

# **Semidefinite programming in two-party quantum cryptography**

## **Part I : Basics of semidefinite programming**

**Presenter: Akshay Bansal (Slides courtesy: Jamie Sikora)**

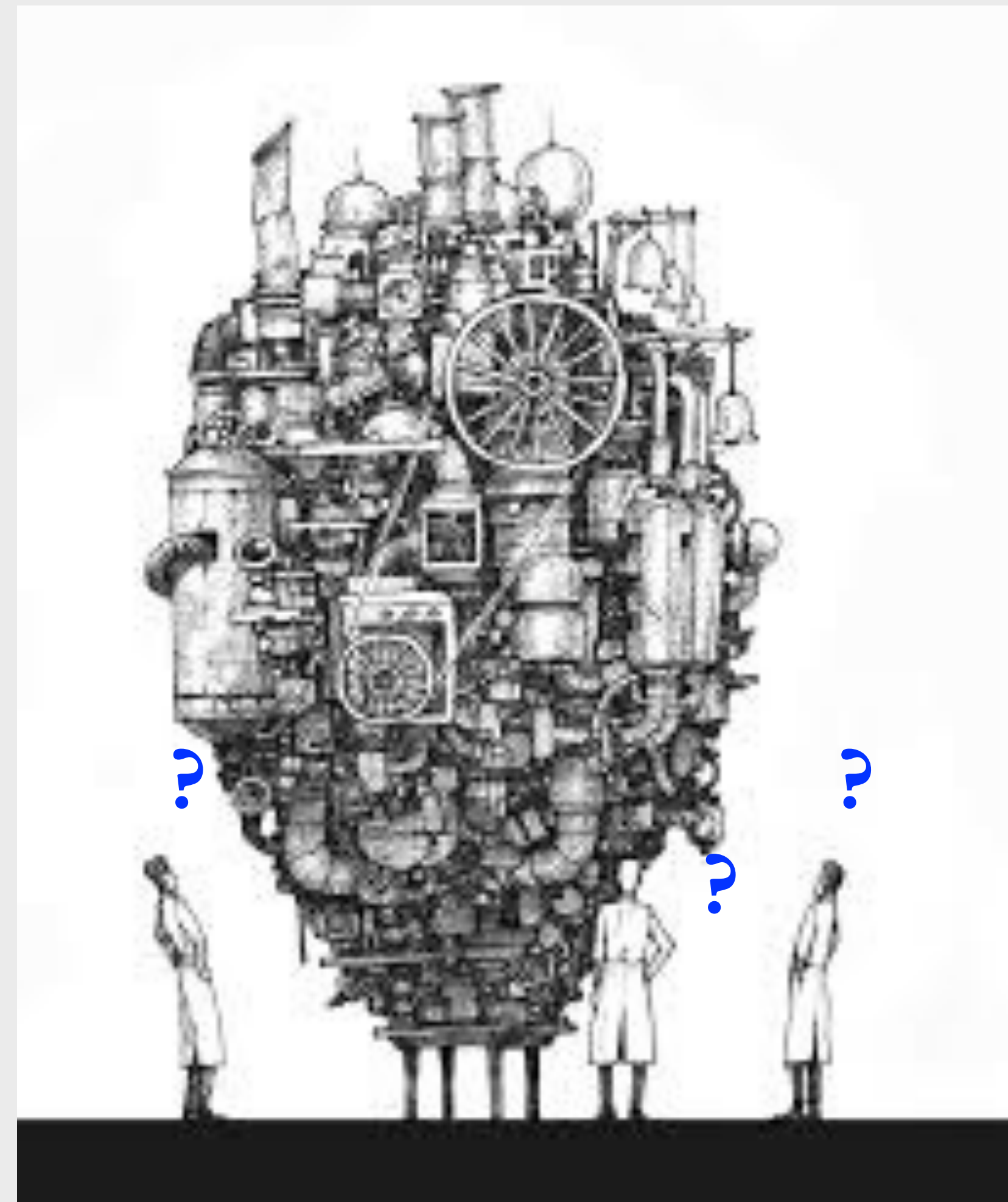
Should I pay  
attention?



# Abstract

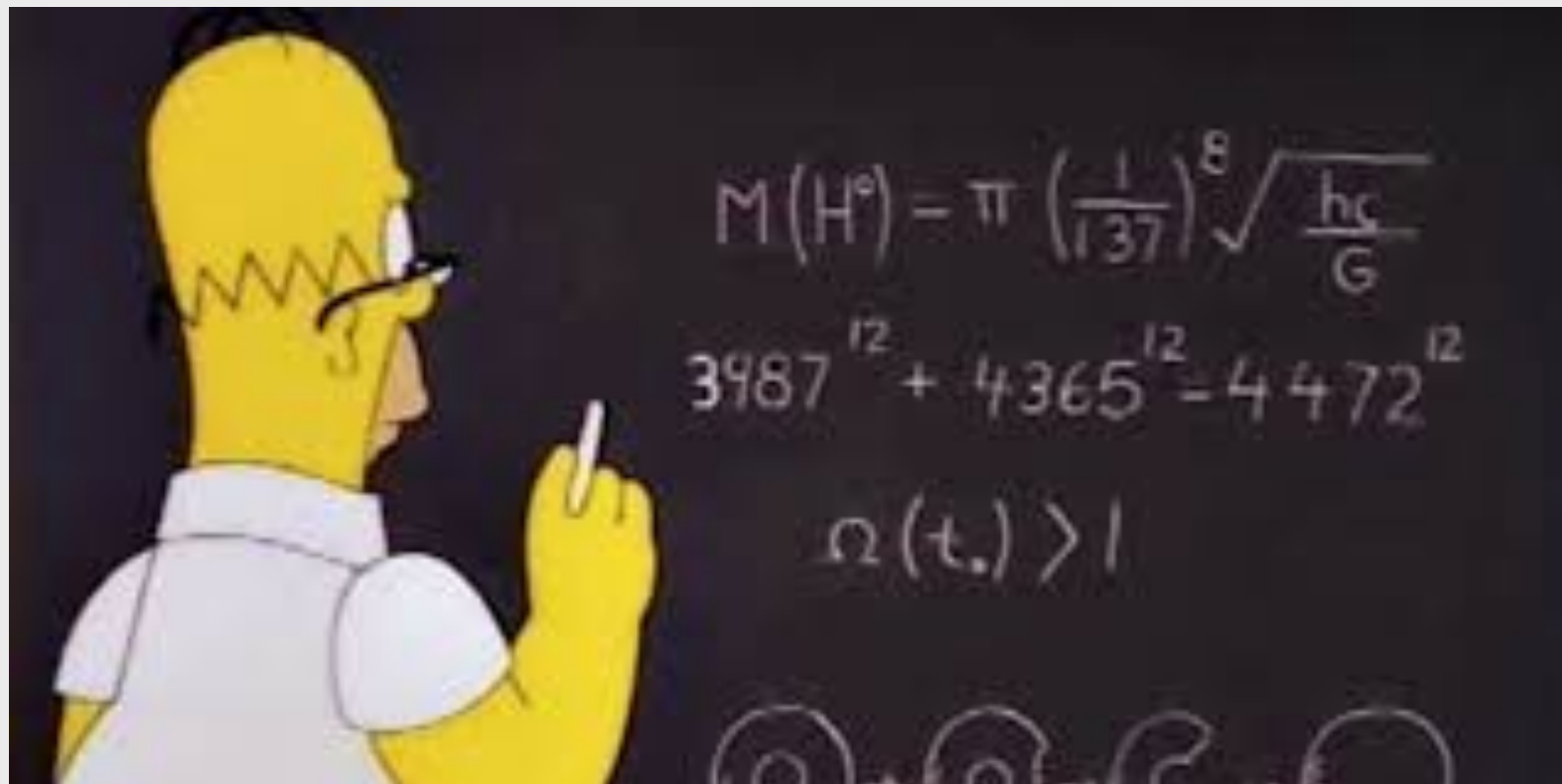
## Quantum Mechanics

A bunch of **positive  
semidefinite** things that  
interact with other  
**positive semidefinite**  
things in some kind of  
**linear** way



# Abstract

## Semidefinite Programming (Optimization)



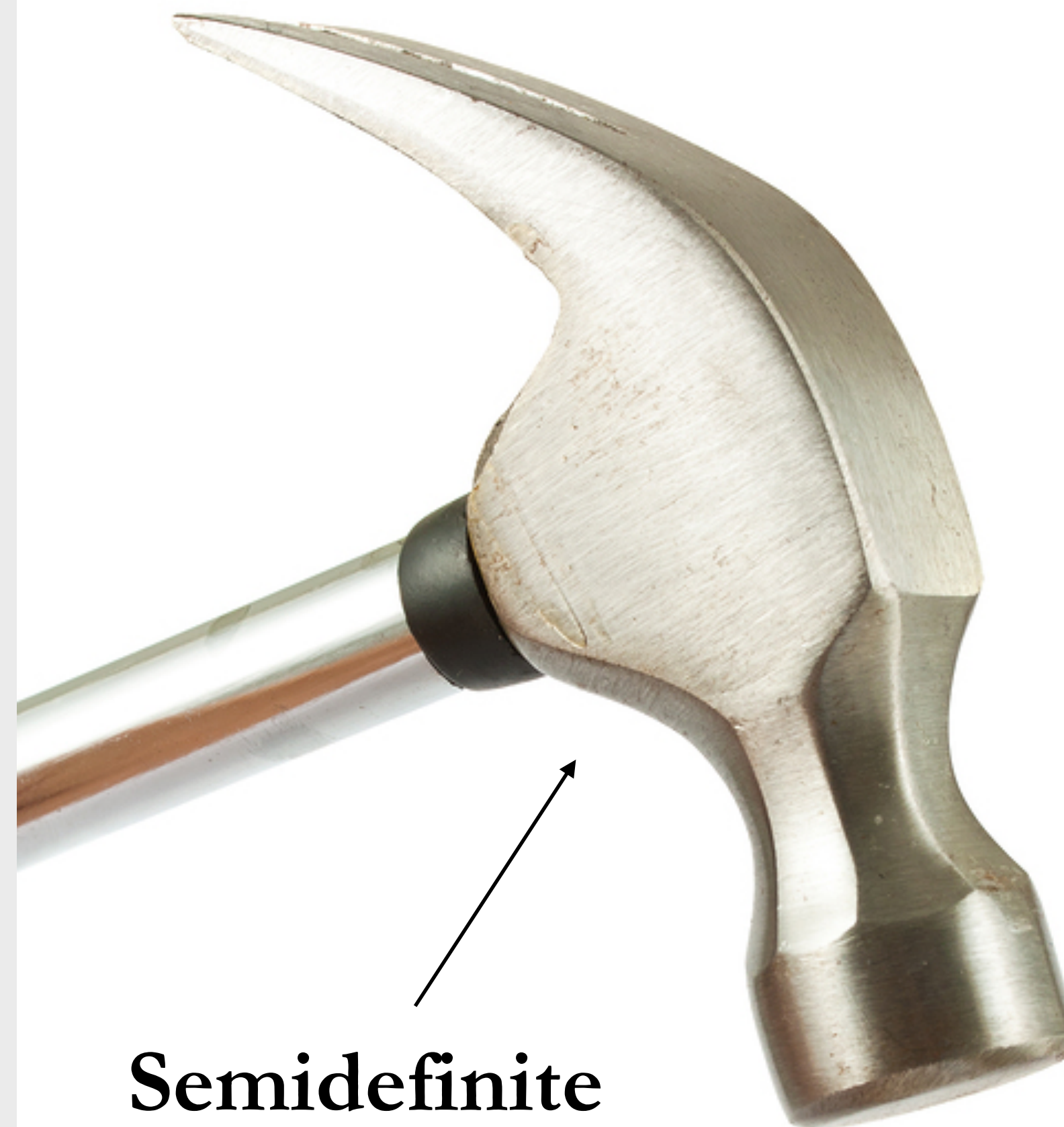
Optimizing **linear**  
functions of **positive  
semidefinite** things that  
satisfy some **linear**  
conditions

# Where do semidefinite programs appear?

Quantum... Cryptography  
Complexity Theory  
Query Complexity  
Information Theory  
Entanglement Theory  
Graph Theory

Linear Optics  
Bell Non-locality  
Causal Structures  
and many more...





Semidefinite  
Programming

Your  
problem



What is a  
semidefinite  
program?



# SDPs

A semidefinite program (SDP) is an optimization problem of a linear function over a positive semidefinite variable subject to affine constraints.



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$$\begin{aligned} \alpha = \text{maximize: } & \langle A, X \rangle \\ \text{subject to: } & \Phi(X) = B \\ & X \in \text{Pos}(\mathcal{X}) \end{aligned}$$

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$\mathcal{X}, \mathcal{Y}$  are vector spaces  
 $A \in \text{Herm}(\mathcal{X})$   
 $B \in \text{Herm}(\mathcal{Y})$   
 $\Phi$  is linear and maps  
 $\text{Herm}(\mathcal{X})$  to  $\text{Herm}(\mathcal{Y})$   
 $(A, B, \Phi)$  is the **data**

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$(A, B, \Phi)$  is the **data**

$X$  is the **variable**

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Objective  
function

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$$X \in \text{Pos}(\mathcal{X})$$

Constraints



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$$\boxed{\alpha} = \text{maximize: } \langle A, X \rangle$$
$$\text{subject to: } \Phi(X) = B$$
$$X \in \text{Pos}(\mathcal{X})$$

Optimal objective  
function value  
(or, simply, the  
value)

This could be  
finite,  $-\infty$ , or  $+\infty$

# SDPs

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$\mathcal{A} = \{X \in \text{Pos}(\mathcal{X}) : \Phi(X) = B\}$  is called the **feasible region**.

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If  $\mathcal{A} = \emptyset$ , then the SDP is **infeasible**. Otherwise, the SDP is **feasible**.

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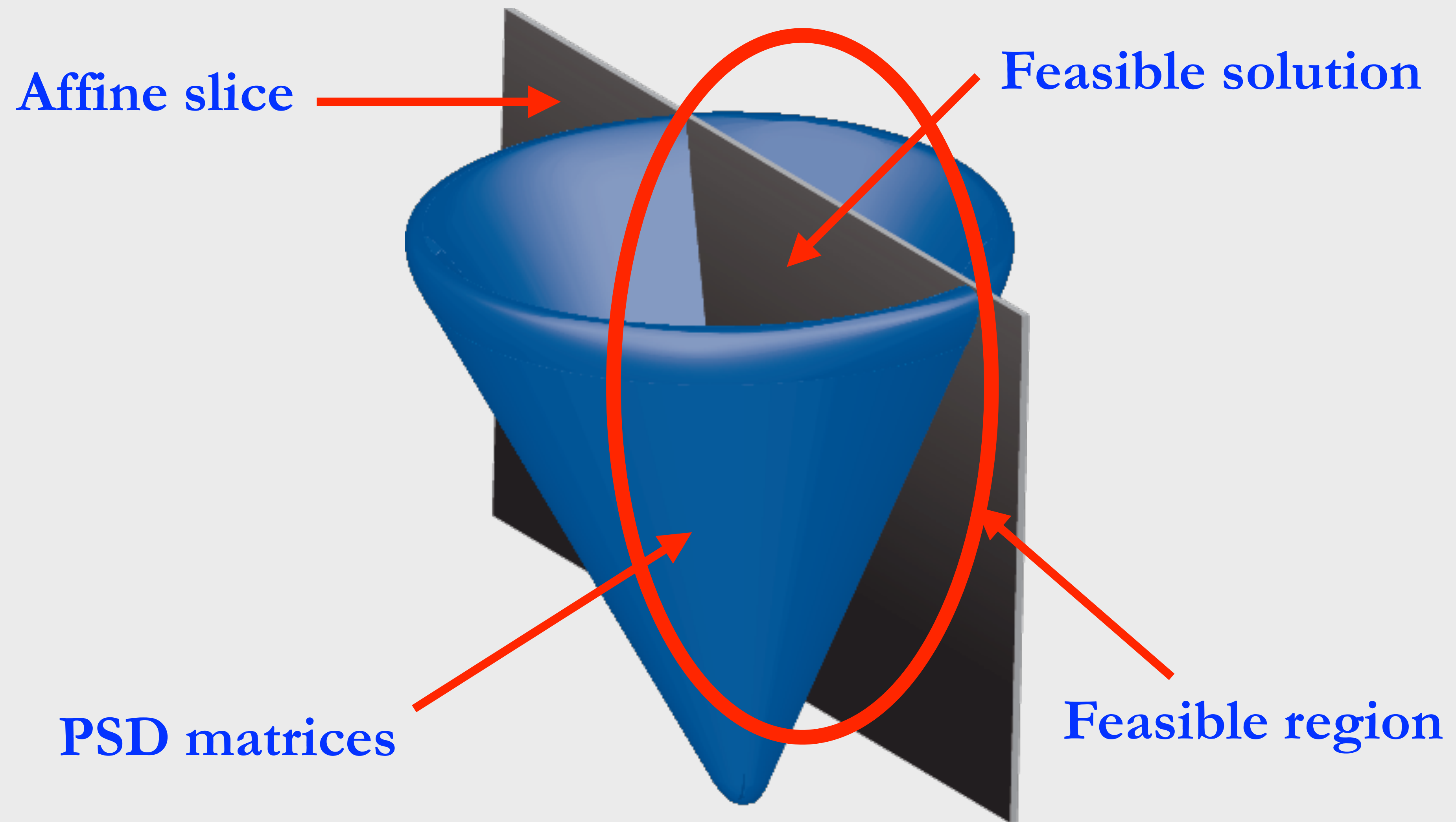
If  $\mathcal{A} = \emptyset$ , then the SDP is **infeasible**. Otherwise, the SDP is **feasible**.

$X \in \mathcal{A}$  is called **feasible**.

$X \in \mathcal{A} \cap \text{Pd}(\mathcal{X})$ , it is called **strictly feasible**.

$\mathcal{A} = \{X \in \text{Pos}(\mathcal{X}) : \Phi(X) = B\}$  is called the **feasible region**.

# Geometry



Credit: cvxr.com



# SDPs

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If  $\mathcal{A} = \emptyset$ , i.e., it is infeasible, then  $\alpha = -\infty$ .

If  $\mathcal{A} \neq \emptyset$ , i.e., it is feasible, then  $\alpha > -\infty$ .

If  $\alpha = +\infty$  then it is said to be **unbounded**.

If  $X \in \mathcal{A}$  satisfies  $\langle A, X \rangle = \alpha$ , then  $X$  is called an **optimal solution**.

(Note that even if  $\alpha$  is finite, an optimal solution may not exist!)

# Examples

$\alpha = \text{maximize: } \text{Tr}(X)$   
 $\text{subject to: } X = I_2$   
 $X \in \text{Pos}(\mathbb{C}^2)$

We have  $\mathcal{A} = \{I_2\}$  (and thus feasible)

$\alpha = 2$

The optimal solution is  $X = I_2$ .

$\alpha = \text{maximize: } \text{Tr}(X)$   
 $\text{subject to: } X = -I_2$   
 $X \in \text{Pos}(\mathbb{C}^2)$

We have  $\mathcal{A} = \emptyset$  (it is infeasible)

$\alpha = -\infty$

An optimal solution *does not exist*.

$\alpha = \text{maximize: } \text{Tr}(X)$   
 $\text{subject to: } X \geq I_2$   
 $X \in \text{Pos}(\mathbb{C}^2)$

We have  $\mathcal{A} = \{X \in \text{Pos}(\mathcal{X}) : X \geq I\}$

$\alpha = +\infty$  (the SDP is unbounded).

An optimal solution *does not exist*.

# Nomenclature

$$\begin{aligned} \alpha = \text{minimize: } & \langle A, X \rangle \\ \text{subject to: } & \Phi(X) = B \\ & X \in \text{Pos}(\mathcal{X}) \end{aligned}$$

We can minimize as well.

The SDP is unbounded if  $\alpha = -\infty$  in this case.

Also, if the SDP is infeasible, then  $\alpha = +\infty$ .

All the definitions generalize as you'd expect them too.

# Weird behaviour

$$\begin{array}{ll} \alpha = \text{minimize:} & s \\ \text{subject to:} & \begin{bmatrix} t & 1 \\ 1 & s \end{bmatrix} \in \text{Pos}(\mathbb{C}^2) \end{array}$$

$(s, t) = (1, 1)$  is feasible, thus  $\alpha \leq 1$

The facts below imply that  $s > 0$ , thus  $\alpha \geq 0$

$(s, t) = (\epsilon, 1/\epsilon)$ , where  $\epsilon > 0$ , is feasible.  
Since  $s$  can be made arbitrarily close to 0  
we have  $\alpha = 0$ .

But there does not exist an optimal solution!

Fact: If  $\begin{bmatrix} t & b \\ b^* & s \end{bmatrix} \in \text{Pos}(\mathbb{C}^2)$  and  $s = 0$ , then we must have  $b = 0$  as well.

Fact: If  $\begin{bmatrix} t & b \\ b^* & s \end{bmatrix} \in \text{Pos}(\mathbb{C}^2)$ , then  $s, t \geq 0$  and  $st \geq |b|^2$

Fact: The converse of the above is true.

# Quantum example

$$\begin{aligned} \alpha = \text{maximize: } & \langle H, X \rangle \\ \text{subject to: } & \text{Tr}(X) = 1 \\ & X \in \text{Pos}(\mathcal{X}) \end{aligned}$$

$H$  is Hermitian.

You can think of  $H$  as a Hamiltonian and  $\alpha$  as its maximum energy (if you are familiar with such things).

We can also write this succinctly, below.

$$\begin{aligned} \alpha = \text{maximize: } & \langle H, X \rangle \\ \text{subject to: } & X \in D(\mathcal{X}) \end{aligned}$$

This is an optimization over quantum states!

Where  $D(\mathcal{X}) := \{X \geq 0 : \text{Tr}(X) = 1\}$  are density operators



# Quantum example

Given quantum states  $\rho_1, \dots, \rho_n \in D(\mathcal{X})$ , consider the SDP:

$$\alpha = \text{maximize: } \frac{1}{n} \sum_{i=1}^n \langle \rho_i, M_i \rangle$$

$$\text{subject to: } \sum_{i=1}^n M_i = I$$

$$M_i \in \text{Pos}(\mathcal{X})$$

This is an optimization  
over POVMs.

# Quantum example

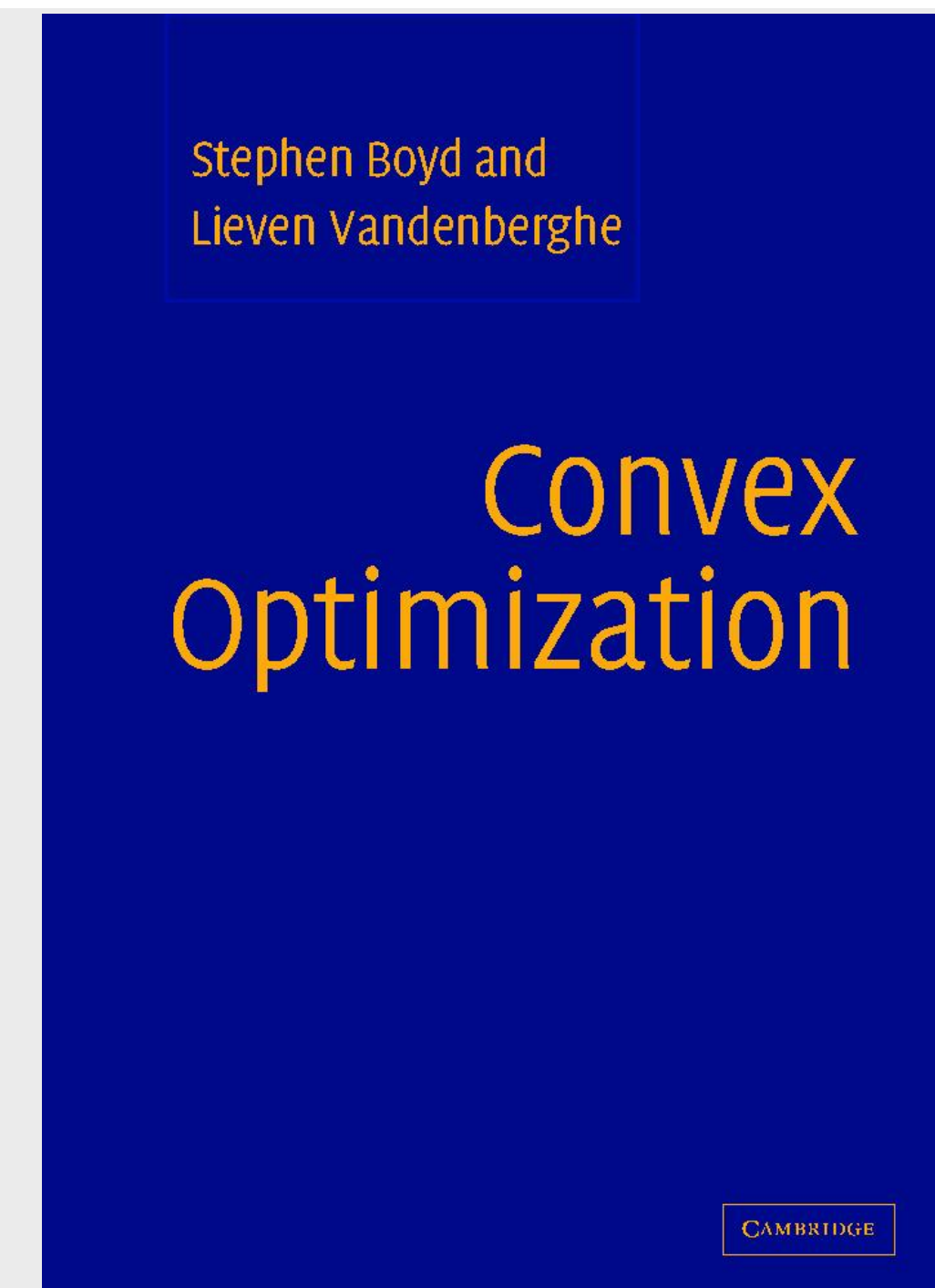
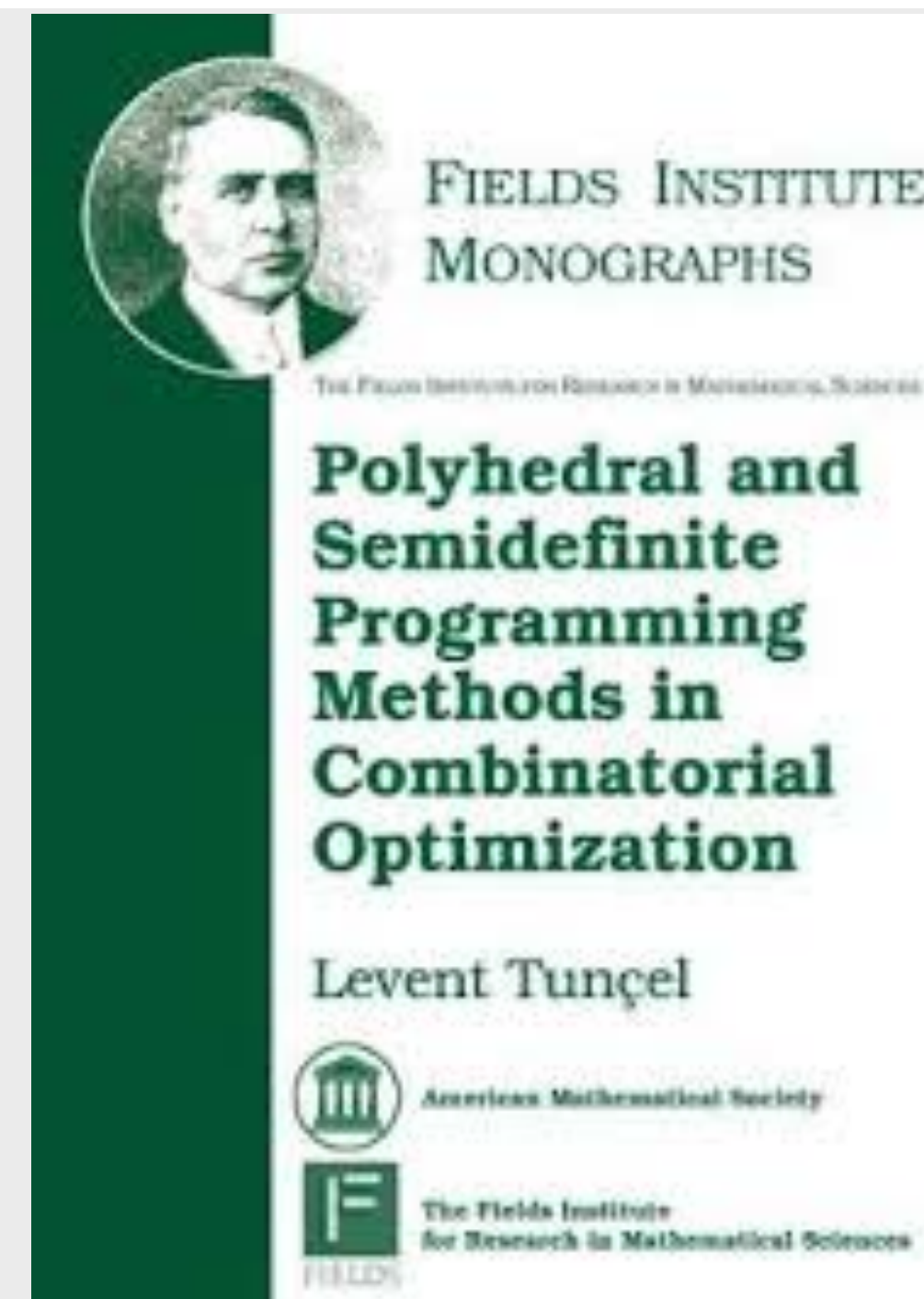
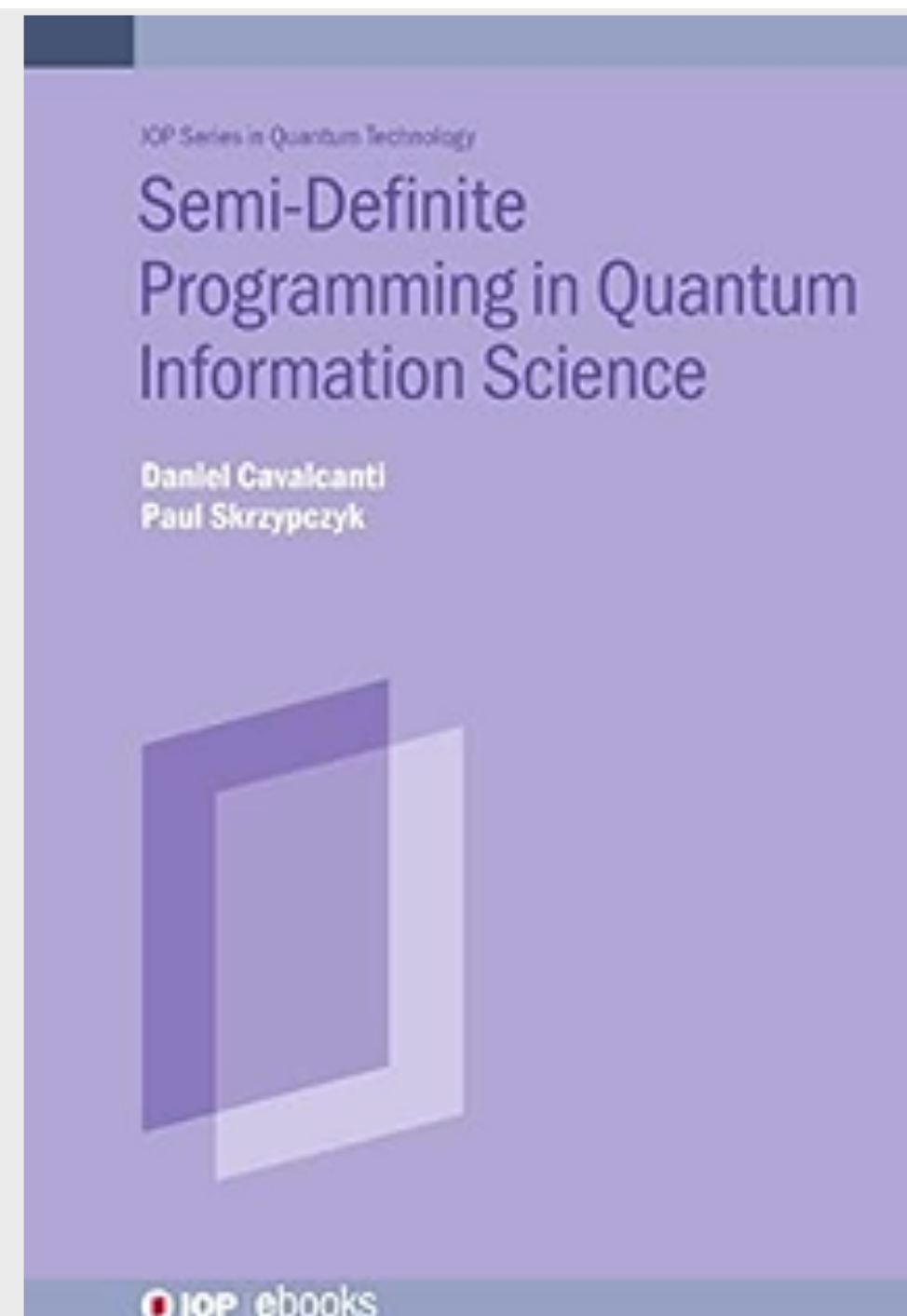
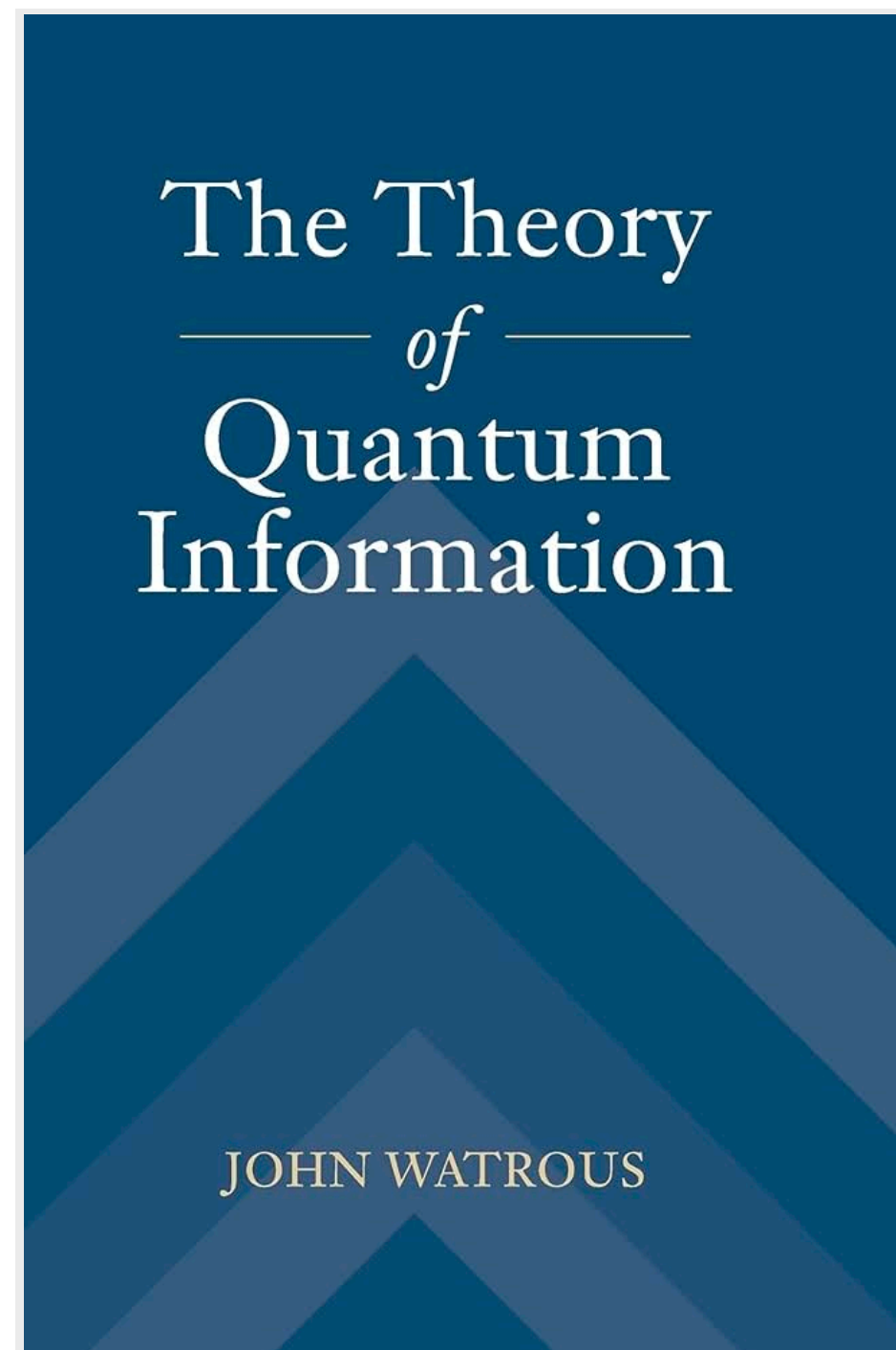
Given a linear map  $\Psi \in L(\mathcal{X}, \mathcal{Y})$  and its Choi representation  $C \in L(\mathcal{Y} \otimes \mathcal{X})$ , consider the SDP:

$$\begin{aligned} &\text{maximize: } \langle C, J \rangle \\ &\text{subject to: } \text{Tr}_{\mathcal{Y}}(J) = I_{\mathcal{X}} \\ &\quad J \in \text{Pos}(\mathcal{Y} \otimes \mathcal{X}) \end{aligned}$$

This computes the maximum overlap a linear map has with a quantum channel.

# References

- [Slides courtesy] Short course by Jamie Sikora at QIPSS School 2023
- Semidefinite programs in quantum information, 2011 (Ashwin Nayak)
- Advanced topics in quantum information theory (John Watrous)



# **Semidefinite programming in two-party quantum cryptography**

**Part II : Semidefinite programming for two-party cryptography**

**Presenter: Akshay Bansal**

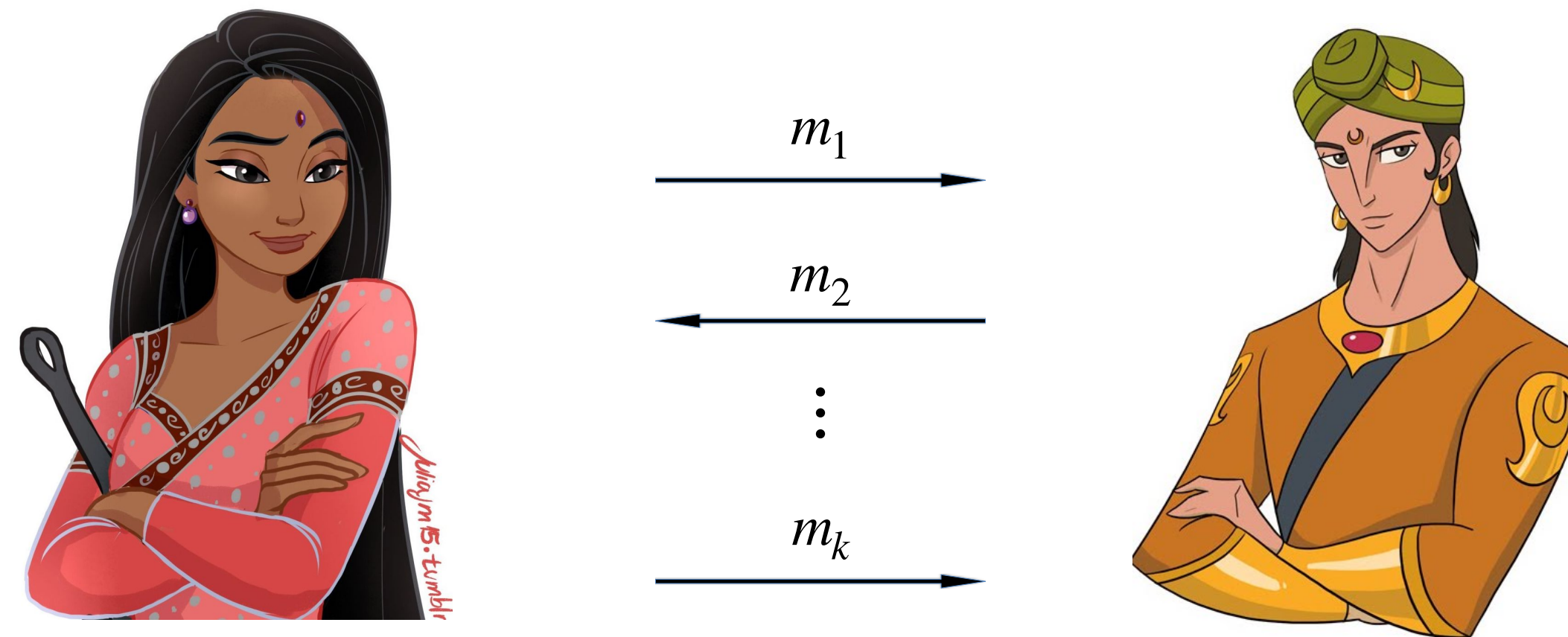
# Outline of this talk

- Introduction to the two-party setup and security definitions
- Newer protocols for the two-party tasks
- Open questions



# Introduction to two-party setup and security definitions

# A general two-party cryptography setup



$$P_A = \max_S \Pr [\text{Alice successfully cheats}]$$

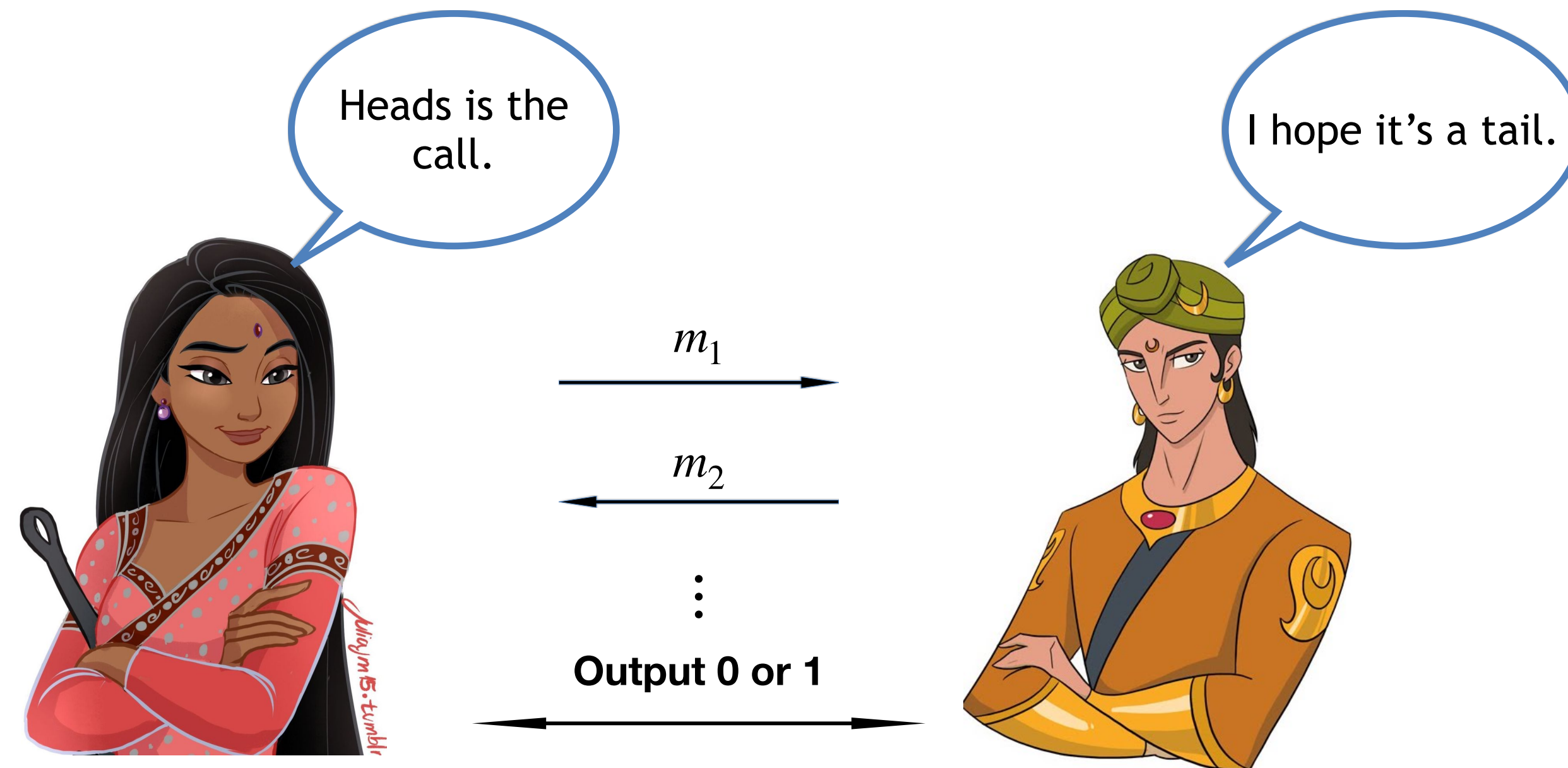
$$P_B = \max_S \Pr [\text{Bob successfully cheats}]$$

$$\text{Security of the protocol } (\mathcal{S}) := \max\{P_A, P_B\}$$

# Some useful cryptographic primitives

- Coin flipping (weak and strong) - Commitment schemes, etc.
- Oblivious transfer (1-out-of-2, Rabin) - Secure MPC, PIR, secure auctions/voting, etc.
- Bit commitment - Secure coin flipping, ZKP, etc.

# The task of coin flipping

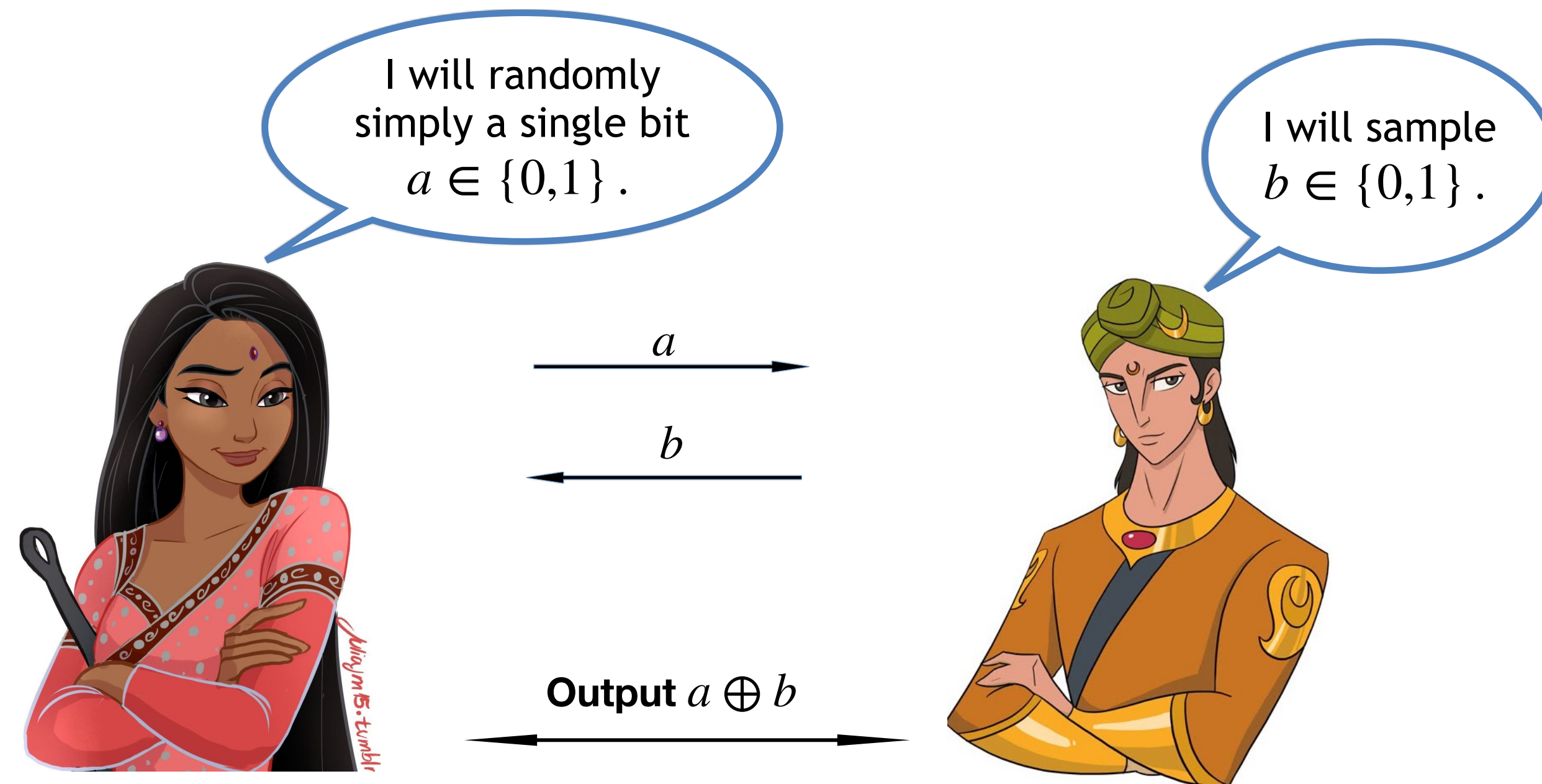


$$P_A = \max_S \Pr [\text{Dishonest Alice successfully forces outcome heads}]$$

$$P_B = \max_S \Pr [\text{Dishonest Bob successfully forces outcome tails}]$$

$$\text{Security of the protocol } (\mathcal{S}) := \max\{P_A, P_B\}$$

# A bad coin flipping protocol



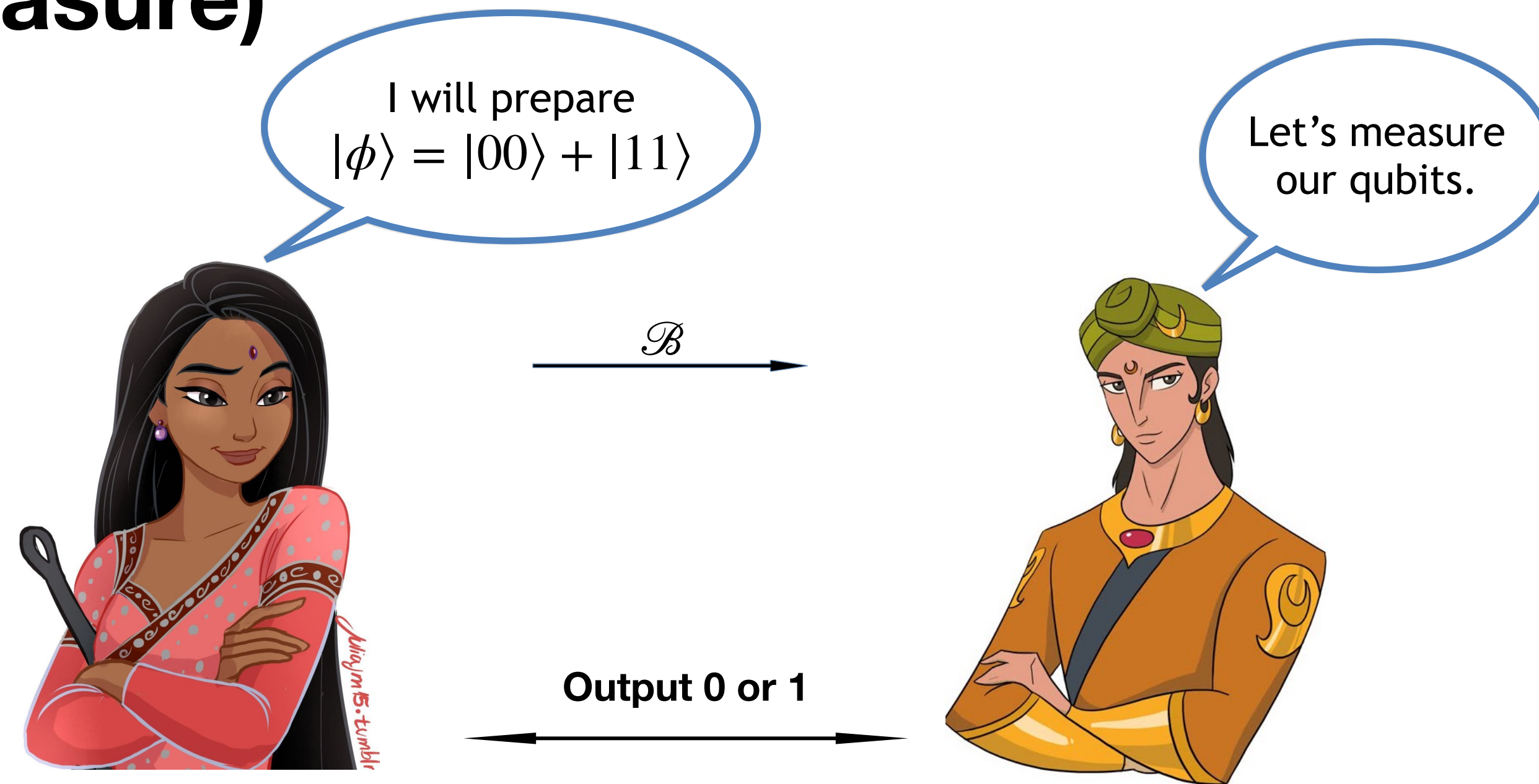
Strategy: Dishonest Bob can simply send  $a \oplus 1$

Security of the protocol  $(\mathcal{S}) := \max\{P_A, P_B\} = 1$



# Another bad coin flipping protocol (quantum)

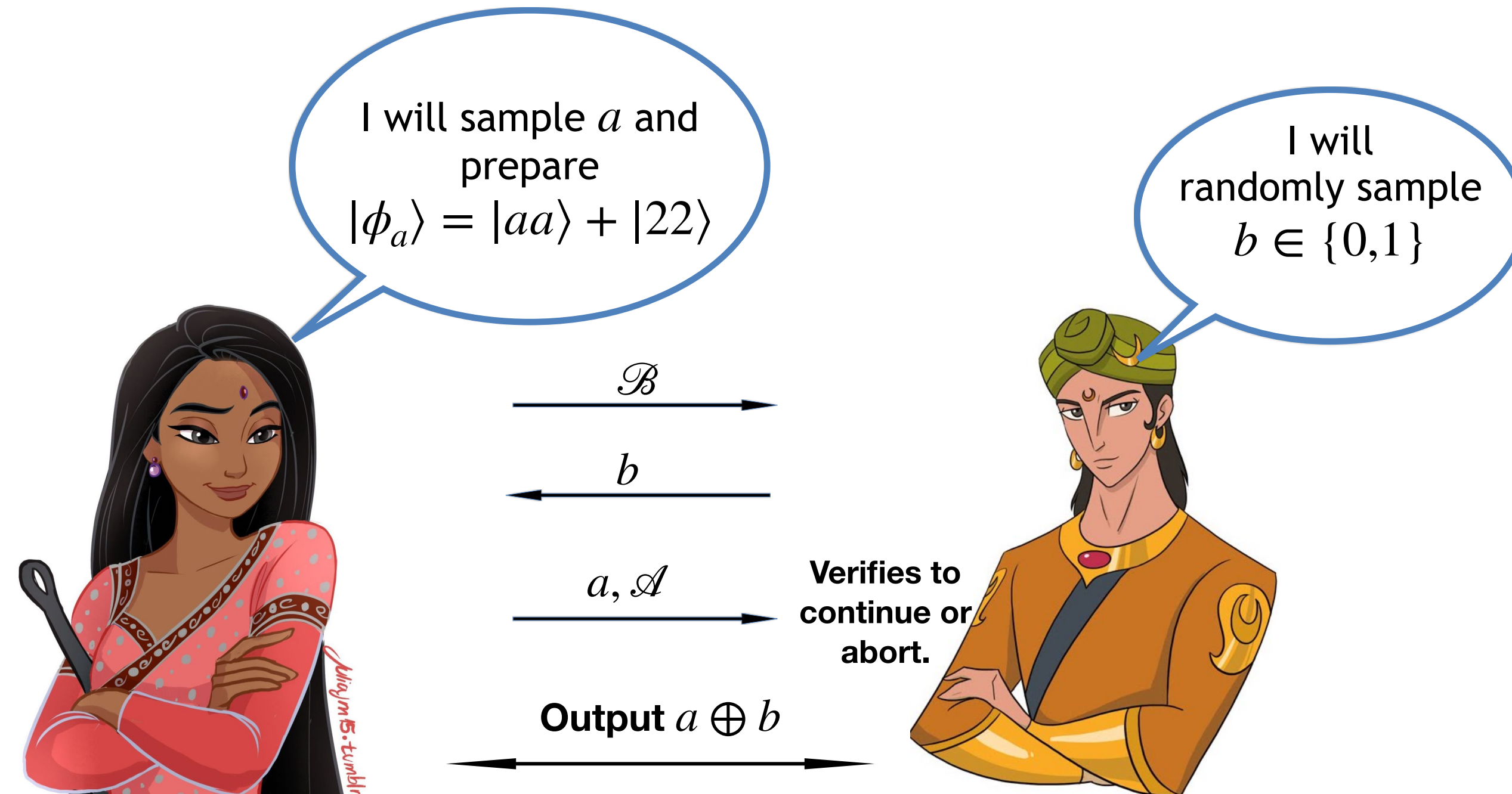
## (Prepare-and-measure)



Strategy: Dishonest Alice can simply prepare  $|00\rangle$ .



# A decent coin flipping protocol [Nayak & Shor, 2003]



Strategy: ?

# A security analysis using SDPs

## Cheating Bob

$$\max. \quad \frac{1}{2} \langle M_0, \mathcal{M}_A(|\phi_0\rangle\langle\phi_0|) \rangle + \frac{1}{2} \langle M_1, \mathcal{M}_A(|\phi_0\rangle\langle\phi_0|) \rangle$$

subject to:

$$M_0 + M_1 = \mathbb{1},$$

$$M_0, M_1 \geq 0.$$

## Cheating Alice

$$\max. \quad \frac{1}{2} \langle \sigma_0, |\phi_0\rangle\langle\phi_0| \rangle + \frac{1}{2} \langle \sigma_1, |\phi_1\rangle\langle\phi_1| \rangle$$

subject to:

$$\mathcal{M}_A(\sigma_0) = \mathcal{M}_A(\sigma_1) = \sigma,$$

$$\mathcal{M}(\sigma_0) = \mathcal{M}(\sigma_1) = \mathbb{1},$$

$$\sigma_0, \sigma_1, \sigma \geq 0.$$

# Some results on weak coin flipping

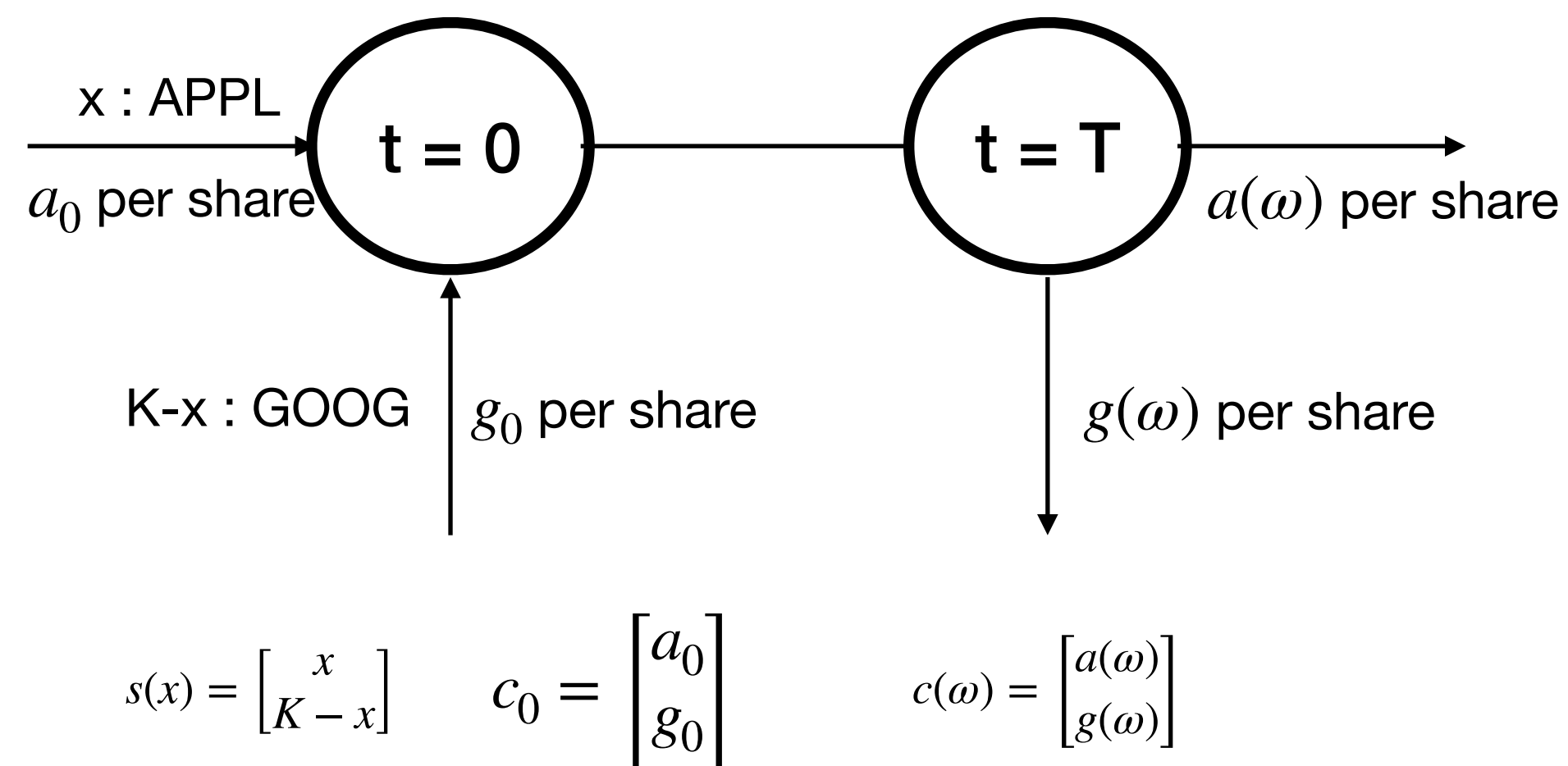
- [Moc07] Given  $\epsilon > 0$ , there exists quantum protocol with  $\max\{P_A^{WCF}, P_B^{WCF}\} < 1/2 + \epsilon$ .
- [ARV21] Explicit construction of protocols with arbitrarily small bias.
- [Mil20] Impossibility of efficient weak coin flipping.
- [WHBT24] (In)composable security of weak coin flipping.

**Newer protocols for the two-party tasks**

# Stochastic programming

(An classical example from stock investment)

Given a total  $K$  number of shares to be invested between two different stocks (under certain constraints), propose a useful investment strategy.

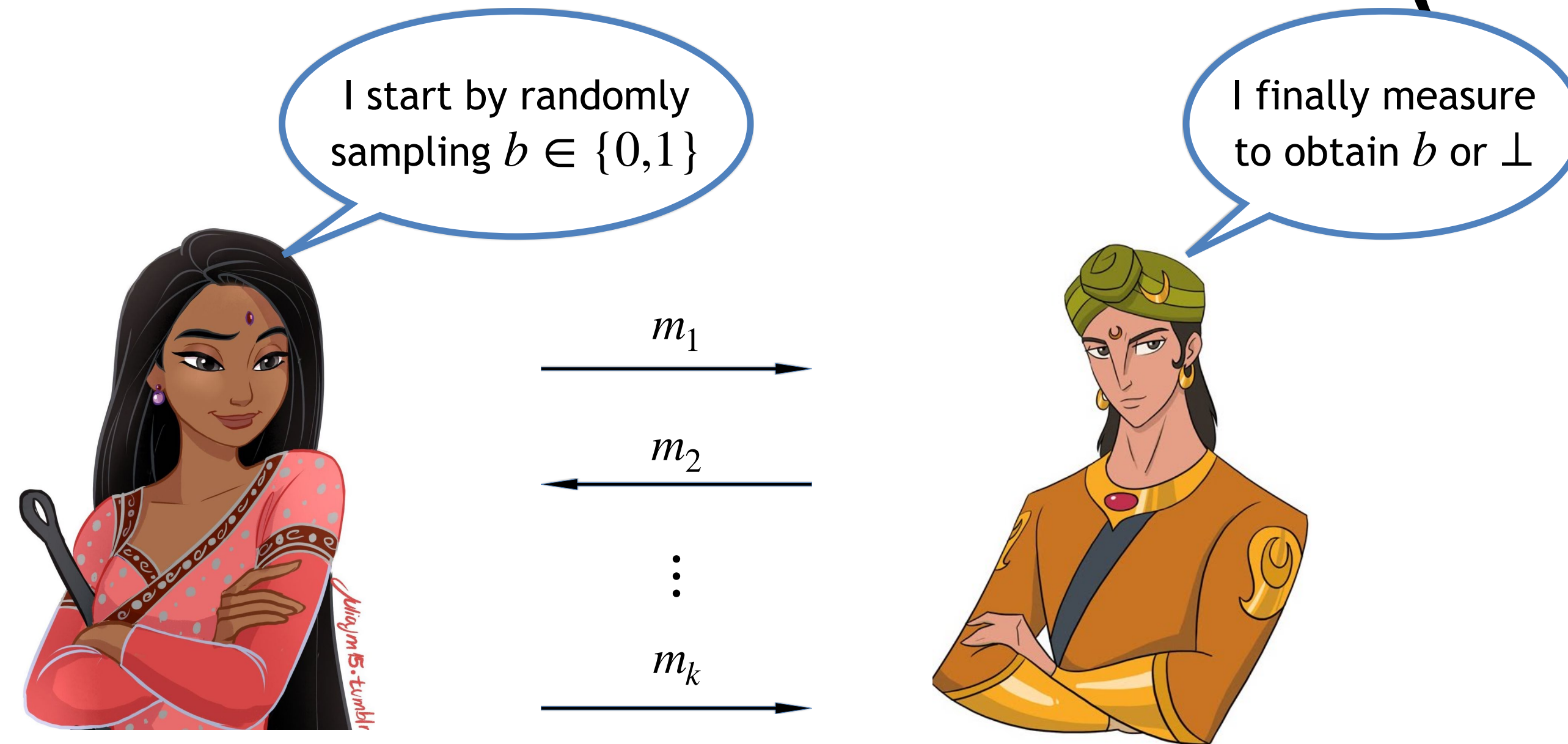


$$\max_x \mathbb{E}[c(\omega)^T s(x)] - c_0^T s(x)$$

subject to:  $s(x) \in \mathcal{S}(\omega)$

# Rabin oblivious transfer

How to exchange secrets with oblivious transfer? (Rabin, 1981)

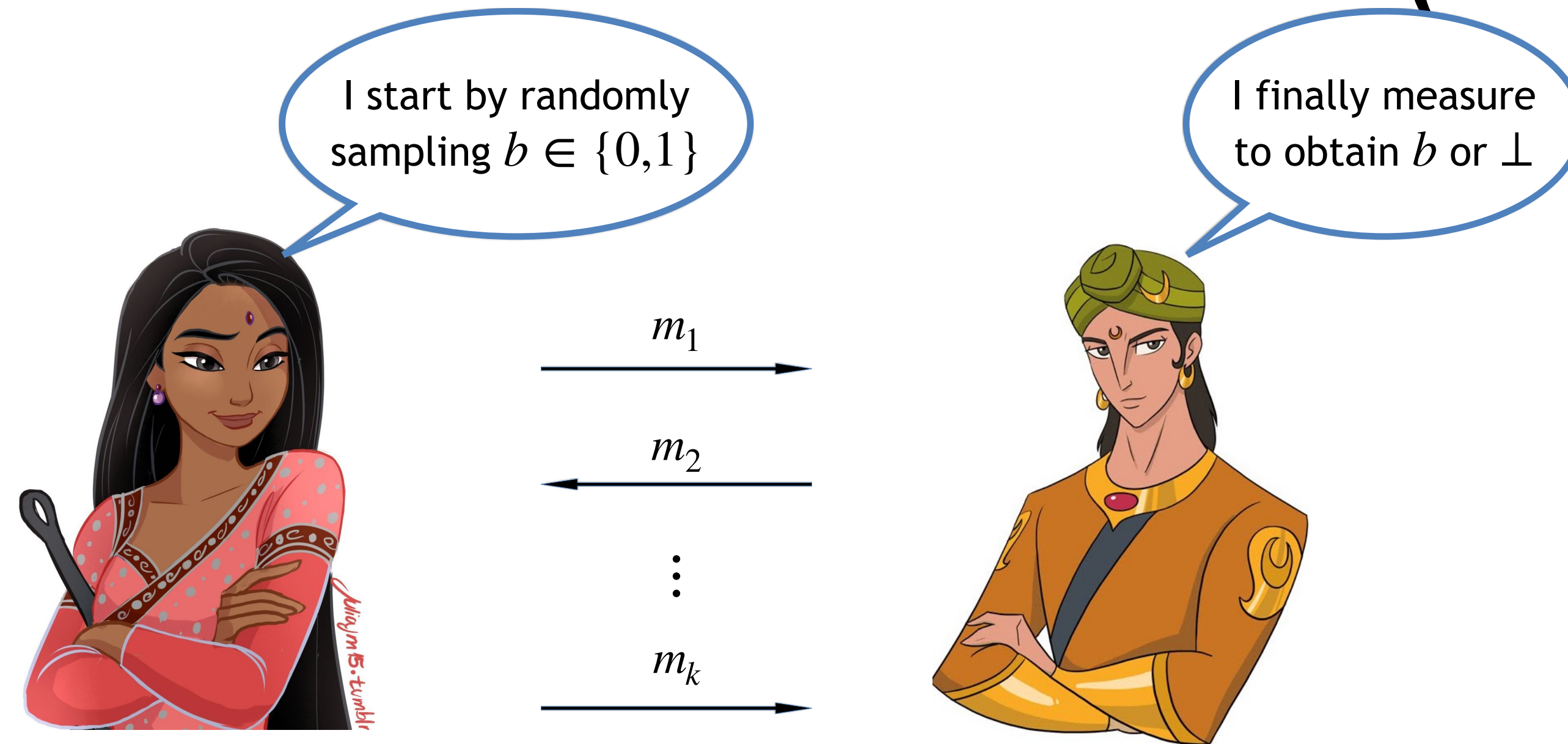


Rabin oblivious transfer is the cryptographic task where Alice sends a bit  $b \in \{0,1\}$  to Bob which he receives with probability  $1/2$  and with the probability  $1/2$  he receives  $\perp$  indicating that the bit was lost.



# Rabin oblivious transfer

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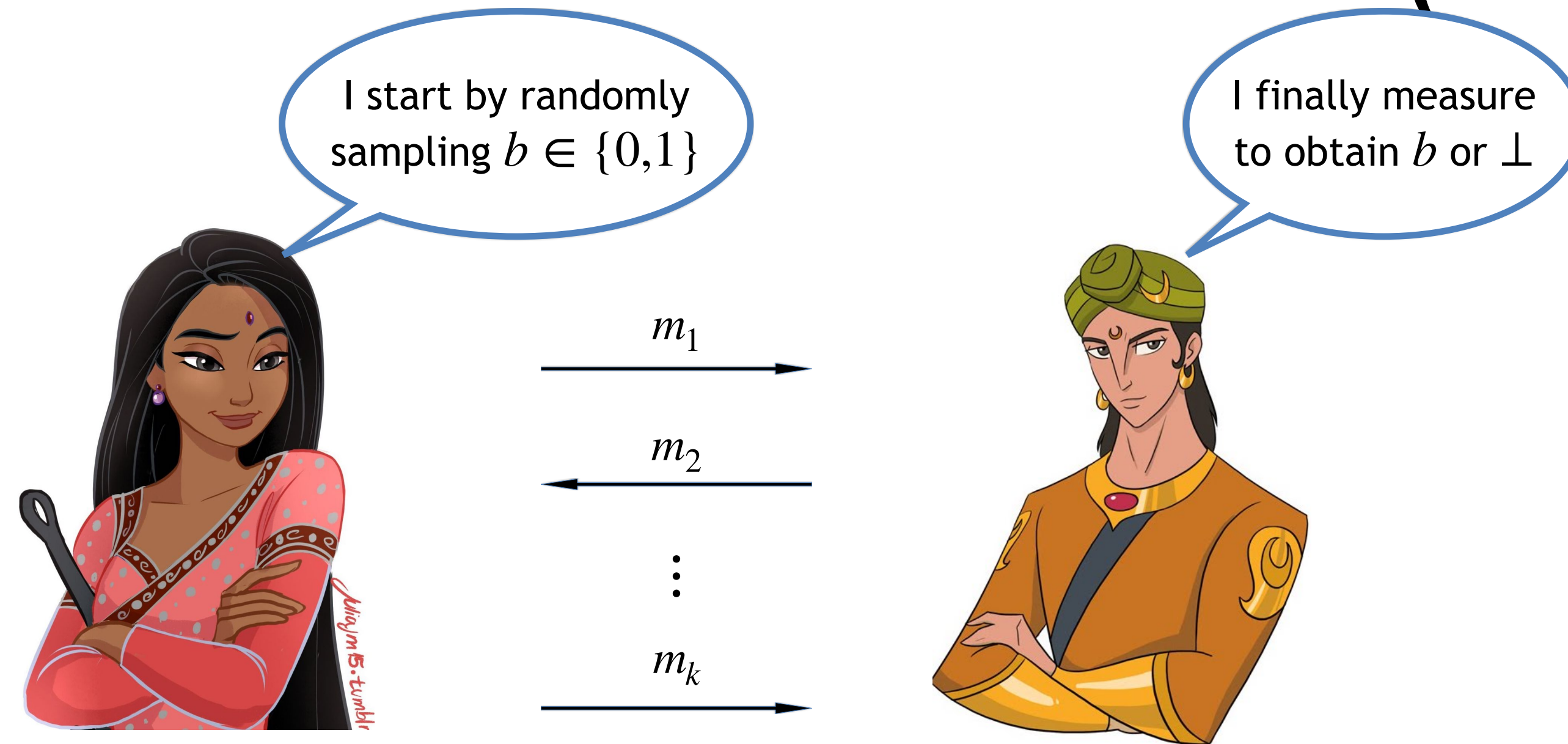


$$P_A^{ROT}(\mathcal{P}) = \max_S \Pr [\text{Alice correctly guesses whether Bob asserts } b \text{ or } \perp]$$

$$P_B^{ROT}(\mathcal{P}) = \max_S \Pr [\text{Bob correctly guesses } b]$$

# Rabin oblivious transfer

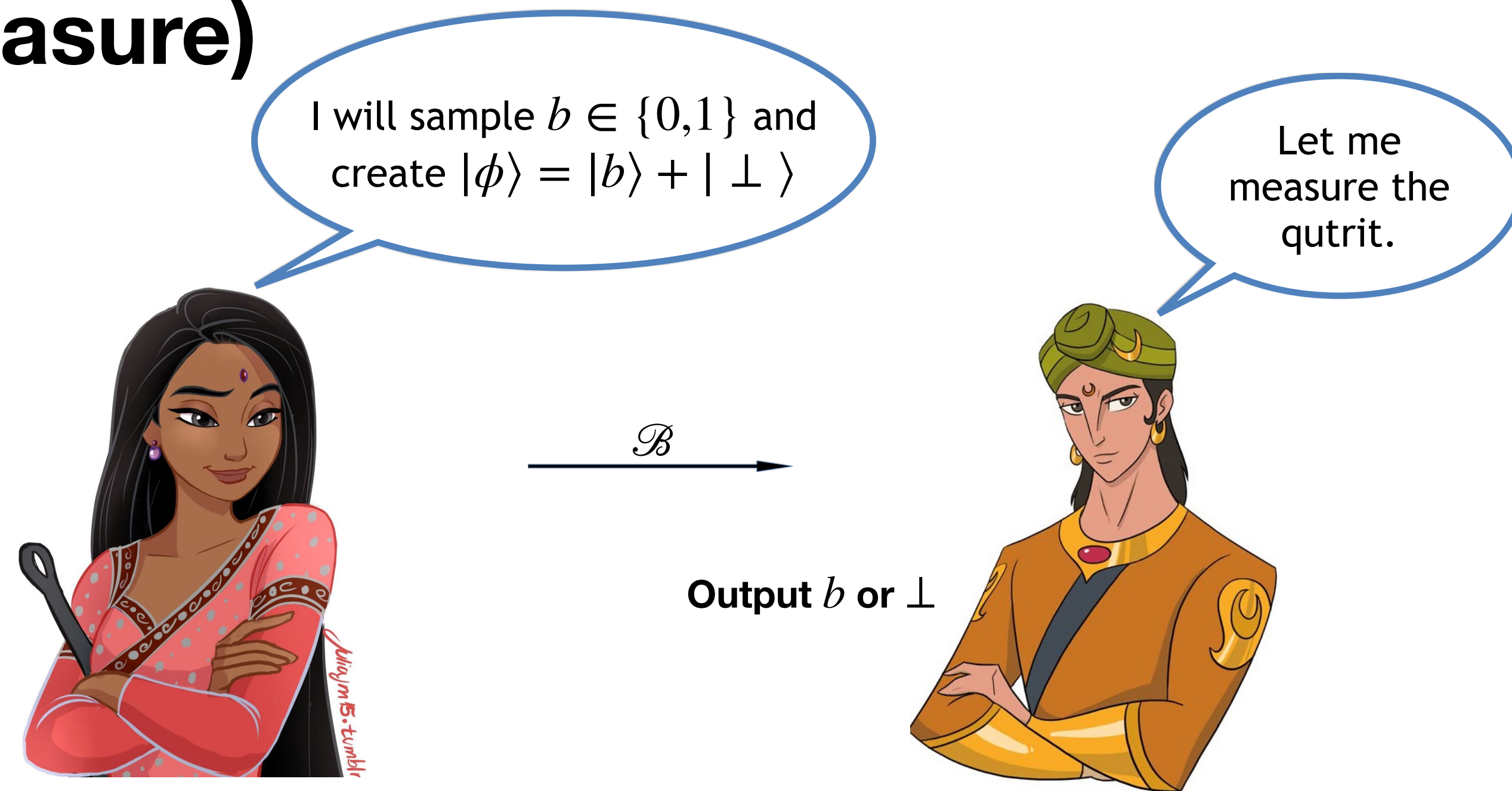
How to exchange secrets with oblivious transfer? (Rabin, 1981)



$$\mathcal{S}(\mathcal{P}) := \max \{ P_A^{ROT}(\mathcal{P}), P_B^{ROT}(\mathcal{P}) \}$$

**Motivation:** Almost nothing is known about the security of Rabin oblivious transfer task under the regime of unconditional security.

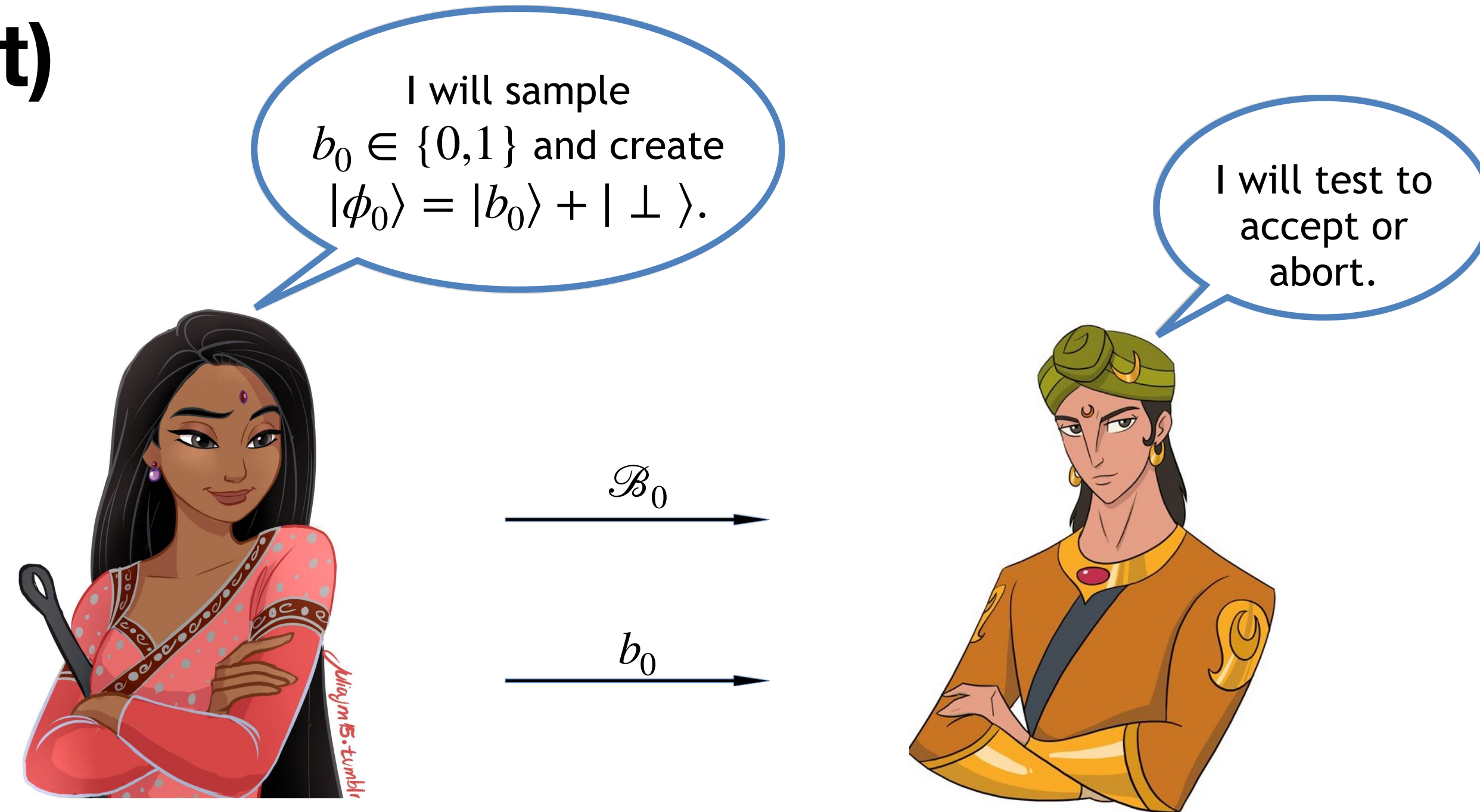
# A bad Rabin-OT protocol (Prepare-and-measure)



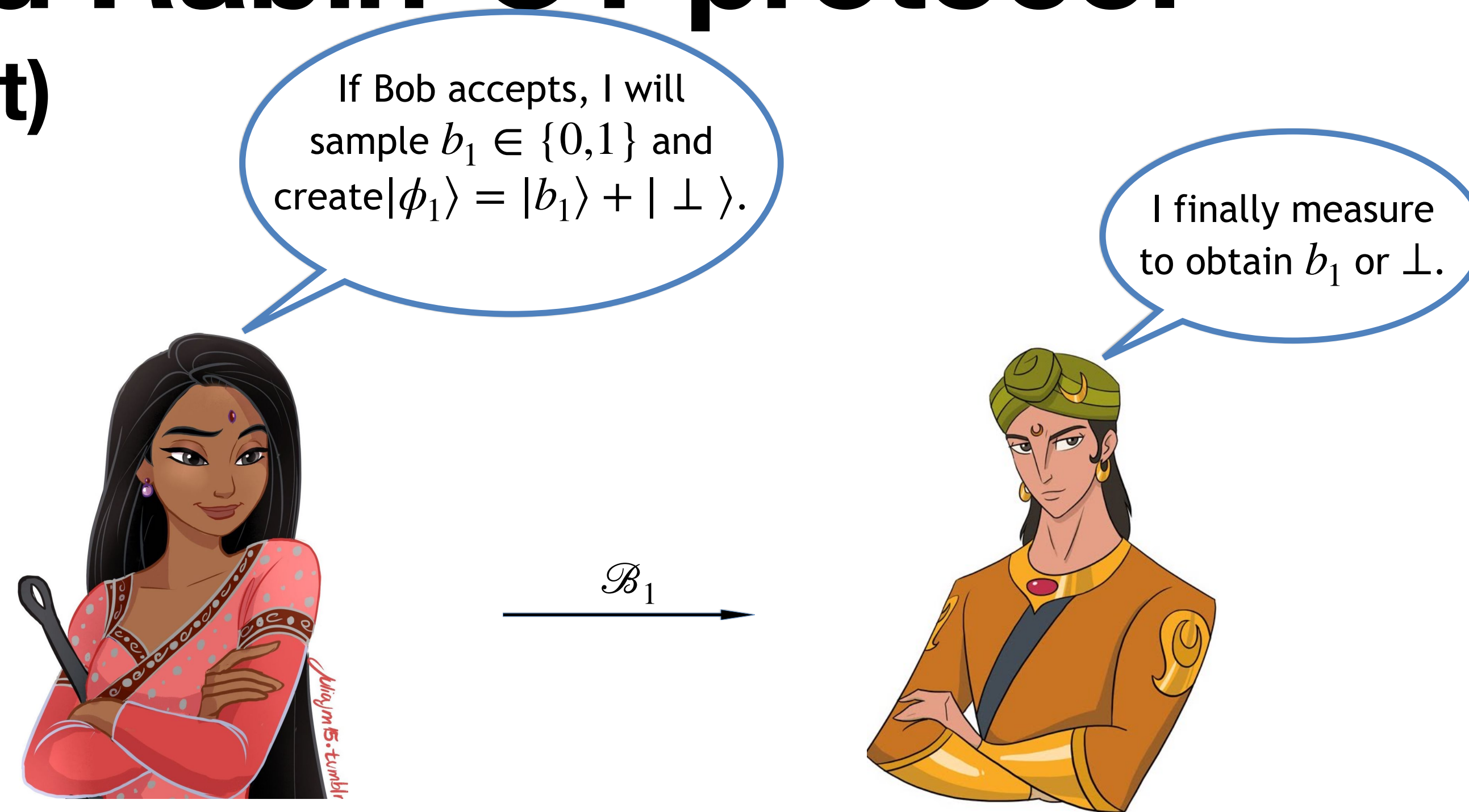
Strategy: Dishonest Alice can simply send  $|\perp\rangle$ .



# Another bad Rabin-OT protocol (Prepare-and-test)



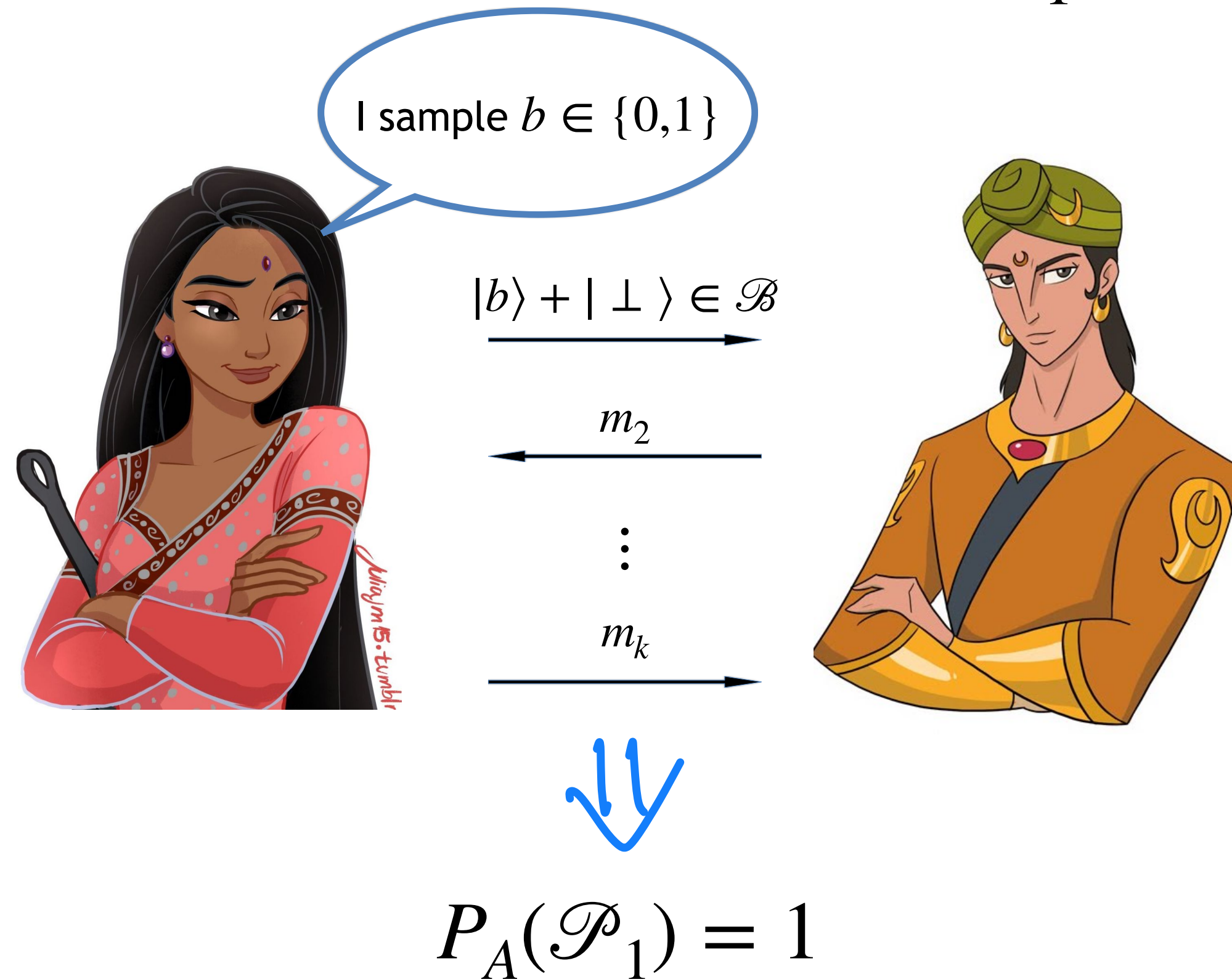
# Another bad Rabin-OT protocol (Prepare-and-test)



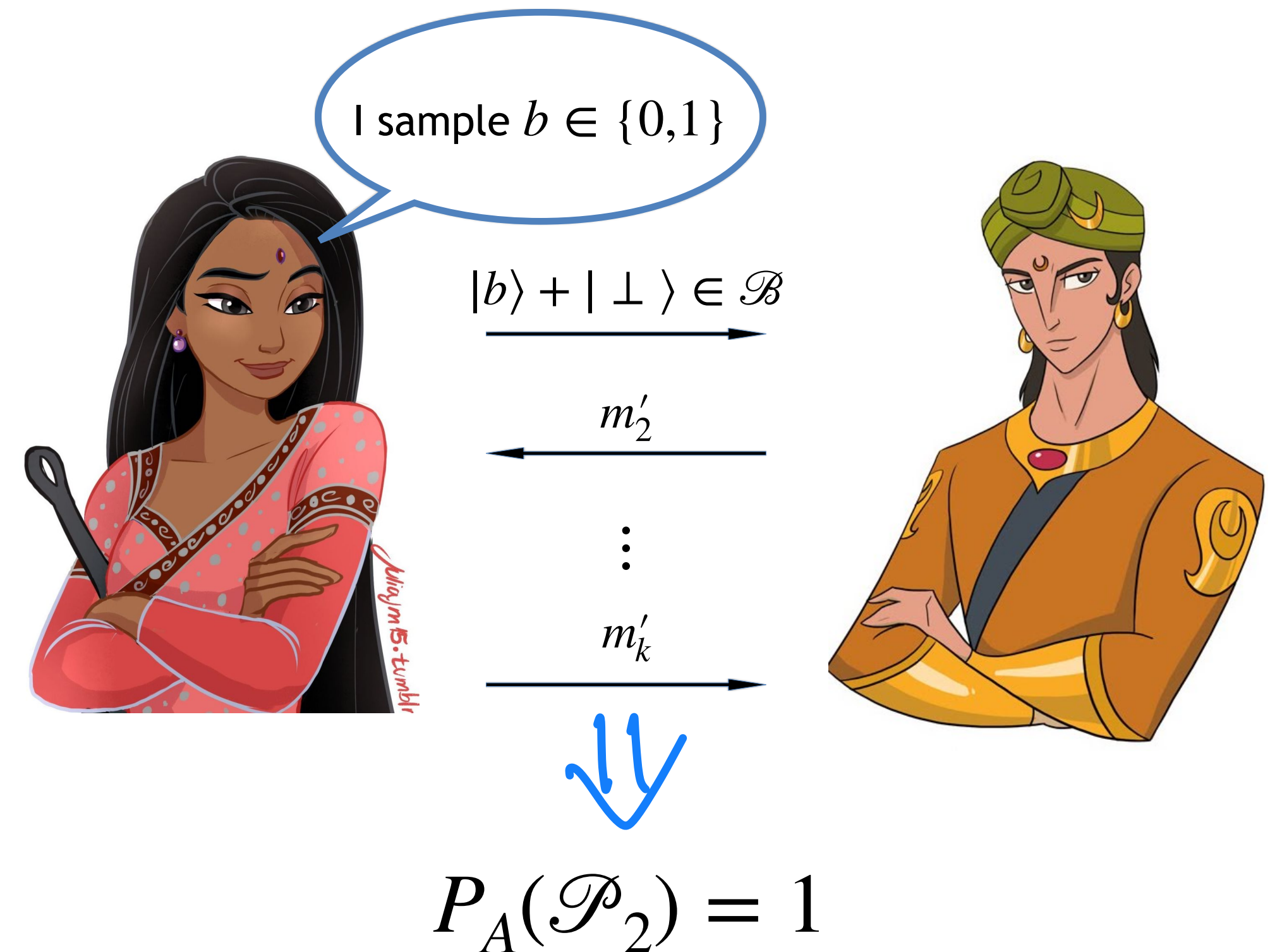
Strategy: Dishonest Alice can prepare  $|\phi_0\rangle$  to always accept and send  $|\perp\rangle$  next.

# Some bad Rabin OT protocols

## Prepare-and-measure ( $\mathcal{P}_1$ )



## Prepare-and-test ( $\mathcal{P}_2$ )

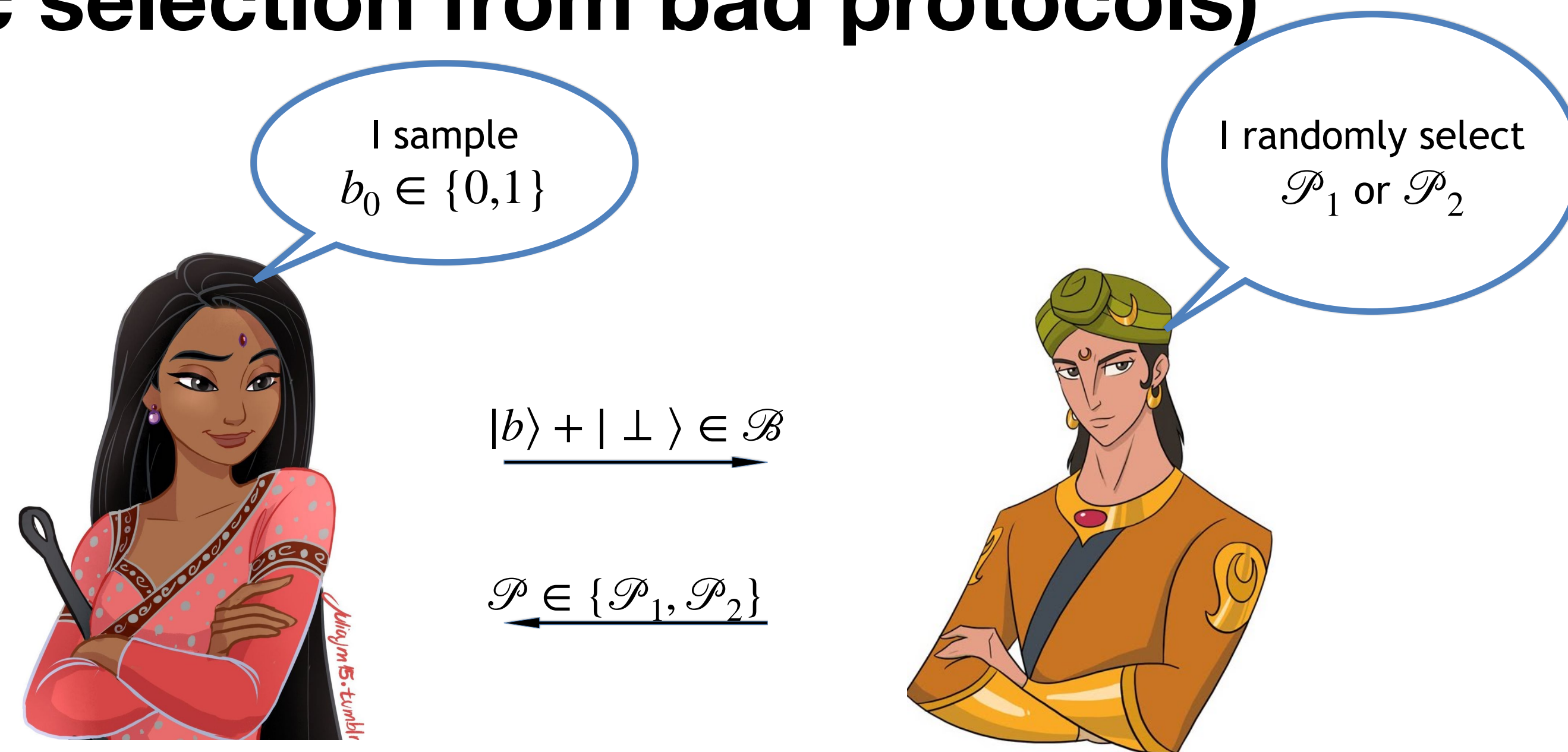


Alice can cheat perfectly in both  $\mathcal{P}_1$  and  $\mathcal{P}_2$ .



# A useful Rabin-OT protocol

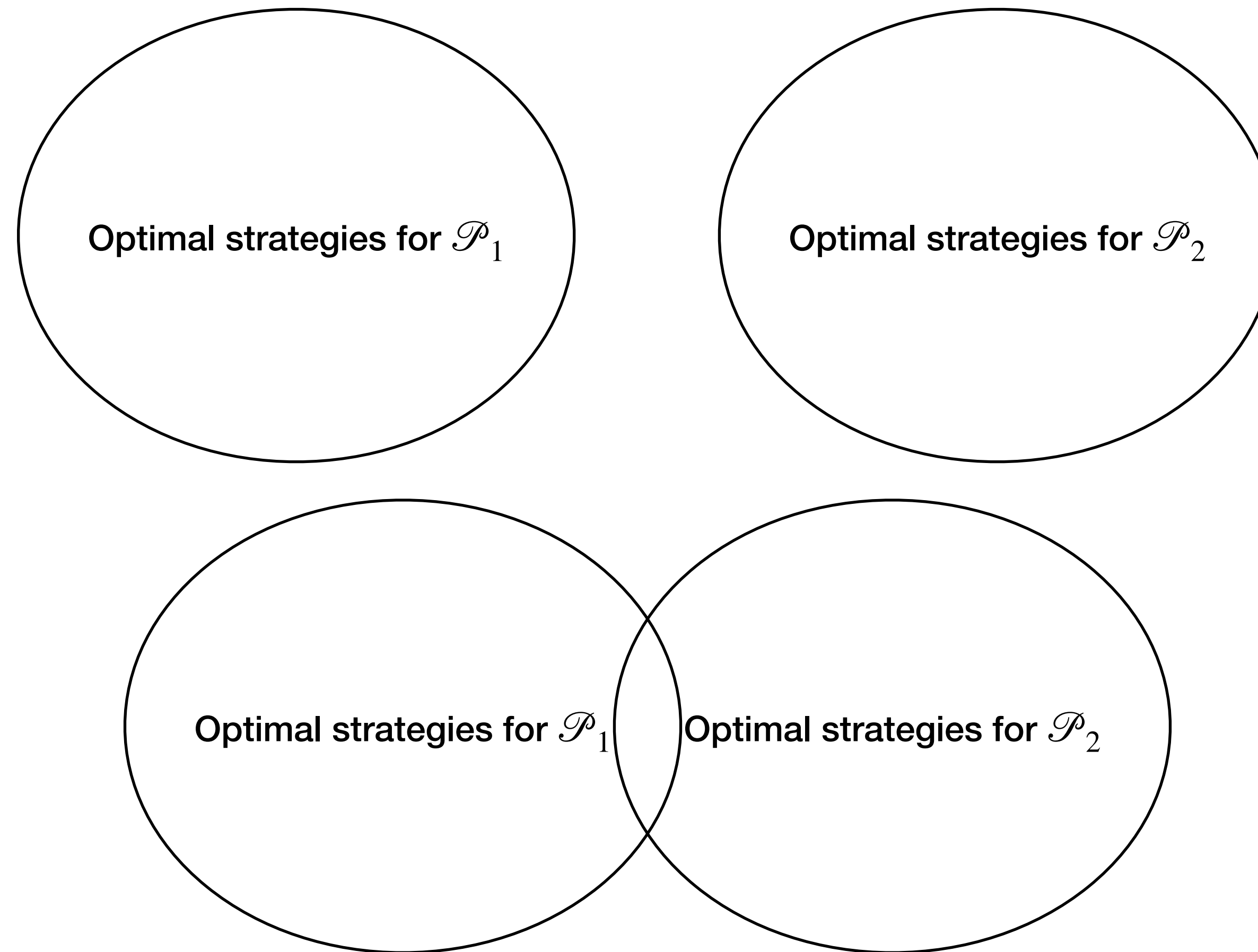
(Using stochastic selection from bad protocols)



**Theorem [BS25]:** There exists a quantum protocol for Rabin OT where Alice can correctly guess whether Bob received the message or  $\perp$  with probability at most 0.9330 and Bob can learn Alice's bit with probability at most 0.9691 implying

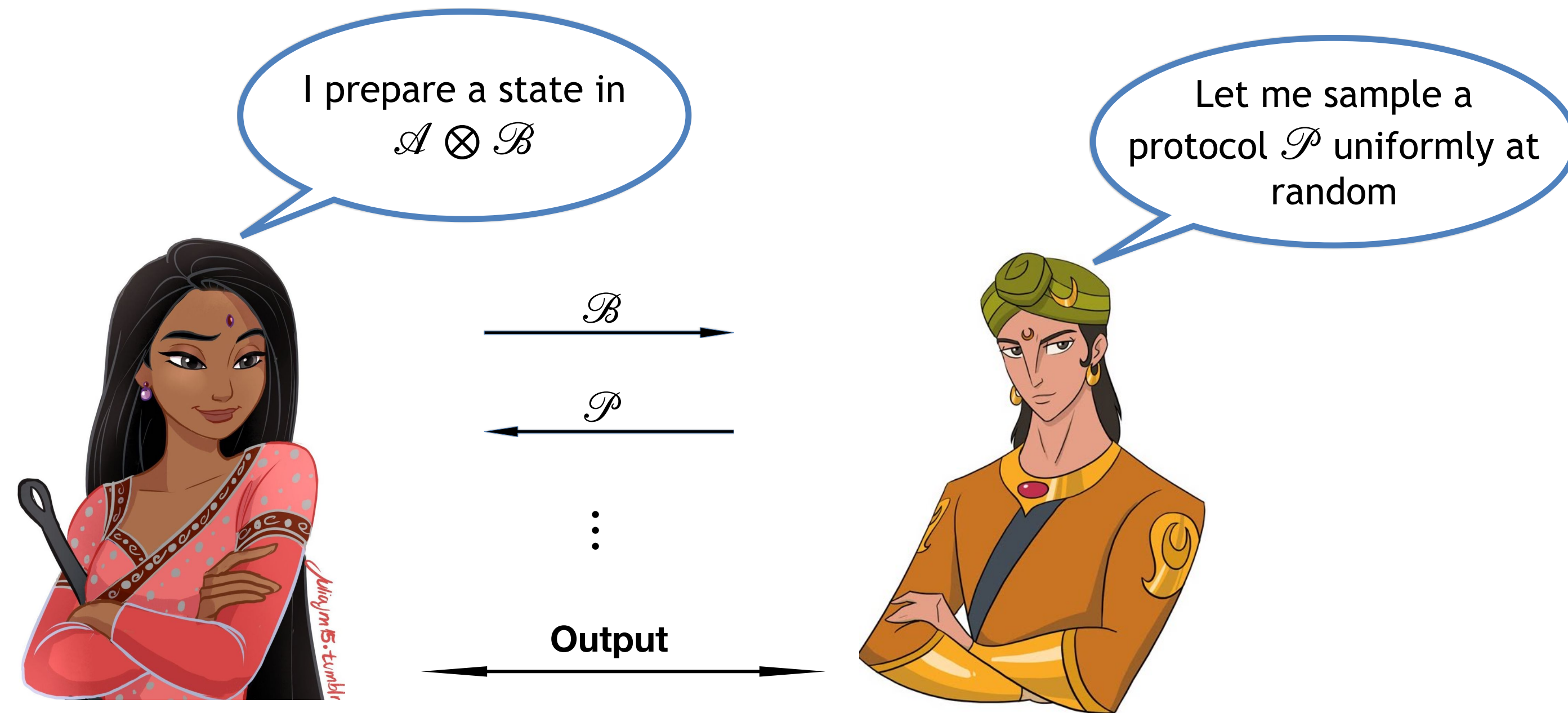
$$\max\{P_A^{ROT}, P_B^{ROT}\} = 0.9691 < 1$$

# An optimization viewpoint



**Fact:** The security of the protocol with stochastic selection is strictly better than the constituent protocols iff the optimal strategies do not overlap.

# General stochastic selection setup



$$P_A = \max_S \Pr [\text{Alice cheats successfully}] = \max \sum p_j P_A^{(j)}$$

$$P_B = \max_S \Pr [\text{Bob cheats successfully}] = \max \sum \Pr[j] P_B^{(j)}$$

# Cheating Alice in stochastic selection (2/3)

Protocol 1

$$\max \langle C_1, Y_1 \rangle$$

$$\Phi(Y_1) = B_1$$

$$\Xi(Y_1) = X_1$$

$$X_1, Y_1 \geq 0$$

Protocol 2

$$\max \langle C_2, Y_2 \rangle$$

$$\Phi(Y_2) = B_2$$

$$\Xi(Y_2) = X_2$$

$$X_2, Y_2 \geq 0$$

$$\boxed{X_1 = X_2}$$

# Cheating Alice in stochastic selection (3/3)

$$\begin{aligned} \max \quad & \mathbb{E}_{\omega}[\langle C_{\omega}, Y_{\omega} \rangle] \\ & \Phi(Y_{\omega}) = B_{\omega}, \forall \omega \\ & \Xi(Y_{\omega}) = X, \forall \omega \\ & Y_{\omega} \geq 0, \forall \omega \\ & X \geq 0. \end{aligned}$$

Note: For large  $|\Omega|$ , use techniques based on Benders decomposition.

# Some open questions

- Protocols with optimal communication complexity for WCF.
- Optimality of [CK09] and bounds on communication complexity for SCF.
- Secure device independent weak coin flipping protocol [**BAHS24**]
- Optimal protocols and lower bounds for 1-out-of-2-OT and Rabin OT [**ABSW25**].
- Composability of oblivious transfer (Ongoing work with Wu)



# References

- [ARV21] Arora, Atul Singh, Jérémie Roland, and Chrysoula Vlachou. "Analytic quantum weak coin flipping protocols with arbitrarily small bias." *Proceedings of the 2021 ACM-SIAM Symposium on Discrete Algorithms (SODA)*. Society for Industrial and Applied Mathematics, 2021.
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