

Edge-Weighted Hypergraph Transversals & Contextuality

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This is the abstract.

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I. INTRODUCTION

A. Applications

II. MARGINAL SATISFIABILITY

A. Definitions

To every random variable¹ v there corresponds a prescribed set of **outcomes** \mathcal{O}_v and a set of **events over** v denoted $\Omega(v)$ corresponding to the set of all functions of

the form $\omega : \{v\} \rightarrow \mathcal{O}_v$. Evidently, $\Omega(v)$ and \mathcal{O}_v are isomorphic structures and their distinction can be confounding. There is rarely any harm in referring synonymously to either as outcomes. Nonetheless, a sheaf-theoretic treatment of contextuality [1] demands the distinction. Specifically for this work, the distinction becomes essential for the exploitation of marginal symmetries in Section III D. As a natural generalization we define the event over a collection of random variables $V = \{v_1, \dots, v_n\}$ in a parallel manner:

$$\Omega(V) \equiv \{\omega : V \rightarrow \mathcal{O}_V \mid \forall v \in V, \omega(v) \in \mathcal{O}_v\}$$

Furthermore, the **domain** $\mathcal{D}(\omega)$ of an event ω is the set of random variables it valuates, i.e. if $\omega \in \Omega(V)$ then $\mathcal{D}(\omega) = V$.

For every $V' \subset V$ and $\omega \in \Omega(V)$, the **restriction of ω onto V'** (denoted $\omega|_{V'}$) corresponds to the unique event in $\Omega(V')$ that agrees with ω for all valuations of variables in V' , i.e. $\forall v' \in V' : \omega|_{V'}(v') = \omega(v')$. Using this notational framework, a probability distribution or simply **distribution** \mathbf{p}_V is a probability measure on $\Omega(V)$, assigning to each $\omega \in \Omega(V)$ a real number $\mathbf{p}_V(\omega) \in [0, 1]$ such that $\sum_{\omega \in \Omega(V)} \mathbf{p}_V(\omega) = 1$. The set of all distributions over $\Omega(V)$ is denoted \mathcal{P}_V . Moreover, given $\mathbf{p}_V \in \mathcal{P}_V$ and $V' \subset V$, there is an induced distribution $\mathbf{p}_{V'}|_{V'} \in \mathcal{P}_{V'}$ obtained by *marginalizing* \mathbf{p}_V :

$$\mathbf{p}_{V'}|_{V'}(\omega') = \sum_{\substack{\omega \in \Omega(V) \\ \omega|_{V'} = \omega'}} \mathbf{p}_V(\omega) \quad (1)$$

Presently, the reader is equipped with sufficient notation and terminology to comprehend the **marginal (satisfiability) problem**: given a collection of m distributions $\{\mathbf{p}_{V_1}, \dots, \mathbf{p}_{V_m}\}$, does there exist a distribution $\mathbf{p}_\Lambda \in \mathcal{P}_\Lambda$ where $\Lambda \equiv \bigcup_{i=1}^m V_m$ such that $\forall i : \mathbf{p}_\Lambda|_{V_i} = \mathbf{p}_{V_i}$?

To facilitate further discussion of this problem, several pieces of nomenclature will be introduced. First, the set $\mathcal{V} = \{V_1, \dots, V_m\}$ is called the **marginal scenario** while its elements are called the **marginal contexts**. The collection of distributions $\mathbf{p}_{\mathcal{V}} \equiv \{\mathbf{p}_{V_1}, \dots, \mathbf{p}_{V_m}\}$ ² is called the **marginal model** [2]³. The distribution \mathbf{p}_Λ ,

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¹ Throughout this document, it is assumed that all random variables are discrete and have finite cardinality.

² The subscript $*$ preceding \mathcal{V} is added for clarity; $\mathbf{p}_{*\mathcal{V}}$ is *not* a distribution but a set of distributions over \mathcal{V} . The $_{*\mathcal{V}}$ convention is adopted throughout this report.

³ In [1], $\mathbf{p}_{*\mathcal{V}}$ is instead called an *empirical model*.

if it exists, is termed the **joint distribution**. Strictly speaking, as defined by [2], a marginal scenario forms an *abstract simplicial complex*, meaning it satisfies the supplementary required that all subsets of contexts are also contexts, i.e. $\forall V \in \mathcal{V} : V' \subset V \implies V' \in \mathcal{V}$. Throughout this work, we exclusively consider (without loss of generality) *maximal* marginal scenarios, restricting our focus to the contexts which are contained in no others. Finally, a marginal model $\mathbf{p}_{\mathcal{V}}$ is said to be **contextual**, and will be denoted $\mathbf{p}_{\mathcal{V}} \in \bar{\mathcal{N}} \subseteq \mathcal{P}_{\mathcal{V}}$ if it does not admit a joint distribution and **non-contextual** otherwise ($\mathbf{p}_{\mathcal{V}} \notin \bar{\mathcal{N}}$). Equipped with additional terminology and notation, the marginal problem now reads: given $\mathbf{p}_{\mathcal{V}}$, is $\mathbf{p}_{\mathcal{V}} \in \bar{\mathcal{N}}$ or not?

B. Linearity

An essential feature of the marginal problem is linearity; the marginalization of \mathbf{p}_{Λ} onto the marginal contexts $\{\mathbf{p}_{\Lambda}|_V \mid V \in \mathcal{V}\}$ is a linear transformation, requiring only the summations pursuant to Eq. (1). Consequently, it is advantageous to consider the statement of the marginal problem as a matrix multiplication. To this end, for each marginal scenario \mathcal{V} we define a bitwise matrix \mathcal{M} called the **incidence matrix** which implements this mapping. The columns of \mathcal{M} are indexed by *joint events* $j \in \Omega(\Lambda)$ and the rows are indexed by *marginal events* $m \in \Omega(V)$ for some $V \in \mathcal{V}$. By deliberate abuse of notation, we will denote the set of all marginal events as $\Omega(\mathcal{V})$ and is defined as the following disjoint union:

$$\Omega(\mathcal{V}) \equiv \coprod_{V \in \mathcal{V}} \Omega(V)$$

The $|\Omega(\mathcal{V})| \times |\Omega(\Lambda)|$ incidence matrix \mathcal{M} is then defined element-wise for $m \in \Omega(\mathcal{V})$ and $j \in \Omega(\Lambda)$:

$$\mathcal{M}_j^m = \begin{cases} 1 & j|_{\mathcal{D}(m)} = m \\ 0 & \text{otherwise} \end{cases}$$

Conceptually, the entries of this matrix are populated with ones whenever the marginal event (row) m is the restriction of some joint event (column) j . For a given marginal scenario \mathcal{V} , \mathcal{M} represents the tuple of restriction maps $\mathcal{M} : \Omega(\Lambda) \rightarrow \prod_{V \in \mathcal{V}} \Omega(V) :: j \mapsto \{j|_V \mid V \in \mathcal{V}\}$ [1].

To illustrate this concretely, consider the following example. Let Λ be 3 binary variables $\{a, b, c\}$ and \mathcal{V} be the marginal scenario $\mathcal{V} = \{\{a, b\}, \{b, c\}, \{a, c\}\}$. The

incidence matrix for \mathcal{V} becomes:

$$(a, b, c) \mapsto \begin{pmatrix} (0,0,0) & (0,0,1) & (0,1,0) & (0,1,1) & (1,0,0) & (1,0,1) & (1,1,0) & (1,1,1) \\ (a \mapsto 0, b \mapsto 0) & \mathbf{1} & \mathbf{1} & 0 & 0 & 0 & 0 & 0 \\ (a \mapsto 0, b \mapsto 1) & 0 & 0 & \mathbf{1} & \mathbf{1} & 0 & 0 & 0 \\ (a \mapsto 1, b \mapsto 0) & 0 & 0 & 0 & 0 & \mathbf{1} & \mathbf{1} & 0 \\ (a \mapsto 1, b \mapsto 1) & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{1} & \mathbf{1} \\ (b \mapsto 0, c \mapsto 0) & \mathbf{1} & 0 & 0 & 0 & \mathbf{1} & 0 & 0 & 0 \\ (b \mapsto 0, c \mapsto 1) & 0 & \mathbf{1} & 0 & 0 & 0 & \mathbf{1} & 0 & 0 \\ (b \mapsto 1, c \mapsto 0) & 0 & 0 & \mathbf{1} & 0 & 0 & 0 & \mathbf{1} & 0 \\ (b \mapsto 1, c \mapsto 1) & 0 & 0 & 0 & \mathbf{1} & 0 & 0 & 0 & \mathbf{1} \\ (a \mapsto 0, c \mapsto 0) & \mathbf{1} & 0 & \mathbf{1} & 0 & 0 & 0 & 0 & 0 \\ (a \mapsto 0, c \mapsto 1) & 0 & \mathbf{1} & 0 & \mathbf{1} & 0 & 0 & 0 & 0 \\ (a \mapsto 1, c \mapsto 0) & 0 & 0 & 0 & 0 & \mathbf{1} & 0 & \mathbf{1} & 0 \\ (a \mapsto 1, c \mapsto 1) & 0 & 0 & 0 & 0 & 0 & \mathbf{1} & 0 & \mathbf{1} \end{pmatrix} \quad (2)$$

In addition, for any joint distribution $\mathbf{p}_{\Lambda} \in \mathcal{P}_{\Lambda}$ we associate a joint distribution *vector* \mathbf{p}_{Λ} (identically denoted) indexed by $j \in \Omega(\Lambda)$, i.e. $\mathbf{p}_{\Lambda}^j \equiv \mathbf{p}_{\Lambda}(j)$. Analogously, for each marginal model $\mathbf{p}_{\mathcal{V}} \in \mathcal{P}_{\mathcal{V}}$ there is an associated marginal distribution *vector* $\mathbf{p}_{\mathcal{V}}$ indexed by $m \in \Omega(\mathcal{V})$ such that $\mathbf{p}_{\mathcal{V}}^m \equiv \mathbf{p}_{\mathcal{D}(m)}(m)$. Using these vectors, the marginal problem becomes the following linear program: given a marginal distribution vector $\mathbf{p}_{\mathcal{V}}$, does there exist a joint distribution vector $\mathbf{p}_{\Lambda} \succeq 0$ such that Eq. (3) holds?

$$\mathbf{p}_{\mathcal{V}} = \mathcal{M} \cdot \mathbf{p}_{\Lambda} \iff \mathbf{p}_{\mathcal{V}}^m = \sum_{j \in \Omega(\Lambda)} \mathcal{M}_j^m \mathbf{p}_{\Lambda}^j \quad (3)$$

Todo (TC Fraser): Discuss dual linear program, inequalities, general marginal problem etc

C. Marginal Polytopes

The complete space of marginal models over \mathcal{V} (denoted $\mathcal{P}_{\mathcal{V}}$) can be partitioned into two spaces: the contextual marginal models ($\bar{\mathcal{N}}$) and the non-contextual marginal models ($\mathcal{N} \equiv \mathcal{P}_{\mathcal{V}} \setminus \bar{\mathcal{N}}$). Pitowsky [3] demonstrates that \mathcal{N} forms a *convex* polytope commonly referred to as the **marginal polytope** for \mathcal{V} . When embedded in $\mathbb{R}^{|\Omega(\mathcal{V})|}$, the extremal rays of the marginal polytope correspond to the columns of \mathcal{M} which further correspond to all *deterministic* joint distributions $\mathbf{p}_{\Lambda} \in \mathcal{P}_{\Lambda}$ ⁴. The normalization of \mathbf{p}_{Λ} ($\sum_j \mathbf{p}_{\Lambda}^j = 1$) defines the convexity of the polytope; each marginal model $\mathbf{p}_{\mathcal{V}} \in \mathcal{P}_{\mathcal{V}}$ must be a convex mixture of the deterministic marginal models pursuant to Eq. (3). Consequently, characterizing the contextuality of marginal models is manifestly a problem of polytope description. Notably, the **facets** of a marginal polytope correspond to a finite set of linear inequalities that are complete in the sense

⁴ A deterministic distribution \mathbf{p}_{Λ} is a distribution in which a singular event $j \in \Omega(\Lambda)$ occurs with certainty, i.e. $\mathbf{p}_{\Lambda}^j = 1$ and $\forall j' \neq j : \mathbf{p}_{\Lambda}^{j'} = 0$.

that all contextual distributions violate at least one facet inequality [4]. From the perspective of a marginal polytope, convex hull algorithms or linear quantifier elimination can be used to compute a representation of the complete set of linear inequalities and completely solve the marginal problem. A popular tool for linear quantifier elimination is *Fourier-Motzkin elimination* [5–8]. In this report, we will avoid expounding upon the Fourier-Motzkin procedure and instead recall a few of its notable features and consequences.⁵

Definition 1. [9, Section 12.2] Given a system of linear inequality constraints $\mathcal{S} = \{A \cdot x \leq b\}$ constraining some free variables x , the **Fourier-Motzkin elimination** procedure eliminates some of the variables in x and returns a system of linear inequality constraints $\mathcal{S}' = \{A' \cdot x' \leq b'\}$ over $x' \subset x$ such that any solution x' of \mathcal{S}' will permit at least one compatible solution x of \mathcal{S} (and vice versa).

$$\exists x' : A' \cdot x' \leq b' \iff \exists x : A \cdot x \leq b \quad (4)$$

In particular, the following system of linear inequalities defines the marginal polytope for \mathcal{V} :

$$\begin{aligned} \forall m \in \Omega(\mathcal{V}) : \quad & \mathbf{p}_{*\mathcal{V}}^m - \sum_j \mathcal{M}_j^m \mathbf{p}_\Lambda^j \geq 0 \\ \forall m \in \Omega(\mathcal{V}) : \quad & -\mathbf{p}_{*\mathcal{V}}^m + \sum_j \mathcal{M}_j^m \mathbf{p}_\Lambda^j \geq 0 \\ \forall j \in \Omega(\Lambda) : \quad & \mathbf{p}_\Lambda^j \geq 0 \\ & \sum_j \mathbf{p}_\Lambda^j \geq 1 \\ & -\sum_j \mathbf{p}_\Lambda^j \geq -1 \end{aligned} \quad (5)$$

Using the Fourier-Motzkin elimination procedure, it is possible to eliminate the variables \mathbf{p}_Λ^j relating to joint events and obtain a system of linear inequalities constraining only marginal events $\mathbf{p}_{*\mathcal{V}}^m$ which completely characterizes the set of non-contextual marginal models $\mathcal{N} \subseteq \mathcal{P}_{*\mathcal{V}}$.

Lemma 2.⁶ *There exists a finite set of integral vectors $\Gamma = \{\gamma_1, \dots, \gamma_q\}$ such that for all $\mathbf{p}_{*\mathcal{V}} \in \mathcal{P}_{*\mathcal{V}}$:*

$$\mathbf{p}_{*\mathcal{V}} \in \mathcal{N} \iff \forall \gamma \in \Gamma : \gamma \cdot \mathbf{p}_{*\mathcal{V}} \geq 0 \quad (6)$$

Proof. The finiteness and existence of Γ is a fundamental property of polytopes [5, 7, 8, 10, 11]. The fact that each vector $\gamma \in \Gamma$ need only be integer-valued follows from the integer-valued coefficients that constrain Eq. (5). Finally, the homogeneity of the constraints in Eq. (6) follows from the assumption that each $\mathbf{p}_{*\mathcal{V}} \in \mathcal{P}_{*\mathcal{V}}$ a priori satisfies normalization constraints context-wise; i.e. $\forall V \in \mathcal{V} : \sum_{m \in \Omega(V)} \mathbf{p}_V^m = 1$.⁷ \square

⁵ Applying the Fourier-Motzkin procedure to completely solve the marginal problem is discussed in more detail in Fritz and Chaves [2].

⁶ This is a stronger variant of [7, Proposition 7].

⁷ Specifically, any inhomogeneous constraint $\gamma \cdot \mathbf{p}_{*\mathcal{V}} \geq \alpha$ can be homogenized by replacing α with $\sum_{m \in \Omega(V)} \alpha \mathbf{p}_V^m$.

D. Logical Contextuality

Let $a \in \Omega(\mathcal{V})$ be *any* marginal event and $C = \{c_1, \dots, c_n\} \subseteq \Omega(\mathcal{V})$ be a subset of marginal events such that the following logical implication holds for *all* marginal models $\mathbf{p}_{*\mathcal{V}} \in \mathcal{P}_{*\mathcal{V}}$:

$$a \implies c_1 \vee \dots \vee c_n = \bigvee_{c \in C} c \quad (7)$$

Which can be dictated: *whenever the event a occurs, at least one event in C occurs.* In accordance with the logical form of Eq. (7), a will be referred to as the **antecedent** and C as the **consequent set**. To clarify, a marginal model $\mathbf{p}_{*\mathcal{V}} \in \mathcal{P}_{*\mathcal{V}}$ satisfies Eq. (7) if there always at least one $c \in C$ that is *possible* ($\mathbf{p}_{*\mathcal{V}}^c > 0$) whenever a is possible. A marginal model violates Eq. (7) whenever *none* of events in c are possible while a remains possible. Marginal models that violate logical statements such as Eq. (7) are known as **Hardy Paradoxes** [6, 12, 13]. Motivated by a greater sense of robustness compared to possibilistic constraints, the concept of witnessing quantum contextuality on a logical level has been analyzed thoroughly for decades [7, 14].

III. AN OBSERVATION

A. An Antecedent Hierarchy

B. The Antecedent Hypergraph

Given an antecedent multi-set γ where $\gamma \preceq 0$, we identify the **inhibiting set** of joint events $\mathcal{I}(\gamma) \subseteq \Omega(\Lambda)$ preventing $\gamma \cdot \mathcal{M}$ from being positive semi-definite:

$$\mathcal{I}(\gamma) \equiv \left\{ j \in \Omega(\Lambda) \mid \sum_{m \in \Omega(\mathcal{V})} \gamma^m \mathcal{M}_m^j < 0 \right\}$$

The inhibiting set $\mathcal{I}(\gamma)$ of γ completely characterizes the **antecedent hypergraph** $\mathcal{H}(\gamma)$ whose edges \mathcal{E}_j are indexed by the inhibiting events $j \in \mathcal{I}(\gamma)$. Each edge $\mathcal{E}_j \subseteq \Omega(\mathcal{V})$ corresponds to the set of the marginal events $m \in \Omega(\mathcal{V})$ which are restrictions of j . Specifically,

$$\begin{aligned} \mathcal{H}(\gamma) &\equiv \{\mathcal{E}_j \mid j \in \mathcal{I}(\gamma)\} \\ \mathcal{E}_j &\equiv \{m \in \Omega(\mathcal{V}) \mid m = j|_{\mathcal{D}(m)}, \gamma^m = 0\} \end{aligned}$$

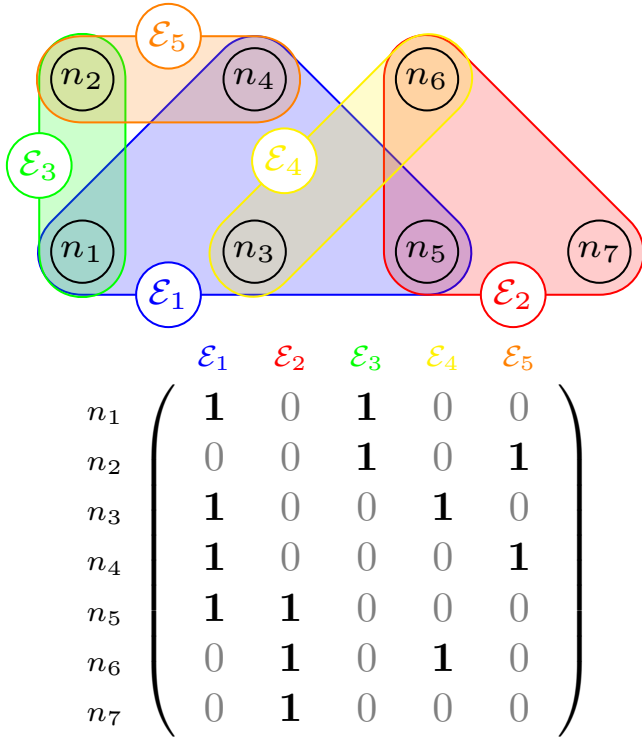


FIG. 1. Dual-representations of a hypergraph $\mathcal{H} = \{\mathcal{E}_1, \mathcal{E}_2, \mathcal{E}_3, \mathcal{E}_4, \mathcal{E}_5\}$.

C. Irreducibility

D. Marginal Symmetries

E. Curated Inequalities

F. Targeted Searches

G. Relaxations

IV. EDGE-WEIGHTED HYPERGRAPH TRANSVERSALS

A. Preliminaries

B. Hypergraph Transversals

C. Adding Weights

V. CONCLUSIONS

ACKNOWLEDGMENTS

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- [1] S. Abramsky and A. Brandenburger, “The Sheaf-Theoretic Structure Of Non-Locality and Contextuality,” *New J. Phys.* **13**, 113036 (2011).
 - [2] T. Fritz and R. Chaves, “Entropic Inequalities and Marginal Problems,” *IEEE Trans. Info. Theor.* **59**, 803 (2011).
 - [3] I. Pitowsky, “Correlation polytopes: Their geometry and complexity,” *Math. Prog.* **50**, 395 (1991).
 - [4] N. Brunner, D. Cavalcanti, S. Pironio, V. Scarani, and S. Wehner, “Bell nonlocality,” *Rev. Mod. Phys.* **86**, 419 (2013).
 - [5] G. B. Dantzig and B. C. Eaves, “Fourier-Motzkin elimination and its dual,” *J. Combin. Theor. A* **14**, 288 (1973).
 - [6] E. Wolfe, R. W. Spekkens, and T. Fritz, “The Inflation Technique for Causal Inference with Latent Variables,” (2016), arXiv:1609.00672.
 - [7] S. Abramsky and L. Hardy, “Logical Bell inequalities,” *Phys. Rev. A* **85**, 062114 (2012).
 - [8] C. Jones, E. C. Kerrigan, and J. Maciejowski, *Equality set projection: A new algorithm for the projection of polytopes in halfspace representation*, Tech. Rep. (Cambridge University Engineering Dept, 2004).
 - [9] A. Schrijver, *Theory of Linear and Integer Programming* (Wiley, 1998).
 - [10] B. G. Jiri Matousek, *Understanding and Using Linear Programming (Universitext)* (Springer, 2013).
 - [11] G. M. Ziegler, *Lectures on Polytopes* (Springer New York, 1995).
 - [12] S. Mansfield and T. Fritz, “Hardy’s Non-locality Paradox and Possibilistic Conditions for Non-locality,” *Found. Phys.* **42**, 709 (2011).
 - [13] L. Mančinská and S. Wehner, “A unified view on Hardy’s paradox and the Clauser–Horne–Shimony–Holt inequality,” *J. Phys. A* **47**, 424027 (2014).
 - [14] D. M. Greenberger, “Bell’s theorem without inequalities,” *Am. J. Phys.* **58**, 1131 (1990).