

# **Robust Interior Point Method for Quantum Key Distribution Rate Computation**

# Introduction

# Motivation: Why do we compute key rate for QKD?

#### Quantum Key Distribution (QKD)

A secure, quantum-resistant communication mechanism used for **sharing secrets** over a public channel between two parties

#### Example

10 (qu)bits used in QKD 5 (qu)bits are used to form the secret  $\rightarrow$  key rate  $\frac{5}{10} = \frac{1}{2}$ Under the presence of Eve who disrupts the communication  $\rightarrow$  key rate goes down to  $\frac{1}{10}$ 

#### Question

Q. How many (qu)bits need to be used get n bits of secret key under Eve's attack?

A. Model using a convex optimization problem [Ref 2]

## **Optimization Problem: Objective & Constraint**

$$(\mathsf{QKD}) \qquad p^* := \min_{\rho} \{ f(\rho) \ : \ \Gamma(\rho) = \gamma, \ \rho \succeq 0 \}$$

**Objective Function** : composite of quantum relative entropy function and two linear maps After simplification,

$$f(\rho) = \operatorname{trace}(\mathcal{A}(\rho) \log \mathcal{A}(\rho) - \mathcal{B}(\rho) \log \mathcal{B}(\rho)),$$

where 
$$\mathcal{A}(\rho) = \sum_{j} A_{j} \rho A_{j}^{*}$$
, and  $\mathcal{B}(\rho) = \sum_{j} B_{j} \rho B_{j}^{*}$ .

**Constraint**: spectrahedron

 $\{\rho \in \mathbb{H}^n_+ : \Gamma(\rho) = \gamma\},\$ 

where  $(\Gamma(\rho))_i = \operatorname{trace}(\Gamma_i \rho) = \gamma_i, \forall i = 1, \dots, m$ , with  $\Gamma_i \in \mathbb{H}^n$  and  $\gamma_i \in \mathbb{R}$ .

### Difficulties with the Model: Failure of Regularity

- Constraint:  $\{\rho \in \mathbb{H}^n_+ : \Gamma(\rho) = \gamma\}$ There is no positive definite  $\rho \rightarrow |$  Slater condition fails Strong duality may not hold Small noise could yield large error
- Remedy  $\rightarrow$  facial reduction
- 2. Objective: trace( $\mathcal{A}(\rho) \log \mathcal{A}(\rho) \mathcal{B}(\rho) \log \mathcal{B}(\rho)$ ) There are no positive definite  $\mathcal{A}(\rho), \mathcal{B}(\rho) \to \mathbb{C}$ annot differentiate  $f(\rho)$

ex) 
$$\rho = \begin{bmatrix} 1/2 & 0 \\ 0 & 1/2 \end{bmatrix} \succ 0$$
,  $\mathcal{A}(\rho) = \sum_{j} A_{j} \rho A_{j}^{*} = \begin{bmatrix} 1/2 & 0 & 0 \\ 0 & 1/2 & 0 \\ 0 & 0 & 0 \end{bmatrix} \succeq 0$ 

Remedy  $\rightarrow$  facial reduction

### Our Approach

- Strong Reformulation: *Two types* of facial reduction
- Facial reduction on the constraint set
- Facial reduction on the objective (new!)
- 2. Good Choice of Algorithm: Solve the reformulated model using a *stable* interio

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# Reformulation

# **Facial Reduction Towards Slater: Const**

Every face F of  $\mathbb{H}^n_+$  is exposed, i.e.,  $\exists Z \in \mathbb{H}^n_+$ ,  $V \in \mathbb{C}^{n \times r}$ ,  $r \leq n$ , such that  $F = \mathbb{H}^n_+ \cap Z^\perp = V \mathbb{H}^r_+ V^*$ 

Geometric view: restriction on a slice  $(V\mathbb{H}^r_+V^*)$  of  $\mathbb{H}^n_+$ 

 $\mathbf{H}^{\mathbf{n}}_{\!\!+\!}$ feasible set  $\mathcal{F}$ 

# Facial Reduction Towards Differentiability: Objective $f(\rho)$

<i>V</i> *	V	0	R	0	V*
$(V^*)^\perp$			0	0	0
Rotation					

Second term trace( $\mathcal{B}(\rho) \log \mathcal{B}(\rho)$ )

Similarly via facial reduction,  $\mathcal{B}(\rho) = V_B R_B V_B^*$ ,

Reduced Objective

 $f(\rho) = \operatorname{trace}(\mathcal{A}(\rho)\log\mathcal{A}(\rho) - \mathcal{B}(\rho)\log\mathcal{B}(\rho))$  $\downarrow V_A R_A V_A^* = \mathcal{A}(\rho) \implies R_A = \\
\downarrow V_B R_B V_B^* = \mathcal{B}(\rho) \implies R_B =$  $\widehat{f}(\rho) = \operatorname{trace}(\widehat{\mathcal{A}}(\rho) \log \widehat{\mathcal{A}}(\rho)) - \operatorname{trace}(\widehat{\mathcal{B}}(\rho))$ 

# Facially Reduced Model: Reduction = Redefining Problem Data!

	(QKD)	$p^* := \min_{\rho} \{ f(\rho) : \Gamma(\rho) = \gamma, \ \rho \succeq 0 \}$
	$\Downarrow$	substitute $\rho \leftarrow V_{\rho}R_{\rho}V_{\rho}^{*}, \ \mathcal{A}(\rho) \leftarrow V_{A}$
	(QKD)	$p^* := \min_{R_{ ho}} \{ \widehat{f}(R_{ ho}) : \widehat{\Gamma}(R_{ ho}) = \gamma, R_{ ho} \}$
r point mothod	( <b>QKD</b> )	replace $\rho \leftarrow R_{\rho}$ , $f(\rho) \leftarrow \widehat{f}(\rho)$ $p^* := \min\{f(\rho) : \Gamma(\rho) = \gamma, \ \rho \succeq 0\}$
		$\rho \qquad \qquad$

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traint 
$$\{\rho \in \mathbb{H}^n_+ : \Gamma(\rho) = \gamma\}$$

$$(AR_A V_A^*, R_A \succ 0)$$

$$R_B \succ 0 \implies \operatorname{trace} R_B \log R_B$$

$$(\rho)) = V_A^* \mathcal{A}(\rho) V_A =: \widehat{\mathcal{A}}(\rho) \\= V_B^* \mathcal{B}(\rho) V_B =: \widehat{\mathcal{B}}(\rho) \\= \log \widehat{\mathcal{B}}(\rho))$$

$$\begin{aligned} & \sum_{A} R_{A} V_{A}^{*}, \ \mathcal{B}(\rho) \leftarrow V_{B} R_{B} V_{B}^{*} \\ & \rho \succeq 0 \end{aligned}$$

# **Algorithm: Gauss-Newton Method**

#### **Optimality Conditions**

dual feasibility primal feasibility perturbed compleme

Using the optimality conditions, form  $||F_{\mu}(\rho, y, Z)||^2 = ||F_{\mu}(\rho, y, Z)||^2$ 

Solve the nonlinear least squares problem

If we find  $(\rho, y, Z)$  satisfying  $||F_0(\rho, y, Z)||^2 = 0 \implies$  Optimality Note: nonlinear overdetermined least squares problem!

Gauss-Newton direction,  $d_{GN}$  = least squares solution of the linearization

$$F'_{\mu}d_{GN} \approx -F_{\mu} \text{ i.e., } \begin{bmatrix} \nabla^2 f(\rho)\Delta\rho + \Gamma^*(\Delta y) - \Delta Z \\ \mathcal{N}(\Delta v) - \Delta\rho \\ Z\Delta\rho + \Delta Z\rho \end{bmatrix} = - \begin{bmatrix} F^d_{\mu} \\ F^p_{\mu} \\ F^c_{\mu} \end{bmatrix}.$$

We use projected Gauss-Newton direction for computational efficiency (e.g.,  $\Delta Z$  is eliminated)

# **Bounding: Our Approach**

The main goal of (**QKD**): Obtain a provable, tight lower bound to the optimal value  $p^*$ The dual problem

$$d^* = \max_{y, Z \succeq 0} \min_{\rho \in \mathbb{H}^n} L(\rho, y) - \langle Z, \rho \rangle.$$

We can always find a dual feasible point that minimizes the dual functional  $\bar{Z} = \nabla f(\hat{\rho}) + \Gamma^*(\hat{y}) \succeq 0.$ 

#### Lower Bound via Lagarangian dual

$$\begin{aligned} * &= d^* & (\text{strong duality}) \\ &\geq \min_{\rho} L(\rho, y) - \langle \bar{Z}, \rho \rangle & (\bar{Z} = \nabla f(\hat{\rho}) + \Gamma^*(\hat{y}) \succeq 0) \\ &= f(\hat{\rho}) + \langle \hat{y}, \Gamma(\hat{\rho}) - \gamma \rangle - \langle \hat{\rho}, \bar{Z} \rangle & (\hat{\rho} = \operatorname{argmin}_{\rho} L(\rho, \hat{y}) - \langle \bar{Z}, \rho \rangle) \end{aligned}$$

#### Upper Bound via Projection

$$\bar{\rho} = \operatorname{argmin}_{\rho} \left\{ \frac{1}{2} \| \rho - \hat{\rho} \|^2 : \Gamma(\rho) = \gamma \right\}, \quad \bar{\rho} \succeq 0 \implies p^* \leq f(\bar{\rho}).$$

- 6, 2022)
- Ref 2. Adam Winick, Norbert Lütkenhaus, and Patrick J. Coles.

# Algorithm

$$\begin{array}{l} : \ F^d_\mu = \nabla_\rho f(\rho) + \Gamma^*(y) - Z = 0 \\ : \ F^p_\mu = \Gamma(\rho) - \gamma = 0 \\ \\ \text{entarity} \ : \ F^c_\mu = Z\rho - \mu I = 0, \ Z, \rho \succ 0. \end{array}$$

$$\Gamma^{d}_{\mu}(\rho, y, Z) \|_{F}^{2} + \|F^{p}_{\mu}(\rho)\|_{2}^{2} + \|F^{c}_{\mu}(\rho, Z)\|_{F}^{2}.$$

 $\min_{\rho, Z \succ 0, y} \frac{\mathbf{1}}{2} \| F_{\mu}(\rho, y, Z) \|^2$ 

### References

• Ref 1. Hao Hu, Haesol Im, Jie Lin, Nobert Lütkenhaus, and Henry Wolkowicz. Robust Interior Point Method for Quantum Key Distribution Rate Computation (Quantum 6, Vol

Reliable numerical key rates for quantum key distribution (Quantum vol 2, p.77, 2018)