

Automated Reasoning by Convex Optimization

Proof Simplicity, Duality and Sparsity

Chee Wei Tan

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Hilbert's Twenty-Fourth Problem

“Criteria of simplicity, or **proof of the greatest simplicity of certain proofs**. Develop a theory of the method of proof in mathematics in general. Under a given set of conditions there can be but one simplest proof.”



The Problem

Design a **scalable** algorithm to **automatically** construct **the simplest** analytic proof or disproof for the given information inequality.

S. W. Ho, L. Ling, C. W. Tan and R. W. Yeung, Proving and Disproving Information Inequalities: Theory and Scalable Algorithms, IEEE Transactions on Information Theory, 2020.

Examples

Prove: $H(X, Y, Z) - H(X|Y, Z) - H(Y|X, Z) - H(Z|X, Y) \geq 0$

Proof #1

$$= I(X; Y) + I(X; Z|Y) + I(Y; Z|X) \geq 0$$

Proof #2

$$\begin{aligned} &= 0.8(I(X; Y) + I(X; Z|Y) + I(Y; Z|X)) + \\ &\quad 0.1(I(X; Z) + I(X; Y|Z) + I(Y; Z|X)) + \\ &\quad 0.1(I(Y; Z) + I(X; Z|Y) + I(X; Y|Z)) \geq 0 \end{aligned}$$

Proof Simplicity

What is the “criteria of simplicity”?

“The elegance of a mathematical theorem is directly proportional to the number of independent ideas one can see in the theorem and inversely proportional to the effort it takes to see them”

— George Pólya

In our problem, we can quantify the simplicity of a proof by the number of elemental inequalities involved.

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A Toy Example

$$H(A|B) \leq H(A)$$

Rewrite using joint-entropies

$$H(A) + H(B) - H(A, B) \geq 0$$

Define $\mathbf{h} = \begin{bmatrix} H(A) \\ H(B) \\ H(A, B) \end{bmatrix}$, $\mathbf{b} = \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix}$

Prove

$$\mathbf{b}^T \mathbf{h} \geq 0$$

Shannon's Elemental Inequalities Constraints

$$\mathbf{h} = \begin{bmatrix} H(A) \\ H(B) \\ H(A, B) \end{bmatrix} \text{ should follow some constraints. e.g.,}$$

$$I(A; B) = H(A) + H(B) - H(A, B) \geq 0$$

$$H(A|B) = H(A, B) - H(B) \geq 0$$

$$H(B|A) = H(A, B) - H(A) \geq 0$$

We group them into constraint matrix \mathbf{D} ($\mathbf{Dh} \geq \mathbf{0}$).

Problem specific constraints: \mathbf{E} ($\mathbf{Eh} = \mathbf{0}$).

The Primal and Dual Linear Programs

Primal:

$$\begin{array}{ll}\min & \mathbf{b}^T \mathbf{h} \\ \text{s.t.} & \mathbf{D}\mathbf{h} \geq \mathbf{0} \\ & \mathbf{E}\mathbf{h} = \mathbf{0} \\ \text{var.} & \mathbf{h}\end{array}$$



Geometric aspect



Verify the information inequality

Dual:

$$\begin{array}{ll}\max & \mathbf{y}^T \mathbf{0} \\ \text{s.t.} & \mathbf{D}^T \mathbf{y} = \mathbf{b} + \mathbf{E}^T \boldsymbol{\mu} \\ & \mathbf{y} \geq \mathbf{0} \\ \text{var.} & \mathbf{y}, \boldsymbol{\mu}\end{array}$$



Algebraic aspect



Construct an analytic proof for the
information inequality

Geometric Aspect (The Primal Problem)

$$p^* = \min_{\mathbf{h}} \{ \mathbf{b}^T \mathbf{h} \mid \mathbf{D}\mathbf{h} \geq \mathbf{0}, \mathbf{E}\mathbf{h} = \mathbf{0} \}$$

- $p^* \geq 0 \implies$ The inequality is true (it's Shannon-type).
- $p^* < 0 \implies$ The inequality is false or it's a non-Shannon-type inequality.

A verifier that *verifies* information inequalities.

Algebraic Aspect (The Dual Problem)

Dual constraints:

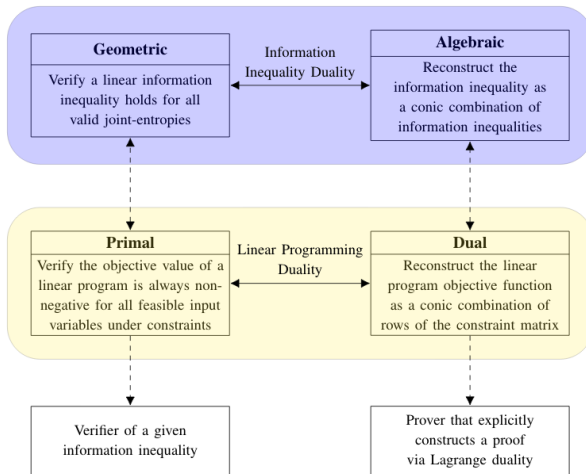
$$\begin{aligned}\mathbf{D}^T \mathbf{y} &= \mathbf{b} + \mathbf{E} \mu \\ \mathbf{y} &\geq \mathbf{0}\end{aligned}$$

Intuition: If the dual problem is feasible, reconstruct the original inequality as

$$\begin{aligned}\mathbf{b}^T \mathbf{h} &= \mathbf{y}^{*T} \mathbf{D} \mathbf{h} - \mu^{*T} \mathbf{E} \mathbf{h} \\ &\geq 0 \quad (\text{the proof!})\end{aligned}$$

A prover that constructs analytic proofs to information inequalities.

Linear Programming Framework



Back to the Toy Example

Prove $H(A|B) \leq H(A) \implies \mathbf{b}^T \mathbf{h} \geq 0$,

$$\text{where } \mathbf{h} = \begin{bmatrix} H(A) \\ H(B) \\ H(A, B) \end{bmatrix}, \mathbf{b} = \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix} \text{ and } \mathbf{D} = \begin{bmatrix} 1 & 1 & -1 \\ 0 & -1 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

Optimal dual solution: $\mathbf{y} = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}^T$

The input inequality can be written as the **first** row of \mathbf{D} , which is non-negative. (Recall that $\mathbf{b} = \mathbf{D}^T \mathbf{y}$, $\mathbf{y} \geq \mathbf{0}$ and $\mathbf{D}^T \mathbf{h} \geq \mathbf{0}$)

Generated proof:

$$H(A|B) \leq H(A) \Rightarrow H(A) + H(B) - H(A, B) \geq 0 \Rightarrow I(A; B) \geq 0$$

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Definition

A *shortest proof* of an information inequality is considered as a proof involving the least number of elemental inequalities. For a given Shannon-type information inequality, there often exist multiple shortest proofs.

Obtaining a Shortest Proof

$$\begin{aligned} \min \quad & \left\| \begin{bmatrix} \mathbf{y}^T & \boldsymbol{\mu}^T \end{bmatrix}^T \right\|_0 \\ \text{s.t.} \quad & \mathbf{D}^T \mathbf{y} = \mathbf{b} + \mathbf{E}^T \boldsymbol{\mu}, \mathbf{y} \geq 0 \end{aligned}$$

Convex Relaxation

$$\begin{aligned} \min \quad & \mathbf{1}^T \mathbf{y} + \mathbf{1}^T \mathbf{z} \\ \text{s.t.} \quad & \mathbf{D}^T \mathbf{y} = \mathbf{b} + \mathbf{E}^T \boldsymbol{\mu}, \mathbf{y} \geq 0 \\ & -\mathbf{z} \leq \boldsymbol{\mu} \leq \mathbf{z} \end{aligned}$$

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Scalability Issue

- We need vertex solutions to generate short, concise proofs or counter-examples. \implies Simplex-based methods
- The simplex method has exponential worst case time complexity, while the size of our LP grows exponentially with n .
 \implies Doubly exponential complexity
- The LP is sparse and highly degenerate, so the performance of the simplex method deteriorates.

Solution: Use iterative algorithms and perform “crossover” as a post-processing step.

Problem Reformulation

$$\begin{array}{ll}\min & \mathbf{b}^T \mathbf{h} \\ \text{s.t.} & \mathbf{B} \mathbf{h} + \mathbf{y} = \mathbf{c} \\ \text{var.} & \mathbf{h}, \mathbf{y},\end{array}$$

$$\text{where } \mathbf{B} = \begin{bmatrix} \mathbf{D} \\ \mathbf{D} \\ \mathbf{E} \end{bmatrix}, \mathbf{y} = \begin{bmatrix} -\mathbf{u} \\ \mathbf{v} \\ \mathbf{0} \end{bmatrix}, \mathbf{u}, \mathbf{v} \geq \mathbf{0} \text{ and } \mathbf{c} = \begin{bmatrix} \mathbf{0} \\ \mathbf{1} \\ \mathbf{0} \end{bmatrix}.$$

The ρ -augmented Lagrangian is

$$L_\rho = \mathbf{b}^T \mathbf{h} + \nu^T (\mathbf{B} \mathbf{h} + \mathbf{y} - \mathbf{c}) + \frac{\rho}{2} \|\mathbf{B} \mathbf{h} + \mathbf{y} - \mathbf{c}\|^2.$$

AITIP Algorithm

ALGORITHM 1: AITIP Algorithm

repeat

1. **h**-update: $\mathbf{h}^{k+1} = -\frac{1}{\rho}(\mathbf{B}^T \mathbf{B})^{-1}(\mathbf{b} + \mathbf{B}^T \boldsymbol{\nu}^k + \rho \mathbf{B}^T \mathbf{y}^k - \rho \mathbf{B}^T \mathbf{c})$
2. **u**-update: $\mathbf{u}^{k+1} = (\mathbf{D} \mathbf{h}^{k+1} + \frac{1}{\rho} \boldsymbol{\nu}_u^k)_+$
3. **v**-update: $\mathbf{v}^{k+1} = (\mathbf{1} - \mathbf{D} \mathbf{h}^{k+1} - \frac{1}{\rho} \boldsymbol{\nu}_v^k)_+$
4. $\boldsymbol{\nu}$ -update: $\boldsymbol{\nu}^{k+1} = \boldsymbol{\nu}^k + \rho(\mathbf{B} \mathbf{h}^{k+1} + \mathbf{y}^{k+1} - \mathbf{c})$

until *Stopping criteria is met;*

Each step has a closed-form solution.

Toward High Scalability

- Each step is just a (sparse) linear algebra computation, which can be easily parallelized to multiple cores or GPU (cuBLAS and cuSPARSE).
- The LLT (Cholesky) decomposition of the large matrix $\mathbf{B}^T \mathbf{B}$ matrix can be done beforehand. \implies Do a large part of the computation beforehand to improve the runtime performance.

These two points naturally lead to **cloud computing**.

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The AITIP Software-as-a-Service

<https://aitip.org>

Examples:

- $I(A1;A2) \geq I(A1;A3)$ s.t. $A1 \rightarrow A2 \rightarrow A3$ (data processing inequality)
- $H(X1, X2, X3, X4) \leq H(X1) + H(X2) + H(X3) + H(X4)$ (independence bound for entropy)

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Open Issues and Future Work

- Solving large LPs is still challenging
 - Dimension grows exponentially
 - Highly degenerate problems
- The logical correctness in mathematical reasoning cannot be susceptible to computational issues
 - Inaccurate numerical approximation
 - Floating point errors
- An end-to-end method to explore the proof space, refine problem-specific constraints and to automatically construct a formal proof or valid counterexample requires more in-depth investigation