same holds for $I = \{3, 4\}$ and $I = \{4, 5\}$, since for both $I_1 = \{1\}$ is the required set.

Suppose that for each fixed order k of interaction, $k \in \{2, \dots, t\}$, the sets $I_{k,r}$, $r = 1, \dots, s_k$, satisfy the assumptions of Lemma 1. For each $I_{k,r}$ then there is a full rank sub-matrix $M_{k,r}$ of $D(\beta)$ with rows d_{I_s} , $d_{\{V, I_s\}}$, $V \subseteq I_{s+1}$, and columns β_{I_s} and $\beta_{\{0, I_s\}}$, $s \in \{0, \dots, q\}$. We denote with P_k the matrix formed by all rows of $D(\beta)$ and columns used to build all the matrices $M_{k,r}$, $r \in \{1, \dots, s_k\}$. By construction, a row, and therefore a column, cannot appear in more than one $M_{k,r}$. Then, P_k is a sub-matrix of $D(\beta)$ which is full column rank as it is block-triangular matrix with full-rank blocks $M_{k,r}$. In fact, the matrix P_k has zero components in the columns associated to $\beta_{\{I_{k,r'}\}}$ and $\beta_{\{0, I_{k,r'}\}}$ for $r' \neq r$, so P_k is a lower block-triangular matrix with blocks full rank everywhere in the parameter space, and is therefore full rank for all $\beta \in \Omega$. The following result then holds.

Proposition 4. *Let $P = [P_2 \mid \dots \mid P_t]$ be the sub-matrix of $D(\beta)$, with P_k , $k \in \{2, \dots, t\}$, constructed as previously described. If for any clique C of G^O with $|C_0| > 1$ there is a generalized identifying sequence, then P is full column rank everywhere in the parameter space.*

Proof. From the fact that the model is graphical, P is lower block-triangular matrix, as if $\beta_I = 0$ then $\beta_{I'} = 0$ for all $I' \supset I$. Then the blocks are full column rank everywhere in the parameter space by Lemma 1. \square

We can then prove the following theorem.

Theorem 2. *Let β be the vector of the parameters of an undirected graphical model G^K over the binary variables (A_0, A_1, \dots, A_n) , with A_0 latent and $(0, u) \in E$, for all $u \in O$. A necessary and sufficient condition for $D(\beta)$ to be full rank everywhere in the parameter space is that:*

- (i) \bar{G}^O contains at least one m -clique C , with $m \geq 3$;
- (ii) for each clique C_0 in G^O with $|C_0| > 1$ there exists a generalized identifying sequence.

Proof. See Appendix A. \square

As already noticed, violation of assumption (i) of Theorem 2 implies that the graph G^O is composed either by two and only two complete components that are not connected or by one connected component. The first case has been discussed in Section 3 and leads to models that are not even generically identified. The second case leads to models that are locally identified almost everywhere in Ω . The subset where identification breaks down is derived in Appendix A.

Violation of assumption (ii) of Theorem 2 implies that there is a subspace of null measure in which $D(\beta)$ is not full rank, which can be so determined. If there is a clique having no generalized identifying sequence, there is (at least) a complete set I_0 in G^O having no complete set I_1 in G^O containing nodes that are connected in \bar{G}^O to a node of I_0 . Then, we need to find the set $bd_{\bar{G}^O}(I_0)$ of nodes adjacent to at least a node in I_0 in the complementary graph \bar{G}^O . In this set, find all V_0 subsets that are complete in G^O . The expression of the subspace may be derived by equation (A.2) in Appendix A. This is:

$$\beta_{\{0, V_0\}} + \sum_{I \subseteq I_0} \delta(V_0, I) \beta_{\{0, I, V_0\}} = 0 \quad \text{for any } V_0 \subseteq bd_{\bar{G}^O}(I_0), \quad (4)$$

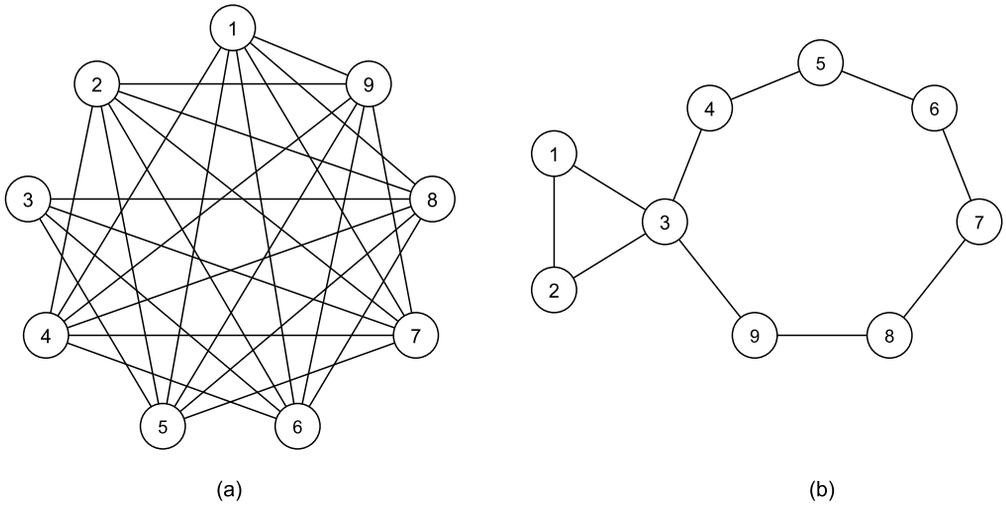


Figure 4. The graph (a) G^O and (b) its complementary graph \bar{G}^O of the model in Example 5.

where $\delta(V_0, I) = 1$ if $\{V_0, I\}$ is complete in G^O and 0 otherwise. Note that the sets that have a non-zero contribution to $\sum_{I \subseteq I_0} \delta(V_0, I) \beta_{\{0, I, V_0\}}$ are necessarily subsets of $I_0^{V_0}$ sets.

Example 5. Let the cliques in the graph G^O be the following $C_1 = \{1, 4, 7, 9\}$, $C_2 = \{1, 4, 6, 9\}$, $C_3 = \{1, 4, 6, 8\}$, $C_4 = \{2, 4, 7, 9\}$, $C_5 = \{2, 4, 6, 9\}$, $C_6 = \{2, 4, 6, 8\}$, $C_7 = \{1, 5, 7, 9\}$, $C_8 = \{2, 5, 7, 9\}$, $C_9 = \{3, 5, 8\}$, $C_{10} = \{3, 6, 8\}$, $C_{11} = \{1, 5, 8\}$, $C_{12} = \{2, 5, 8\}$, $C_{13} = \{3, 5, 7\}$. In Figure 4(a) and (b) the corresponding graphs G^O and \bar{G}^O are represented. We can verify from the graph \bar{G}^O that the assumptions of the Theorem 2 hold. For example, for the clique $C_{11} = C_0 = \{1, 5, 8\}$ we have the generalized identifying sequence: $S_1 = \{2, 4, 9\}$, $S_2 = \{3\}$. By considering $C_3 = S_0 = \{1, 4, 6, 8\}$ we have the generalized identifying sequence $S_1 = \{3, 7\}$, $S_2 = \{4, 6\}$ and $S_3 = \{5\}$. The corresponding graphical model is therefore locally identified everywhere in the parameter space.

Example 6. The model associated to the graphs in Figure 5 satisfies condition (i) of Theorem 2. However, condition (ii) does not hold for $\{1, 2, 3, 4\}$, $\{4, 5\}$, $\{4, 6\}$.

For $C_0 = \{1, 2, 3, 4\}$ we have $bd_{\bar{G}^O}(C_0) = \{5, 6\}$, which is complete in \bar{G}^O . Then, the complete sets V_0 are $\{5\}$ and $\{6\}$. From (4), $V_0 = \{5\}$ ($V_0 = \{6\}$) gives rise to the first (second) equation of the system below.

For $C_0 = \{4, 5\}$, the $bd_{\bar{G}^O}(C_0) = \{1, 2, 3, 6\}$. The sets V_0 are all possible complete subsets of $\{1, 2, 3\}$ and $\{6\}$. From (4), the equations of the system below are formed, with the exclusion of the first one. Analogously, for $C_0 = \{4, 6\}$ the equations of the system below are formed, with

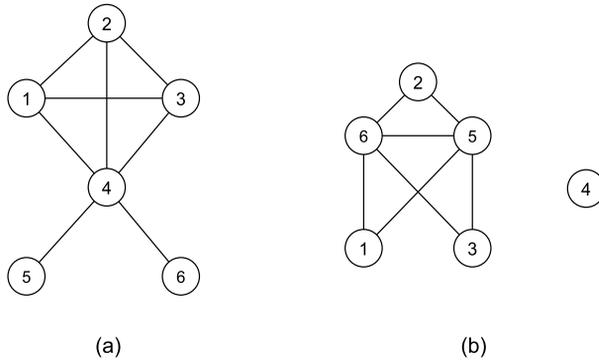


Figure 5. The graphs (a) G^O and (b) \bar{G}^O of Example 6.

the exclusion of the second one. So we have:

$$\begin{cases} \beta_{\{0,5\}} + \beta_{\{0,4,5\}} = 0, \\ \beta_{\{0,6\}} + \beta_{\{0,4,6\}} = 0, \\ \beta_{\{0,1\}} + \beta_{\{0,1,4\}} = 0, \\ \beta_{\{0,2\}} + \beta_{\{0,2,4\}} = 0, \\ \beta_{\{0,3\}} + \beta_{\{0,3,4\}} = 0, \\ \beta_{\{0,1,2\}} + \beta_{\{0,1,2,4\}} = 0, \\ \beta_{\{0,1,3\}} + \beta_{\{0,1,3,4\}} = 0, \\ \beta_{\{0,2,3\}} + \beta_{\{0,2,3,4\}} = 0, \\ \beta_{\{0,1,2,3\}} + \beta_{\{0,1,2,3,4\}} = 0. \end{cases}$$

The rank of $D(\beta)$ is equal 40 everywhere except in the subspace above. Notice that clique $C_0 = \{1, 2, 3, 4\}$ contains the following 7 complete subsets with cardinality greater than 1 having no identifying sequence: $\{1, 2, 4\}$, $\{1, 3, 4\}$, $\{2, 3, 4\}$, $\{1, 4\}$, $\{2, 4\}$, $\{3, 4\}$. For all these sets, $bd_{\bar{G}^O}(I_0) = \{5, 6\}$ and from (4) the first two equations of the system above are formed. From these derivations, we can see that some intermediate situations can occur: the rank of $D(\beta)$ degenerates of 8 in the subspace formed by the first (second) equation only while it degenerates of 2 in the subspace formed by the last seven equations only. While in the subspace given from all the above equations, $D(\beta)$ degenerates to 30 due to the 9 complete subsets with no identifying sequence (i.e., the 7 aforementioned complete subsets of $\{1, 2, 3, 4\}$ plus $\{4, 5\}$ and $\{4, 6\}$) and to the fact that the node 4 is not connected to the other nodes in \bar{G}^O (see (3) of Proposition 2).

We now extend the condition for local identification to more general models with observable random variables $v \in O$ with a finite number of levels l_v .

Theorem 3. Let β be the vector of parameters of an undirected graphical model G^K over the discrete variables (A_0, A_1, \dots, A_n) , with A_0 latent binary variable and $(0, u) \in E$, for all $u \in O$. A necessary and sufficient condition for $D(\beta)$ to be full rank everywhere in the parameter space is that:

- (i) \bar{G}^O contains at least one m -clique C , with $m \geq 3$;
- (ii) for each clique C_0 in G^O with $|C_0| > 1$ there exists a generalized identifying sequence.

Proof. See Appendix A. □

All models that are locally identified for the binary case are also identified for the more general case, provided that the latent variable is binary. Note that, for models that are locally identified everywhere except in a subspace of null measure, the equation of the subspace can be found by making repeated use of equation (4), after noting that the parameters expressing the interaction terms of a subset I are as many as the product of the levels $\prod_v (l_v - 1)$, $v \in I$.

Note that, for the particular case of a binary hidden variable, Theorem 3 extends the class of (generically) identified models according to Allman *et al.* [1], as their identification criteria allows for conditional independence between blocks of observable variables given the latent one only, and therefore excludes models with G^O connected. Note further that Theorem 3 implies that only the models with connected complementary graph can be identifiable. This contrasts with the condition of globally identifiability in graphical Gaussian models given in [10,11]. The two conditions coincide only in the case with $n = 3$ or $n = 4$. In this second case, an identified model (under both the discrete and Gaussian distribution) has conditional independence graph as in Figure 2(a).

5. Concluding remarks

One of the issues in estimating graphical models with latent variables concerns identifiability. In this paper, a characterization of locally identified undirected discrete graphical models with one hidden binary node has been presented, through a necessary and sufficient condition which can be checked from the associated concentration graph. Investigation on the consequences of violation of the given condition led to distinguish between models that are locally identified everywhere but in a subspace of null measure and models that are not locally identified. In the first case, the derivations allow to determine the subspace of null measure where identifiability fails.

Issues of identification of all models that are obtainable as a one to one reparametrization of the discrete undirected graphical model can be addressed using the results here presented. We also conjecture that results on block-triangularity of the matrix $D(\beta)$ can be extended to deal with models with one discrete latent node with more than two levels. The derivations in this paper also pave the way to graphical models with more than one hidden variable as well as directed acyclic graphs.

Appendix A: Proofs of derivations in Section 4

Algorithm for reordering $D(\beta)$

Let $U \subseteq \bar{C}$ be the set of unordered nodes. Given C , for any v node in \bar{C} , let π_v be (one of) the shortest paths connecting v to a node in C and let λ_v be its length. This path exists whenever

the graph \bar{G}^O is connected. Let a_i be (one of) the farthest node among those in $U \subseteq \bar{C}$ such that $\lambda_{a_i} = \max_{v \in U} \lambda_v$. Let W_i be the ordered set of nodes in the path π_i in the direction emanating from C to a_i . (The path π_i may contain nodes which do not belong to U .) Denote with b_i the last node of W_i belonging either to C or to $\bar{C} \setminus U$.

Step 1. $U \leftarrow \bar{C}$, $T \leftarrow C$.

Step 2. Check if U is empty, in this case \bar{C} is ordered; otherwise search for the a_i node, with the corresponding W_i and b_i .

Step 3. Let J_i be the ordered set obtained from W_i by deleting the elements before b_i and b_i .

Step 4. If b_i is in C , then append J_i to T as the last group of elements (so $T \leftarrow \{T, J_i\}$); otherwise, if b_i is in $T \setminus C$ order J_i just after b_i in T (so $T \leftarrow \{C, \dots, b_i, J_i, \dots\}$); let $U \leftarrow U \setminus J_i$; go to Step 2.

Proof of Lemma 1

We prove the sufficiency first. Consider all the sub-matrices of $M_{k,r}$. Observe that a row, and therefore a column, cannot be chosen twice in a $M_{k,r}$ matrix, as $I_s \neq I_{s'}$ (see Remark 3). By ordering the rows and columns according to the sequence of $\{I_s\}_0^{q+1}$, the matrix $M_{k,r}$ is seen to be lower block triangular. The blocks are N_0, \dots, N_q where N_s is formed by the rows d_{I_s} and $d_{\{V, I_s\}}$ with $V \subset I_{s+1}$ (from Remark 2 the intersection I_s and I_{s+1} is empty) by the columns associated to β_{I_s} and $\beta_{\{0, I_s\}}$. Therefore, N_s is as in (2).

Then, $\text{rank}(M_{k,r}) = \sum_{s=0}^q \text{rank}(N_s)$ and is full if and only if the blocks are full rank, that is if the rank of each block is equal to 2.

Suppose that there is no index s such that N_s has full rank, that is, there is no $V \subseteq I_{s+1}$ generating a sub-block of N_s with rank equal to 2. Then, from (2)

$$\sum_{I \subseteq \{I_s \cup V\}, I \not\subseteq I_s} \delta(I) \beta_{\{0, I\}} = 0 \quad \text{for all } V \subseteq I_{s+1}.$$

From the fact that the model is graphical, we obtain:

$$\sum_{I \subseteq I_s^V} \beta_{\{0, V, I\}} = 0 \quad \text{for all } V \subseteq I_{s+1}, \quad (\text{A.1})$$

where for $V = I_{s+1}$ one has $I_s^{s+1} = \emptyset$. This implies that $\beta_{\{0, V\}} = 0$, which contradicts the assumptions since I_{s+1} is a complete subgraph of G^O . Therefore, for each s there exists a full rank block N_s and the square sub-matrix $M_{k,r}$ is full rank everywhere in the parameter space.

We now prove the necessity. Since $D(\beta)$ is full rank everywhere, the sub-matrix of $D(\beta)$ formed by all rows of $D(\beta)$ and by the columns $\beta_{I_{k,r}}, \beta_{\{0, I_{k,r}\}}$ is full column rank for all $\beta \in \Omega$. Going by contradiction, suppose that there is a clique C in G^O admitting no generalized identifying sequence. Then, from Proposition 3 there is a $I_{k,r} = I_0$ such that there is no identifying sequence. Then, we can suppose without loss of generality that there is no complete subgraph I_1 in G^O such that for each $i \in I_0$ there is $j \in I_1$ with $(i, j) \notin E$. Select the sub-matrix $C_{k,r}$ formed by the columns $\beta_{I_0}, \beta_{\{0, I_0\}}$ and all the rows such that these two columns have non-zero

components, that is select all rows d_V , $V \supseteq I_0$. (Note that in all other rows the two elements are both 0.) Denote with $\Omega_{k,r} \subset \Omega$ the following subspace:

$$\beta_{\{0, V_0\}} + \sum_{I \subseteq I_0^{V_0}} \beta_{\{0, I, V_0\}} = 0, \tag{A.2}$$

where V_0 is any complete subgraph in G^O such that for each $j \in V_0$ there is at least a $i \in I_0$ with $(i, j) \in E$. Violation of assumption (a) of Definition 2 implies that $I_0^{V_0} \neq \emptyset$. Then, it is easy to verify that for $\beta \in \Omega_{k,r}$ as defined by (A.2) the columns of $C_{k,r}$ are linearly dependent. As a matter of fact, every 2×2 sub-matrix formed by any two rows of $C_{k,r}$ has the form of (2) with $b' = 0$. This contradicts the assumption that $D(\beta)$ is full rank everywhere.

Suppose now the violation of assumption (b) of Definition 2, that is, that there exists a $I_0 = I_{k,r}$ such that there is no sequence for I_0 such that $|I_{q+1}| < k$. We can find a 2×2 full rank submatrix of $D(\beta)$ with columns associated to β_{I_s} and $\beta_{\{0, I_s\}}$, $s \in \{0, \dots, q\}$. From the previous derivations, we should consider the rows associated to I_s and $V_S = \{I_s, I_{s+1}\}$ (otherwise $D(\beta)$ is not full rank for $\beta \in \Omega_{k,s}$ as defined by (A.2)). But, as there is no I_{q+1} such that $|I_{q+1}| < k$, I_{q+1} coincides with some I_s in the sequence. Therefore, we cannot find the required 2×2 sub-matrix with full rank.

Proof of Theorem 2

We prove the sufficiency first. Let D_C be the sub-matrix of $D(\beta)$ with rows corresponding to the cells with values zeros for all variables not in C , and columns $\mu, \beta_i, \beta_{\{0,i\}}$, $i \in C$. By (i) the graph G^C corresponds to a binary latent class model and so by Proposition 1, D_C is full column rank. Let $D_{\bar{C}}$ be the sub-matrix of $D(\beta)$ having rows $d_i, d_{\{i,j\}}$ and columns $\beta_i, \beta_{\{0,i\}}$, $i \in \bar{C}$ and j such that $(i, j) \in \bar{E}$ (j could belong to C). From (ii) and Proposition 3, it follows that for any complete subgraph in G^O there is an identifying sequence. Then, from Lemma 1, $D_{\bar{C}}$ is full column rank. The matrix $D(\beta)$ can be so written:

$$D(\beta) = \begin{bmatrix} D_C & 0 & 0 \\ B_1 & D_{\bar{C}} & 0 \\ B_2 & B_3 & P \end{bmatrix},$$

where B_1, B_2 and B_3 are non-zero matrix (we omit the dimension for brevity), while P is as in Proposition 4. Therefore, $D(\beta)$ is full rank everywhere.

To prove the necessity, it is enough to note that $D(\beta)$ is full rank only if the following matrices $D_C, D_{\bar{C}}$ and P are full rank. If D_C is full rank, then by Proposition 1, condition (i) holds. From Lemma 1, $D_{\bar{C}}$ and P full rank imply that for any clique of G^O there is a generalized identifying sequence, and so by Proposition 3, condition (ii) holds.

Subset where identifiability breaks down in models with no m -clique in \bar{G}^O , $m \geq 3$, and G^O is connected

If there is no m -clique, $m \geq 3$, then for any triple of nodes i_1, i_2, i_3 there is at least an edge between two of them missing in \bar{G}^O . Consider the sub-matrix $D_3(\beta)$ of $D(\beta)$ related to the rows $\{(0, 0, 0), (0, 1, 0), (1, 1, 0), (1, 0, 0), (0, 0, 1), (0, 1, 1), (1, 1, 1), (1, 0, 1)\}$ and columns $\mu, \beta_0, \beta_{i_r}, \beta_{\{0, i_r\}}, r = 1, \dots, 3$. Then the matrix $D_3(\beta)$ has the following structure:

$$D_3(\beta) = \begin{bmatrix} D_2(\beta) & 0_{4 \times 2} \\ D_2(\beta) & P_{4 \times 2} \end{bmatrix},$$

where $0_{4 \times 2}$ is a zero sub-matrix and

$$D_2(\beta) = \begin{bmatrix} a_{11} & a_{12} & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & a_{21} & a_{22} \\ a_{31} & a_{32} & a_{31} & a_{32} & a_{31} & a_{32} \\ a_{41} & a_{42} & a_{41} & a_{42} & 0 & 0 \end{bmatrix}.$$

Note that the generic elements of the matrix $D_2(\beta)$ are

$$a_{i1} = e^{\mu + \sum_{I \subseteq I_i} \delta(I)\beta_I} (1 + e^{\beta_0 + \sum_{I \subseteq I_i} \delta(I)\beta_{\{0, I\}}}),$$

$$a_{i2} = e^{\mu + \beta_0 + \sum_{I \subseteq I_i} \delta(I)\beta_{\{0, I\}}}$$

with I_i the set of random variables taking value 1 in row i and $\delta(I) = 1$ if I is complete in G^O . The matrix $D_2(\beta)$ is not full rank in the subspace of Ω where all the 4×4 square sub-matrix of $D_2(\beta)$ are not full rank. Analogously, the matrix $P_{4 \times 2}$ is not full rank for β in $\sum_{I \subseteq I_i, I \not\subseteq I_j} \delta(I)\beta_{\{0, I\}} = 0$ for all $i, j \in \{5, \dots, 8\}$, with $j > i$.

Proof of Theorem 3

First, assume that all the variables are binary except the A_1 variable which has three levels. Partition β into three subsets $\beta^a = \{\mu, \beta_0\}$, β^b corresponding to the non-zero interaction terms of any order for value in $\{0, 1\}$ of the observable random variables and β^c containing all other parameters. After ordering in a way such that the A_1 variable is running the slowest, the $D(\beta)$ matrix has the following structure:

$$D(\beta) = \begin{bmatrix} D(\beta^a) & D(\beta^b) & 0_{2^n \times |\beta^c|} \\ D^*(\beta^a) & 0_{2^{(n-1)} \times |\beta^b|} & D^*(\beta^c) \end{bmatrix},$$

where $[D(\beta^a) | D(\beta^b)]$ is the sub-matrix of the derivatives of β^a and β^b . It has full rank if conditions (i) and (ii) of Theorem 2 hold. Note that by construction, $D^*(\beta^c)$ has a similar structure of the sub-matrix of $D(\beta^b)$ formed by the last $2^{(n-1)}$ rows and all columns. Therefore, $D^*(\beta^c)$ is full rank if conditions (i) and (ii) of Theorem 2 hold.

To see the necessity note that $D(\beta^b)$ is full rank only if Theorem 2 is verified. Proof of the theorem for A_1 having l_v levels follows straightforwardly. By a similar argument, extension to a generic number of levels of the A_i variables, $i \in O$, follows.

Appendix B: Proof of Theorem 1

Note that T_1 is the set of observable variables such that $(i, O) \notin E$. We first focus on models with only binary variables. Let $T_2 \subseteq S \setminus \{0\}$ be the set of observable variables such that $(i, j) \in E$, $i \in T_1$, $j \in T_2$. If T_1 or T_2 is empty the proof is trivial.

To start with, we assume $|T_1| = 1$. Partition β into the subsets β^d containing all the non-zero interaction terms among the variables in S and β^e containing all the other elements. The non-zero interaction terms among the latent variable and the observable random variables are in β^d . The matrix $D(\beta)$ has the following structure:

$$D(\beta) = \begin{bmatrix} D(\beta^d) & 0_{2^{|S|-1} \times |\beta^e|} \\ F & D(\beta^e) \end{bmatrix},$$

$D(\beta^d)$ and $D(\beta^e)$ are the derivative sub-matrices for the corresponding elements. The sub-matrix $D(\beta^e)$ is full rank because it corresponds to the rank of the design matrix of the model for $T_1 \cup T_2$. The conclusion follows easily from the block-diagonality of the matrix and from the fact that by Theorem 3 $D(\beta^d)$ has full rank if and only if (i) and (ii) hold. Extension to a generic number of variables in T_1 follows after noting that the matrix $D(\beta)$ is so built:

$$D(\beta) = \begin{bmatrix} D(\beta^d) & 0_{2^{|S|-1} \times |\beta^e|} \\ F^* & D(\beta^e) \end{bmatrix},$$

where $D(\beta^e)$ is the derivative sub-matrix for the vector β^e defined as in the previous step. $D(\beta^d)$ is the derivative sub-matrix for the vector $\beta^d = \beta \setminus \beta^e$; F^* is a sub-matrix with the same number of rows as $D(\beta^e)$. The same considerations as in the previous case hold. Extension to a generic number of levels of the A_i variables, $i \in O$, follows by induction, as done in the proof of Theorem 3.

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