

Causal Compatibility Inequalities Admitting of Quantum Violations in the Triangle Scenario

T. C. Fraser¹

¹Perimeter Institute for Theoretical Physics
Ontario, Canada

Quantum Networks, 2016

References I

Todo (TC Fraser): Figure out how to get references at the end

[1] K. F. Pál and T. Vértesi.

Maximal violation of a bipartite three-setting, two-outcome bell inequality using infinite-dimensional quantum systems.

Phys. Rev. A, 82(2), aug 2010.

[2] C. Spengler, M. Huber, and B. C. Hiesmayr.

A composite parameterization of unitary groups, density matrices and subspaces.

2010.

[3] E. Wolfe, R. W. Spekkens, and T. Fritz.

The inflation technique for causal inference with latent variables, 2016.

Table of Contents

Tools

Symmetries

Searching for New Distributions

Introduction

1. Todo (TC Fraser):

Notation

- ▶ Complete set of random variables are the **joint random variables**

$$\mathcal{J} = \{v_1, \dots, v_n\}$$

- ▶ A subset of $V \subset \mathcal{J}$ is a **marginal context**
- ▶ **Marginal scenario** \mathcal{M}

$$\mathcal{M} = \{V_1, \dots, V_k \mid V_i \subset \mathcal{J}\} \quad \mathcal{J} = \bigcup_i V_i$$

- ▶ Marginal scenario forms a *simplicial complex*

$$V \in \mathcal{M}, V' \subseteq V \implies V' \in \mathcal{M}$$

- ▶ Restrict focus to *maximal* marginal scenario where only the largest contexts are present

$$\forall V_i, V_j \in \mathcal{M} : V_i \not\subseteq V_j$$

Notation Cont'd

- ▶ **Marginal model** $P^{\mathcal{M}}$ is collection of probability distributions

$$P^{\mathcal{M}} = \{P_{V_1}, \dots, P_{V_k}\}$$

- ▶ **Causal Structure** $\mathcal{G} = (\mathcal{N}, \mathcal{E})$ is a directed acyclic graph (DAG)
- ▶ Nodes classified into **latent nodes** \mathcal{N}_L and **observed nodes** \mathcal{N}_O

Todo (TC Fraser): Insert generic causal structure

Graph Theory [Optional Slide]

Let $n, m \in \mathcal{N}$ be nodes of the graph \mathcal{G} .

- ▶ **parents of n** : $\text{Pa}_{\mathcal{G}}(n) \equiv \{m \mid m \rightarrow n\}$
- ▶ **children of n** : $\text{Ch}_{\mathcal{G}}(n) \equiv \{m \mid n \rightarrow m\}$
- ▶ **ancestry of n** : $\text{An}_{\mathcal{G}}(n) \equiv \bigcup_{i \in \mathbb{W}} \text{Pa}_{\mathcal{G}}^i(n)$

$$\text{Pa}_{\mathcal{G}}^0(n) = n \quad \text{Pa}_{\mathcal{G}}^i(n) \equiv \text{Pa}_{\mathcal{G}}(\text{Pa}_{\mathcal{G}}^{i-1}(n))$$

Notation extends to sets of nodes $N \subseteq \mathcal{N}$,

- ▶ **parents of N** : $\text{Pa}_{\mathcal{G}}(N) \equiv \bigcup_{n \in N} \text{Pa}_{\mathcal{G}}(n)$
- ▶ **children of N** : $\text{Ch}_{\mathcal{G}}(N) \equiv \bigcup_{n \in N} \text{Ch}_{\mathcal{G}}(n)$
- ▶ **ancestry of N** : $\text{An}_{\mathcal{G}}(N) \equiv \bigcup_{n \in N} \text{An}_{\mathcal{G}}(n)$

An **induced subgraph** of $\mathcal{G} = (\mathcal{N}, \mathcal{E})$ due to $N \subseteq \mathcal{N}$

$$\text{Sub}_{\mathcal{G}}(N) = (N, \{e \in \mathcal{E} \mid e \subseteq N\})$$

Causal Compatibility

Question: Is a marginal model $P^{\mathcal{M}}$ **compatible** with a causal structure \mathcal{G} ?

$$\mathcal{M} = \{V_1, \dots, V_k \mid V_i \subset \mathcal{N}_O\}$$

Answer: $P^{\mathcal{M}}$ is compatible with \mathcal{G} if there exists a set of **casual parameters**

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

Such that for each $V \in \mathcal{M}$, P_V can be recovered:

1. $P_{\mathcal{N}} = \prod_{n \in \mathcal{N}} P_{n|\text{Pa}_{\mathcal{G}}(n)}$
2. $P_V = \sum_{\mathcal{N} \setminus V} P_{\mathcal{N}}$

A **casual compatibility inequality** is an inequality over $P^{\mathcal{M}}$ that is satisfied by all compatible $P^{\mathcal{M}}$

Triangle Inequalities

└ Tools

└ Causal Compatibility

Question: Is a marginal model P^M compatible with a causal structure G ?

$$\mathcal{M} = \{V_1, \dots, V_k \mid V_i \subset N_G\}$$

Answer: P^M is compatible with G if there exists a set of causal parameters

$$\{P_{\alpha(p_{\alpha}(n)} \mid n \in N_i\}$$

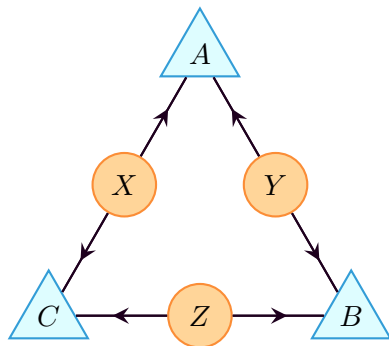
Such that for each $V \in \mathcal{M}$, P_V can be recovered:

1. $P_N = \prod_{V \in \mathcal{N}} P_{\alpha(p_{\alpha}(n)}$
2. $P_V = \sum_{N \setminus V} P_N$

A causal compatibility inequality is an inequality over P^M that is satisfied by all compatible P^M .

1.

Triangle Scenario



- ▶ Three parties $\mathcal{N}_O = \{A, B, C\}$
- ▶ Pair-wise sharing three latent variables $\mathcal{N}_L = \{X, Y, Z\}$
- ▶ **Todo (TC Fraser): Inject info about existing work**
- ▶ There exists *quantum-accessible* distributions P_{ABC} that are *incompatible* with the triangle scenario

Fritz Distribution

The Fritz Distribution P_F :

- ▶ three-party $P_F = P_{ABC}$
- ▶ each party has four outcomes

Inflation Technique

- Developed by Wolfe, Spekkens, and Fritz [3]

Definition

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

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

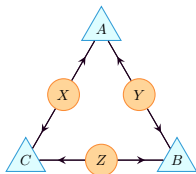
Where $\text{AnSub}_{\mathcal{G}}(n)$ denotes the ancestral sub-graph of n in \mathcal{G}

$$\text{AnSub}_{\mathcal{G}}(n) = \text{Sub}_{\mathcal{G}}(\text{An}_{\mathcal{G}}(n))$$

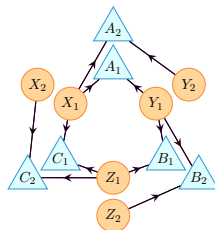
And ' \sim ' is a **copy-index** equivalence relation

$$A_1 \sim A_2 \sim A \not\sim B_1 \sim B_2 \sim B$$

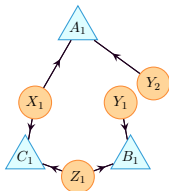
Inflations of the Triangle Scenario



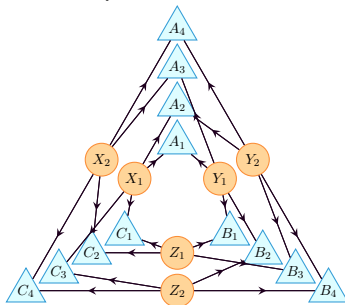
The Triangle Scenario



Spiral Inflation



Cut Inflation



Large Inflation

Inflation Lemma

If one has obtained \mathcal{G} , inflation \mathcal{G}' and *compatible* marginal distribution P_N where $N \subseteq \mathcal{N}$, then:

1. There exists causal parameters $\{P_{n|\text{Pa}_{\mathcal{G}}(n)} \mid n \in \mathcal{N}\}$ such that

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

2. $\text{AnSub}_{\mathcal{G}'}(n') \sim \text{AnSub}_{\mathcal{G}}(n) \implies \text{Pa}_{\mathcal{G}'}(n') \sim \text{Pa}_{\mathcal{G}}(n)$
3. Construct **inflated causal parameters**

$$\forall n' \in \mathcal{N}' : P_{n'|\text{Pa}_{\mathcal{G}'}(n')} \equiv P_{n|\text{Pa}_{\mathcal{G}}(n)}$$

4. Obtain *compatible* marginal distributions over any $N' \subseteq \mathcal{N}'$

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

Inflation Lemma Cont'd

- ▶ Inflation procedure holds for any $N \in \mathcal{N}, N' \in \mathcal{N}'$ where $N \sim N'$
- ▶ Define **injectable sets of \mathcal{G}'** and **images of the injectable of \mathcal{G}**

$$\begin{aligned}\text{Inj}_{\mathcal{G}}(\mathcal{G}') &\equiv \{N' \subseteq \mathcal{N}' \mid \exists N \subseteq \mathcal{N} : N \sim N'\} \\ \text{ImInj}_{\mathcal{G}}(\mathcal{G}') &\equiv \{N \subseteq \mathcal{N} \mid \exists N' \subseteq \mathcal{N}' : N \sim N'\}\end{aligned}$$

- ▶ For $N' \in \text{Inj}_{\mathcal{G}}(\mathcal{G}')$ there is a *unique* $N \subseteq \mathcal{N}$ such that $N \sim N'$
- ▶ For $N \in \text{ImInj}_{\mathcal{G}}(\mathcal{G}')$ there can *exist many* $N' \subseteq \mathcal{N}'$ such that $N \sim N'$

Inflation Lemma Cont'd

Lemma

The Inflation Lemma: [3, lemma 3] Given a particular inflation \mathcal{G}' of \mathcal{G} , if a marginal model $\{P_N \mid N \in \text{ImInj}_{\mathcal{G}}(\mathcal{G}')\}$ is compatible with \mathcal{G} then all marginal models $\{P_{N'} \mid N' \in \text{Inj}_{\mathcal{G}}(\mathcal{G}')\}$ are compatible with \mathcal{G}' provided that $P_N = P_{N'}$ for all instances where $N \sim N'$.

Corollary

*Any causal compatibility inequality I' constraining the injectable sets $\text{Inj}_{\mathcal{G}}(\mathcal{G}')$ can be **deflated** into a causal compatibility inequality I constraining the images of the injectable sets $\text{ImInj}_{\mathcal{G}}(\mathcal{G}')$.*

Inflation Lemma Cont'd

Lemma

The Inflation Lemma: [3, lemma 3] Given a particular inflation \mathcal{G}' of \mathcal{G} , if a marginal model $\{P_N \mid N \in \text{ImInj}_{\mathcal{G}}(\mathcal{G}')\}$ is compatible with \mathcal{G} then all marginal models $\{P_{N'} \mid N' \in \text{Inj}_{\mathcal{G}}(\mathcal{G}')\}$ are compatible with \mathcal{G}' provided that $P_N = P_{N'}$ for all instances where $N \sim N'$.

Corollary

*Any causal compatibility inequality I' constraining the injectable sets $\text{Inj}_{\mathcal{G}}(\mathcal{G}')$ can be **deflated** into a causal compatibility inequality I constraining the images of the injectable sets $\text{ImInj}_{\mathcal{G}}(\mathcal{G}')$.*

Inflation Pipeline

1. Walk through how the inflation pipeline works

Outcomes and Events

- ▶ Set of **outcomes** O_v for each variable v
- ▶ Set of **events** for a set of variables V

$$\mathcal{E}(V) \equiv \{s : V \rightarrow O_V \mid \forall v \in V, s(v) \in O_v\}$$

Definition

The set of events over the joint variables $\mathcal{E}(\mathcal{J})$ are termed the **joint events**.

Definition

The set of events over the marginal contexts are the **marginal events**

$$\mathcal{E}(\mathcal{M}) \equiv \coprod_{V \in \mathcal{M}} \mathcal{E}(V)$$

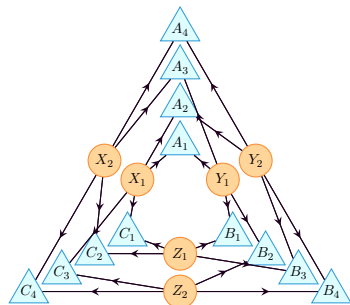
Incidence Matrix

- ▶ Incidence matrix M is a bit-wise matrix
- ▶ Row-indexed by marginal events $m \in \mathcal{E}(\mathcal{M})$
- ▶ Column-indexed by joint events $j \in \mathcal{E}(\mathcal{J})$

$$M_{m,j} = \begin{cases} 1 & m \text{ compatible with } j \\ 0 & \text{otherwise} \end{cases}$$

Application to Large Inflation

- ▶ Tackling Large inflation
- ▶ 12 pre-injectable sets (to follow)



Large Inflation Pre-injectable Sets

Maximal Pre-injectable Sets

$\{A_1, B_1, C_1, A_4, B_4, C_4\}$

$\{A_1, B_2, C_3, A_4, B_3, C_2\}$

$\{A_2, B_3, C_1, A_3, B_2, C_4\}$

$\{A_2, B_4, C_3, A_3, B_1, C_2\}$

$\{A_1, B_3, C_4\}$

$\{A_1, B_4, C_2\}$

$\{A_2, B_1, C_4\}$

$\{A_2, B_2, C_2\}$

$\{A_3, B_3, C_3\}$

$\{A_3, B_4, C_1\}$

$\{A_4, B_1, C_3\}$

$\{A_4, B_2, C_1\}$

Ancestral Independences

$\{A_1, B_1, C_1\} \perp \{A_4, B_4, C_4\}$

$\{A_1, B_2, C_3\} \perp \{A_4, B_3, C_2\}$

$\{A_2, B_3, C_1\} \perp \{A_3, B_2, C_4\}$

$\{A_2, B_4, C_3\} \perp \{A_3, B_1, C_2\}$

$\{A_1\} \perp \{B_3\} \perp \{C_4\}$

$\{A_1\} \perp \{B_4\} \perp \{C_2\}$

$\{A_2\} \perp \{B_1\} \perp \{C_4\}$

$\{A_2\} \perp \{B_2\} \perp \{C_2\}$

$\{A_3\} \perp \{B_3\} \perp \{C_3\}$

$\{A_3\} \perp \{B_4\} \perp \{C_1\}$

$\{A_4\} \perp \{B_1\} \perp \{C_3\}$

$\{A_4\} \perp \{B_2\} \perp \{C_1\}$

Large Inflation Incidence

- ▶ Joint variables are all of the observable nodes $\mathcal{N}'_O = \mathcal{J}$

$$\mathcal{J} = \{A_1, A_2, A_3, A_4, B_1, B_2, B_3, B_4, C_1, C_2, C_3, C_4\}$$

- ▶ Marginal scenario is composed of pre-injectable sets $\mathcal{M} = \text{PreInj}_{\mathcal{G}}(\mathcal{G}')$
- ▶ Inequalities Violated by Fritz distribution are inherently 4-outcome
- ▶ Incidence matrix M is very large $\sim 2.25\text{Gb}$

$$\# \text{Columns} = \prod_{v \in \mathcal{J}} O_v = 4^{12} = 16,777,216$$

$$\# \text{Rows} = \sum_{V \in \mathcal{M}} \prod_{v \in V} O_v = 4 \times 4^6 + 8 \times 4^3 = 16,896$$

Inequalities Found

Causal Symmetry

Symmetric Incidence

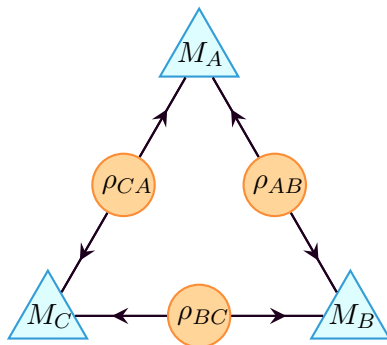
Symmetric Inequalities

Numerical Optimization

Parameterizing Quantum Distributions

For our purposes, we need to parameterize the space of quantum-accessible distributions that are *realized* on the Triangle Scenario

$$P_{ABC}(abc) = \text{Tr}[\Pi^T \rho_{AB} \otimes \rho_{BC} \otimes \rho_{CA} \Pi M_{A,a} \otimes M_{B,b} \otimes M_{C,c}]$$



Parameterizing Unitary Group

- ▶ Spengler, Huber and Heismayr [2] demonstrate a parameterization of $\mathcal{U}(d)$ where the parameters are organized in a $d \times d$ -matrix of real values $\lambda_{n,m}$

$$U = \left[\prod_{m=1}^{d-1} \left(\prod_{n=m+1}^d R_{m,n} R P_{n,m} \right) \right] \left[\prod_{l=1}^d G P_l \right]$$

- ▶ Global Phase Terms: $G P_l = \exp(i P_l \lambda_{l,l})$
- ▶ Relative Phase Terms: $R P_{m,n} = \exp(i P_n \lambda_{n,m})$
- ▶ Rotation Terms: $R_{n,m} = \exp(i \sigma_{m,n} \lambda_{m,n})$
- ▶ Projection Operators: $P_l = |l\rangle\langle l|$
- ▶ Anti-symmetric σ -matrices: $\sigma_{m,n} = -i|m\rangle\langle n| + i|n\rangle\langle m|$

Parameterizing Unitary Group Cont'd

- ▶ Each parameter $\lambda_{n,m}$ has physical interpretation
- ▶ Degeneracies are easily eliminated such as global phase

$$\forall l = 1, \dots, d : \lambda_{l,l} = 0 \implies GP_l = 1$$

- ▶ Parameterize $U \in \mathcal{U}(d)$ up to global phase denoted $\tilde{U} \in \mathcal{U}(d)$
- ▶ Computationally efficient

$$GP_l = \mathbb{1} + P_l(e^{i\lambda_{l,l}} - 1)$$

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

$$\begin{aligned} R_{n,m} = \mathbb{1} &+ (|m\rangle\langle m| + |n\rangle\langle n|)(\cos \lambda_{n,m} - 1) \\ &+ (|m\rangle\langle n| - |n\rangle\langle m|)\sin \lambda_{n,m} \end{aligned}$$

Parameterizing States

- ▶ Each latent resource $\rho \in (\rho_{AB}, \rho_{BC}, \rho_{CA})$ modeled as bipartite qubit state acting on $\mathcal{H}^{d/2} \otimes \mathcal{H}^{d/2}$
- ▶ $d \times d$ positive semi-definite (PSD) hermitian matrices with unitary trace
- ▶ **Cholesky Parametrization** allows one to write any hermitian PSD as $\rho = T^\dagger T$
- ▶ For $d = 4$:

$$T = \begin{bmatrix} \lambda_1 & 0 & 0 & 0 \\ \lambda_2 + i\lambda_3 & \lambda_4 & 0 & 0 \\ \lambda_5 + i\lambda_6 & \lambda_7 + i\lambda_8 & \lambda_9 & 0 \\ \lambda_{10} + i\lambda_{11} & \lambda_{12} + i\lambda_{13} & \lambda_{14} + i\lambda_{15} & \lambda_{16} \end{bmatrix}$$

- ▶ d^2 real-valued parameters
- ▶ Normalized $\rho = T^\dagger T / \text{Tr}(T^\dagger T)$ adds degeneracy

Parameterizing States Cont'd

- ▶ **SHH parameterization** [2] exploits spectral decomposition; for rank $k \leq d$ density matrix

$$\rho = \sum_{i=1}^k p_i |\psi_i\rangle\langle\psi_i| \quad p_i \geq 0, \sum_i p_i = 1$$

- ▶ Orthonormal k -element sub-basis $\{|\psi_i\rangle\}$ of \mathcal{H}^d can be transformed into computational basis $\{|i\rangle\}$ by unitary $U \in \mathcal{U}(d)$ such that $|\psi_i\rangle = U|i\rangle$
- ▶ Freedom to choose k
- ▶ Parameterize ρ through $\{p_i\}$ and \tilde{U}_k

$$\tilde{U}_k = \prod_{m=1}^k \left(\prod_{n=m+1}^d R_{m,n} R P_{n,m} \right)$$

- ▶ $d^2 - (d - k)^2 - k + (k - 1) = 2dk - k^2 - 1$ real-valued parameters (no-degeneracy)

Parameterizing POVMs

- ▶ Each party (A, B, C) is assigned a **projective-operator valued measure (POVM)** (M_A, M_B, M_C)

$$\forall |\psi\rangle \in \mathcal{H}^d : \langle \psi | M_\chi | \psi \rangle \geq 0 \quad M_\chi = M_\chi^\dagger$$

- ▶ n -outcome measurement

$$M_\chi = \{M_{\chi,1}, \dots, M_{\chi,n}\} \quad \sum_{i=1}^n M_{\chi,i} = \mathbb{1}$$

- ▶ For $n = 2$ outcomes, a parameterization exists by constraining the eigenvalues of $M_{\chi,i}$; for $n > 2$ not aware of anything
- ▶ Warrants consideration of **projective-valued measures (PVMs)** (for $n = d$ this is without loss of generality)

Triangle Inequalities

Searching for New Distributions

Parameterizing POVMs

- Each party (A, B, C) is assigned a **projective-operator valued measure (POVM)** (M_A, M_B, M_C)

$$\forall |\psi\rangle \in \mathcal{H}^d : \langle \psi | M_k | \psi \rangle \geq 0 \quad M_k = M_k^\dagger$$

- n -outcome measurement

$$M_k = \{M_{k,1}, \dots, M_{k,n}\} \quad \sum_{i=1}^n M_{k,i} = 1$$

- For $n = 2$ outcomes, a parameterization exists by constraining the eigenvalues of $M_{k,i}$ for $n > 2$ not aware of anything
- Warrants consideration of **projective-valued measures (PVMs)** (for $n = d$ this is without loss of generality)

1. Naimark's Dilation Theorem

Parameterizing PVMs

- ▶ Each party (A, B, C) is assigned n -outcome (M_A, M_B, M_C) such that,

$$M_{\chi,i} M_{\chi,j} = \delta_{ij} M_{\chi,i} \quad M_{\chi,i} = |m_{\chi,i}\rangle\langle m_{\chi,i}|$$

- ▶ Inspired by [1], parameterizing PVMs means parameterizing a n -element sub-basis $\{|m_{\chi,i}\rangle\}$
- ▶ Use unitary transformation again

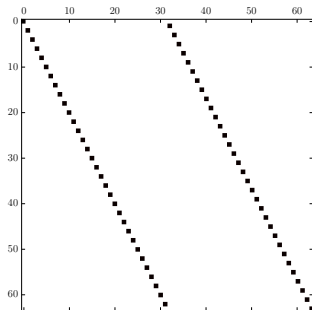
$$\{|m_{\chi,1}\rangle, \dots, |m_{\chi,n}\rangle\} = \{U|1\rangle, \dots, U|n\rangle\}$$

- ▶ Global phase and remaining basis irrelevant: \tilde{U}_n requires $2dn - n^2 - 1$ real-valued parameters
- ▶ PVMs are computationally more efficient

$$P_{ABC}(abc) = \langle m_{A,a} m_{B,b} m_{C,c} | \Pi^\top \rho_{AB} \otimes \rho_{BC} \otimes \rho_{CA} \Pi | m_{A,a} m_{B,b} m_{C,c} \rangle$$

Network Permutation Matrix

- ▶ States and measurements in the Triangle Scenario are not aligned
- ▶ Without Π , P_{ABC} would be separable
- ▶ Required to align B 's measurement over $\text{Tr}_{A,C}(\rho_{AB} \otimes \rho_{BC})$
- ▶ Π is a $2^6 \times 2^6$ matrix
- ▶ Shifts one qubit to the left



$$\Pi \equiv \sum_{|q_i\rangle \in \{|0\rangle, |1\rangle\}} |q_2 q_3 q_4 q_5 q_6 q_1\rangle \langle q_1 q_2 q_3 q_4 q_5 q_6|$$

Maximally Violating Distributions

Non-Trivial Inequalities For Large Inflation

Conclusions

Post-doc Opportunities At Perimeter