

Semidefinite Programming (SDP)

Semi-definite Positive Matrix

$M \geq 0$ if

(M is either hermitian $M = M^T$ or symmetric $M = M^t$)

$\sum_{i,j} c_i^* M_{ij} c_j \geq 0 \quad \forall c_i$

- \Rightarrow • All eigenvalues are positive $\lambda_i \geq 0$
- $\det(M) \geq 0$ & all principal minors ≥ 0

SDP is {

minimize

$\sum_{i=1}^N c_i x_i$

subject to

$x = \sum F_i x_i - f_0$

$x \geq 0$

Coefficient matrices

Example 1

Given 3 random variables A, B, C

We have the correlation (covariance) matrix

$$\begin{pmatrix} 1 & P_{AB} & P_{AC} \\ P_{AB} & 1 & P_{BC} \\ P_{AC} & P_{BC} & 1 \end{pmatrix} \succeq 0$$

Suppose (by experiments) we find

$$-0.2 \leq P_{AB} \leq -0.1$$

$$0.4 \leq P_{BC} \leq 0.5$$

We want to find the upper and lower bound of

$$\boxed{P_{AC}}$$

How to build in inequalities

• Slack variables

$$P_{AB} + s_1 = -0.1$$

$$P_{AB} - s_2 = -0.2$$

$$P_{BC} + s_3 = 0.5$$

$$P_{BC} - s_4 = 0.4$$

• Enlarge the matrix (block diagonal)

$$\begin{pmatrix} 1 & P_{AB} & P_{AC} & 0 & 0 & 0 & 0 \\ P_{AB} & 1 & P_{AC} & 0 & 0 & 0 & 0 \\ P_{AC} & P_{AC} & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & s_1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & s_2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & s_3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & s_4 \end{pmatrix} \leq 0$$

2d ~~effective~~ Yang-Mills theory ^{SU(N)} $\mathcal{L} = \frac{1}{4g^2} \text{Tr}(F_{\mu\nu} F^{\mu\nu})$

$Z_{IP} = \int \mathcal{D}U e^{\frac{1}{2\lambda} \text{Tr}(U+U^\dagger)}$
 $\left[Z_{20} = Z_{IP}^{N_p} \right]$
 \uparrow $\int_{\text{AdS}_2} \int_{\text{S}^2} \text{Tr}(U)$

Where

$U = \begin{pmatrix} e^{i\theta} & \\ & e^{-i\theta} \end{pmatrix}$

$W_n = \frac{1}{N} \langle \text{Tr}(U^n) \rangle$
 $S_{\text{eff}} = -\frac{1}{\lambda} W_1 + \sum_{n=1}^{\infty} \frac{W_n}{n}$

$Z \sim e^{-\beta F}$
 \uparrow S_{eff}

$W_1 = \begin{cases} \frac{1}{2\lambda} & \lambda \geq 1 \text{ S.C.} \\ 1 - \frac{\lambda}{2} & \lambda \leq 1 \text{ W.C.} \end{cases}$

Naively Minimizing S_{eff} gives ~~us~~

$\frac{\partial S_{\text{eff}}}{\partial W_1} = 0 \Rightarrow W_1 = \frac{1}{2\lambda}$

$\frac{\partial S_{\text{eff}}}{\partial W_n} = 0 \Rightarrow W_n = 0 \quad n > 1$

S.C. result!

However fails at W.C.

Why? doesn't take into account SU(N) properties that are lost when tracing

Consider

$$A = \sum_{i=0}^L c_i U^i$$

$$\Rightarrow \text{Tr}(A^+ A) \geq 0$$

$$\frac{1}{N} \text{Tr}(A^+ A) = \sum_{i,j} c_j^* c_i \underbrace{\text{Tr}(U^{+j} U^i)}_{\rho_{ij}} \geq 0$$

by definition

$$\frac{1}{N} \text{Tr}(A^+ A) = \sum_{i,j} c_j^* c_i \frac{1}{N} \text{Tr}(U^{+j} U^i) \geq 0$$

$$\rho = \begin{pmatrix} 1 & w_1 & w_2 & w_3 & \dots & w_L \\ w_1 & 1 & w_1 & w_2 & \dots & \\ w_2 & w_1 & 1 & \dots & \dots & \\ \vdots & \vdots & \dots & \dots & \dots & \\ w_L & & & & & 1 \end{pmatrix}$$

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Minimize (S_{eff})

s.t. $P \succeq 0$

S_{eff} is quadratic and SDP only handles linear constraints ... or does it?

Consider the matrix

$$S = \begin{pmatrix} t & (W_1 - \frac{1}{2\lambda}) & \frac{W_2}{\sqrt{2}} & \frac{W_3}{\sqrt{3}} & \dots \\ (W_1 - \frac{1}{2\lambda}) & 1 & 0 & 0 & \\ \frac{W_2}{\sqrt{2}} & 0 & 1 & 0 & \\ \frac{W_3}{\sqrt{3}} & 0 & 0 & 1 & \\ \vdots & & & & \ddots \end{pmatrix}$$

$$\det(S) = t - \frac{1}{4\lambda^2} + \frac{W_1}{\lambda} - \sum_{n=1}^L \frac{W_n^2}{n} \geq 0$$

$$t \geq S_{\text{eff}} + \frac{1}{2\lambda^2}$$

Now minimize t s.t. $S \succeq 0$ & $P \succeq 0$

Smallest Eigenvalue

Given some $M \succeq 0$

~~M~~ define

$M - tI$ ~~as~~ as semi-definite

maximize (t)

②

Gamma Matrices in d dimensions using pauli matrices

$$\sigma_i \sigma_j = \delta_{ij} + i \epsilon_{ijk} \sigma_k$$

d=2

$$\Gamma^0 = i\sigma_2 = \epsilon$$

$$\Gamma^1 = \sigma_1$$

$$\Gamma^2 = i\Gamma^0\Gamma^1 = \sigma_3$$

$$\{\Gamma^\mu, \Gamma^\nu\} = 2\eta^{\mu\nu}$$

$$SO(1, d-1)$$

d=4

Kronecker Product

$$A \otimes B = \begin{pmatrix} A_{11}B & \dots & A_{1n}B \\ \vdots & \ddots & \vdots \\ A_{m1}B & \dots & A_{mn}B \end{pmatrix}$$

Weyl basis

$$\gamma^\mu = \begin{pmatrix} 0 & \sigma^\mu \\ \bar{\sigma}^\mu & 0 \end{pmatrix}$$

or

$$\gamma^0 = i\sigma_2 \otimes \sigma_0 = \epsilon \otimes \sigma_0$$

$$\gamma^i = \sigma_1 \otimes \sigma_i = \sigma_1 \otimes \sigma_i$$

$$\gamma^0 \gamma^0 = \epsilon^2 \otimes \sigma_0^2 = -\mathbb{1}_4$$

$$\Gamma = -i \gamma^0 \gamma^1 \gamma^2 \gamma^3$$

$$= -i \epsilon \sigma_1 \sigma_1 \sigma_1 \otimes \sigma_0 \sigma_1 \sigma_2 \sigma_3$$

$$= +i^4 \sigma_3 \otimes \sigma_0 = \begin{pmatrix} +1 & & & \\ & +1 & & \\ & & -1 & \\ & & & -1 \end{pmatrix}$$

$$L = \frac{1}{2} (1 + \Gamma) \quad R = \frac{1}{2} (1 - \Gamma)$$

Majorana Basis (Real)

- $\epsilon \otimes \sigma_0$ -
- $\sigma_3 \otimes \sigma_3$ +
- $\sigma_1 \otimes \sigma_0$ +
- $\sigma_3 \otimes \sigma_1$ +

$$\Gamma = -i \epsilon \sigma_3 \sigma_1 \sigma_3 \otimes \sigma_3 \sigma_1$$

$$= -i^3 \sigma_3 \otimes -i \sigma_2$$

$$= i^4 \sigma_3 \otimes \sigma_2 = \sigma_3 \otimes \sigma_2$$

SO(5,5)

- $\Gamma^0 = \epsilon \otimes \sigma_0 \otimes \sigma_0 \otimes \sigma_0 \otimes \sigma_0$ -
- $\Gamma^1 = \sigma_3 \otimes \epsilon \otimes \sigma_0 \otimes \sigma_0 \otimes \sigma_0$ -
- $\Gamma^2 = \sigma_3 \otimes \sigma_3 \otimes \epsilon \otimes \sigma_0 \otimes \sigma_0$ -
- $\Gamma^3 = \sigma_3 \otimes \sigma_3 \otimes \sigma_3 \otimes \epsilon \otimes \sigma_0$ -
- $\Gamma^4 = \sigma_3 \otimes \sigma_3 \otimes \sigma_3 \otimes \sigma_3 \otimes \epsilon$ -
- $\Gamma^5 = \sigma_1 \otimes \sigma_0 \otimes \sigma_0 \otimes \sigma_0 \otimes \sigma_0$ +
- $\Gamma^6 = \sigma_3 \otimes \sigma_1 \otimes \sigma_0 \otimes \sigma_0 \otimes \sigma_0$ +
- $\Gamma^7 = \sigma_3 \otimes \sigma_3 \otimes \sigma_1 \otimes \sigma_0 \otimes \sigma_0$ +
- $\Gamma^8 = \sigma_3 \otimes \sigma_3 \otimes \sigma_3 \otimes \sigma_1 \otimes \sigma_0$ +
- $\Gamma^9 = \sigma_3 \otimes \sigma_3 \otimes \sigma_3 \otimes \sigma_3 \otimes \epsilon$ +

$$\lambda = C \bar{\lambda}^T$$

$$\lambda = \pm \Gamma \lambda$$