Inequalities Witnessing Quantum Incompatibility in The Triangle Scenario

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This document is my current working draft of a paper to do with causal inference, inflation, incompatibility inequalities, hypergraph transversals and quantum correlations.

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I. INTRODUCTION

II. DEFINITIONS & NOTATION

Definition 1. Borrowing the notation from [?], each random variable v has a set of all possible outcomes called the **outcome space** or **valuation space** and is denoted O_v. When referencing a *specific* element of O_v or *valuation* of v, the notation $o[v]$ is used. This notation generalizes to set of random variables $V = \{v_1, \dots, v_{|V|}\}$; a specific outcome of $o[V] \in O_V$ is used to reference a particular tuple or vector of outcomes,

$$o[V] \equiv \left(o[v_1], o[v_2], \dots, o\left[v_{|V|}\right]\right) = (o[v])_{v \in V} \tag{1}$$

It is important to note that the ordering of events in **??** is irrelevant. Similarly, the outcome space O_V for a set of random variables V is the **valuation product** of the individual outcome spaces,

$$O_V \equiv O_{v_1} \times \cdots \times O_{v_{|V|}}$$

Where '$\times$' denotes is defined such that,

$$o[A] \times o[B] \equiv \left(o[a_1], \dots, o\left[a_{|A|}\right], o[b_1], \dots, o\left[b_{|B|}\right]\right)$$

When referencing the probability that and set of variables V has outcome $o[V]$ (say $v_1 = 0, v_2 = 3$), we intend for the following class of notations to be used interchangeably.

$$P_V(o[V]) = P(o[V]) = P(o[v_1]\, o[v_2]) = P(v_1 = 0, v_2 = 3) = P(v_2 = 3, v_1 = 0) = P_{v_1,v_2}(03)$$

Definition 2. An outcome $o[V]$ is said to be **extendable** to an outcome $o[W]$ (where $V \subseteq W$) if there exists an outcome $o[W \setminus V]$ such that:

$$o[W] = o[W \setminus V] \times o[V]$$

The idea being that a *less specific* outcome $o[V]$ can be made *more specific* by assigning outcomes to the remaining random variables in $W \setminus V$. If such an outcome $o[W \setminus V]$ exists, it is unique.

Definition 3. The set of all extendable outcomes of $o[V]$ in O_W is called the **extendable set** and can be written as,

$$o[V] \times O_{W \setminus V} \equiv \{o[W] \in O_W \mid \exists o[W \setminus V] : o[W \setminus V] \times o[V] = o[W]\}$$

The extendable set of $o[V]$ in W is the set of all outcomes of O_W that *agree* with $o[V]$ about valuations for variables in V. In this language, two outcomes $o[V]$ and $o[W]$ are **compatible** if they are both extendable to some outcome $o[V \cup W]$. Equivalently, $o[V]$ and $o[W]$ agree on their valuations of $V \cap W$.

Example 4. Consider two sets of random variables $V = \{a, b\}$ and $W = \{a, b, c\}$. Clearly $V \subseteq W$; a prerequisite for extendability. Also take all individual outcome spaces to be finite and of order 3: $O_a = O_b = O_c = \{1, 2, 3\}$. Then $o[V] = o[\{a, b\}] = (a = 1, b = 2)$ is extendable to the outcome $o[W] = (a = 1, b = 2, c = 1)$, and the extendable set of $o[V]$ in O_W is,

$$o[\{a, b\}] \times O_c = \{(a = 1, b = 2, c = 1), (a = 1, b = 2, c = 2), (a = 1, b = 2, c = 3)\}$$

Definition 5. A **graph** is an ordered tuple $(\mathcal{N}, \mathcal{E})$ of *nodes* and *edges* respectively where the nodes can represent any object and the edges are pairs of nodes. For convenience of notation, one defines an index set over the nodes denoted $\mathcal{I}_{\mathcal{N}}$.

$$\mathcal{N} = \{n_i \mid i \in \mathcal{I}_{\mathcal{N}}\} \quad \mathcal{E} = \{\{n_j, n_k\} \mid j, k \in \mathcal{I}_{\mathcal{N}}\}$$

Definition 6. A **directed graph** $\mathcal{G}$ is an ordered tuple $(\mathcal{N}, \mathcal{E})$ of *nodes* and *edges* respectively where the nodes can represent any object and the edges are *ordered* pairs of nodes. For convenience of notation, one defines an index set over the nodes denoted $\mathcal{I}_{\mathcal{N}}$.

$$\mathcal{N} = \{n_i \mid i \in \mathcal{I}_{\mathcal{N}}\} \quad \mathcal{E} = \{n_j \to n_k \mid j, k \in \mathcal{I}_{\mathcal{N}}\}$$

Definition 7. The following definitions are common language in directed graph theory. Let $n, m \in \mathcal{N}$ be example nodes of the graph $\mathcal{G}$.

- The **parents of a node**: $\mathrm{Pa}_{\mathcal{G}}(n) \equiv \{m \mid m \to n\}$
- The **children of a node**: $\mathrm{Ch}_{\mathcal{G}}(n) \equiv \{m \mid n \to m\}$
- The **ancestry of a node**: $\mathrm{An}_{\mathcal{G}}(n) \equiv \bigcup_{i\in\mathbb{W}} \mathrm{Pa}^{i}_{\mathcal{G}}(n)$ where $\mathrm{Pa}^{i}_{\mathcal{G}}(n) \equiv \mathrm{Pa}_{\mathcal{G}}\big(\mathrm{Pa}^{i-1}_{\mathcal{G}}(n)\big)$ and $\mathrm{Pa}^{0}_{\mathcal{G}}(n) = n$

All of these terms can be generalized to sets of nodes $N \subseteq \mathcal{N}$ through union over the elements,

- The **parents of a node set**: $\mathrm{Pa}_{\mathcal{G}}(N) \equiv \bigcup_{n\in N} \mathrm{Pa}_{\mathcal{G}}(n)$
- The **children of a node set**: $\mathrm{Ch}_{\mathcal{G}}(N) \equiv \bigcup_{n\in N} \mathrm{Ch}_{\mathcal{G}}(n)$
- The **ancestry of a node set**: $\mathrm{An}_{\mathcal{G}}(N) \equiv \bigcup_{n\in N} \mathrm{An}_{\mathcal{G}}(n)$

Moreover, an **induced subgraph** of $\mathcal{G}$ due to a set of nodes $N \subseteq \mathcal{N}$ is the graph composed of N and all edges $e \in \mathcal{E}$ of the original graph that are contained in N.

$$\mathrm{Sub}_{\mathcal{G}}(N) \equiv (N, \{e_i \mid i \in \mathcal{I}_{\mathcal{E}}, e_i \subseteq N\})$$

An **ancestral subgraph** of $\mathcal{G}$ due to $N \subseteq \mathcal{N}$ is the induced subgraph due to the ancestry of N.

$$\mathrm{AnSub}_{\mathcal{G}}(N) \equiv \mathrm{Sub}_{\mathcal{G}}\big(\mathrm{An}_{\mathcal{G}}(N)\big)$$

Definition 8. A **directed acyclic graph** or **DAG** $\mathcal{G}$ is an directed graph **??** with the additional property that no node n is in its set of **ancestors**.

$$\forall n \in \mathcal{N} : n \notin \bigcup_{i\in\mathbb{N}} \mathrm{Pa}^{i}_{\mathcal{G}}(n)$$

Notice the difference between using the natural numbers $\mathbb{N}$ to distinguish *ancestors* from *ancestry*.

Definition 9. A **hypergraph** denoted $\mathcal{H}$ is an ordered tuple $(\mathcal{N}, \mathcal{E})$ of *nodes* and *edges* respectively where the nodes can represent any object and the edges are *subsets* of nodes. For convenience of notation, one defines an index set over the nodes and edges of a hypergraph $\mathcal{H}$ denoted $\mathcal{I}_{\mathcal{N}}$ and $\mathcal{I}_{\mathcal{E}}$ respectively.

$$\mathcal{H} = (\mathcal{N}, \mathcal{E}) \quad \mathcal{N} = \{n_i \mid i \in \mathcal{I}_{\mathcal{N}}\} \quad \mathcal{E} = \{e_i \mid i \in \mathcal{I}_{\mathcal{E}}, e_i \subseteq \mathcal{N}\}$$

Note that whenever the index for an edge or node is arbitrary, it will be omitted. There is a dual correspondence between edges $e \in \mathcal{E}$ and nodes $n \in \mathcal{N}$ in a Hypergraph. An edge e is viewed as a set of nodes $\{n_i\}$, and a node n can be viewed as the set of edges $\{e_i\}$ that contain it.

Definition 10. A **hypergraph transversal** (or edge hitting set) $\mathcal{T}$ of a hypergraph $\mathcal{H}$ is a set of nodes $\mathcal{T} \subseteq \mathcal{N}$ that have non-empty intersections with every edge in $\mathcal{E}$.

$$\mathcal{T} = \{n_i \in \mathcal{N} \mid i \in \mathcal{I}_{\mathcal{T}}\} \quad \forall e \in \mathcal{E} : \mathcal{T} \cap e \neq \emptyset$$

Definition 11. A **minimal hypergraph transversal** $\mathcal{T}$ is any valid transversal (**??**) of $\mathcal{H}$ where every node n is *necessary* to retain validity. For each node n in $\mathcal{T}$, $\mathcal{T} \setminus n$ is no longer a transversal.

$$\mathcal{T} = \{n_i \in \mathcal{N} \mid i \in \mathcal{I}_{\mathcal{T}}\} \quad \forall i \in \mathcal{I}_{\mathcal{T}}, \exists e \in \mathcal{E} : (\mathcal{T} \setminus n_i) \cap e = \emptyset$$

Definition 12. A **weighted hypergraph** $\mathcal{H}_{\mathcal{W}}$ is a regular hypergraph satisfying **??** equipped with a set of weights $\mathcal{W}$ ascribed to each node such that a weighted hypergraph is written as a triplet $(\mathcal{W}, \mathcal{N}, \mathcal{E})$.

$$\mathcal{W} = \{w_i \mid i \in \mathcal{I}_{\mathcal{N}}, w_i \in \mathbb{R}\}$$

One would say that a particular node n_i carries weight w_i for each $i \in \mathcal{I}_{\mathcal{N}}$.

Definition 13. A **bounded transversal** of a weighted hypergraph $\mathcal{H}_{\mathcal{W}}$ is a transversal $\mathcal{T}$ of the unweighted hypergraph $\mathcal{H}$ and a real number t (denoted $\mathcal{T}_{\leq t}$) such that the sum of the node weights of the transversal is bounded by t.

$$\mathcal{T}_{\leq t} = \{n_i \mid i \in \mathcal{I}_{\mathcal{T}}\} \quad \text{s.t.} \sum_{j\in\mathcal{I}_{\mathcal{T}}} w_j \leq t$$

One can definte analogous **(strictly) upper/lower bounded transversals** by considering modifications of the notation: $\mathcal{T}_{<t}, \mathcal{T}_{\geq t}, \mathcal{T}_{>t}$.

Definition 14. A **causal structure** is simply a DAG with the extra classification of each node into one of two categories; the **latent nodes** and **observed nodes** denoted $\mathcal{N}_L$ and $\mathcal{N}_O$. The latent nodes correspond to random variables that are either hidden through some fundamental process or cannot/will not be measured. The observed nodes are random variables that are measurable. Every node is either latent or observed and no node is both:

$$\mathcal{N}_L \cap \mathcal{N}_O = \emptyset \qquad \mathcal{N}_L \cup \mathcal{N}_O = \mathcal{N}$$

Definition 15. The **product distribution** two distributions is denoted as usual with $\times$ and is defined as,

$$\left(P_v \times P_w\right)\left(o[v], o[w]\right) \equiv P_v(o[v])\, P_w(o[w])$$

A product distribution of k distributions is defined recursively,

$$\prod_{i=1}^{k} P_{v_i} \equiv \left(P_{v_1} \times \cdots \times P_{v_k}\right)$$

Definition 16. The **marginalization** of a distribution $P_{v \cup w}$ to the distribution P_v is denoted $\sum_w P_{v\cup w} = P_v$ and is defined such that,

$$\forall o[v] \in O_v : \left(\sum_w P_{v,w}\right)(o[v]) \equiv \sum_{o[w] \in O_w} P_{v,w}(o[v], o[w])$$

Todo (TC Fraser): How many definitions do I need to write??

III. TRIANGLE SCENARIO

Todo (TC Fraser): Discuss the triangle scenario, previous work done on it, etc. Focusing on the inflation depicted in **??**, we obtained the maximally pre-injectable sets through the procedure outlined in [**?**].

$$\begin{array}{cc}
\textbf{Maximal Pre-injectable Sets } \Pi & \textbf{Ancestral Independences} \\
\{A_1, B_1, C_1, A_4, B_4, C_4\} & \{A_1, B_1, C_1\} \perp \{A_4, B_4, C_4\} \\
\{A_1, B_2, C_3, A_4, B_3, C_2\} & \{A_1, B_2, C_3\} \perp \{A_4, B_3, C_2\} \\
\{A_2, B_3, C_1, A_3, B_2, C_4\} & \{A_2, B_3, C_1\} \perp \{A_3, B_2, C_4\} \\
\{A_2, B_4, C_3, A_3, B_1, C_2\} & \{A_2, B_4, C_3\} \perp \{A_3, B_1, C_2\} \\
\{A_1, B_3, C_4\} & \{A_1\} \perp \{B_3\} \perp \{C_4\} \\
\{A_1, B_4, C_2\} & \{A_1\} \perp \{B_4\} \perp \{C_2\} \\
\{A_2, B_1, C_4\} & \{A_2\} \perp \{B_1\} \perp \{C_4\} \\
\{A_2, B_2, C_2\} & \{A_2\} \perp \{B_2\} \perp \{C_2\} \\
\{A_3, B_3, C_3\} & \{A_3\} \perp \{B_3\} \perp \{C_3\} \\
\{A_3, B_4, C_1\} & \{A_3\} \perp \{B_4\} \perp \{C_1\} \\
\{A_4, B_1, C_3\} & \{A_4\} \perp \{B_1\} \perp \{C_3\} \\
\{A_4, B_2, C_1\} & \{A_4\} \perp \{B_2\} \perp \{C_1\}
\end{array} \tag{2}$$

As can be counted, there are 12 maximally pre-injectable sets which will be indexed 1 through 12 in the order seen above ($\Pi = \{\Pi_1, \ldots, \Pi_{12}\}$)

IV. SUMMARY OF THE INFLATION TECHNIQUE

The causal inflation technique, first pioneered by Wolfe, Spekkens, and Fritz [**?**] and inspired by the *do calculus* and *twin networks* of Ref. [**?**], is a family of causal inference techniques that can be used to determine if a probability distribution is compatible or incompatible with a given causal structure. As a preliminary summary, the inflation technique begins by *augmenting* a causal structure with additional nodes, producing the *inflated* causal structure, and then exposes how causal inference tasks on the inflated causal structure can be used to make inferences on the original causal structure. Equipped with the common graph-theoretic terminology and notation of **??**, an inflation can be formally defined as follows:

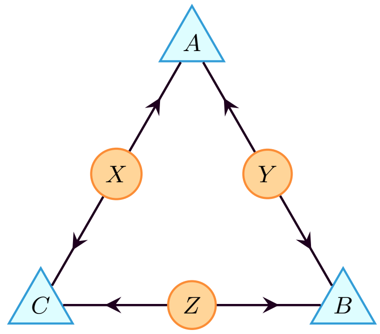

FIG. 1. The casual structure of the triangle scenario. Three variables A, B, C are observable and illustrated as triangles, while X, Y, Z are latent variables illustrated as circles.

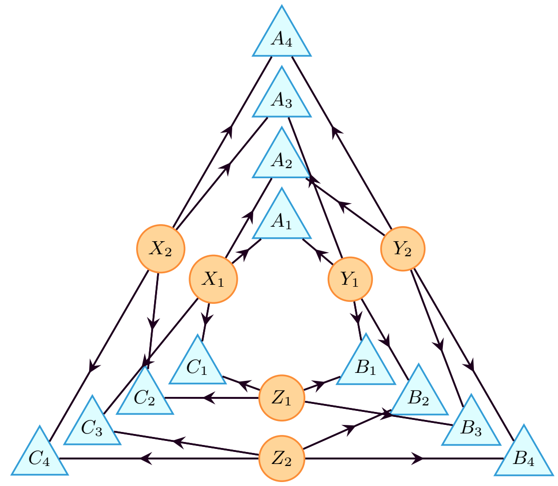

FIG. 2. An inflated causal structure of the triangle scenario **??**.

Definition 17. An **inflation** of a causal structure $\mathcal{G}$ is another causal structure $\mathcal{G}'$ such that:

$$\forall n' \in \mathcal{N}' : \text{AnSub}_{\mathcal{G}'}(n') \sim \text{AnSub}_{\mathcal{G}}(n)$$

Where '$\sim$' is notation for equivalence up to removal of the copy-index. To clarify, each node in an inflated causal structure $n' \in \mathcal{N}'$ shares a *label* assigned to a node $n \in \mathcal{N}$ in the original causal structure together with an additional index called the **copy-index**.

Definition 18. A set of **causal parameters** for a particular causal structure $\mathcal{G}$ is the specification of a conditional distribution for every node $n \in \mathcal{N}$ given it's parents in $\mathcal{G}$.

$$\left\{ P_{n|\text{Pa}_{\mathcal{G}}(n)} \mid n \in \mathcal{N} \right\}$$

Todo (TC Fraser): Clean up what is meant by copy index, example maybe? Todo (TC Fraser): Define injectable sets Todo (TC Fraser): Define pre-injectable sets and then it's connection to probabilities Todo (TC Fraser): Define pre-injectable sets Todo (TC Fraser): State the main Compatibility lemma of inflation

V. COMPATIBILITY, CONTEXTUALITY AND THE MARGINAL PROBLEM

In order to determine if a given marginal distribution P_V or set of marginal distributions $\{P_{V_1}, \ldots, P_{V_k}\}$ is compatible with a causal structure $\mathcal{G}$, one should first formalize what is meant by *compatible*.

Definition 19. A marginal distribution P_V is **compatible** with a causal structure $\mathcal{G}$ (where it is assumed that $V \subseteq \mathcal{N}_O$) if there exists a *choice* of causal parameters $\left\{ P_{n|\text{Pa}_{\mathcal{G}}(n)} \mid n \in \mathcal{N} \right\}$ such that P_V can be *recovered* from the following series of operations:
Todo (TC Fraser): Define this notation here

1. First obtain a joint distribution over *all* nodes of of the causal structure,

$$P_{\mathcal{N}} = \prod_{n \in \mathcal{N}} P_{n|\text{Pa}_{\mathcal{G}}(n)}$$

2. Then marginalize over the latent nodes of $\mathcal{G}$,

$$P_{\mathcal{N}_O} = \sum_{\mathcal{N}_L} P_{\mathcal{N}}$$

3. Finally marginalize over the observed nodes not in V to obtain P_V,

$$P_V = \sum_{\mathcal{N}_O \setminus V} P_{\mathcal{N}_O}$$

A set of marginal distributions $\{P_{V_1}, \dots, P_{V_k}\}$ is compatible with $\mathcal{G}$ if each of the distributions can be made compatible by the *same* choice of causal parameters. A distribution P_V or set of distributions $\{P_{V_1}, \dots, P_{V_k}\}$ is said to be **incompatible** with a causal structure if there *does not exist* a set of causal parameters with the above mentioned property.

Todo (TC Fraser): Source this?

Operations 2 and 3 of **??** are related to the *marginal problem*.

Definition 20. **The Marginal Problem:** Given a set of distributions $\{P_{V_1}, \dots, P_{V_k}\}$ where $V_i \subseteq \mathcal{V}$ for some set of random variables $\mathcal{V}$ and $k \geq 2$, does there exist a joint distribution $P_{\mathcal{V}}$ such that each given distribution P_{V_i} can be obtained from marginalizing $P_{\mathcal{V}}$?

$$\forall i \in \{1, \dots, k\} : P_{V_i} = \sum_{\mathcal{V} \setminus V_i} P_{\mathcal{V}}$$

Typically (although not strictly necessary), $\mathcal{V}$ is taken to mean the union of all V_i's.

$$\mathcal{V} = V_1 \cup \dots \cup V_k = \bigcup_{i=1}^{k} V_i \tag{3}$$

Definition 21. A reoccurring motif of these discussions will be the set of distributions $\{P_{V_1}, \dots, P_{V_k}\}$ mentioned in **??**. In agreement with [**?**] we will call this set of distributions a **marginal model** and denote it $P^{\mathcal{M}}$ provided that they are *compatible*:

$$\forall i \neq j \text{ if } V_i \cap V_j \neq \emptyset \text{ then } \sum_{V_i \setminus V_j} P_{V_i} = \sum_{V_j \setminus V_i} P_{V_j}$$

We call the set of subsets $\{V_1, \dots, V_k\}$ the marginal contexts or the **maximal marginal scenario** and an individual V_i a **marginal context**. Finally we will denote the union of all contexts $\mathcal{V}$ and define it exactly as in **??**

Todo (TC Fraser): Discuss Compatibility, connection to cooperative games/resources, bell incompatibility? Todo (TC Fraser): Connection between contextuality and Compatibility via the marginal problem for causal parameters Todo (TC Fraser): Discuss what is meant by a 'complete' solution to the marginal problem Todo (TC Fraser): Maybe define the possibilistic marginal problem for later

VI. THE FRITZ DISTRIBUTION

The **Fritz distribution** P_F is a quantum-accessible distribution known to be incompatible with the triangle scenario. Explicitly, P_F is a three-party (A, B, C), four-outcome $(1, 2, 3, 4)$ distribution that has form as follows:

$$P_F(111) = P_F(221) = P_F(412) = P_F(322) = P_F(233) = P_F(143) = P_F(344) = P_F(434) = \frac{1}{32}\left(2 + \sqrt{2}\right)$$
$$P_F(121) = P_F(211) = P_F(422) = P_F(312) = P_F(243) = P_F(133) = P_F(334) = P_F(444) = \frac{1}{32}\left(2 - \sqrt{2}\right)$$

Here the notation $P_F(abc) = P_{ABC}(abc) = P(A = a, B = b, C = c)$ is used. The Fritz distribution P_F can be realized with the following quantum configuration:

$$\rho_{AB} = \left|\Psi^+\right\rangle \left\langle\Psi^+\right| \quad \rho_{BC} = \rho_{CA} = \left|\Phi^+\right\rangle \left\langle\Phi^+\right|$$
$$M_A = \left\{\left|0\psi_0\right\rangle \left\langle 0\psi_0\right|, \left|0\psi_\pi\right\rangle \left\langle 0\psi_\pi\right|, \left|1\psi_{-\pi/2}\right\rangle \left\langle 1\psi_{-\pi/2}\right|, \left|1\psi_{\pi/2}\right\rangle \left\langle 1\psi_{\pi/2}\right|\right\}$$
$$M_B = \left\{\left|\psi_{\pi/4}0\right\rangle \left\langle\psi_{\pi/4}0\right|, \left|\psi_{5\pi/4}0\right\rangle \left\langle\psi_{5\pi/4}0\right|, \left|\psi_{3\pi/4}1\right\rangle \left\langle\psi_{3\pi/4}1\right|, \left|\psi_{-\pi/4}1\right\rangle \left\langle\psi_{-\pi/4}1\right|\right\}$$
$$M_C = \{\left|00\right\rangle \left\langle 00\right|, \left|01\right\rangle \left\langle 01\right|, \left|10\right\rangle \left\langle 10\right|, \left|11\right\rangle \left\langle 11\right|\}$$

Where for convenience of notation ψ_x is used to denote the superposition,

$$\left|\psi_x\right\rangle = \frac{1}{\sqrt{2}}\left(\left|0\right\rangle + e^{ix}\left|1\right\rangle\right)$$

Additionally $\left|\Psi^+\right\rangle = \frac{1}{\sqrt{2}}\left(\left|01\right\rangle + \left|10\right\rangle\right)$ and $\left|\Phi^+\right\rangle = \frac{1}{\sqrt{2}}\left(\left|00\right\rangle + \left|11\right\rangle\right)$ are two maximally entangled Bell states. Fritz first proved it's incompatibility [**?**] by showing C acts a moderator to ensure measurement pseudo-settings for A and B are independent, satisfying non-broadcasting requirements for the standard Bell scenario. In fact, by coarse-graining outcomes for A and B and treating C as a measurement-setting moderator, P_F maximally violates the CHSH inequality. To illustrate this, begin with the CHSH inequality [**?**],

$$\langle AB|S_A = 1, S_B = 1\rangle + \langle AB|S_A = 1, S_B = 2\rangle + \langle AB|S_A = 2, S_B = 1\rangle - \langle AB|S_A = 2, S_B = 2\rangle \leq 2 \tag{4}$$

Where $\langle AB|S_A = i, S_B = j\rangle$ is the correlation between A and B given the measurement settings for A (B) is i (j) respectively. Next, each of C's outcomes become the condition settings in **??**,

$$\langle AB|C = 2\rangle + \langle AB|C = 3\rangle + \langle AB|C = 4\rangle - \langle AB|C = 1\rangle \leq 2$$

Finally, specifying the correlation between A and B to be defined in terms of a $\{1,2,3,4\} \to \{(1,4),(2,3)\}$ coarse-graining,

$$\frac{\sqrt{2}}{2} + \frac{\sqrt{2}}{2} + \frac{\sqrt{2}}{2} - \frac{-\sqrt{2}}{2} \leq 2$$

$$2\sqrt{2} \leq 2$$

Which corresponds to the maximum quantum violation of the CHSH inequality **??**

Todo (TC Fraser): Discuss non-uniqueness and relabeling Todo (TC Fraser): Summarize Problem 2.17 in fritz BBT, make it more formal

VII. CERTIFICATE INEQUALITIES

A. Casting the Inflated Marginal Problem as a Linear Program

After obtaining the maximal pre-injectable sets associated with a particular inflation, one can write the marginal problem of **??** as a linear program. The key observation is that marginalization is a *linear* operator that can be performed via a matrix multiplication. To do this, we will define the *marginalization matrix*.

Definition 22. The **marginalization matrix** M for a marginal scenario $\{V_1, \dots, V_k\}$ is a bit-wise matrix where the columns are indexed by *joint* outcomes $o[\mathcal{V}] \in O_{\mathcal{V}}$ and the rows are indexed by *marginal* outcomes corresponding to all outcomes $o[V_i] \in O_{V_i}$ of the marginal contexts V_i. The entries of M are populated whenever a row index is extendable to a column index.

$$M_{(o[V_i], o[\mathcal{V}])} = \begin{cases} 1 & \exists o[\mathcal{V} \setminus V_i] \text{ such that } o[V_i] \times o[\mathcal{V} \setminus V_i] = o[\mathcal{V}] \\ 0 & \text{otherwise} \end{cases}$$

The marginalization matrix has $|O_{\mathcal{V}}|$ columns and $\sum_{i=1}^{k} |O_{V_i}|$ rows. The number of non-zero entries of M is a simple expression,

$$\sum_{i=1}^{k} |O_{V_i}| \left|O_{\mathcal{V} \setminus V_i}\right| = \sum_{i=1}^{k} |O_{\mathcal{V}}| = k\,|O_{\mathcal{V}}|$$

Each of the k elements of $\{V_1, \dots, V_k\}$ contributes a single non-zero entry to each column of M, resulting in $k\,|O_{\mathcal{V}}|$ total non-zero entries.

Note that the row and column indices of the marginalization matrix will be referred to very frequently. We will refer to the

Todo (TC Fraser): Computationally Efficient generation?
To illustrate this concretely, consider the following example:

Example 23. Suppose one has 4 binary random variables $\mathcal{V} = \{a, b, c\}$ in mind and 2 subsets $\{\{a, c\}, \{b\}\}$. Then the marginalization matrix is:

$$M = \begin{array}{c} (a{,}b{,}c){=} \\ (a{=}0{,}c{=}0) \\ (a{=}0{,}c{=}1) \\ (a{=}1{,}c{=}0) \\ (a{=}1{,}c{=}1) \\ (b{=}0) \\ (b{=}1) \end{array} \begin{array}{c} \begin{array}{cccccccc} (0{,}0{,}0) & (0{,}0{,}1) & (0{,}1{,}0) & (0{,}1{,}1) & (1{,}0{,}0) & (1{,}0{,}1) & (1{,}1{,}0) & (1{,}1{,}1) \end{array} \\ \begin{pmatrix} 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 1 & 1 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 \end{pmatrix} \end{array}$$

In order to describe how marginalization can be written as matrix multiplication $M \cdot x = b$, we need to describe how to define two more quantities:

Definition 24. The **joint distribution vector** $\mathcal{P}_{\mathcal{V}}$ for a probability distribution $P_{\mathcal{V}}$ is the vector whose entries are the positive, real-valued probabilities that $P_{\mathcal{V}}$ assigns to each outcome of $o[\mathcal{V}]$ of $O_{\mathcal{V}}$. $\mathcal{P}_{\mathcal{V}}$ shares the same indices as the *column* indices of M.

$$\mathcal{P}_{\mathcal{V}}^{\intercal} = [P_{\mathcal{V}}(o[\mathcal{V}])]_{o[\mathcal{V}]\in O_{\mathcal{V}}}$$

Definition 25. The **marginal distribution vector** $\mathcal{P}_{\{V_1,\dots,V_k\}}$ for a marginal model $\{P_{V_1}, \dots, P_{V_k}\}$ is the vector whose entries are probabilities over the set of **marginal outcomes** $\bigcup_{j=1}^{k} O_{V_j}$. $\mathcal{P}_{\{V_1,\dots,V_k\}}$ shares the same indices as the *row* indices of M.

$$\mathcal{P}_{\{V_1,\dots,V_k\}}^{\intercal} = [P_{V_i}(o[V_i])]_{o[V_i]\in\bigcup_{j=1}^{k} O_{V_j}}$$

The marginal and joint distribution vectors are related via the marginalization matrix M. Given a joint distribution vector $\mathcal{P}_{\mathcal{V}}$ one can obtain the marginal distribution vector $\mathcal{P}_{\{V_1,\dots,V_k\}}$ by multiplying M by $\mathcal{P}_{\mathcal{V}}$.

$$\mathcal{P}_{\{V_1,\dots,V_k\}} = M \cdot \mathcal{P}_{\mathcal{V}} \tag{5}$$

Todo (TC Fraser): Discuss non-unique but consistent ordering of M, $\mathcal{P}_{\mathcal{V}}$ and $\mathcal{P}_{\{V_1,\dots,V_k\}}$
The marginal problem can now be rephrased in the language of the marginalization matrix. Suppose one obtains a marginal distribution vector $\mathcal{P}_{\{V_1,\dots,V_k\}}$. The marginal problem becomes equivalent to the question: *Does there exist a joint distribution vector $\mathcal{P}_{\mathcal{V}}$ such that* **??** *holds?*

Definition 26. **The Marginal Linear Program** is the following linear program:

$$\begin{aligned} \text{minimize:} \quad & \emptyset \cdot x \\ \text{subject to:} \quad & x \succeq 0 \\ & M \cdot x = \mathcal{P}_{\{V_1,\dots,V_k\}} \end{aligned}$$

If this "optimization"[1] is *feasible*, then there exists a vector x than can satisfy **??** and is a valid joint distribution vector. Therefore feasibility implies that $P_{\mathcal{V}} = x$, solving the marginal problem with positive result. Moreover if the marginal linear program is *infeasible*, then there *does not* exist a joint distribution $P_{\mathcal{V}}$ over all random variables.

Definition 27. **The Dual Marginal Linear Program** is the dual of **??** formulated via a procedure similar to [**?**]:

$$\begin{aligned} \text{minimize:} \quad & y \cdot \mathcal{P}_{\{V_1,\dots,V_k\}} \\ \text{subject to:} \quad & y \cdot M \succeq 0 \end{aligned}$$

Where y is a real valued vector with the same length as $\mathcal{P}_{\{V_1,\dots,V_k\}}$.

[1] "Optimization" is presented in quotes here because the minimization objective is trivially always zero ($\emptyset$ denotes the null vector of all zero entries). The primal value of the linear program is of no interest, all that matters is its *feasibility.*

B. Infeasibility Certificates

The dual marginal linear program also provides an answer to the marginal problem. To prove this, first notice that the dual problem is *never infeasible*; by choosing y to be trivially the null vector $\emptyset$ of appropriate size, all constraints are satisfied. Secondly if $y \cdot M \succeq 0$ and $x \succeq 0$, then the following must hold if the primal is feasible:

$$y \cdot \mathcal{P}_{\{V_1,\dots,V_k\}} = y \cdot M \cdot x \geq 0 \tag{6}$$

Therefore the *sign* of the dual value $d \equiv \min \left(y \cdot \mathcal{P}_{\{V_1,\dots,V_k\}} \right)$ solves the marginal problem. If $d < 0$ then **??** is violated and therefore the marginal problem has negative result. Likewise if d satisfies **??**, then a joint distribution $P_{\mathcal{V}}$ exists. Before continuing, an important observation needs to be made. If $d \geq 0$, then it is exactly $d = 0$, due to the existence of the trivial $y = \emptyset$. This observation is an instance of the *Complementary Slackness Property* of [**?**]. Comment (TC Fraser): Is this really the CSP? Moreover, if $d < 0$, then it is unbounded $d = -\infty$. This latter point becomes clear upon recognizing that for any y such that $d < 0$, another y' can be constructed by multiplying y by a real constant α greater than one such that,

$$y' = \alpha y \mid \alpha > 1 \implies d' = \alpha d < d$$

Since a more negative d' can always be found, it must be that d is unbounded. This is a demonstration of the fundamental *Unboundedness Property* of [**?**]; if the dual is unbounded, then the primal is infeasible.

Comment (TC Fraser): Farkas's lemma here?

Definition 28. An **infeasibility certificate** is any vector y that satisfies the constraints of **??** and also permits violation of **??** for some marginal distribution vector $\mathcal{P}_{\{V_1,\dots,V_k\}}$.

$$y \in \mathbb{R}^{\sum_{i=1}^{k} |O_{V_i}|} : y \cdot M \succeq 0, \quad y \cdot \mathcal{P}_{\{V_1,\dots,V_k\}} < 0$$

Furthermore, any y satisfying $y \cdot M \succeq 0$ induces a **certificate inequality** that constraints the space of marginal distribution vectors which takes the symbolic form of **??**,

$$y \cdot \mathcal{P}_{\{V_1,\dots,V_k\}} \geq 0$$

Where the entries of the certificate y act as coefficients for the entries of $\mathcal{P}_{\{V_1,\dots,V_k\}}$.

Todo (TC Fraser): Discuss Infeasibility Certificates basis

Example 29. The marginal problem for the inflated causal structure $\mathcal{G}'$ depicted in **??** concerns itself with whether or not distributions over the pre-injectable sets $\{P_{\Pi_1}, \dots, P_{\Pi_{12}}\}$ admit a joint distribution $P_{\mathcal{N}'}$ over all nodes of $\mathcal{G}'$ where $\mathcal{N}' = \bigcup_{i=1}^{12} \Pi_i$. The marginalization matrix M has $16,896$ rows and $16,777,216$ columns.

$$\# \text{ Rows} = \sum_{i=1}^{12} |O_{\Pi_i}| = \sum_{i=1}^{12} 4^{|\Pi_i|} = 4 \cdot 4^6 + 8 \cdot 4^3 = 16,896$$
$$\# \text{ Columns} = |O_{\mathcal{N}'}| = 4^{|\mathcal{N}'|} = 4^{12} = 16,777,216$$

With $12 \cdot 4^{12} = 201,326,592$ non-zero entries.

Todo (TC Fraser): Discuss the certificate inequalities we found.

VIII. LOGICAL IMPLICATIONS OF NON-CONTEXTUALITY

Following the definition of contextuality given as Definition 2.3 in [**?**] Todo (TC Fraser): Motivate why certificates are not enough, want many solutions

A. Logical Implications & Inequalities

Following the work conducted by Mansfield and Fritz [**?**], we consider a possibilistic implications of the **$(1, n)$-type** to be all implications of the form,

$$A \implies C_1 \vee \dots \vee C_n = \bigvee_{i=1}^{n} C_i \tag{7}$$

Where A and each of the C_i's are simply events or outcomes of a particular set of variables. The letter 'A' is chosen for the event A since it takes the place of the logical **antecedent** of **??**. Likewise, the letter 'C' is chosen to represent logical **consequents**. We refer to the set of all C_i's simply as $C = \{C_i \mid i \in 1, \dots, n\}$. The implication **??** can be read as *whenever A occurs, at least one element of C also occurs.*

It is possible to turn possibilistic $(1, n)$-type implications into probabilistic inequalities by recognizing that the logical implication of **??** induces the inequality,

$$P(A) \leq P\left(\bigvee_{i=1}^{n} C_i\right)$$

Furthermore utilizing Boole's inequality,

$$P\left(\bigvee_{i=1}^{n} C_i\right) \leq \sum_{i=1}^{n} P(C_i) \tag{8}$$

Gives,

$$P(A) \leq \sum_{i=1}^{n} P(C_i) \tag{9}$$

Such that whenever the inequality **??** is violated, the implication in **??** is violated as well. Note that the converse is *not* true; if the inequality **??** holds true, it is still possible for there to be a violation of **??**.

Remark 30. An important result of Boole's inequality is that **??** becomes an exact *equality* whenever elements of C are pairwise disjoint. Therefore, finding a set C of pairwise disjoint events satisfying **??** will give rise to tighter inequalities.

B. Implications in the Marginal Problem

The question then remains, *how does non-contextuality give rise to implications of the form of* **??***?* We begin by making the principle assumption that a joint distribution *does* exist for a family of marginal distributions $\{P_{V_1}, \dots, P_{V_k}\}$. We can then derive logical *tautologies* under this assumption that are of $(1, n)$-type, which we call **marginal implications**, using the following train of logic.

1. Suppose a particular marginal outcome $A \in \bigcup_{i=1}^{k} O_{V_i}$ happens to occur. For reference, take $A = o[V_j] \in O_{V_j}$ to belong to the outcome space of V_j for some index j.

2. Since a joint distribution exists, then A refers to some *incomplete* knowledge about some *joint* event J that actually occured. In fact, J is required to belong to the extendable set of A in $O_{\mathcal{V}}$.

$$J \in A \times O_{\mathcal{V} \setminus V_j}$$

3. Therefore whenever A occurs, one of the elements J of $A \times O_{\mathcal{V} \setminus V_j}$ *has* to occur.

$$A \implies J_1 \vee \dots \vee J_l = \bigvee_{J \in A \times O_{\mathcal{V} \setminus V_j}} J \tag{10}$$

4. Now suppose we could obtain a set of marginal outcomes $C = \{C_1, \dots, C_n\}$ each different from A such that every J is in the extendable set of at least one element C. If such a C can be found, then the possibility of at least one J occurring implies the possibility of at least one C occurring.

$$J_1 \vee \dots \vee J_l \implies C_1 \vee \dots \vee C_n \tag{11}$$

5. Combing **??** with **??**, one obtains **??**.

Todo (TC Fraser): Talk about why this is called hardy paradox

Finding all marginal implications for a chosen marginal outcome A corresponds to finding a set of marginal outcomes $C = \{C_1, \ldots, C_n\}$ whose extendable sets *cover* the extendable set of A. Formally this corresponds to a **set covering** problem Todo (TC Fraser): cite which we elected to cast as the equivalent **hypergraph transversal problem**.

Todo (TC Fraser): Mention sufficient solution to the possibilistic marginal problem Todo (TC Fraser): Illustrate how it can distinguish more than possibilistic differences

Given an antecedent A, we can construct a hypergraph $\mathcal{H}_A$ with nodes $\mathcal{N}_A$ and $\mathcal{E}_A$. The edges are labeled by outcomes in A's extendable set $A \times O_{\mathcal{V}\setminus V_j}$, namely $o[\mathcal{V}]$, and contain all marginal outcomes compatible with $o[\mathcal{V}]$. The nodes are the subset of marginal outcomes compatible with A; equivalently the union of all edges. Todo (TC Fraser): Notation for compatible and extendable?

$$\mathcal{E}_A = \left\{ o[\mathcal{V}] \mid o[\mathcal{V}] \in A \times O_{\mathcal{V}\setminus V_j} \right\}$$

The nodes are all marginal outcomes C compatible with A.

$$\mathcal{N}_A = \left\{ n \in \bigcup_{i=1}^{k} O_{V_i} \mid n \neq A, n \right\}$$

And edges $\mathcal{E}_A$ labeled by elements of A's extendable set $o[\mathcal{V} \setminus V_j] \times$

Todo (TC Fraser): Discuss $(m, n) - \textit{type}$ implications and the non-triviality Todo (TC Fraser): Link to logical bell inequalities/completeness or not?

C. Hypergraph Transversals

Todo (TC Fraser): Convince one how marginal implications are a hypergraph transversal or covering problem Todo (TC Fraser): Existing algorithms Todo (TC Fraser): Discuss the Inequalities Derived/ Trivial and non-trivial Todo (TC Fraser): Weighted transversals and Optimizations Todo (TC Fraser): Seeding inequalities (huge advantage here)

IX. DERIVING SYMMETRIC INEQUALITIES

Todo (TC Fraser): Identify the desired symmetry group Todo (TC Fraser): How we obtained the desired symmetry group Todo (TC Fraser): Group orbits to symmetric marginal description matrix Todo (TC Fraser): Infeasibility on symmetric marginal problem Todo (TC Fraser): Hardy Transversals can't work on the symmetric marginal problem Todo (TC Fraser): Symmetrizing non-symmetric inequalities through avoiding orbits Todo (TC Fraser): higher order transversals on mutually impossible events

X. NON-LINEAR OPTIMIZATIONS

Compatibility inequalities for a given causal structure are fantastic for finding incompatible distributions. In the inflation technique, this is no exception. Parameterizing a space distributions using a set of real-valued parameters λ, enables us to perform numerical optimizations against these inequalities in hopes that a particular set of parameters λ is able to generate an incompatible distribution P. To illustrate this generic procedure and it's reliability, we will first examine the popular CHSH inequality.

A. Numerical Violations of The CHSH Inequality

The CHSH inequality [?] can we viewed as a causal compatibility inequality for iconic the Bell Scenario (Fig. 19 of [?], Fig. 11 of [?], Fig. 1 a) of [?], etc.) corresponding to Bell's notion of local causality [?]. It constrains the set of 2-outcome bipartite distributions over local binary measurement settings for each party $P_{AB|S_A S_B} \equiv \left\{ P_{AB|00}, P_{AB|01}, P_{AB|10}, P_{AB|11} \right\}$. Numerical optimization *should* obtain the algebraic violation associated with the PR-Box correlations [?]. Maintaining full generality, we simply need to parameterize these 4 distributions using **??**, each requiring 4 real-valued parameters.

Todo (TC Fraser): Demonstrate Quantum, Convexity

Todo (TC Fraser): Why Inequalities are great for optimizations Todo (TC Fraser): Non-linearity Todo (TC Fraser): Techniques Used Todo (TC Fraser): Finding maximum violation of CHSH easily Todo (TC Fraser): Unreliance when number of parameters increases Todo (TC Fraser): Issues with local minimum Todo (TC Fraser): Using initial conditions close to fritz, obtain greater violation Todo (TC Fraser): Greater violation shares possibilistic structure of fritz and violates CHSH under definition Todo (TC Fraser): Not realizable with maximally entangled qubit states Todo (TC Fraser): Not realizable with separable measurements Todo (TC Fraser): Many non-trivial inequalities to be tested Todo (TC Fraser): inequality -> dist -> inequality evolution

XI. CONCLUSIONS

Todo (TC Fraser): Inflation technique allows one to witness fritz incompatibility Todo (TC Fraser): Linear optimization induces certificates which are incompatibility witnesses Todo (TC Fraser): There are quantum distributions in the triangle scenario that are incompatible and different from fritz in terms of entanglement but not possibilistic structure

XII. OPEN QUESTIONS & FUTURE WORK

Todo (TC Fraser): Lots of stuff

Appendix A: Computationally Efficient Parametrization of the Unitary Group

Spengler, Huber and Hiesmayr [?] suggest the parameterization of the unitary group $\mathcal{U}(d)$ using a $d \times d$-matrix of real-valued parameters $\lambda_{n,m}$

$$U = \left[\prod_{m=1}^{d-1}\left(\prod_{n=m+1}^{d}\exp\left(iP_n\lambda_{n,m}\right)\exp\left(i\sigma_{m,n}\lambda_{m,n}\right)\right)\right]\cdot\left[\prod_{l=1}^{d}\exp\left(iP_l\lambda_{l,l}\right)\right] \tag{A1}$$

Where P_l are one-dimensional projective operators,

$$P_l = |l\rangle\langle l| \tag{A2}$$

and the $\sigma_{m,n}$ are generalized anti-symmetric σ-matrices,

$$\sigma_{m,n} = -i\,|m\rangle\langle n| + i\,|n\rangle\langle m|$$

Where $1 \leq m < n \leq d$. For the sake of reference, let us label the matrix exponential terms in **??** in a manner that corresponds to their affect on a orthonormal basis $\{|1\rangle, \dots, |d\rangle\}$.

$$\begin{aligned} GP_l &= \exp\left(iP_l\lambda_{l,l}\right) \\ RP_{n,m} &= \exp\left(iP_n\lambda_{n,m}\right) \\ R_{n,m} &= \exp\left(i\sigma_{m,n}\lambda_{m,n}\right) \end{aligned} \tag{A3}$$

It is possible to remove the reliance on matrix exponential operations in **??** by utilizing the explicit form of the exponential terms in **??**. As a first step, recognize the defining property of the projective operators **??**,

$$P_l^k = \left(|l\rangle\langle l|\right)^k = |l\rangle\langle l| = P_l$$

This greatly simplifies the global phase terms GP_l,

$$GP_l = \exp\left(iP_l\lambda_{l,l}\right) = \sum_{k=0}^{\infty}\frac{\left(iP_l\lambda_{l,l}\right)^k}{k!} = \mathbb{I} + \sum_{k=1}^{\infty}\frac{\left(i\lambda_{l,l}\right)^k}{k!}P_l^k = \mathbb{I} + P_l\left[\sum_{k=1}^{\infty}\frac{\left(i\lambda_{l,l}\right)^k}{k!}\right] = \mathbb{I} + P_l\left(e^{i\lambda_{l,l}} - 1\right)$$

Analogously for the relative phase terms $RP_{n,m}$,

$$RP_{n,m} = \cdots = \mathbb{I} + P_n\left(e^{i\lambda_{n,m}} - 1\right)$$

Finally, the rotation terms $R_{n,m}$ can also be simplified by examining powers of $i\sigma_{n,m}$,

$$R_{n,m} = \exp\left(i\sigma_{m,n}\lambda_{m,n}\right) = \sum_{k=0}^{\infty} \frac{\left(|m\rangle\langle n| - |n\rangle\langle m|\right)^k \lambda_{m,n}^k}{k!}$$

One can verify that the following properties hold,

$$\left(|m\rangle\langle n| - |n\rangle\langle m|\right)^0 = \mathbb{I}$$
$$\forall k \in \mathbb{N}, k \neq 0 : \left(|m\rangle\langle n| - |n\rangle\langle m|\right)^{2k} = (-1)^k \left(|m\rangle\langle m| + |n\rangle\langle n|\right)$$
$$\forall k \in \mathbb{N} : \left(|m\rangle\langle n| - |n\rangle\langle m|\right)^{2k+1} = (-1)^k \left(|m\rangle\langle n| - |n\rangle\langle m|\right)$$

Revealing the simplified form of $R_{n,m}$,

$$R_{n,m} = \mathbb{I} + \left(|m\rangle\langle m| + |n\rangle\langle n|\right) \sum_{j=1}^{\infty} (-1)^j \frac{\lambda_{n,m}^{2j}}{(2j)!} + \left(|m\rangle\langle n| - |n\rangle\langle m|\right) \sum_{j=0}^{\infty} (-1)^j \frac{\lambda_{n,m}^{2j+1}}{(2j+1)!}$$

$$R_{n,m} = \mathbb{I} + \left(|m\rangle\langle m| + |n\rangle\langle n|\right)\left(\cos\lambda_{n,m} - 1\right) + \left(|m\rangle\langle n| - |n\rangle\langle m|\right)\sin\lambda_{n,m}$$

Todo (TC Fraser): Explanation of Computational Complexity $\mathcal{O}\left(d^3\right)$ vs. $\mathcal{O}(1)$ using [?] Todo (TC Fraser): Pre-Caching for Fixed dimension d

Appendix B: Parametrization of Quantum States & Measurements

Appendix C: Convex Parametrization of Finite Probability Distributions

As discussed in **??**, there is a need to parameterize the family of all probability distributions P_V over a given set of variables $V = \left(v_1, \dots, v_{|V|}\right)$. If the cardinality of O_V is finite, then this computationally feasible. The space of probability distributions over $n = |O_V|$ distinct outcomes forms a $n-1$ dimensional convex polytope naturally embedded in $\mathbb{R}^n_{\geq 0}$ [?] that is parameterizable by $n-1$ real value parameters; normalization $\sum_{o[V]\in O_V} P_V(o[V]) = 1$ accounts for the '-1'. An example of a non-degenerate parameterization of P_V consists of $n-1$ parameters $\lambda = (\lambda_1, \dots, \lambda_{n-1}), \lambda_i \in [0, \pi/2]$ which generate the probabilities n probability values p_j using hyperspherical coordinates [? ?],

$$p_j = \cos^2\lambda_j \prod_{i=1}^{j-1} \sin^2\lambda_i \quad \forall j \in 1, \dots, n-1$$
$$p_n = \prod_{i=1}^{n-1} \sin^2\lambda_i \tag{C1}$$

Furthermore due to the periodicity of the parameter space λ, **??** can be used for either constrained or unconstrained optimization problems.

Although non-degenerate, this parameterization suffers from uniformity; a randomly sampled vector of parameters λ *does not* translate to a randomly sampled probability P_V. An easy-to-implement, degenerate parameterization of P_V can be constructed by simply beginning with n real parameters $\lambda = (\lambda_1, \dots, \lambda_n)$, then making them positive and normalized by their sum[2].

$$p_j = \frac{|\lambda_j|}{\sum_{i=1}^{n} |\lambda_i|} \quad \forall j \in 1, \dots, n \tag{C2}$$

For various convex optimization tasks sensitive to initial conditions outlined **??**, the latter parameterization of **??** generally performed better that former **??**.

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[2] Strictly speaking, **??** *also* suffers from non-uniformity; being biased toward uniform probability distributions P_V. Todo (TC Fraser): Discuss rejection sampling simplex algorithms