

# Edge-Weighted Hypergraph Transversals & Contextuality

Thomas C. Fraser<sup>1,2,\*</sup>

<sup>1</sup>Perimeter Institute for Theoretical Physics, Waterloo, Ontario, Canada, N2L 2Y5

<sup>2</sup>University of Waterloo, Waterloo, Ontario, Canada, N2L 3G1

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This is the abstract.

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## I. INTRODUCTION

### A. Applications

## II. MARGINAL SATISFIABILITY

### A. Definitions

To every random variable<sup>1</sup>  $v$  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  $\omega$  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  $\omega$  onto  $V'$**  (denoted  $\omega|_{V'}$ ) corresponds to the unique event in  $\Omega(V')$  that agrees with  $\omega$  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  $\mathbf{p}_{\mathcal{V}} \equiv \{\mathbf{p}_{V_1}, \dots, \mathbf{p}_{V_m}\}$ <sup>2</sup> is called the **marginal model** [2]<sup>3</sup>. The distribution  $\mathbf{p}_\Lambda$ ,

\* tcfraser@tcfraser.com

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

<sup>2</sup> 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.

<sup>3</sup> 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  $\mathbf{p}_{\mathcal{V}} \in \mathcal{C} \subseteq \mathcal{P}_{\mathcal{V}}$  if it does not admit a joint distribution and **non-contextual** otherwise ( $\mathbf{p}_{\mathcal{V}} \notin \mathcal{C}$ ). Equipped with additional terminology and notation, the marginal problem now reads: given  $\mathbf{p}_{\mathcal{V}}$ , is  $\mathbf{p}_{\mathcal{V}} \in \mathcal{C}$  or not?

### B. Linearity

An essential feature of the marginal problem is linearity; the marginalization of  $\mathbf{p}_{\Lambda}$  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  $\Lambda$  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:

$$(a, b, c) \mapsto \begin{matrix} (0,0,0) & (0,0,1) & (0,1,0) & (0,1,1) & (1,0,0) & (1,0,1) & (1,1,0) & (1,1,1) \end{matrix}$$

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

In addition, for any joint distribution  $\mathbf{p}_{\Lambda} \in \mathcal{P}_{\Lambda}$  we associate a joint distribution *vector*  $\mathbf{p}_{\Lambda}$  (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?

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

### C. Marginal Polytopes

### 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  $\mathbf{p}_{\mathcal{V}} \in \mathcal{P}_{\mathcal{V}}$ :

$$a \implies c_1 \vee \dots \vee c_n = \bigvee_{c \in C} c \quad (4)$$

Which can be dictated: *whenever the event  $a$  occurs, at least one event in  $C$  occurs*. In accordance with the logical form of Eq. (4),  $a$  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. (4) 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. (4) whenever *none* of events in  $c$  are possible while  $a$  remains possible. Marginal models that violate logical statements such as Eq. (4) are known as **Hardy Paradoxes** [3–5]. 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 [6, 7].

### III. AN OBSERVATION

#### A. An Antecedent Hierarchy

#### B. The Antecedent Hypergraph

Given an antecedent multi-set  $\gamma$  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  $\gamma$  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,

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

#### 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-Local 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] E. Wolfe, R. W. Spekkens, and T. Fritz, “The Inflation Technique for Causal Inference with Latent Variables,” (2016), [arXiv:1609.00672](https://arxiv.org/abs/1609.00672).
  - [4] S. Mansfield and T. Fritz, “Hardy’s Non-locality Paradox and Possibilistic Conditions for Non-locality,” *Found. Phys.* **42**, 709 (2011).
  - [5] L. Mančinska and S. Wehner, “A unified view on Hardy’s paradox and the Clauser–Horne–Shimony–Holt inequality,” *J. Phys. A* **47**, 424027 (2014).
  - [6] S. Abramsky and L. Hardy, “Logical Bell inequalities,” *Phys. Rev. A* **85**, 062114 (2012).
  - [7] D. M. Greenberger, “Bell’s theorem without inequalities,” *Am. J. Phys.* **58**, 1131 (1990).

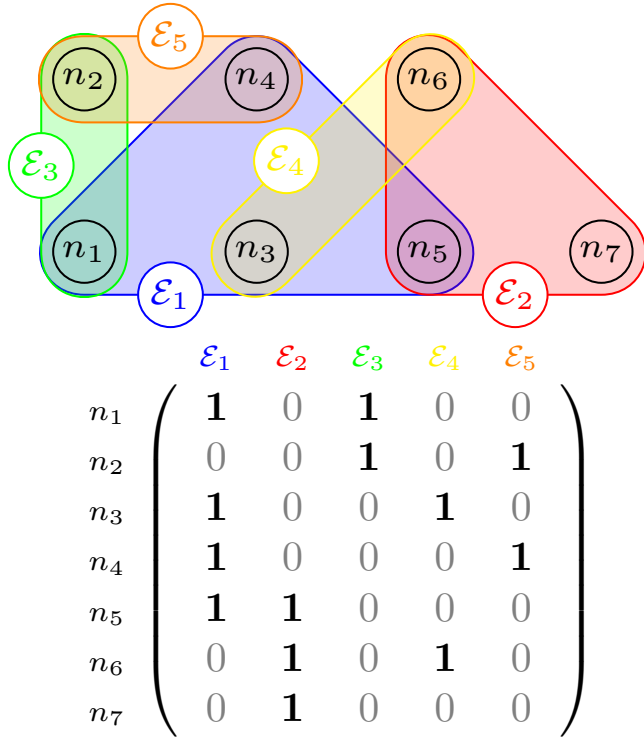


FIG. 1. Dual-representations of a hypergraph  $\mathcal{H} = \{\mathcal{E}_1, \mathcal{E}_2, \mathcal{E}_3, \mathcal{E}_4, \mathcal{E}_5\}$ .