

The quantum comb: theory and applications to quantum networks

Giacomo Mauro D'Ariano

QUIT group, University of Pavia

Institute for Theoretical Physics, University of Innsbruck,
"Seminar/Theory Colloquium", March 19 2009

QIT Group in Pavia



Chiara Macchiavello



Lorenzo Maccone



Massimiliano Sacchi



Paolo Perinotti



Giulio Chiribella



Daniele Magnani

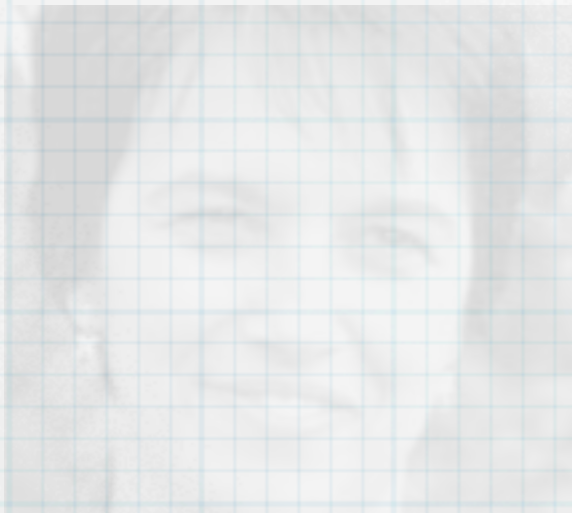


Stefano Facchini

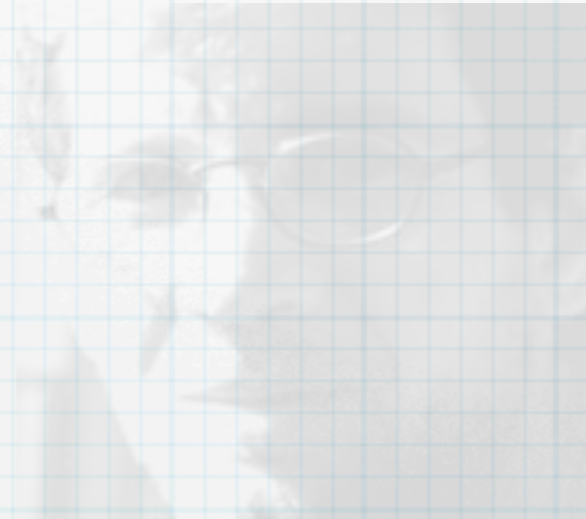


Alessandro Bisio

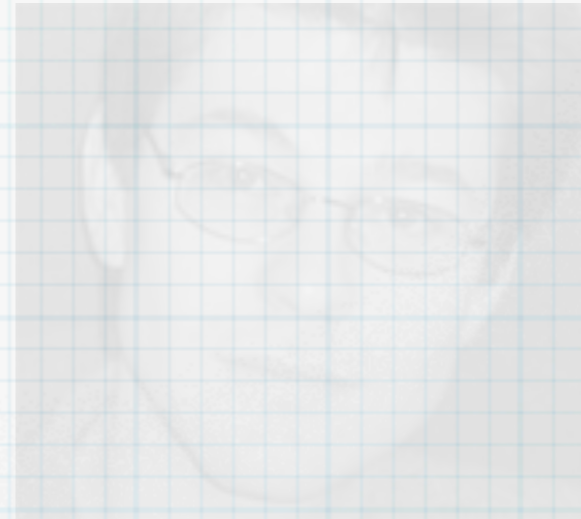
Theory of Quantum Combs in collaboration with



Chiara Macchiavello



Lorenzo Maccone



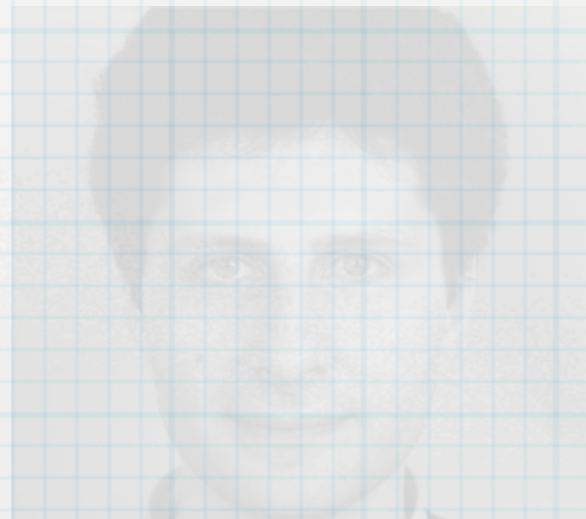
Massimiliano Sacchi



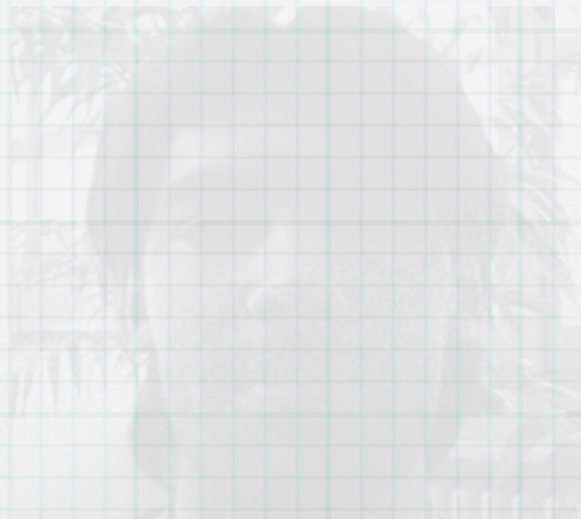
Paolo Perinotti



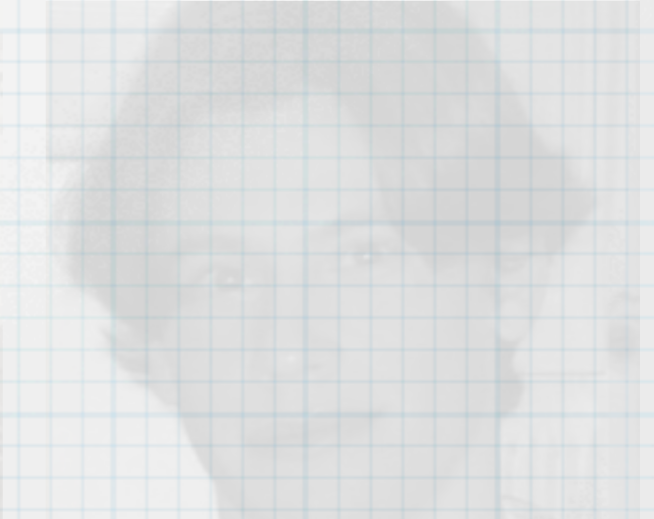
Giulio Chiribella



Daniele Magnani

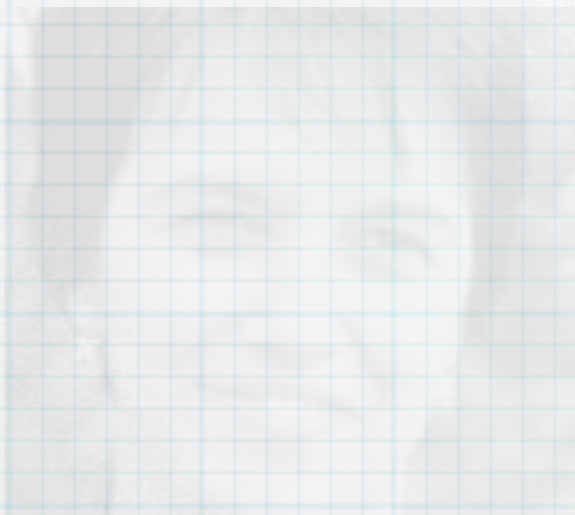


Stefano Facchini

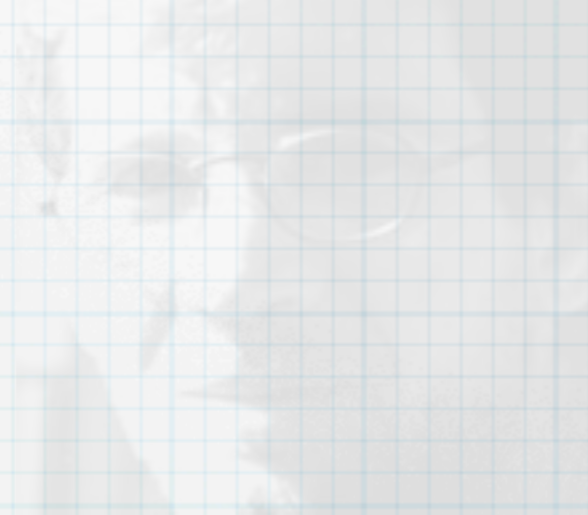


Alessandro Bisio

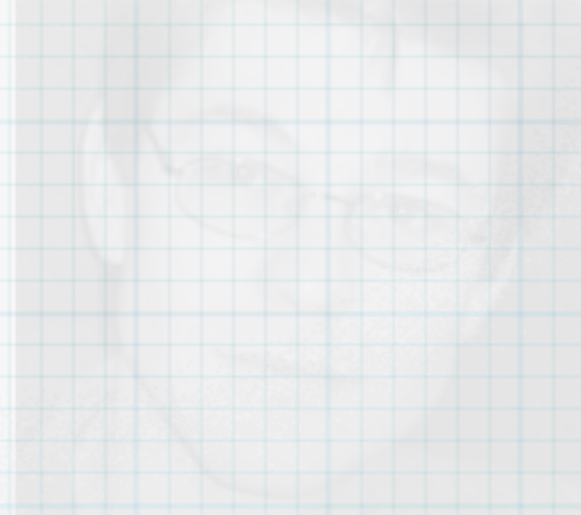
Applications to Optimal Q-Tomography and Q-Learning



Chiara Macchiavello



Lorenzo Maccone



Massimiliano Sacchi



Paolo Perinotti



Giulio Chiribella



Daniele Magnani



Stefano Facchini



Alessandro Bisio

Outline

Outline

- New Quantum Estimation Theory, with multiple copies, and optimization of the setup
- Convex optimization method based on the new notions of **quantum comb** and **quantum tester**

Outline

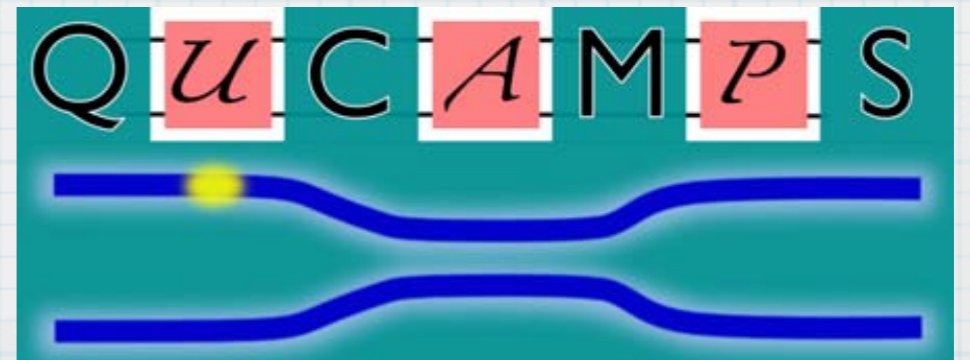
- New Quantum Estimation Theory, with multiple copies, and optimization of the setup
- Convex optimization method based on the new notions of **quantum comb** and **quantum tester**
- Applications:
 - discrimination of unitary operators and of memory channels (quantum oracle-calling algorithms)
 - strategies in quantum protocols, crypto and games
 - quantum-algorithm learning (storing undisclosable unitaries)
 - process-cloning
 - optimal tomography

optimal

Outline

- New Quantum Estimation Theory, with multiple copies, and optimization of the setup
- Convex optimization method based on the new notions of **quantum comb** and **quantum tester**
- Applications:
 - discrimination of unitary operators and of memory channels (quantum oracle-calling algorithms)
 - strategies in quantum protocols, crypto and games
 - quantum-algorithm learning (storing undisclosable unitaries)
 - process-cloning
 - optimal tomography

optimal

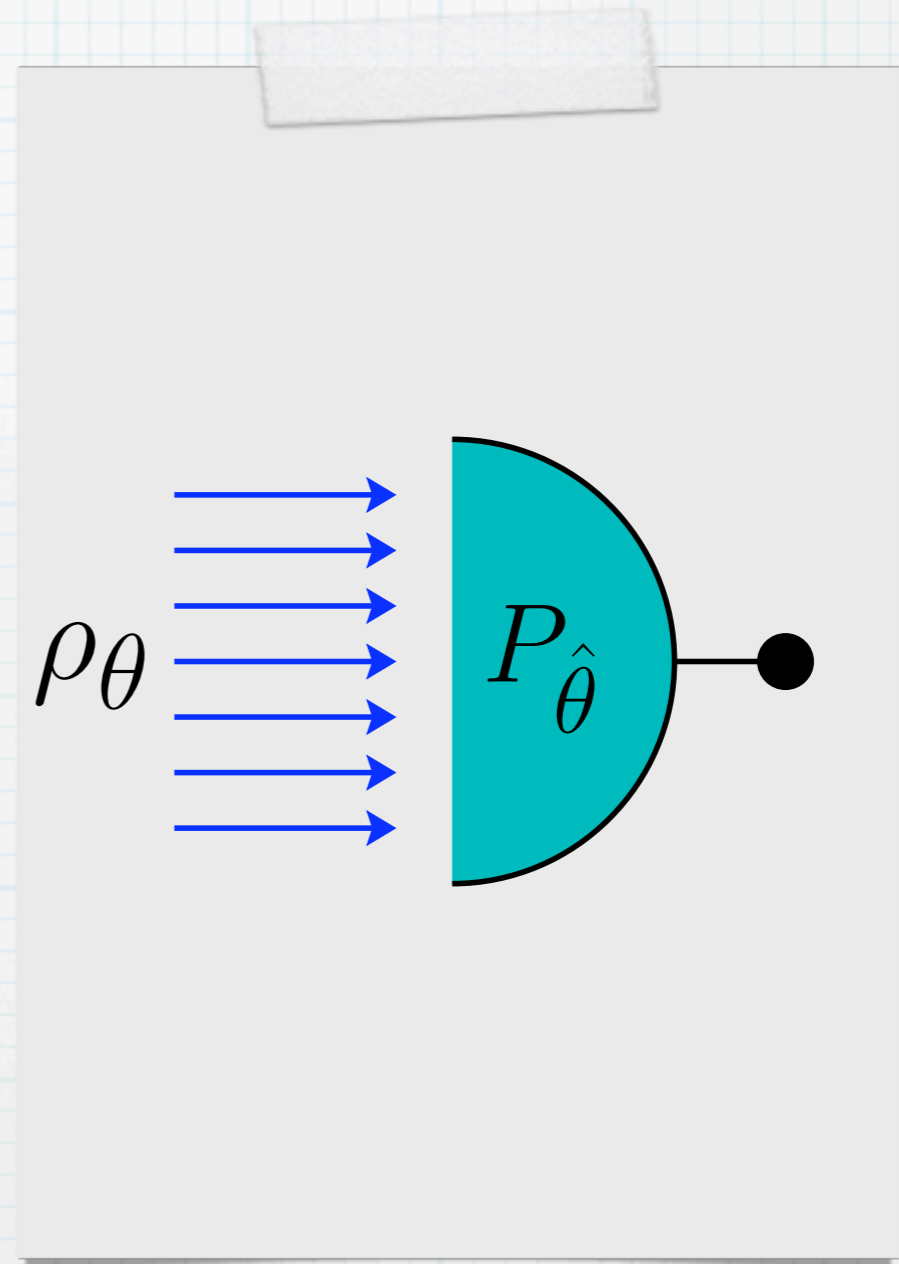


Helstrom-Holevo

Quantum Estimation Theory

Quantum state ρ_θ parameterized by θ

Problem: estimate θ optimally according to the cost function $C(\theta, \hat{\theta})$



Helstrom-Holevo

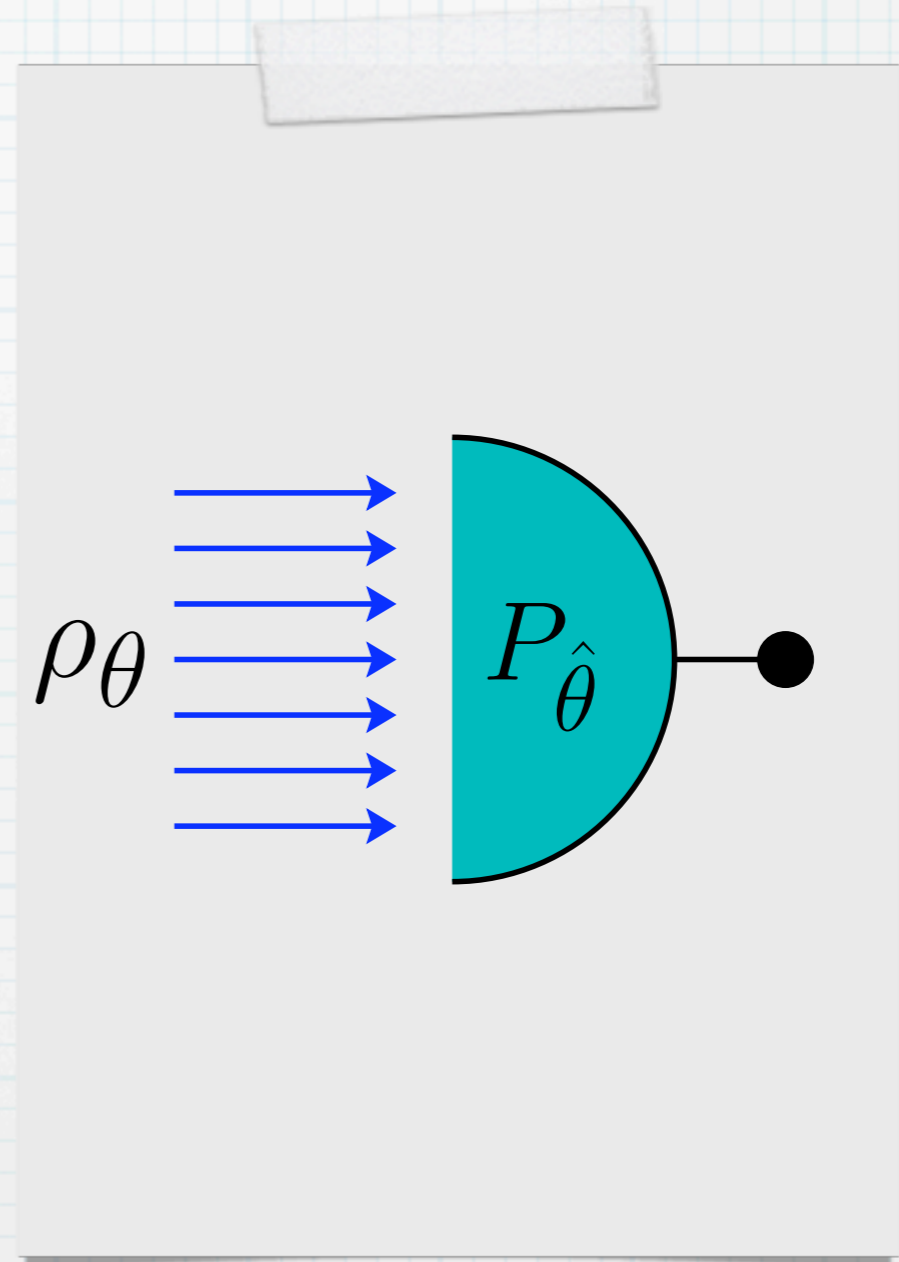
Quantum Estimation Theory

Quantum state ρ_θ parameterized by θ

Problem: estimate θ optimally according to the cost function $C(\theta, \hat{\theta})$

Mathematical formulation:

find the optimal POVM $P_{\hat{\theta}}$ minimizing the cost

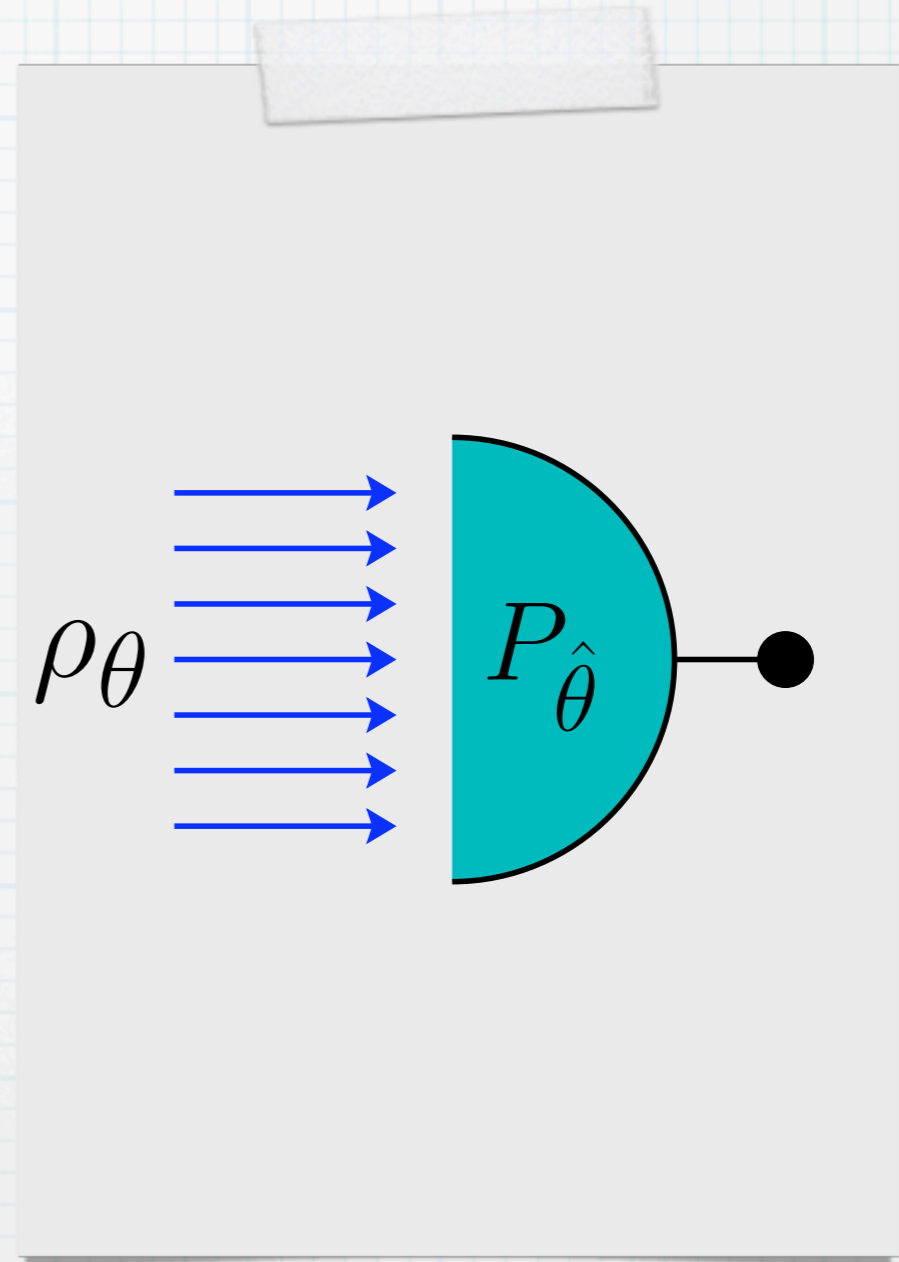


Helstrom-Holevo

Quantum Estimation Theory

Practically interesting situation
(e.g. for the phase of an e.m. mode):

$$\theta \implies \rho_\theta = U_\theta \rho U_\theta^\dagger$$



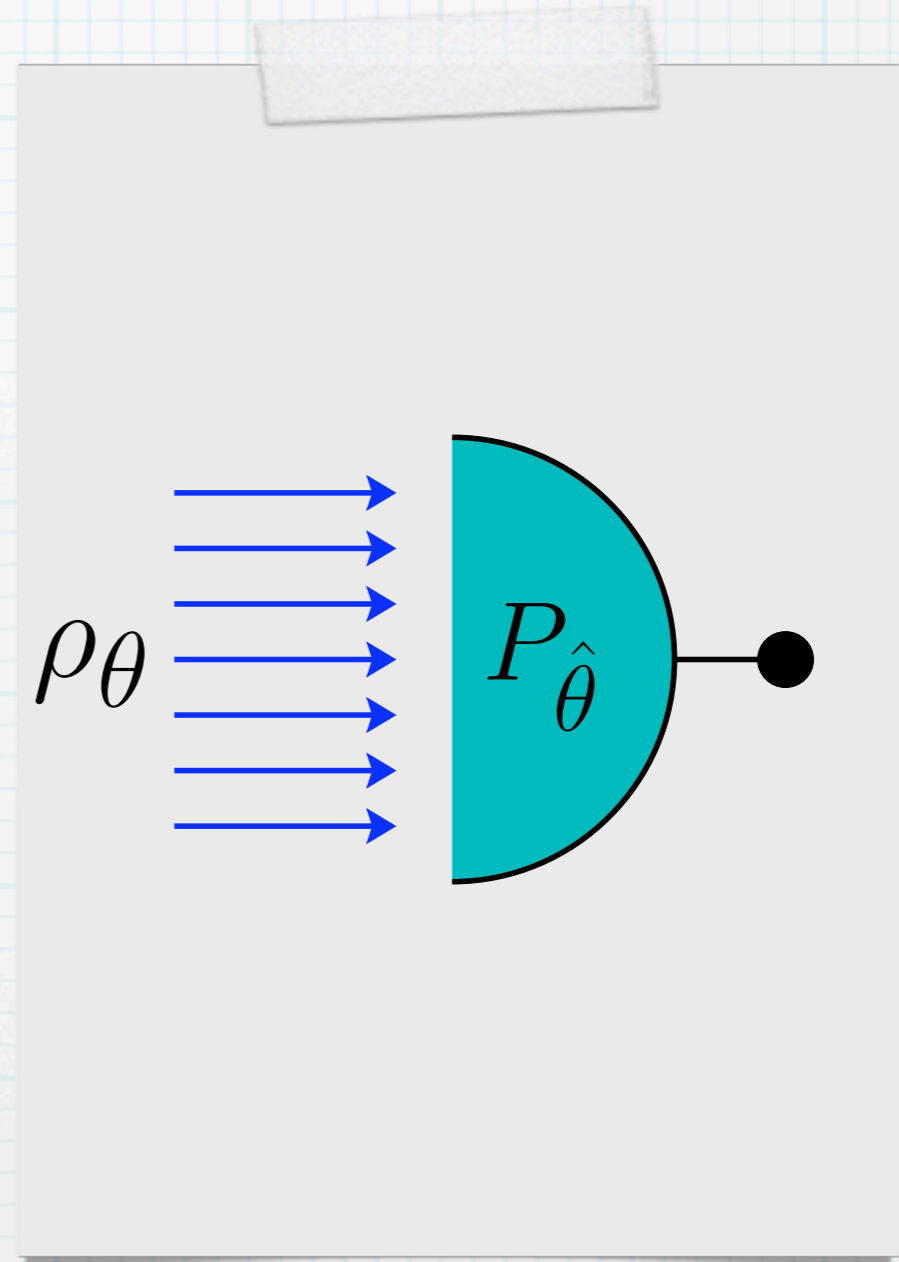
Helstrom-Holevo

Quantum Estimation Theory

Practically interesting situation
(e.g. for the phase of an e.m. mode):

$$\theta \implies \rho_\theta = U_\theta \rho U_\theta^\dagger$$

Then you want also to optimize ρ



Helstrom-Holevo

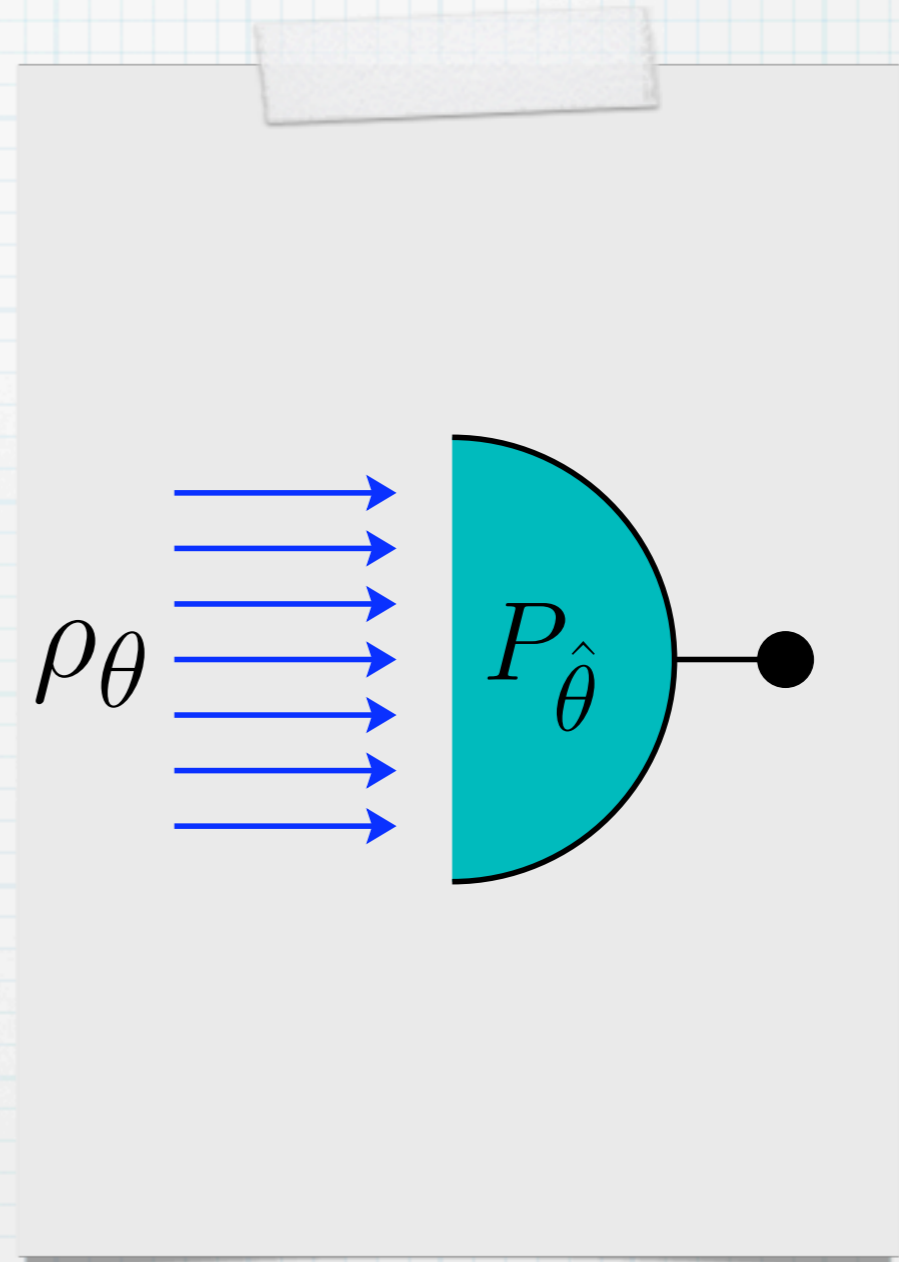
Quantum Estimation Theory

Practically interesting situation
(e.g. for the phase of an e.m. mode):

$$\theta \implies \rho_\theta = U_\theta \rho U_\theta^\dagger$$

Then you want also to optimize ρ

The optimal POVM for
estimating θ depends on ρ



Helstrom-Holevo

Quantum Estimation Theory

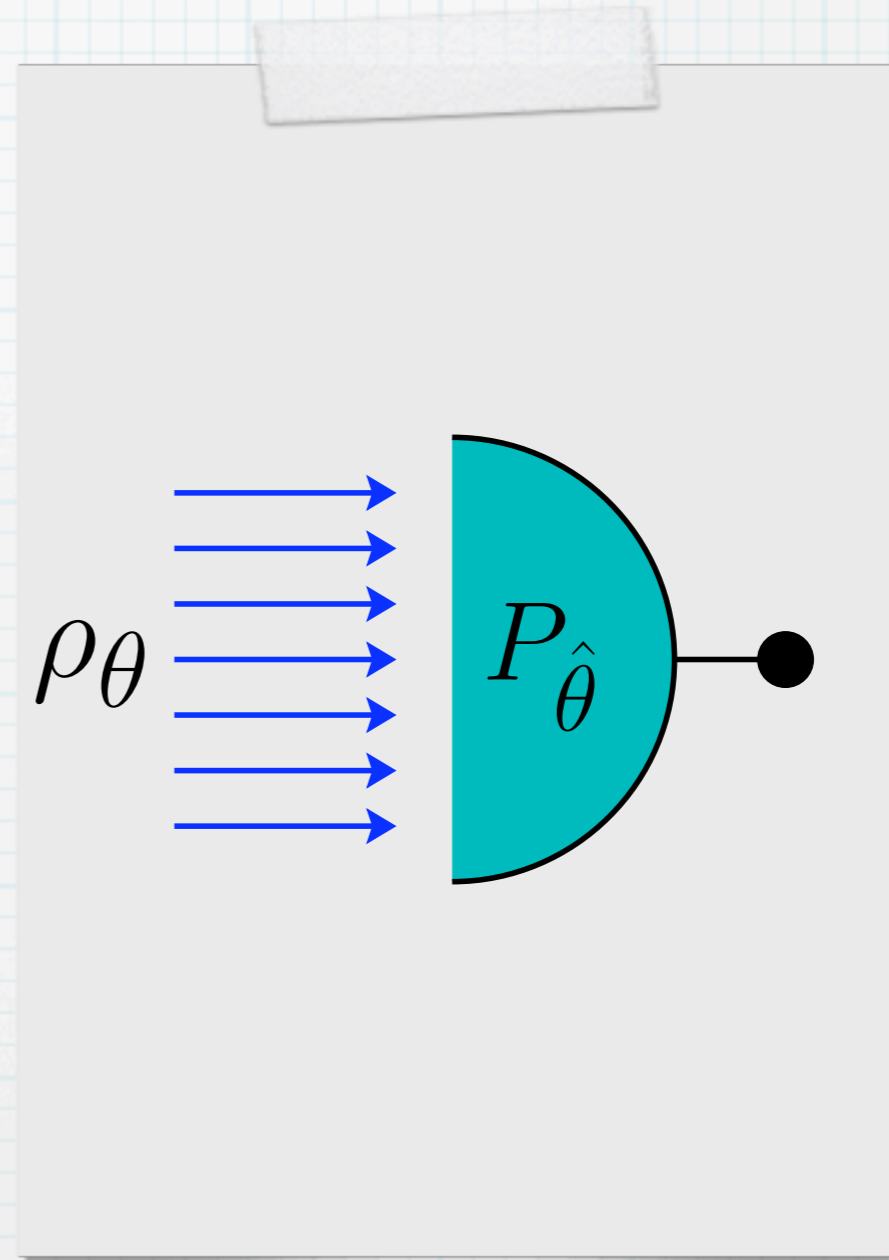
Practically interesting situation
(e.g. for the phase of an e.m. mode):

$$\theta \implies \rho_\theta = U_\theta \rho U_\theta^\dagger$$

Then you want also to optimize ρ

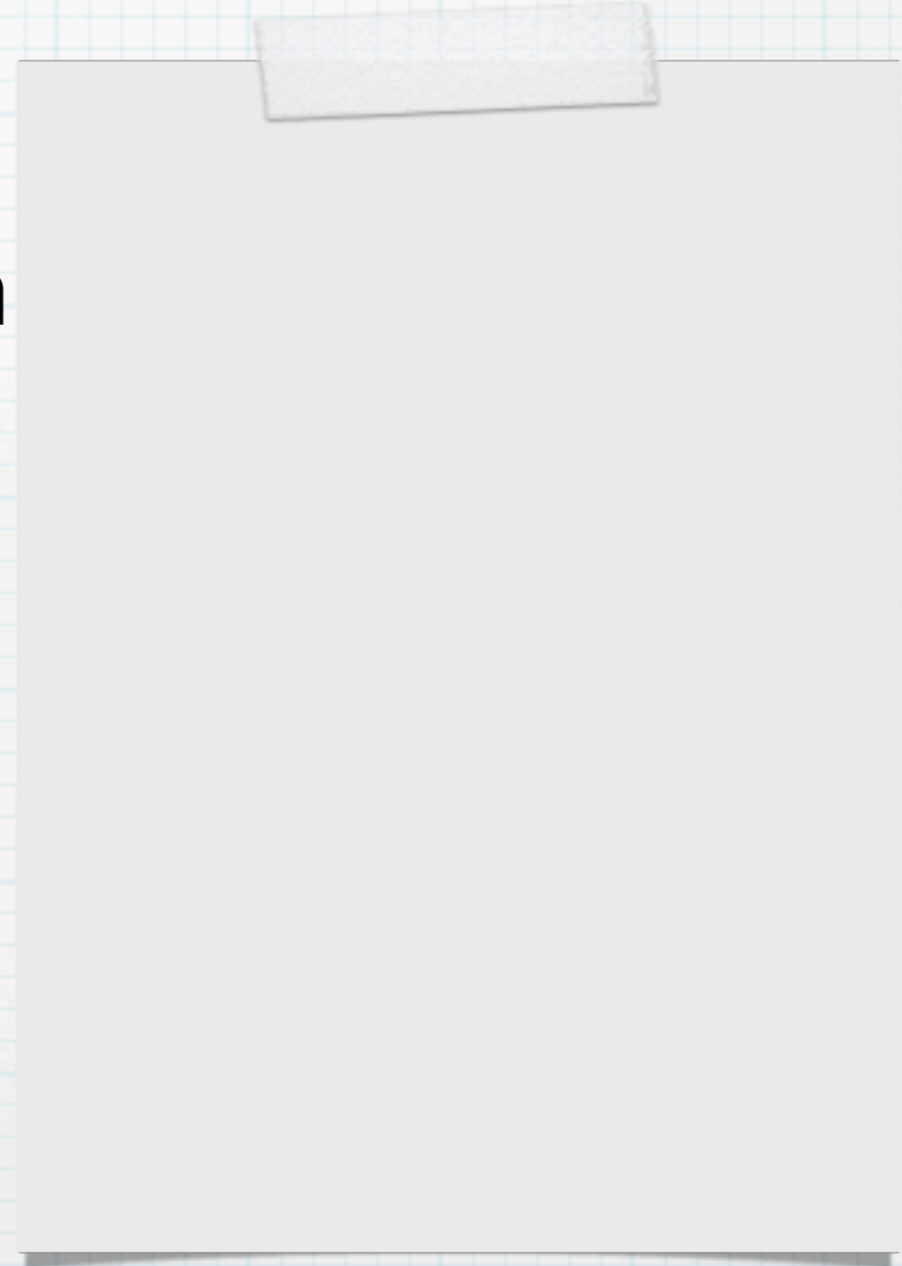
The optimal POVM for
estimating θ depends on ρ

Interesting situation: **the parameter** to be estimated
is encoded on a transformation---not on the state!



Quantum Estimation Theory

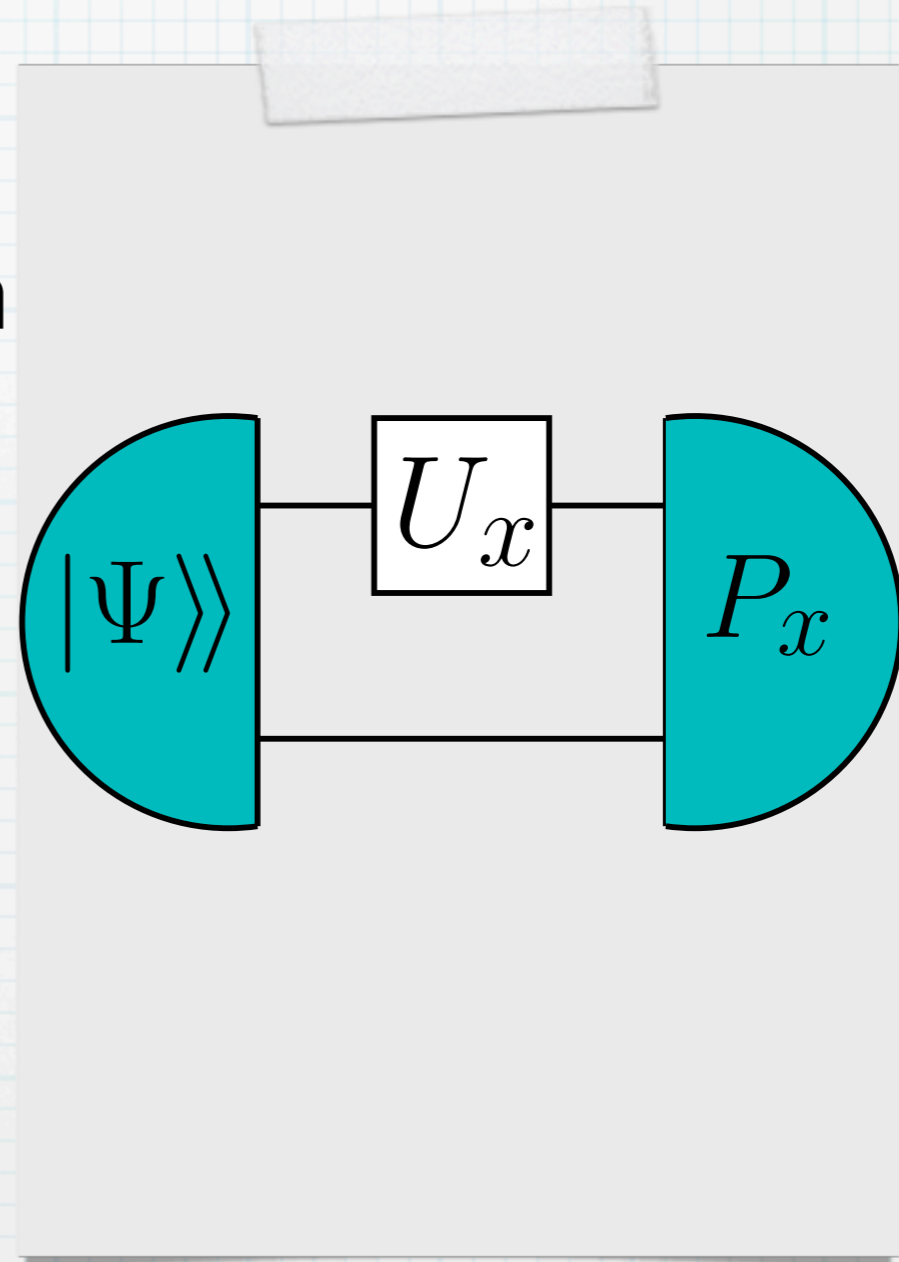
Problem: estimate x parameterizing
the (unitary) transformation U_x
optimally according to the cost function



Quantum Estimation Theory

Problem: estimate x parameterizing the (unitary) transformation U_x optimally according to the cost function

Lesson that we learned from entanglement:

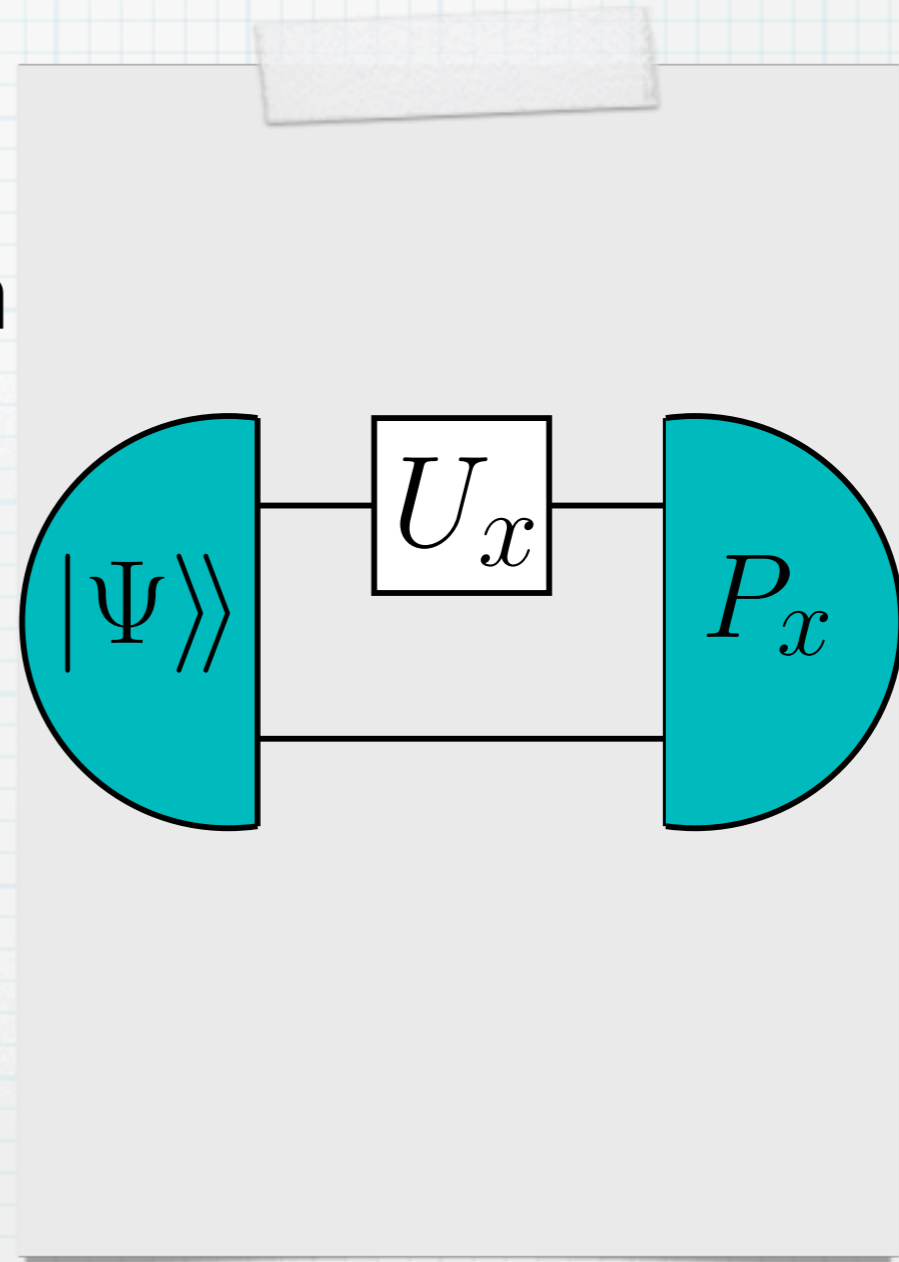


Quantum Estimation Theory

Problem: estimate x parameterizing the (unitary) transformation U_x optimally according to the cost function

Lesson that we learned from entanglement:

Find the optimal entangled state $|\Psi\rangle\rangle$ (with an any possible ancilla) along with the optimal joint POVM P_x



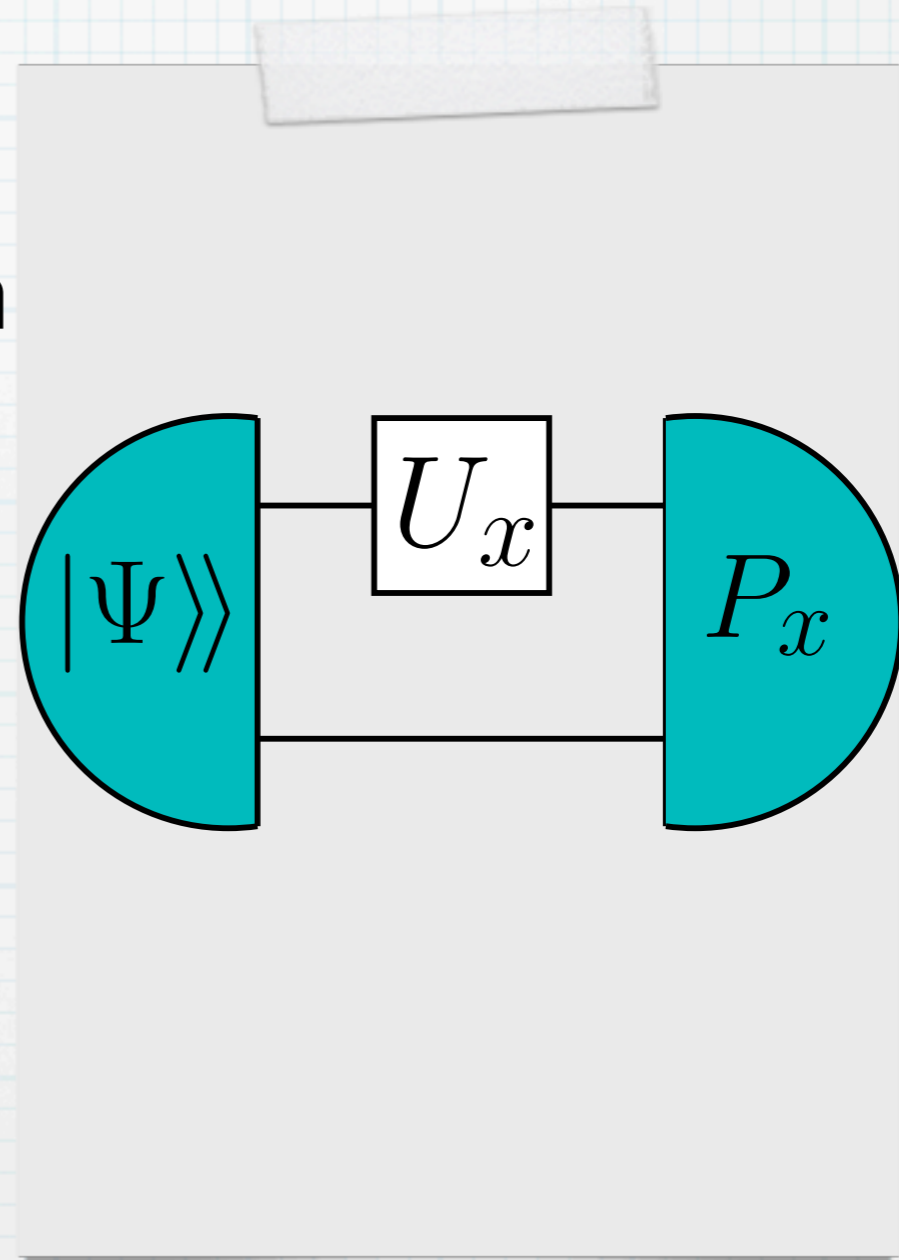
Quantum Estimation Theory

Problem: estimate x parameterizing the (unitary) transformation U_x optimally according to the cost function

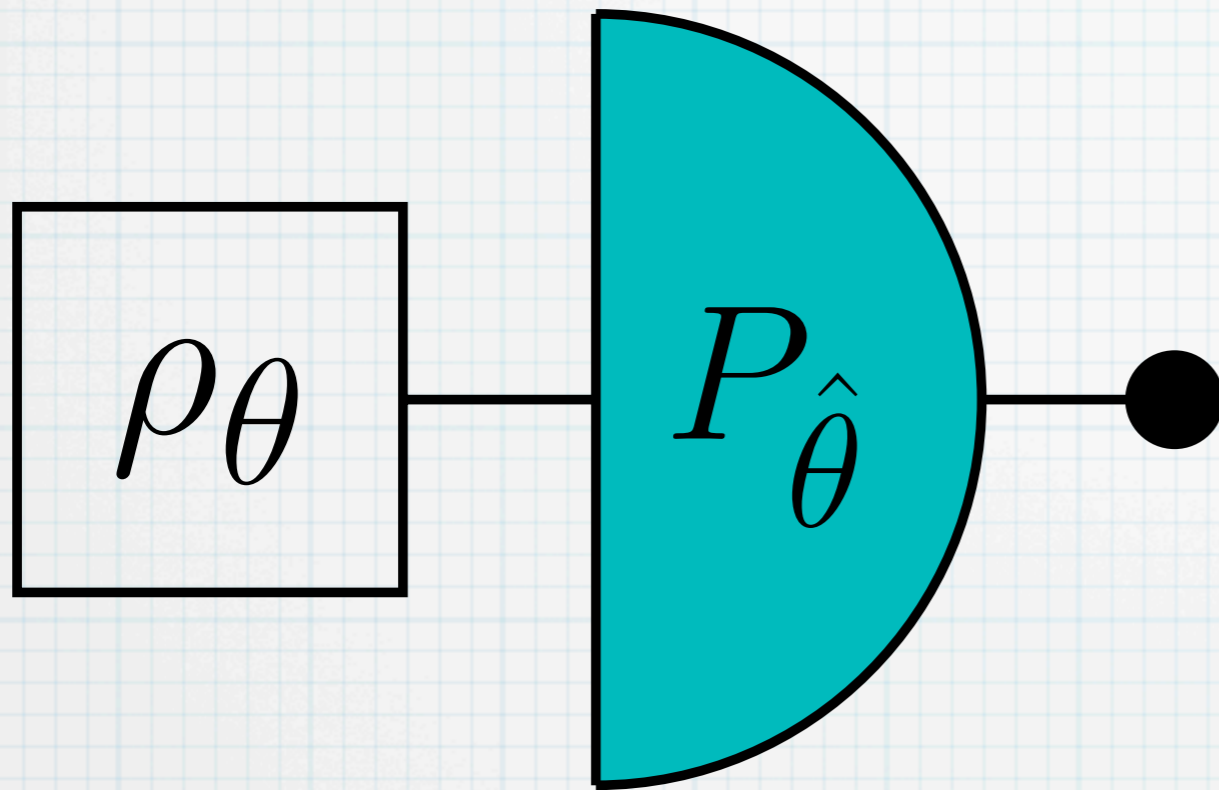
Lesson that we learned from entanglement:

Find the optimal entangled state $|\Psi\rangle\rangle$ (with an any possible ancilla) along with the optimal joint POVM P_x

For the phase no need of entanglement (we were lucky!)

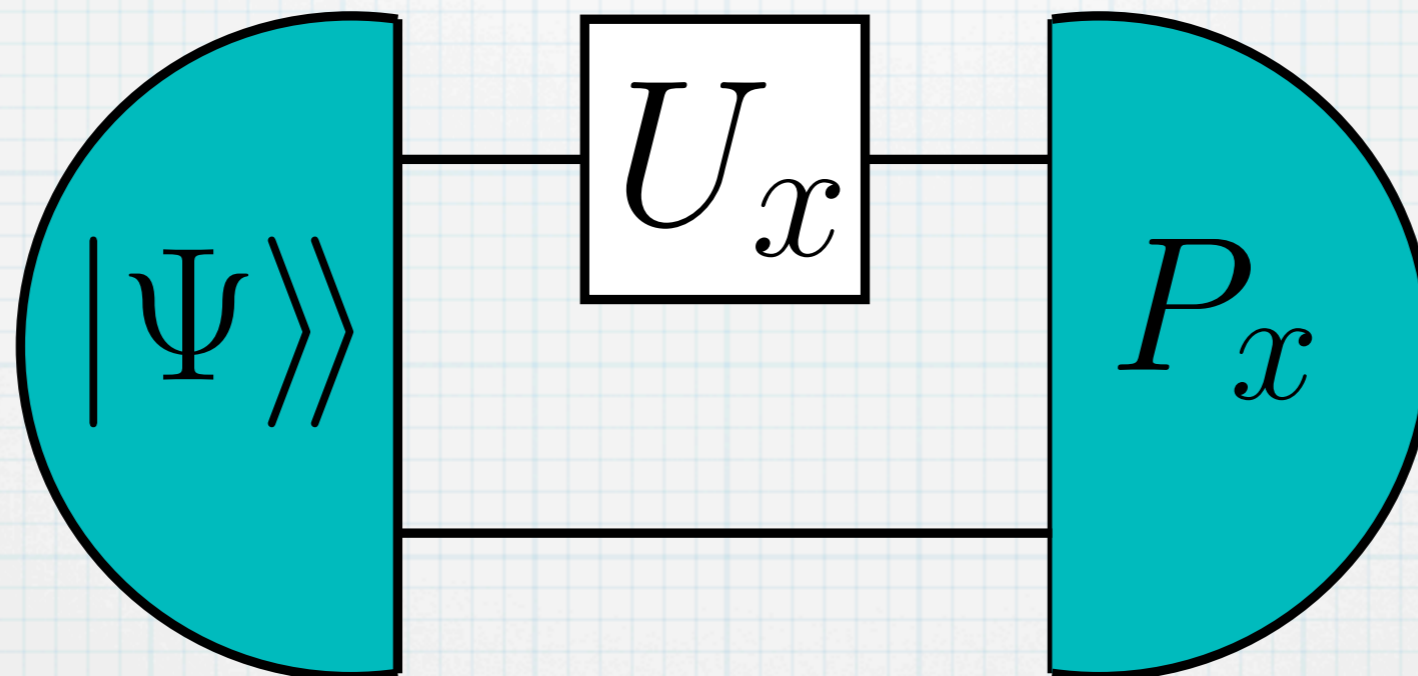


Quantum Estimation Theory

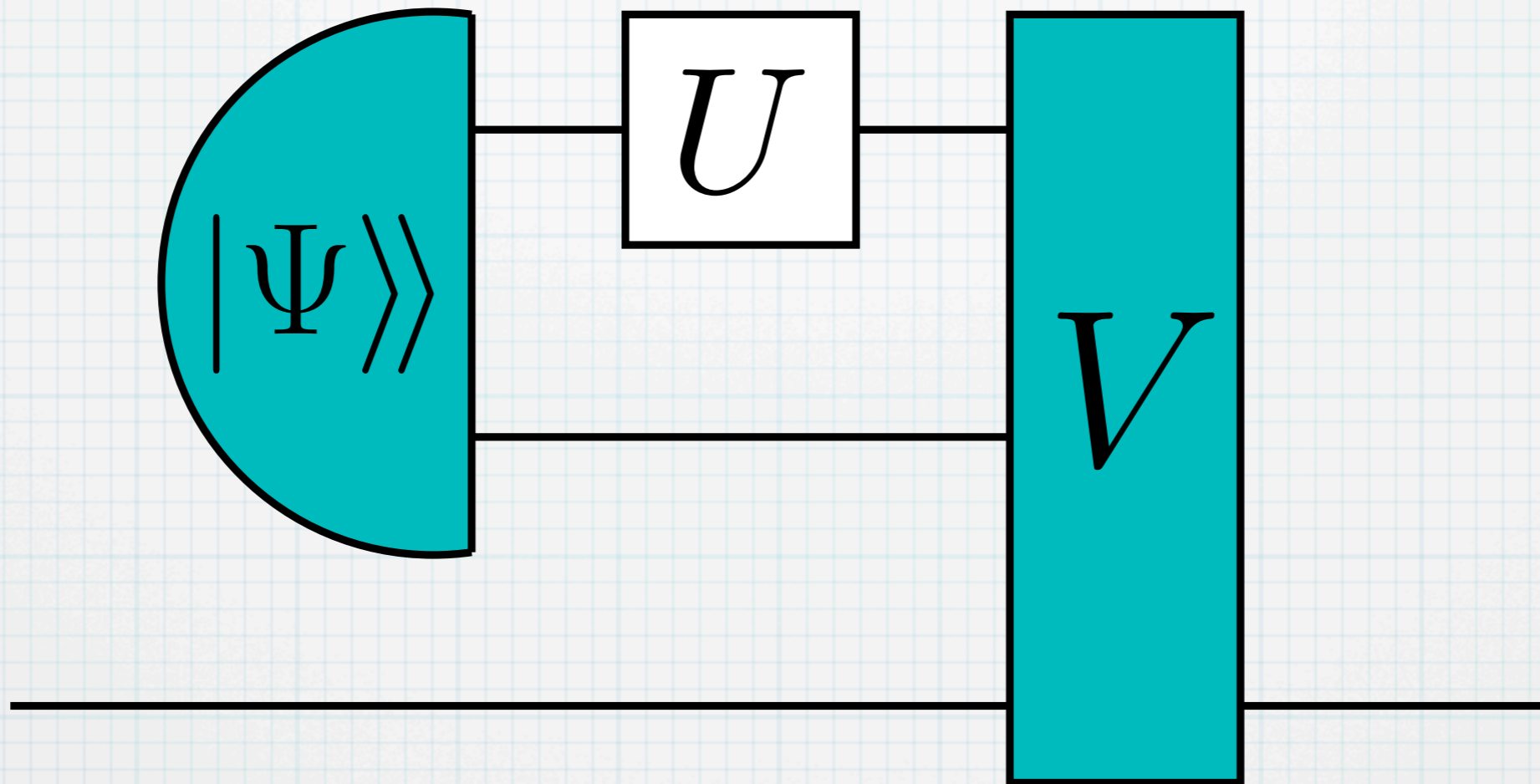


Quantum Estimation Theory

New scheme

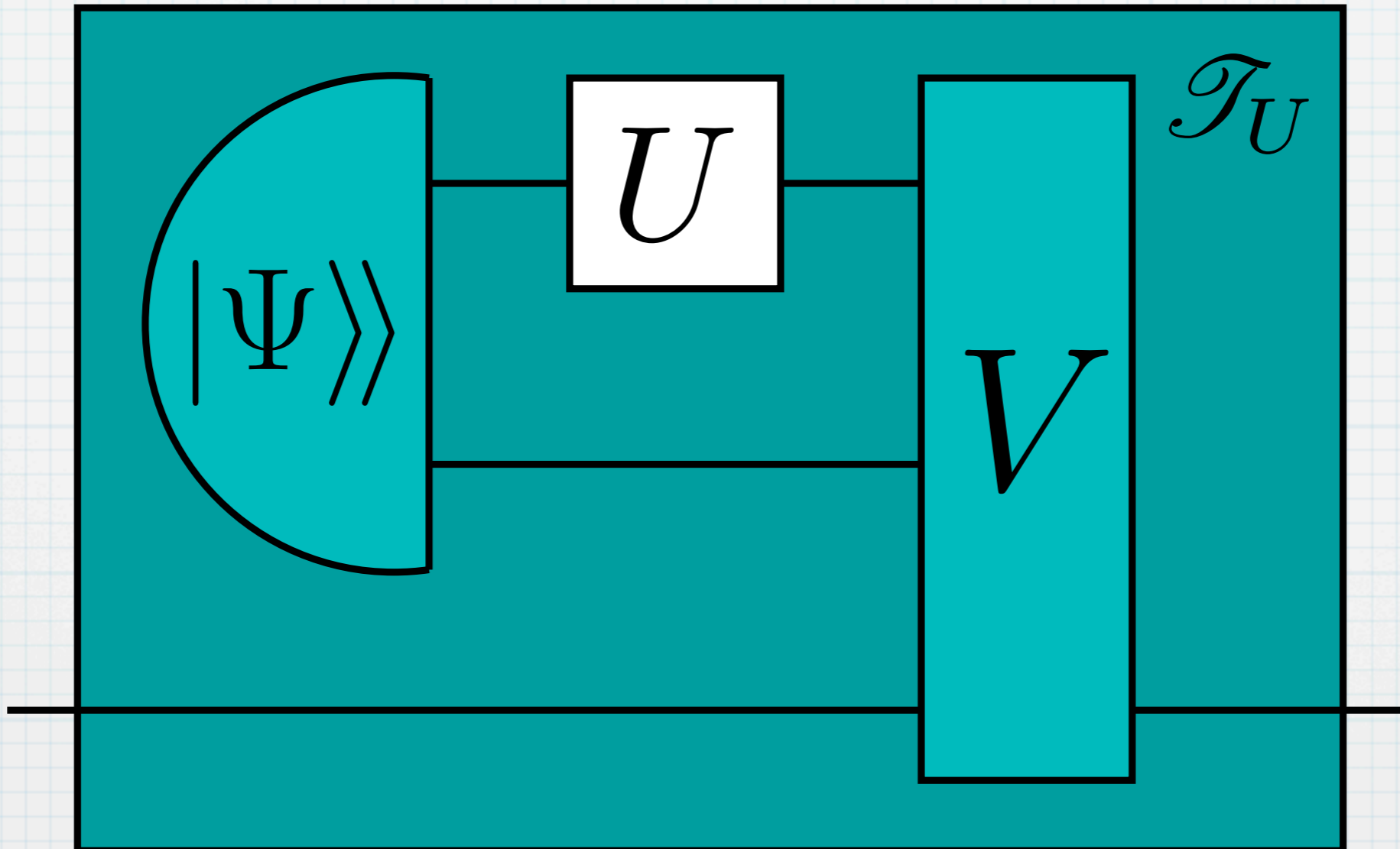


Quantum Feedback



- quantum feedback: perform a transformation \mathcal{T}_U on a system which depends on an unknown unitary transformation U occurring on a (generally different) system (e.g. reference-frames realignment).

Quantum Feedback



- quantum feedback: perform a transformation \mathcal{T}_U on a system which depends on an unknown unitary transformation U occurring on a (generally different) system (e.g. reference-frames realignment).

Multiple copies

- For **parameter estimation**: repeat the estimation N times, gaining a precision factor \sqrt{N}

Multiple copies

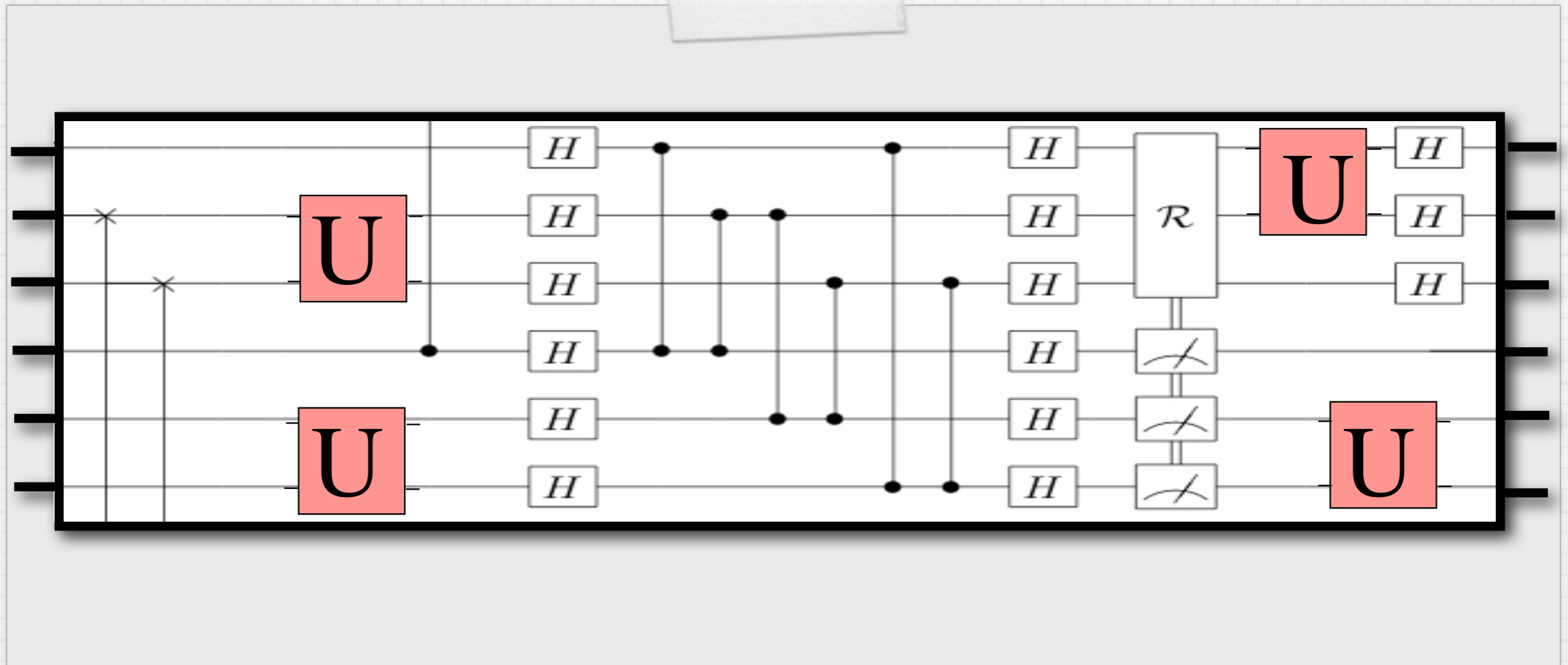
- For **parameter estimation**: repeat the estimation N times, gaining a precision factor \sqrt{N}
- However, you better use a coherent strategy, in which you perform a joint POVM

Multiple copies

- For **parameter estimation**: repeat the estimation N times, gaining a precision factor \sqrt{N}
- However, you better use a coherent strategy, in which you perform a joint POVM
- and you want to do the same for the quantum feedback

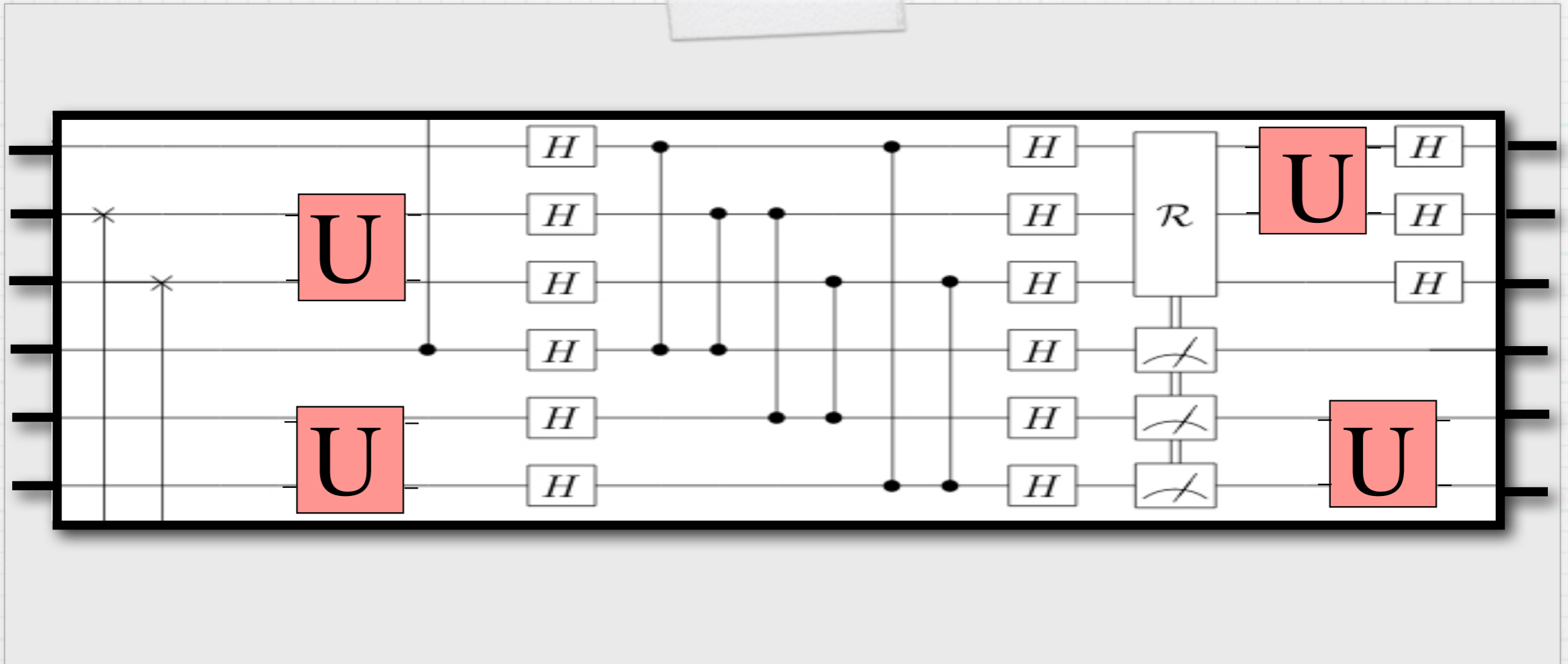
What is the best
that you can do?

Use a Quantum Board!



General scheme: put the copies of the unknown unitary in a suitable quantum circuit which performs the desired transformation/estimation.

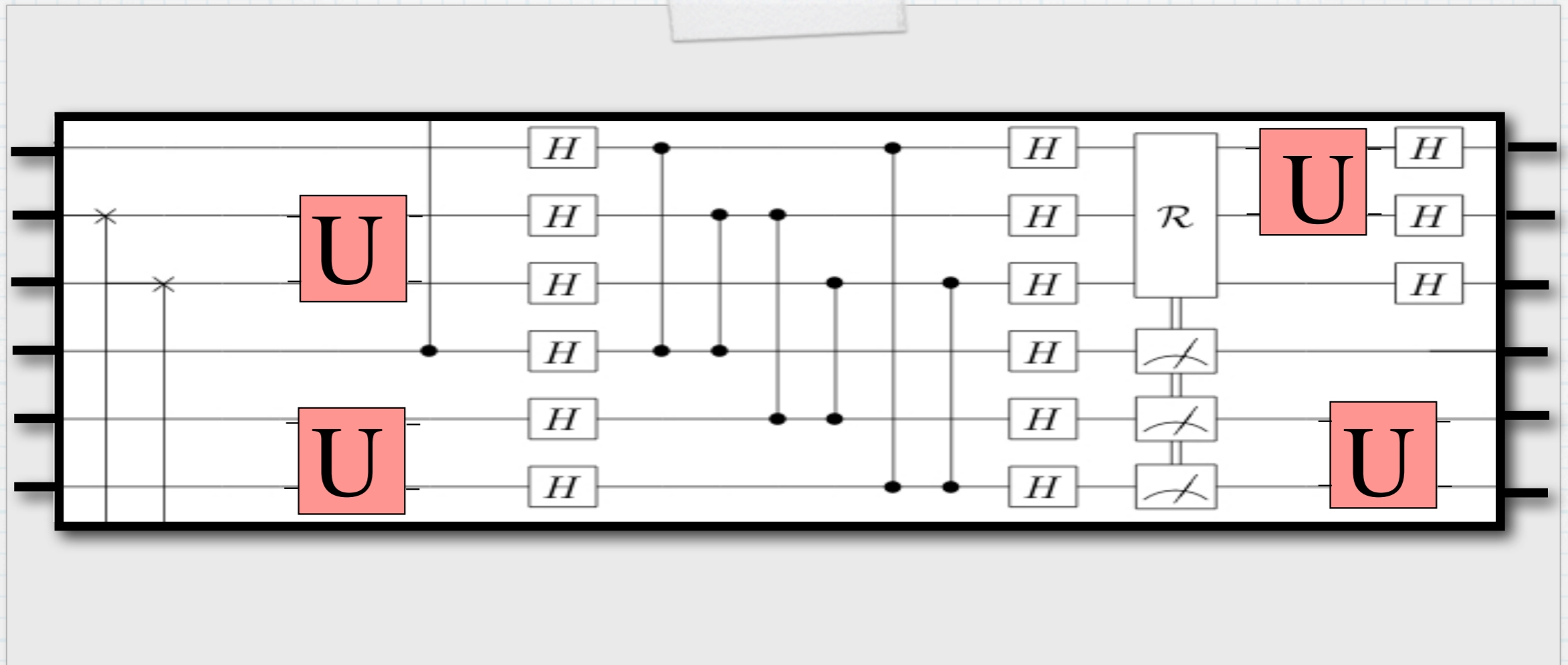
Use a Quantum Board!



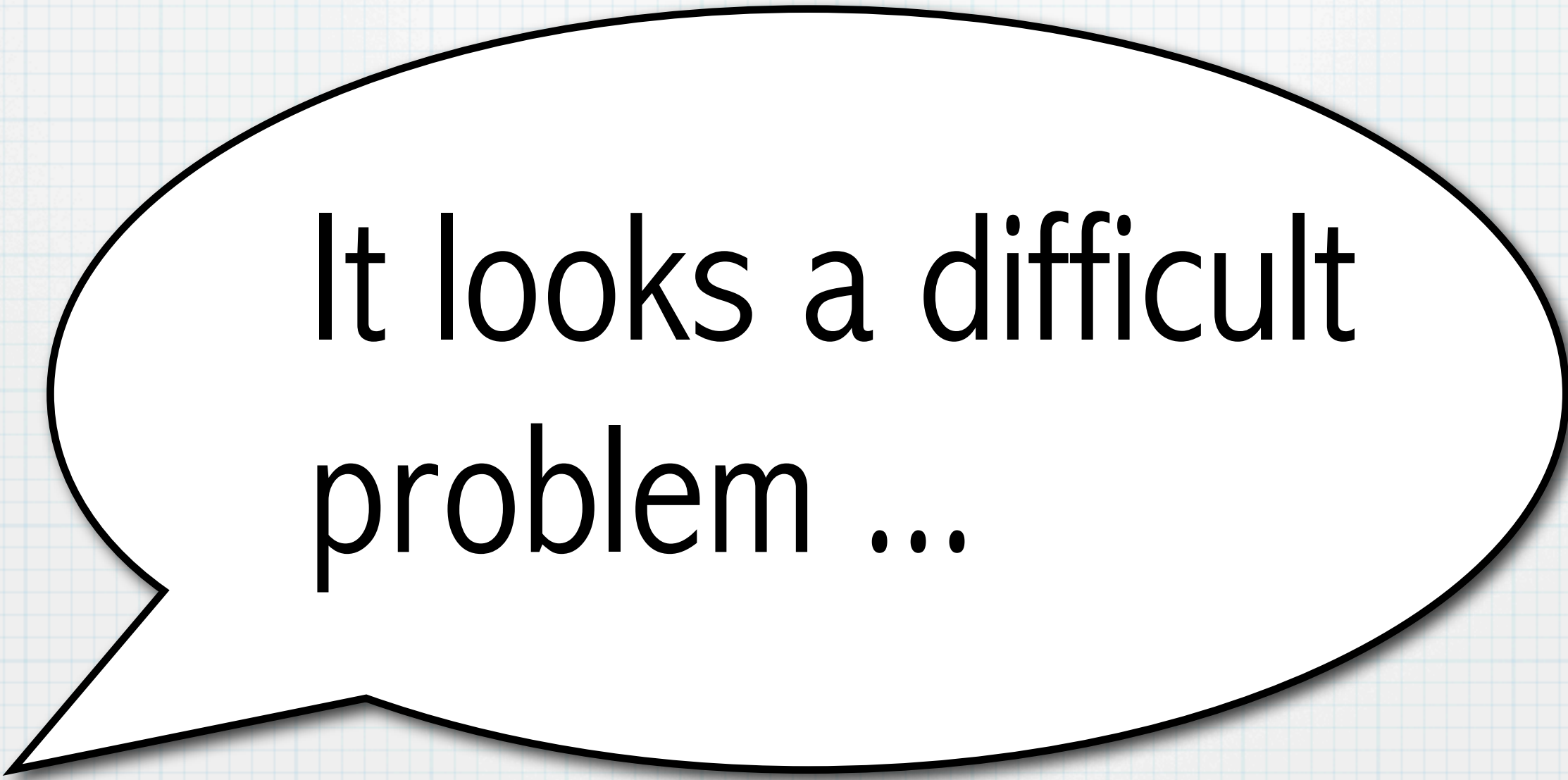
General scheme: put the copies of the unknown unitary in a suitable quantum circuit which performs the desired transformation/estimation.

Quantum circuit board: input and output are themselves circuits that are slotted into the board.

Use a Quantum Board!



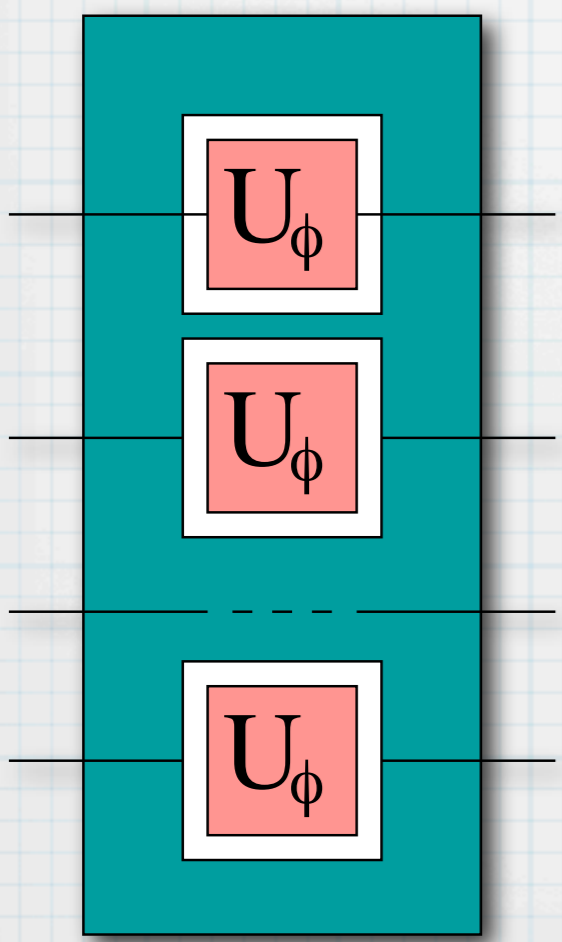
Optimize the quantum circuit board for all possible dispositions of the slots



It looks a difficult
problem ...

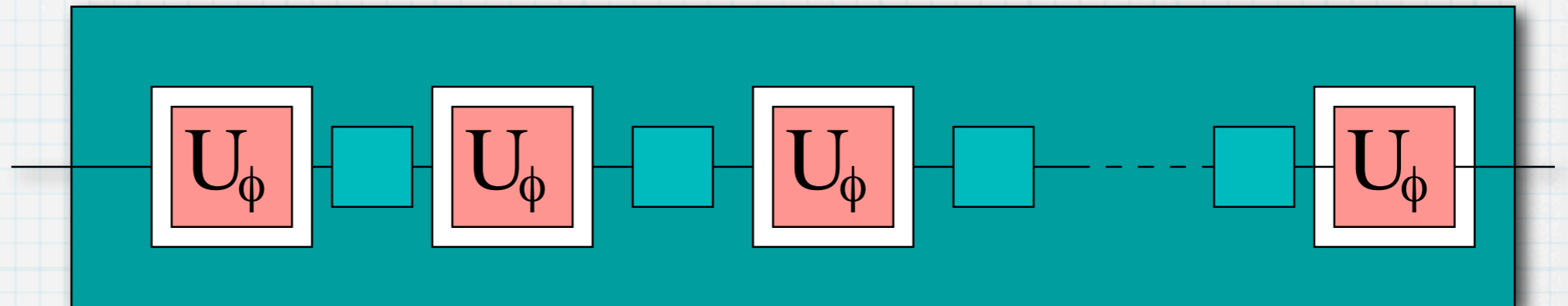
For example: what is the optimal
board for phase estimation?

For example: what is the optimal board for phase estimation?

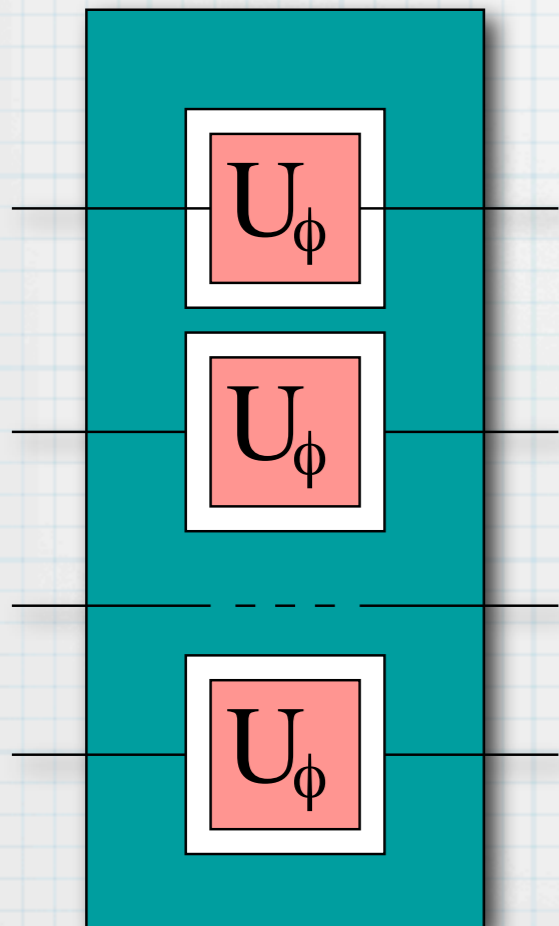


In parallel over a joint entangled state?

For example: what is the optimal board for phase estimation?

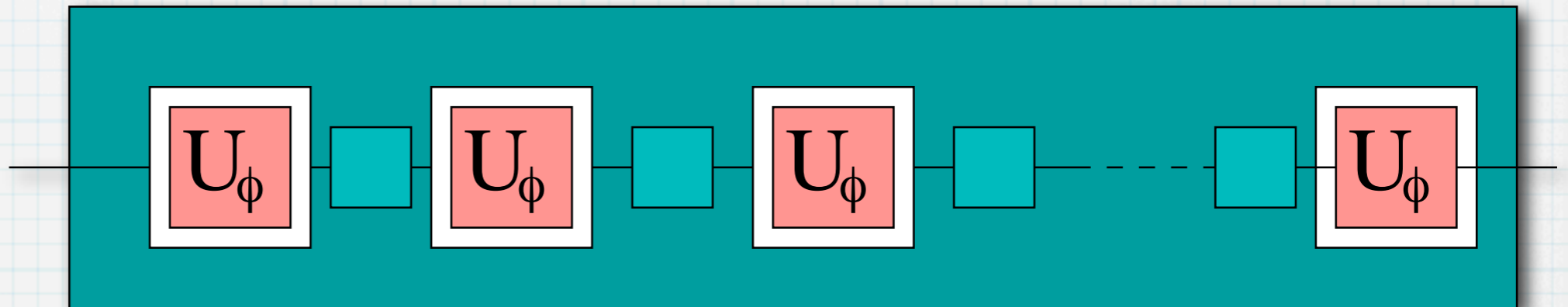


In sequence intercalated by some unitary?

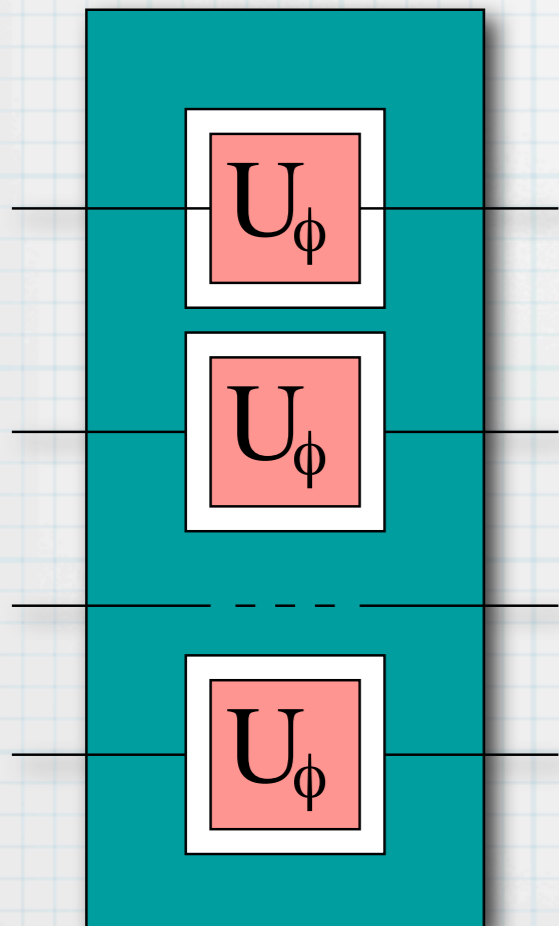


In parallel over a joint entangled state?

For example: what is the optimal board for phase estimation?



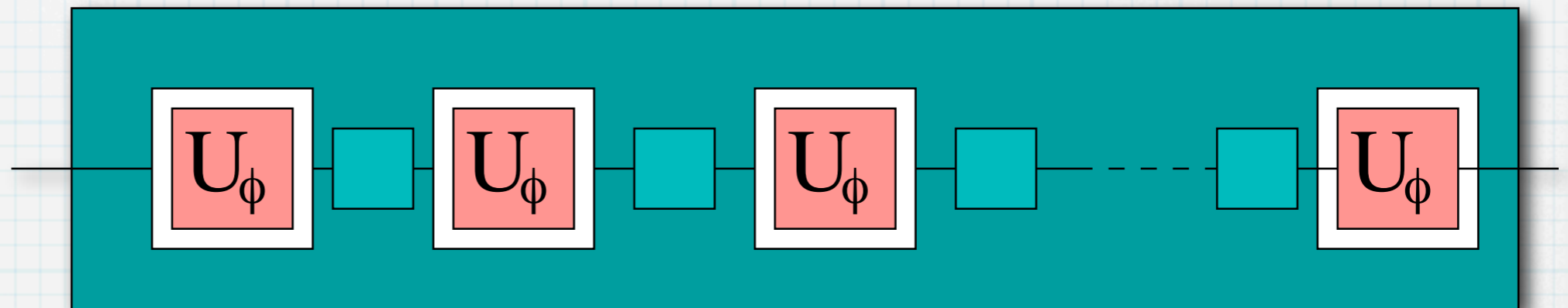
In sequence intercalated by some unitary?



In parallel over a joint entangled state?

Asymptotically: same sensitivity [Giovannetti, Lloyd, Maccone, PRL 96, 010401 (2006)]

For example: what is the optimal board for phase estimation?



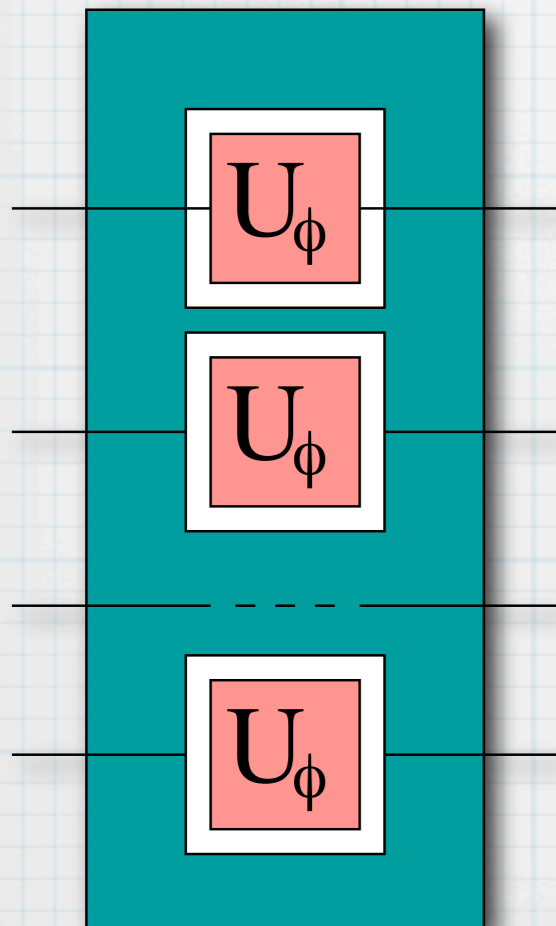
In sequence intercalated by some unitary?

For unitary discrimination: [Duan, Feng, Ying, PRL 98, 100503 (2007)]

In parallel over a joint entangled state?

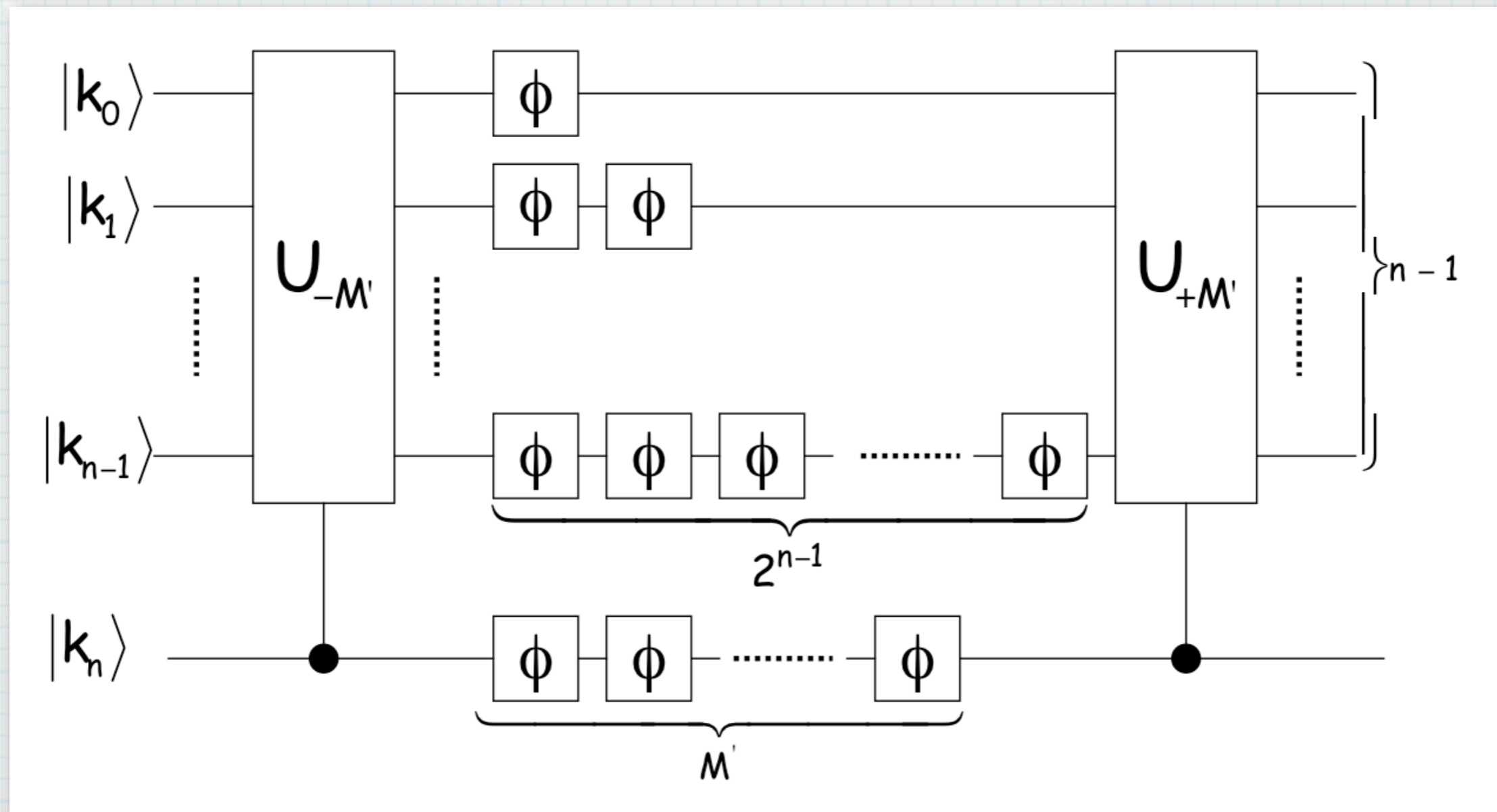
For unitary discrimination: G.M.D'Ariano, P. Lo Presti, M. Paris, PRL 87, 270404 (2001); A. Acín, E. Jané, and G. Vidal, Phys. Rev. A 64, 050302 (2001)

Asymptotically: same sensitivity [Giovannetti, Lloyd, Maccone, PRL 96, 010401 (2006)]



For example: what is the optimal board for phase estimation?

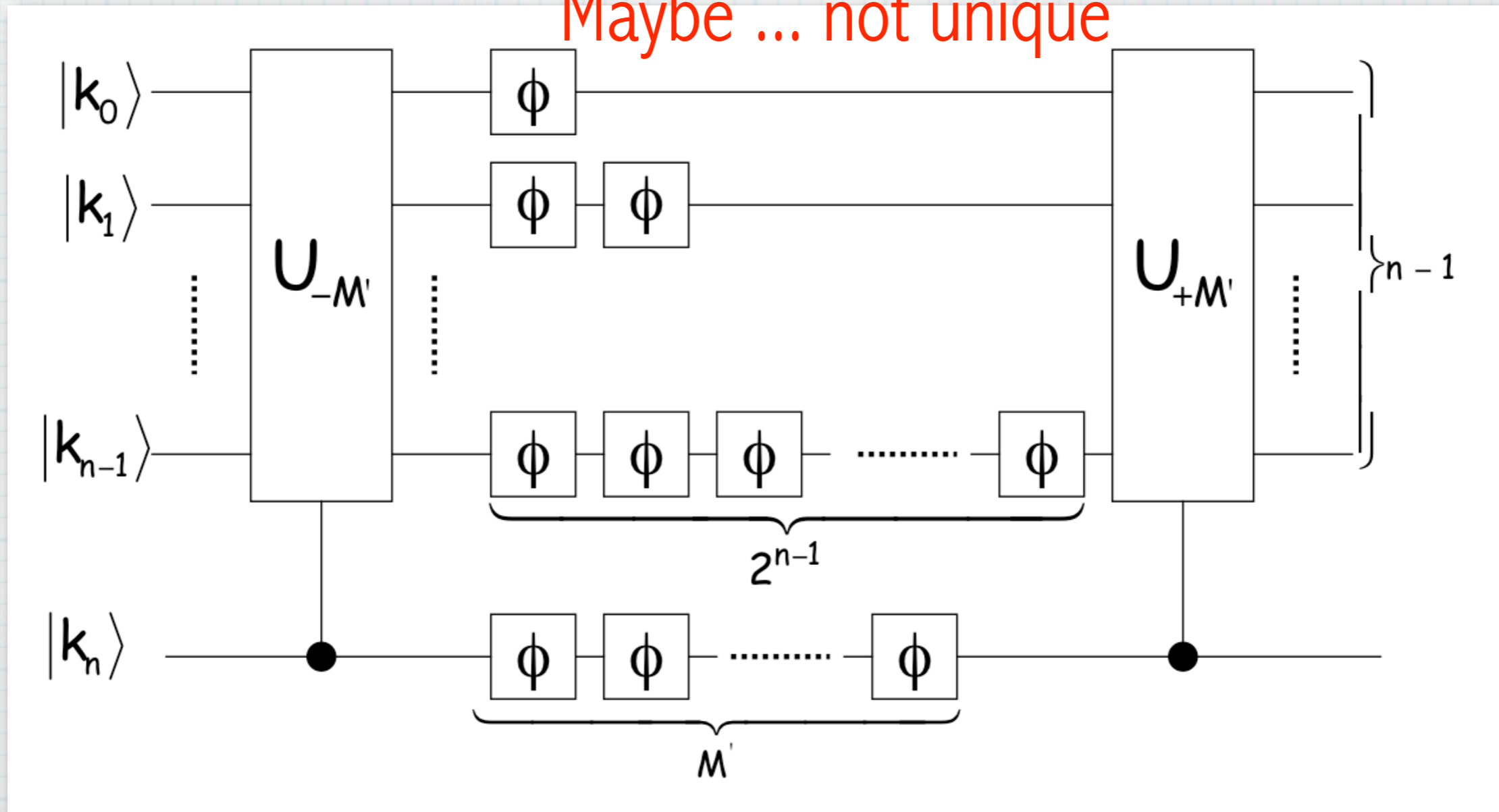
An optimal board architecture [van Dam, D'Ariano, Ekert, Macchiavello, Mosca, PRL 98, 090501 (2007)]



For example: what is the optimal board for phase estimation?

An optimal board architecture [van Dam, D'Ariano, Ekert, Macchiavello, Mosca, PRL 98, 090501 (2007)]

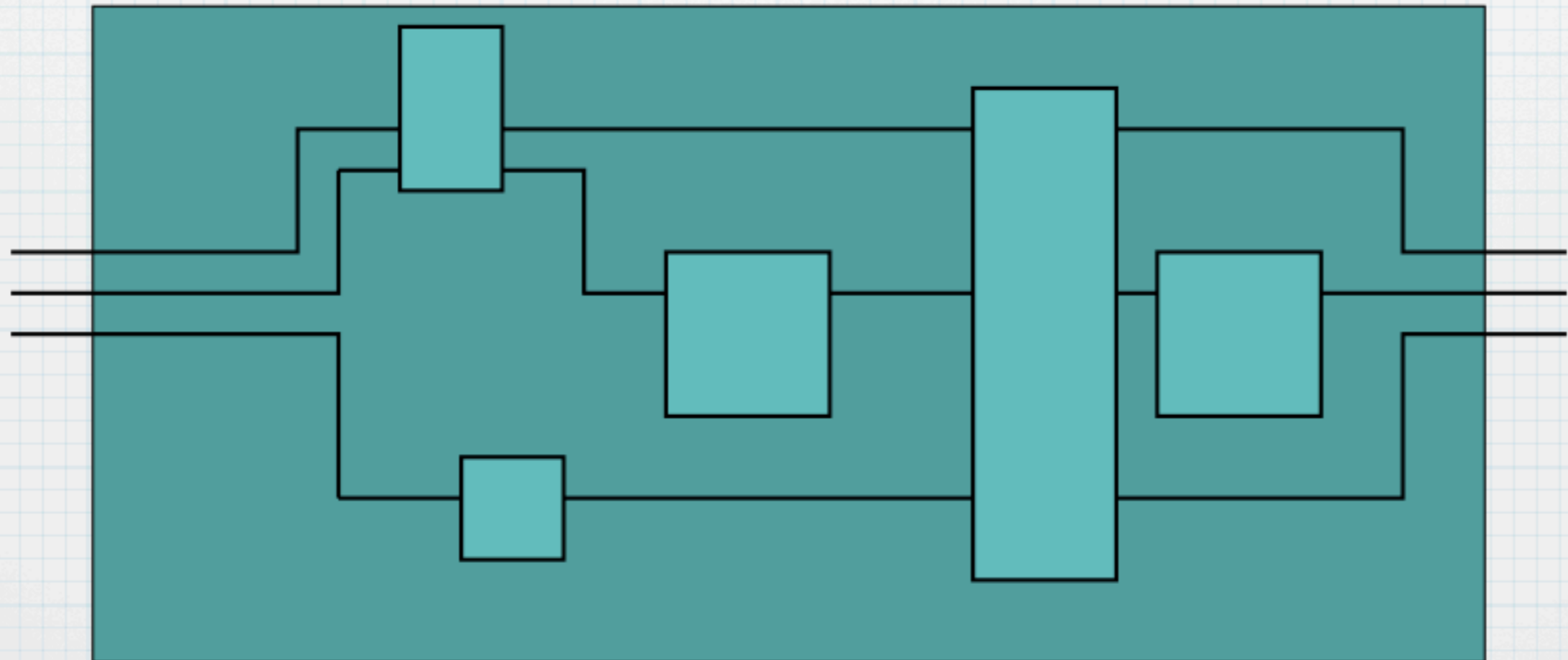
Maybe ... not unique



What is the mathematical
formulation of the
problem?

Quantum Channel

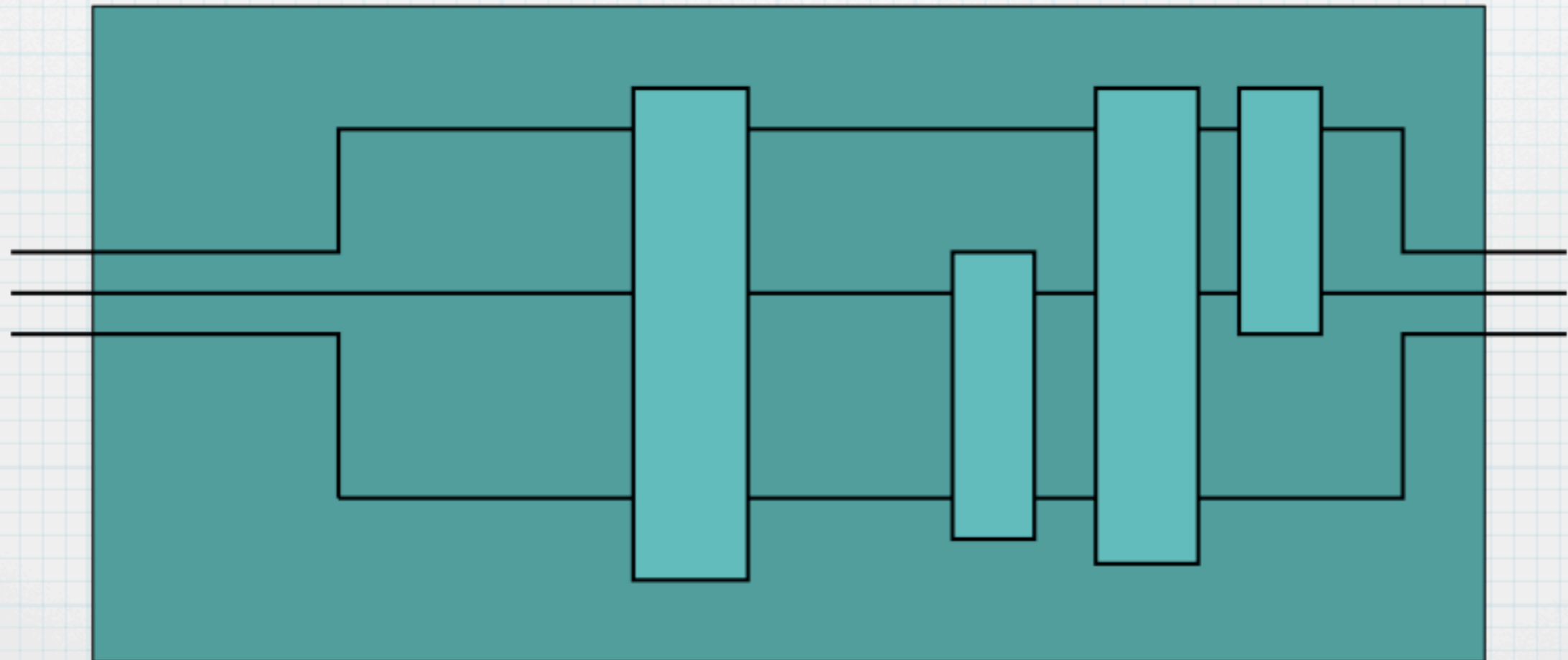
It can be regarded as an equivalence class of quantum circuits performing the same input-output transformation ...



Quantum Channel

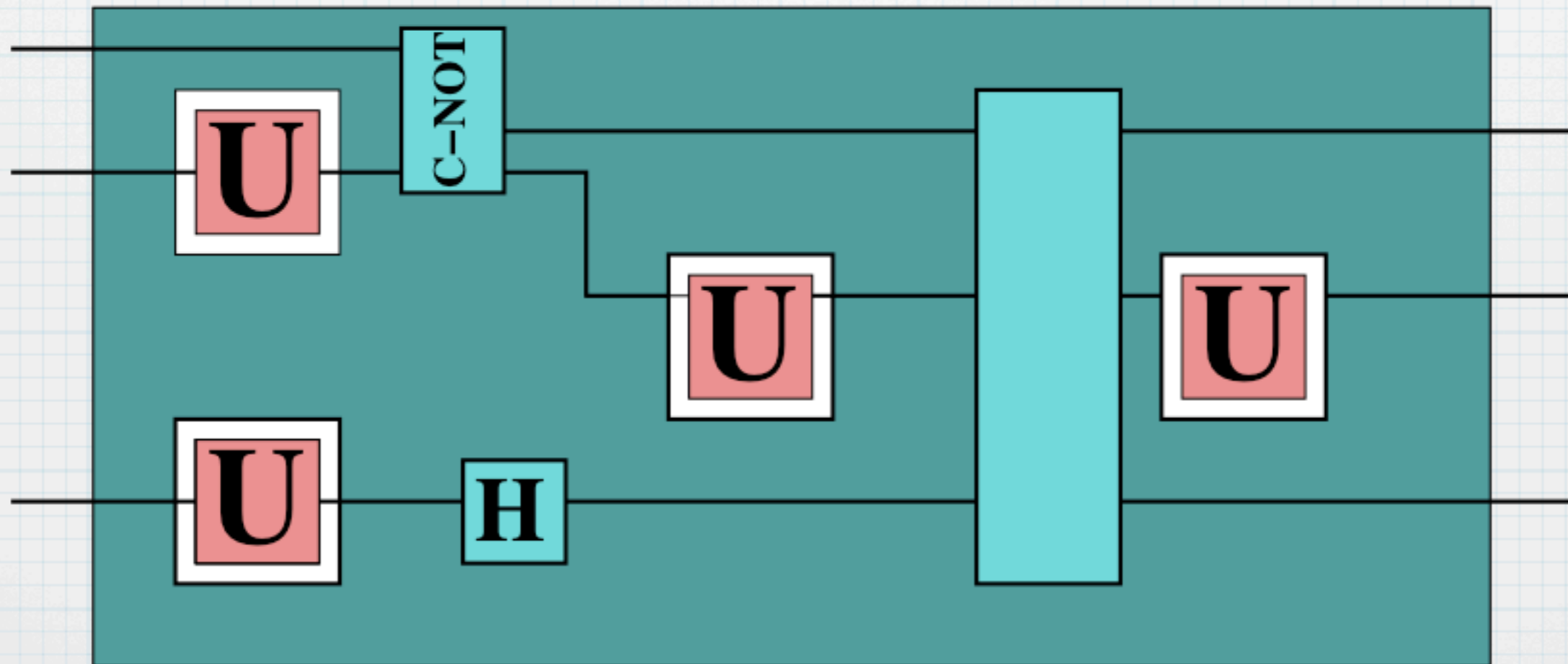
It can be regarded as an equivalence class of quantum circuits performing the same input-output transformation ...

For a channel the input and the output are **states**



Quantum Board

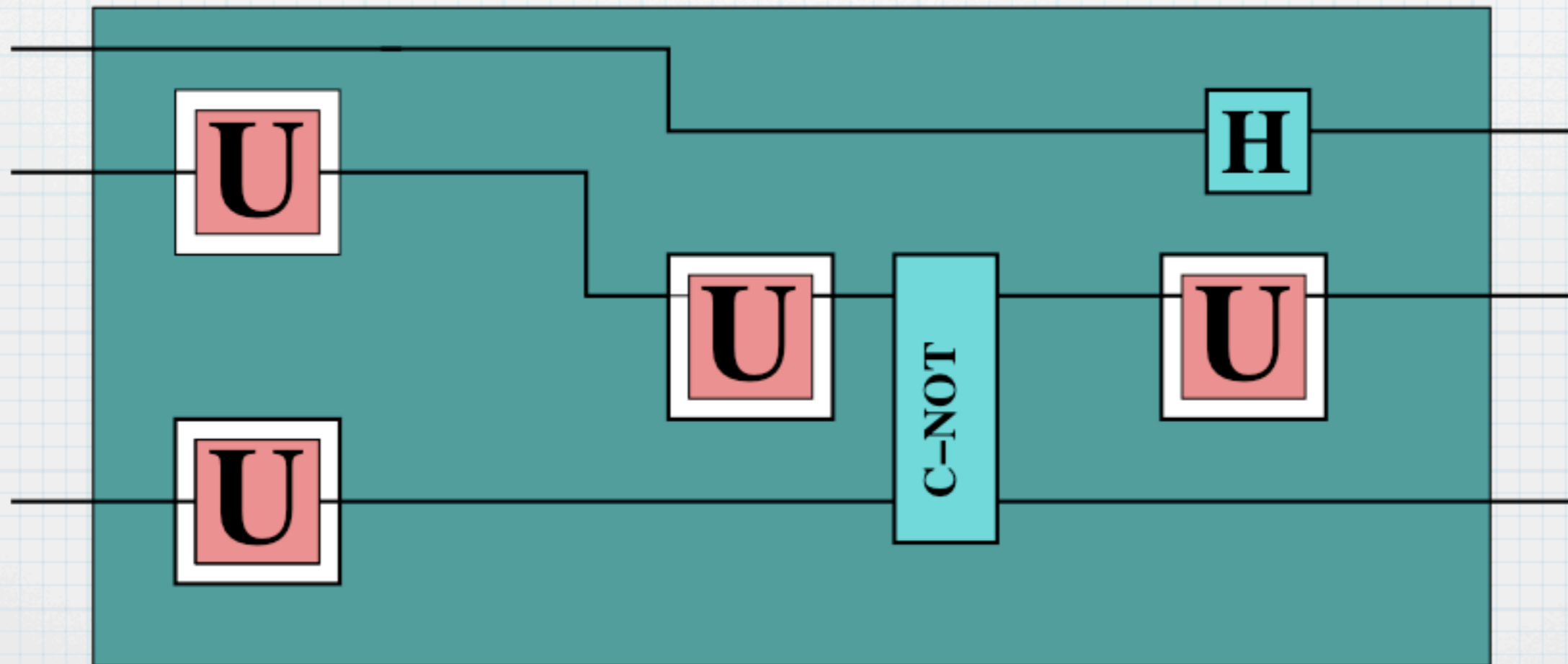
Equivalence class of quantum circuits boards performing the same overall input-output transformation ...



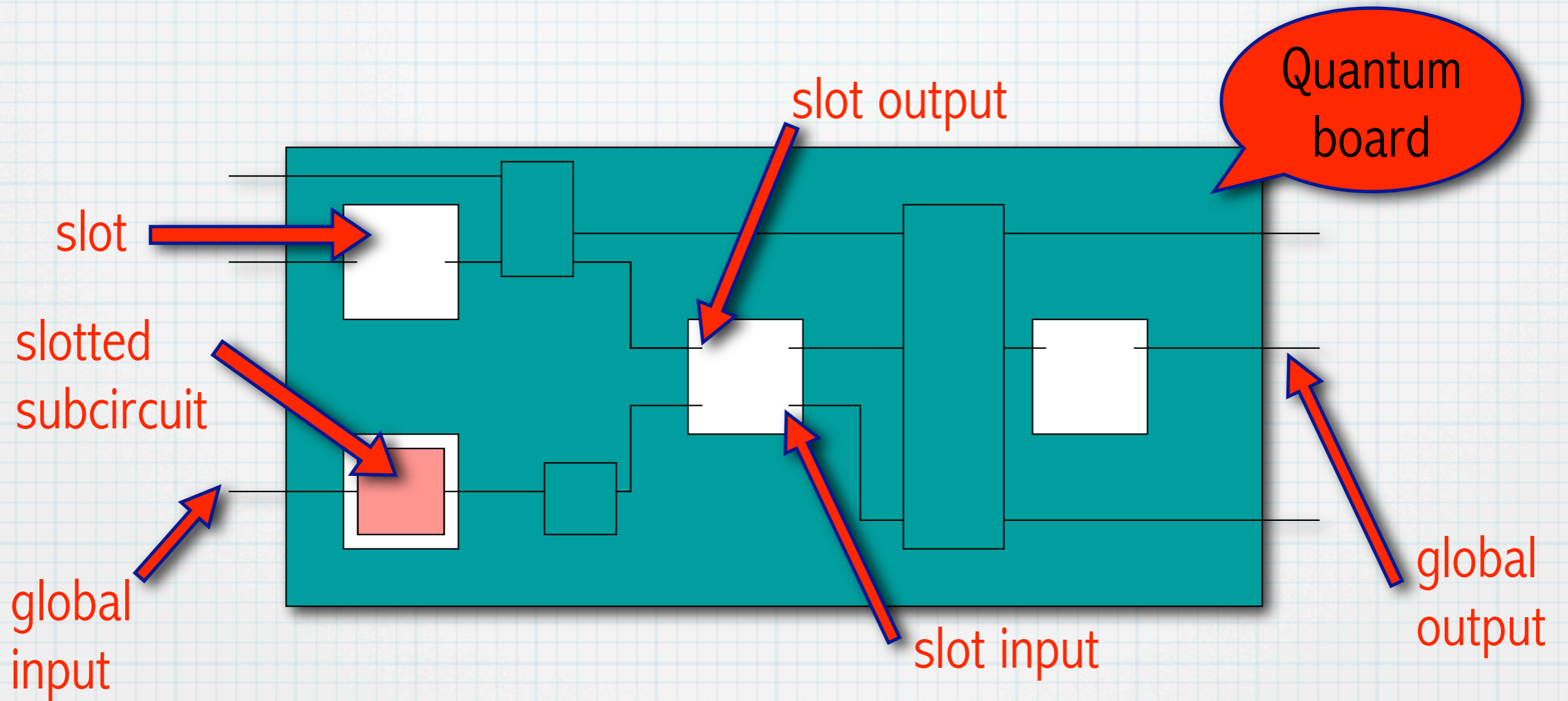
Quantum Board

Equivalence class of quantum circuits boards performing the same overall input-output transformation ...

But now, the input and the output are **transformations**



Quantum Board

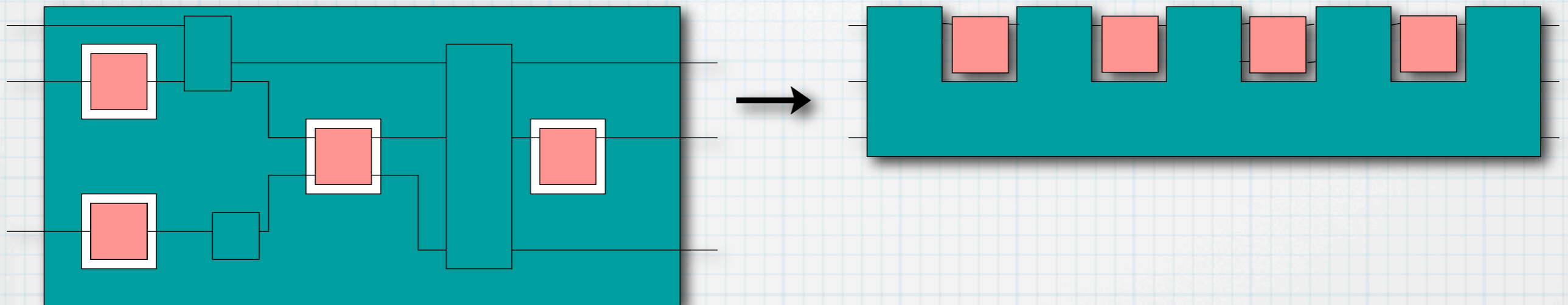


Problem: what is the optimal board for given slots achieving a global input/output transformation optimally according to a given cost function?

Quantum Combs

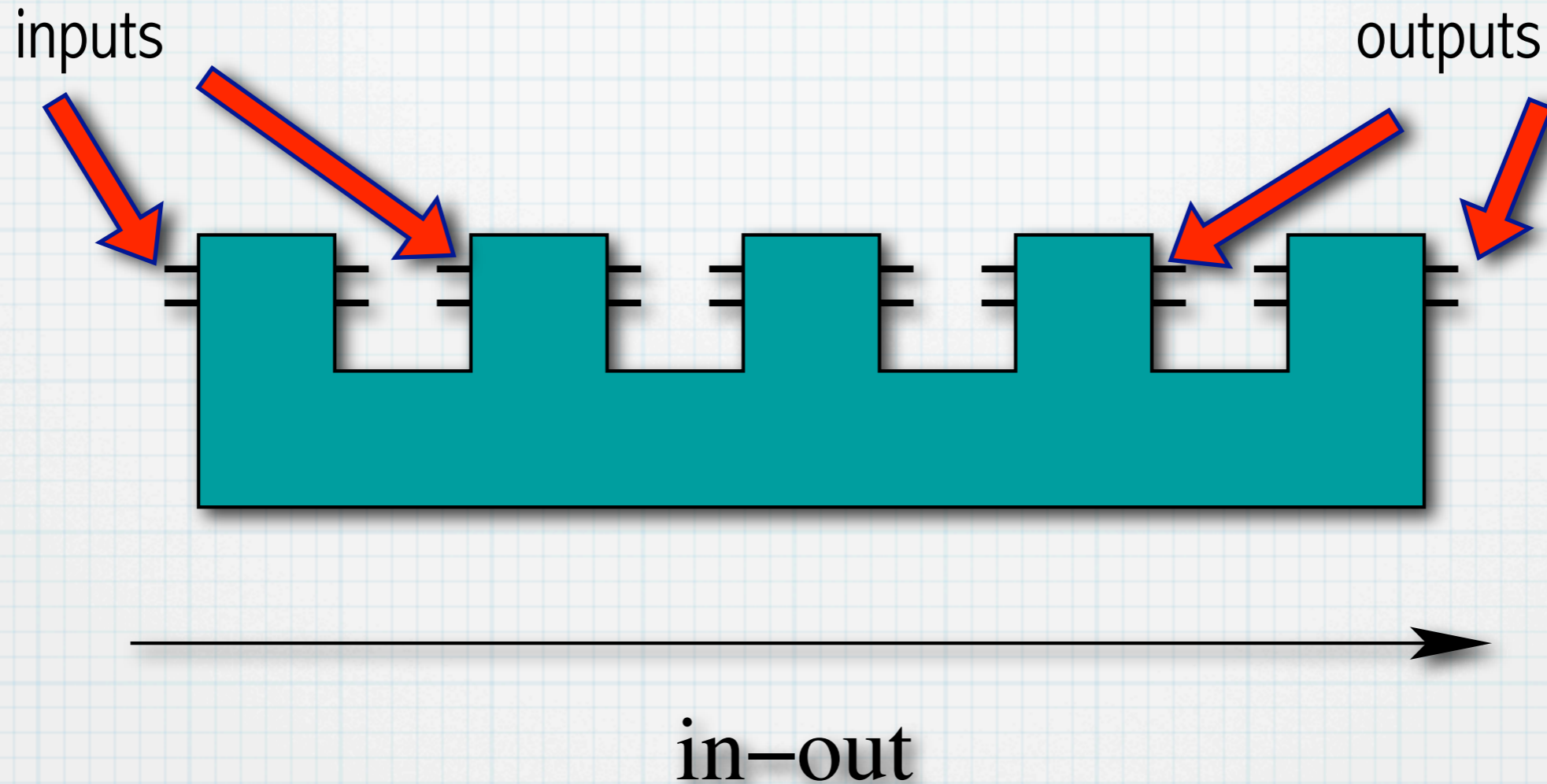
G.Chiribella, G.M.D'Ariano, P.Perinotti, PRL 101 060401 (2008)

All circuits-boards can be reshaped in form of "combs", with an ordered sequence of slots, each between two successive teeth



Quantum Combs

G.Chiribella, G.M.D'Ariano, P.Perinotti, PRL 101 060401 (2008)



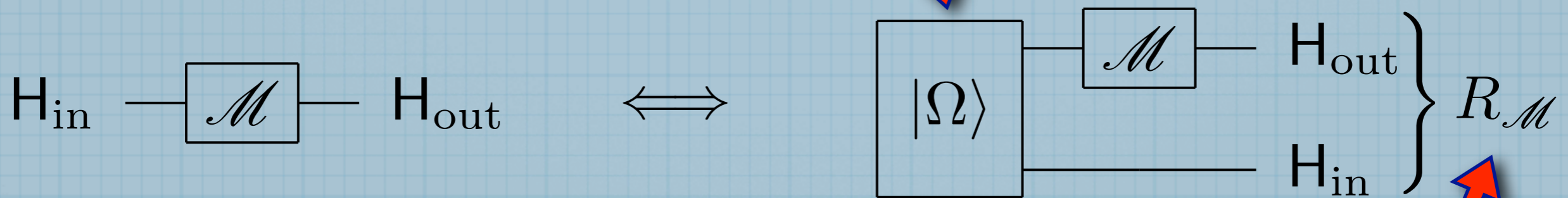
Pins = quantum systems with generally variable dimensions

How do we describe
a quantum comb
mathematically?

Channel: Choi representation

Mathematically the input-output transformation operated by a quantum circuit is a **CP map**, and is **in one-to-one correspondence with a positive operator** called "Choi-Jamiolkowski operator"---the output state of the map applied locally to a maximally entangled state.

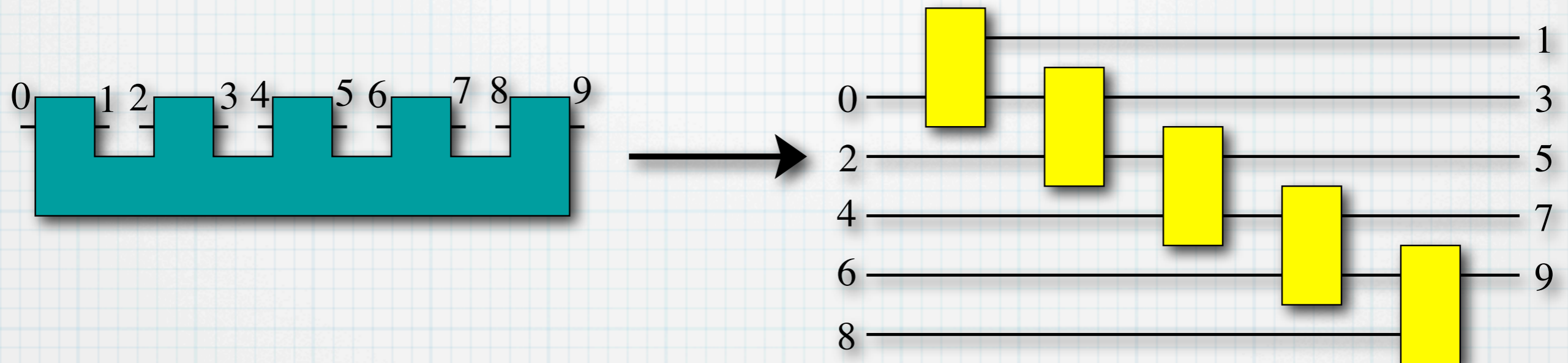
Max-entangled state



Choi-Jamiolkowski operator

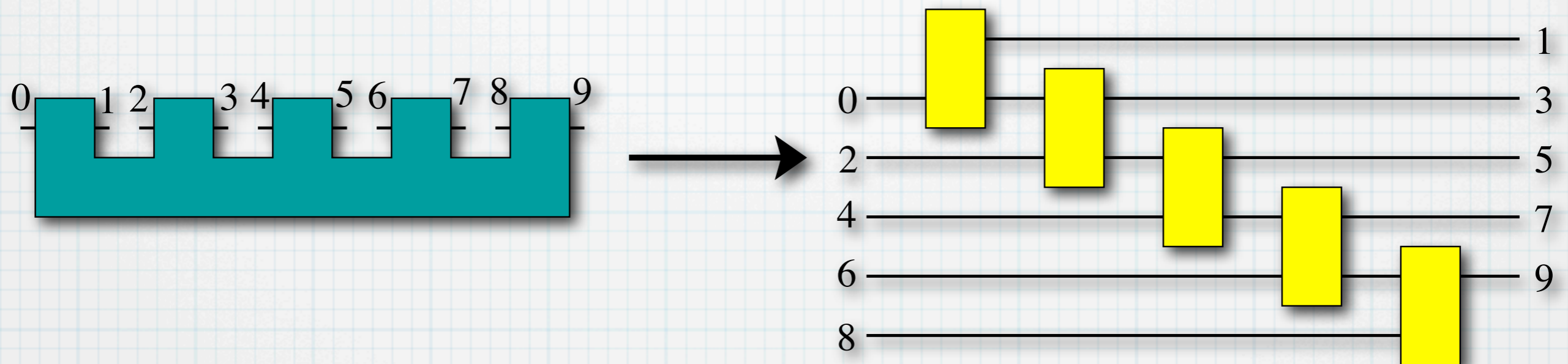
Causal networks

The quantum comb is equivalent to a causal network with all inputs on the left and all outputs on the right

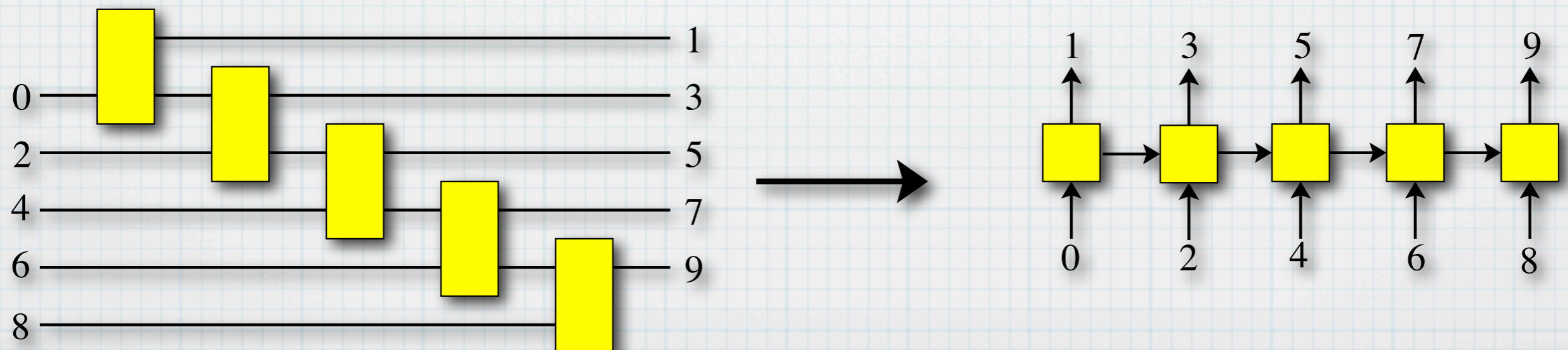


Causal networks

The quantum comb is equivalent to a causal network with all inputs on the left and all outputs on the right

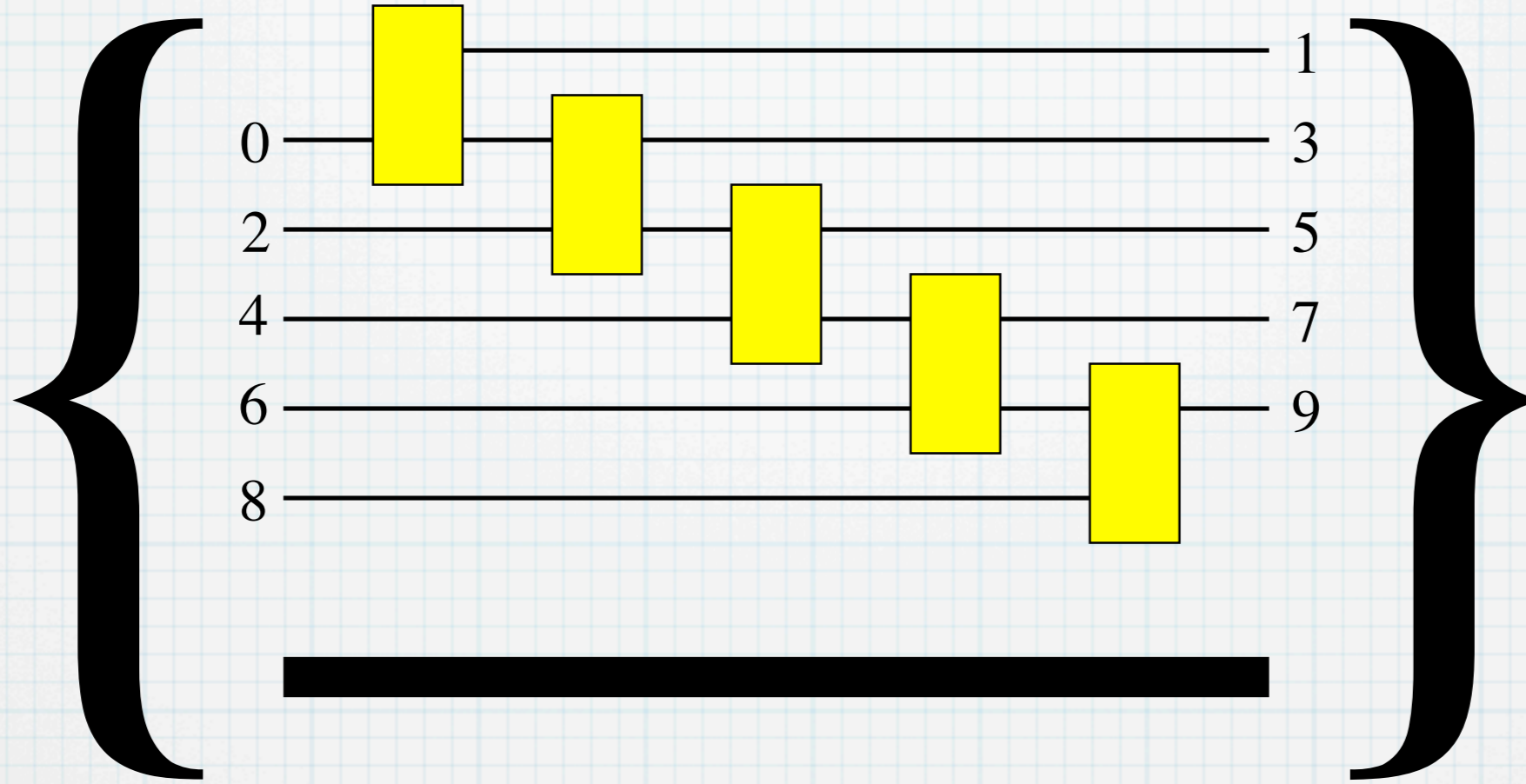


The causal network is also equivalent to the stack of **memory channels**



Choi representation

max entangled state

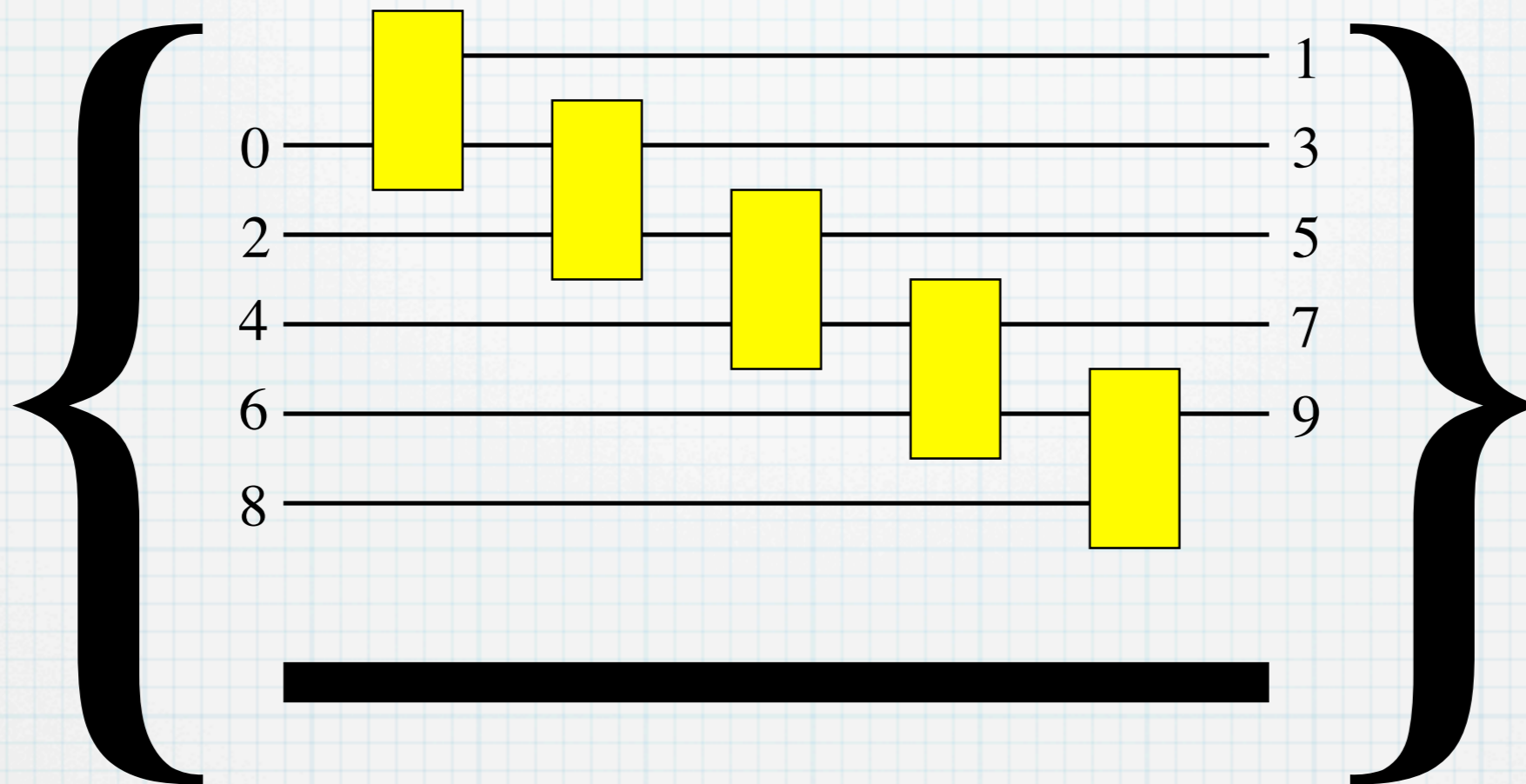


Choi-Jamiołkowski operator

\mathcal{R}

Choi representation

max entangled state



Choi-Jamiołkowski operator

R

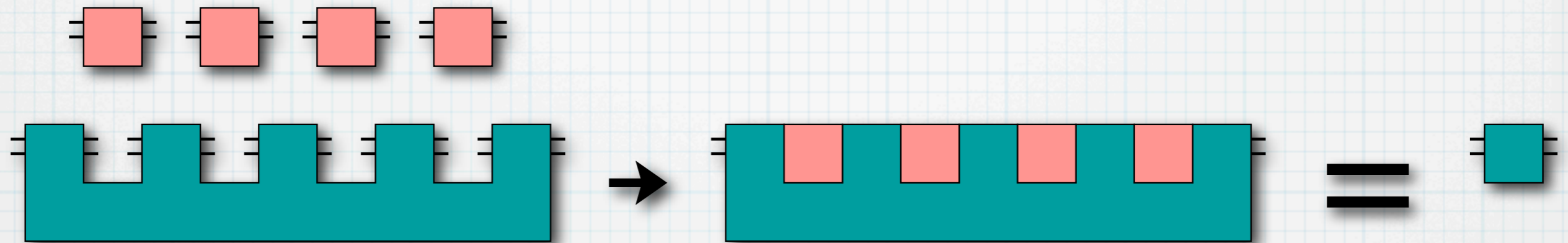
Causality constraints: ($N+1$ inputs/outputs)

$$\text{Tr}_{2n-1}[R^{(n)}] = I_{2n-2} \otimes R^{(n-1)}, \quad n = 1, \dots, N$$

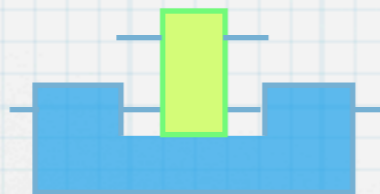
$$R^{(0)} = 1, \quad R^{(n)} = R$$

Supermaps

A quantum comb performs a transformation that is a generalization of the quantum operation: the so called "supermap"

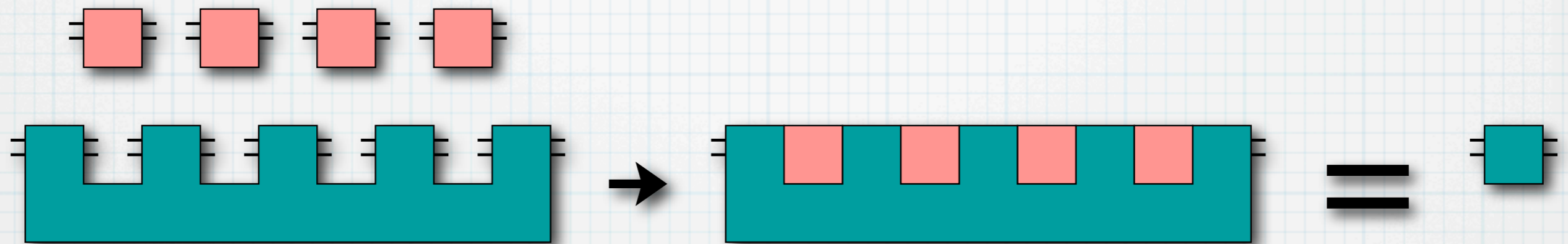


A supermap sends a series of N channels to one channel, also when applied locally, e.g.

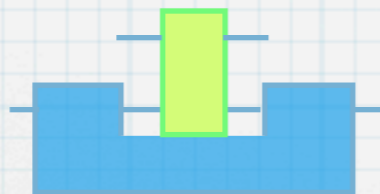


Supermaps

A quantum comb performs a transformation that is a generalization of the quantum operation: the so called "supermap"



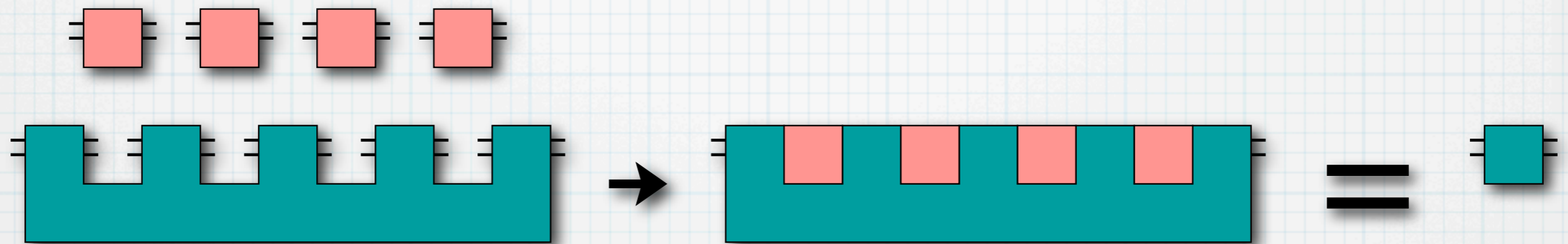
A supermap sends a series of N channels to one channel, also when applied locally, e.g.



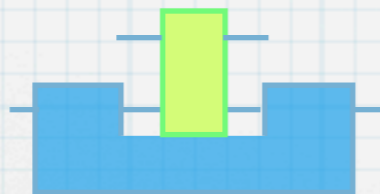
Mathematically it is represented by a CP N -linear map which sends N Choi operators to one Choi operator, and with his own Choi operator satisfying the causality constraints.

Supermaps

A quantum comb performs a transformation that is a generalization of the quantum operation: the so called "supermap"



A supermap sends a series of N channels to one channel, also when applied locally, e.g.

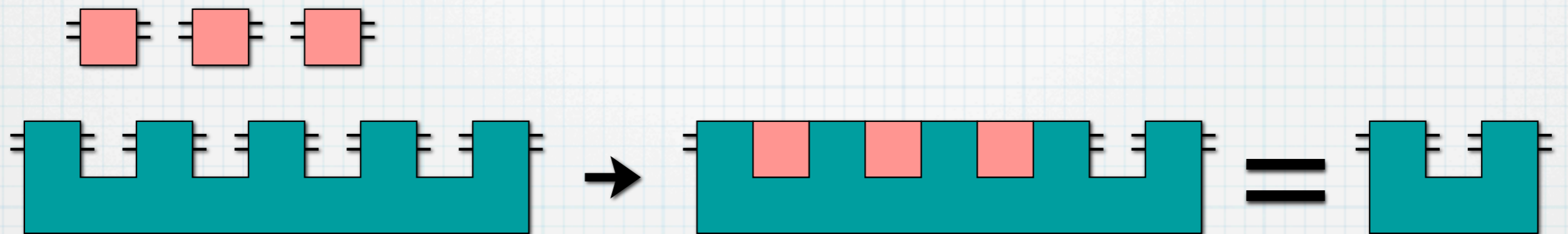


Mathematically it is represented by a CP N -linear map which sends N Choi operators to one Choi operator, and with his own Choi operator satisfying the causality constraints.

(we can likewise consider probabilistic supermaps).

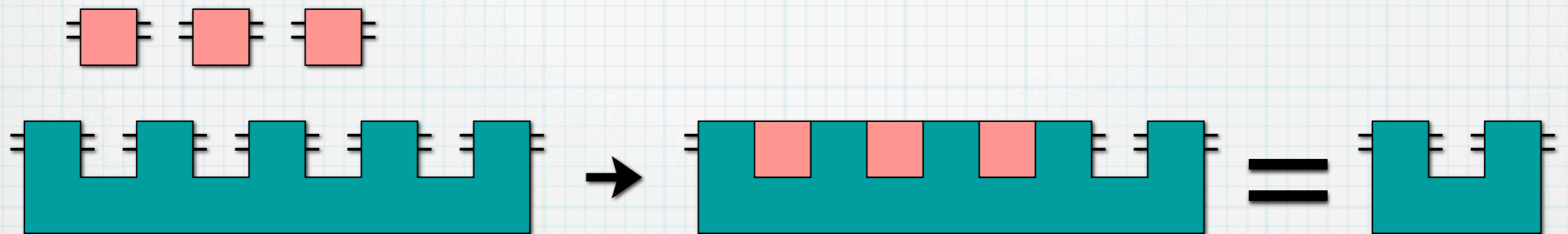
Supermaps

More generally, a quantum comb maps a series of channels into a comb

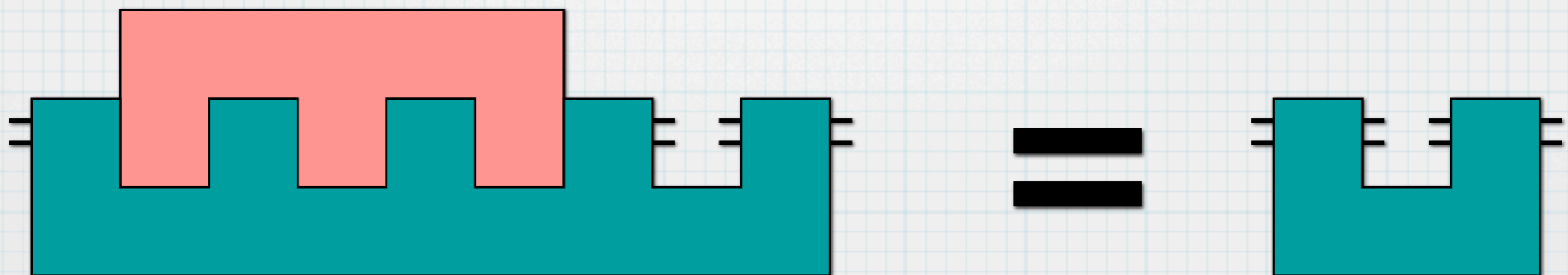


Supermaps

More generally, a quantum comb maps a series of channels into a comb

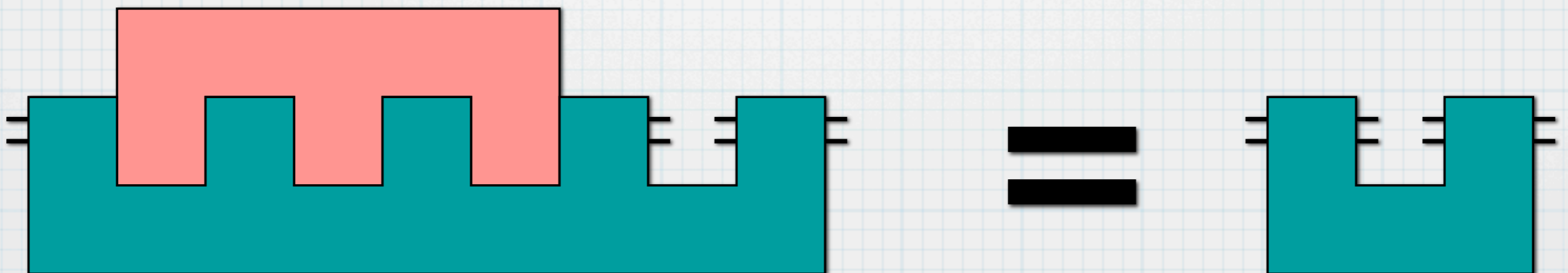


or, even more generally, a comb to a comb

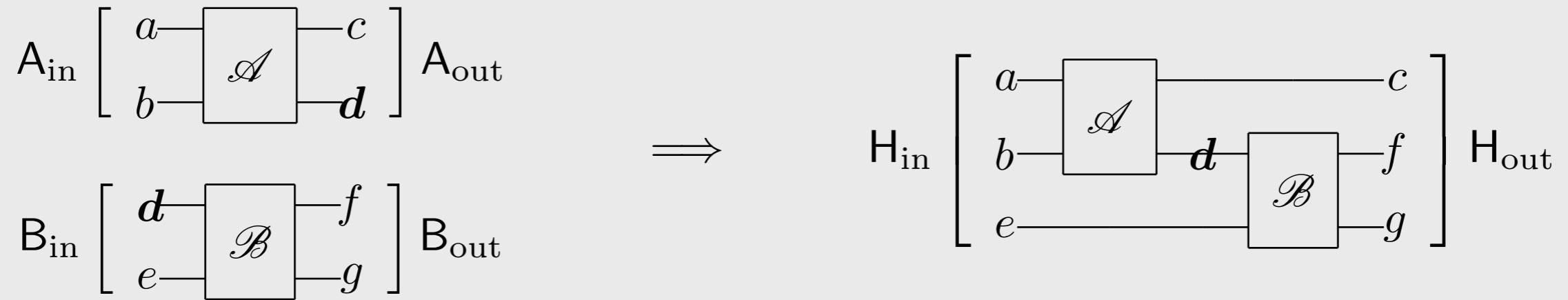


Supermaps

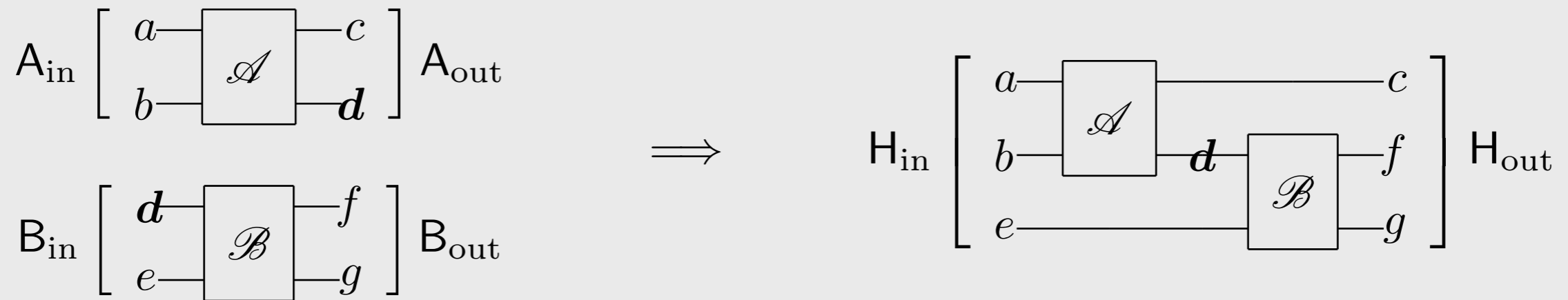
The notion of supermap is the **last level of generalization**,
i.e. “super-supermaps” (mapping supermaps to supermaps)
are still supermaps = quantum combs.



Link product



Link product

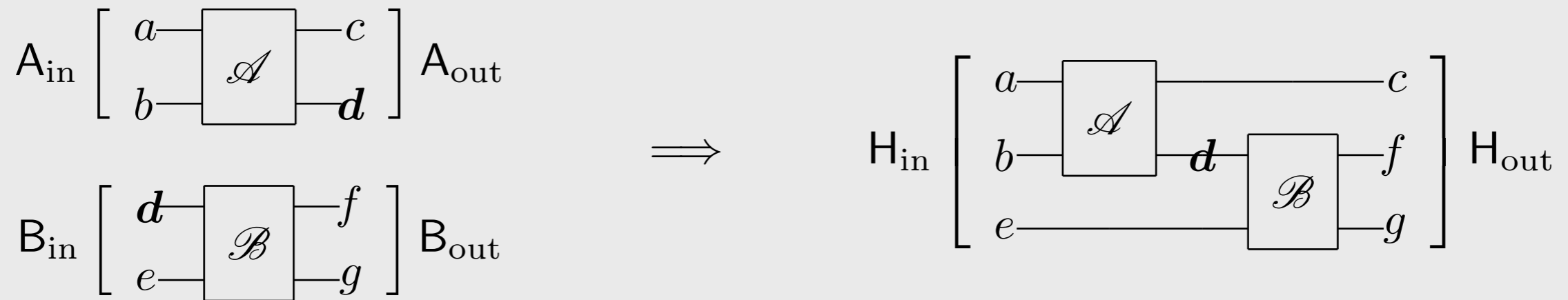


Choi-operator calculus

$$A \in B(A_{\text{out}} \otimes A_{\text{in}}) = B(H_a \otimes H_b \otimes H_c \otimes H_d), \quad J \equiv H_d$$

$$B \in B(B_{\text{out}} \otimes B_{\text{in}}) = B(H_d \otimes H_e \otimes H_f \otimes H_g)$$

Link product



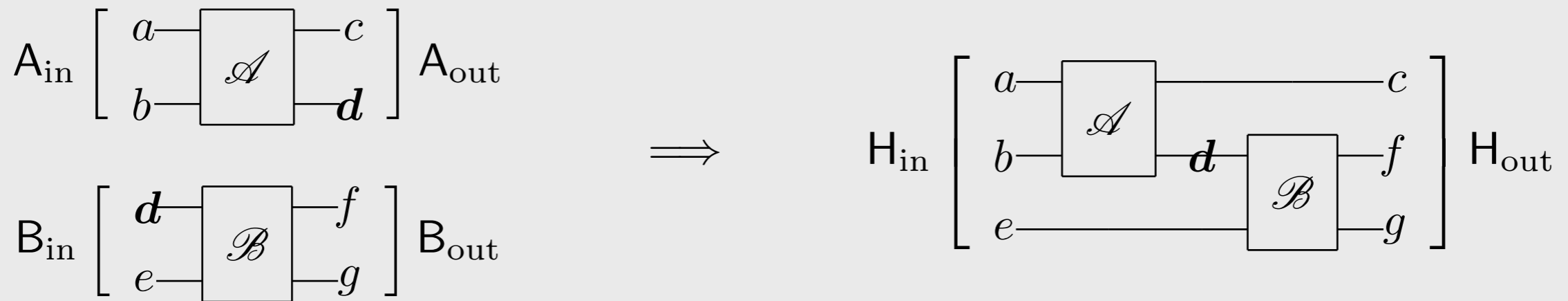
Choi-operator calculus

$$A \in B(A_{\text{out}} \otimes A_{\text{in}}) = B(H_a \otimes H_b \otimes H_c \otimes H_d), \quad J \equiv H_d$$

$$B \in B(B_{\text{out}} \otimes B_{\text{in}}) = B(H_d \otimes H_e \otimes H_f \otimes H_g)$$

$$AB := (A \otimes I_{e,f,g})(I_{a,b,c} \otimes B)$$

Link product



Choi-operator calculus

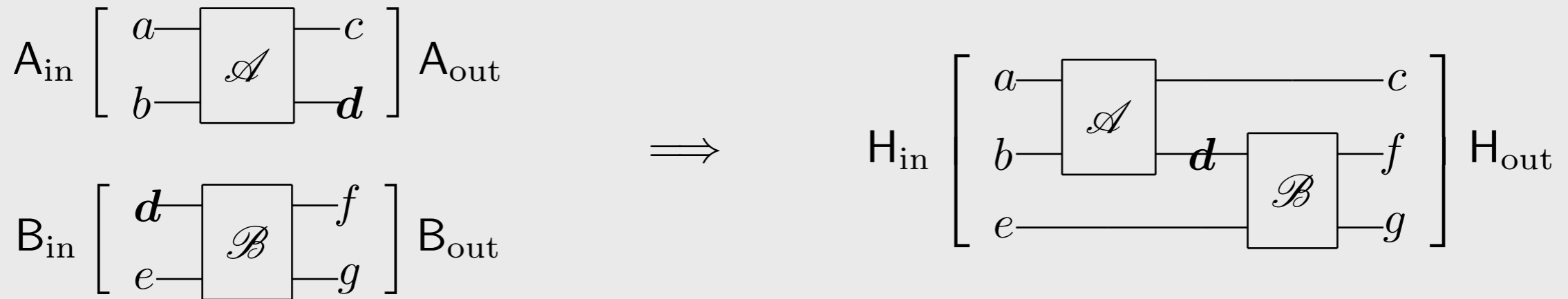
$$A \in \mathcal{B}(A_{\text{out}} \otimes A_{\text{in}}) = \mathcal{B}(H_a \otimes H_b \otimes H_c \otimes H_d), \quad J \equiv H_d$$

$$B \in \mathcal{B}(B_{\text{out}} \otimes B_{\text{in}}) = \mathcal{B}(H_d \otimes H_e \otimes H_f \otimes H_g)$$

$$AB := (A \otimes I_{e,f,g})(I_{a,b,c} \otimes B)$$

$$A * B = \text{Tr}_J[A^{\theta_J} B] \in \mathcal{B}(H_{\text{out}} \otimes H_{\text{in}})$$

Link product



Choi-operator calculus

$$A \in \mathcal{B}(A_{\text{out}} \otimes A_{\text{in}}) = \mathcal{B}(H_a \otimes H_b \otimes H_c \otimes H_d), \quad J \equiv H_d$$

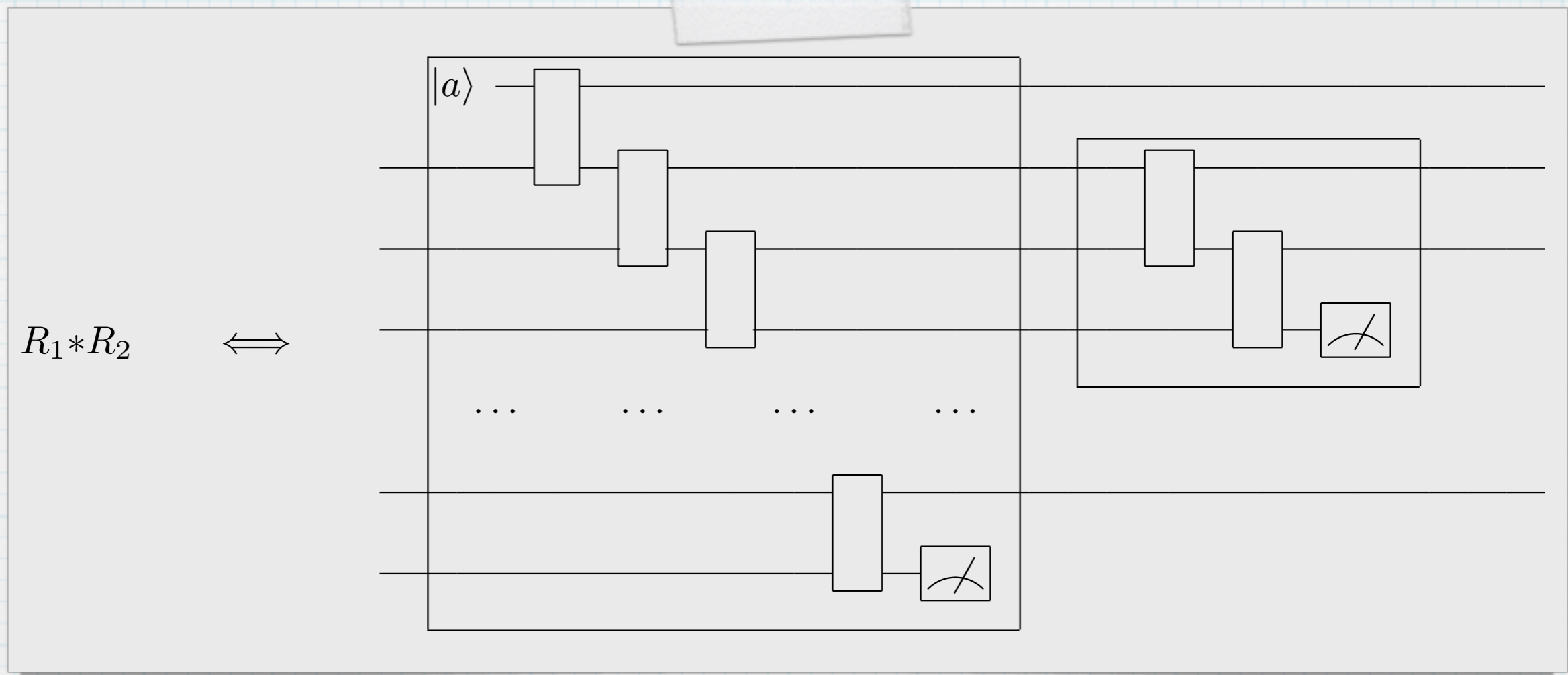
$$B \in \mathcal{B}(B_{\text{out}} \otimes B_{\text{in}}) = \mathcal{B}(H_d \otimes H_e \otimes H_f \otimes H_g)$$

$$AB := (A \otimes I_{e,f,g})(I_{a,b,c} \otimes B)$$

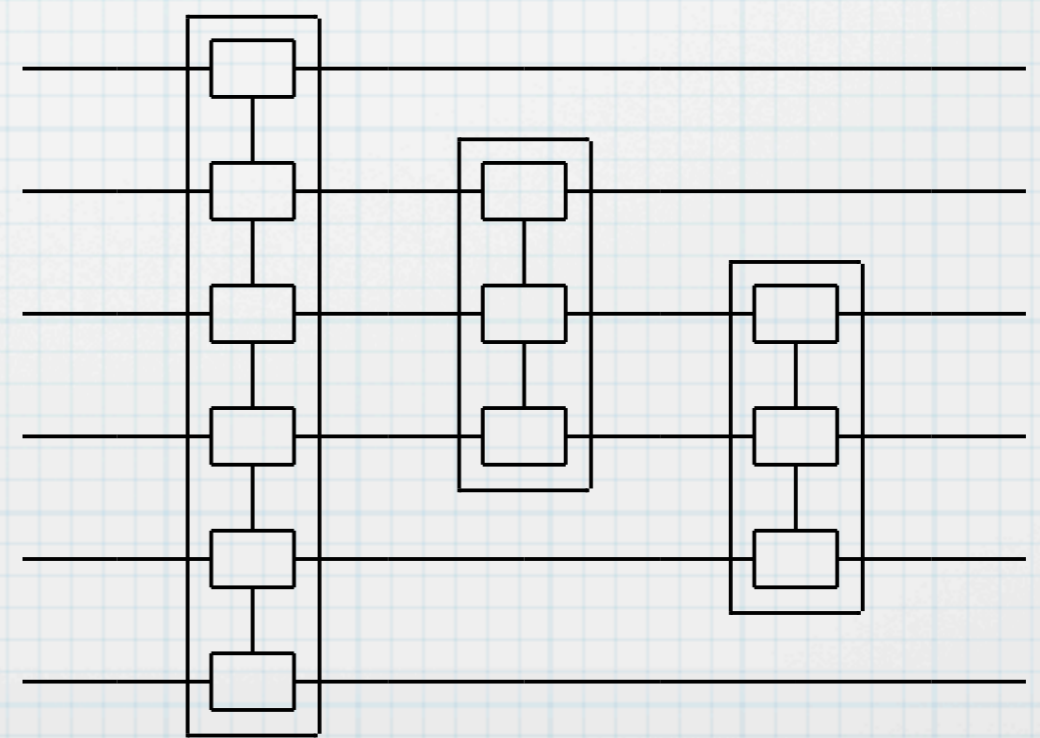
$$A * B = \text{Tr}_J[A^{\theta_J} B] \in \mathcal{B}(H_{\text{out}} \otimes H_{\text{in}})$$

The link-product is commutative!

Link product



$R_1 * R_2 * R_3 \iff$



Special cases:

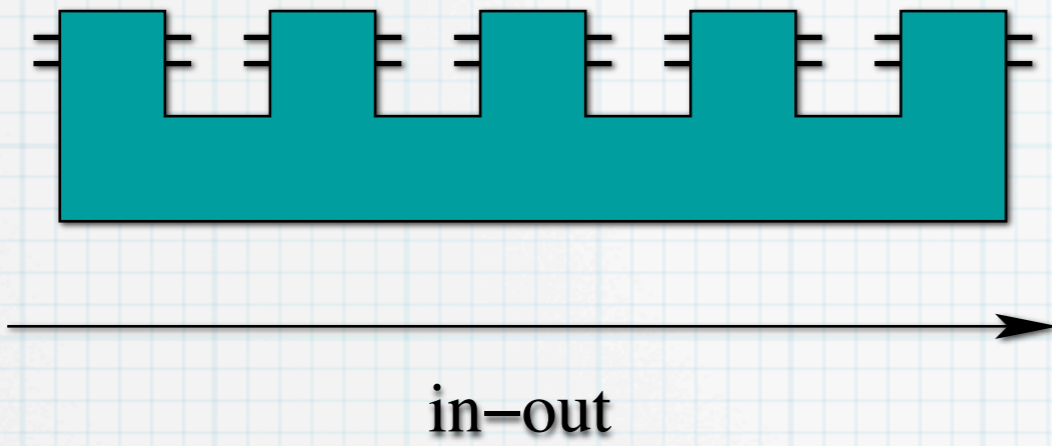
$$\mathcal{M}(\rho) = R_{\mathcal{M}} * \rho \quad \text{quantum operation}$$

$$\text{Tr}[P^t \rho] = P * \rho \quad \text{POVM}$$

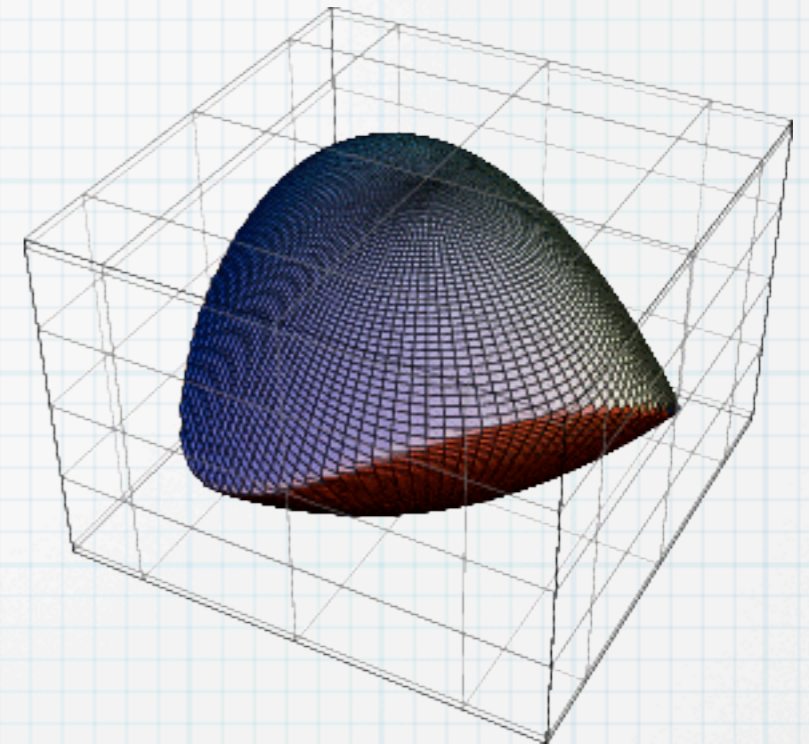
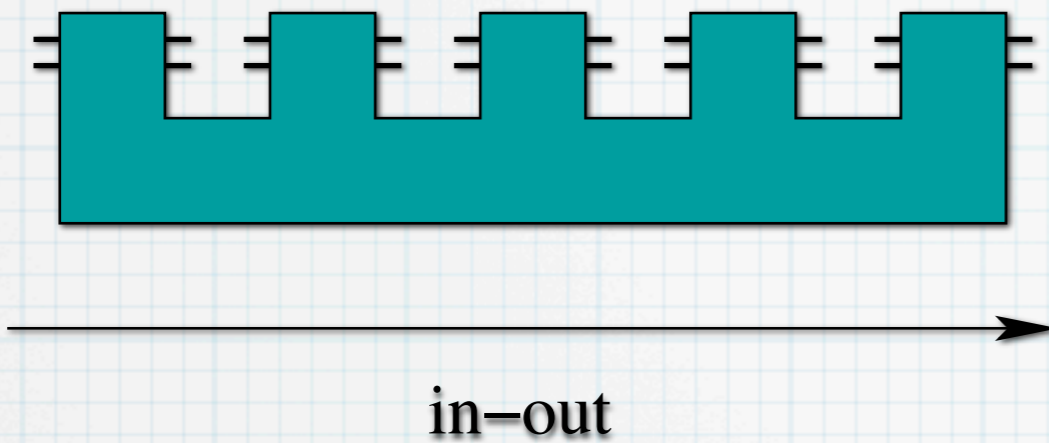
$$\rho \otimes \sigma = \rho * \sigma \quad \text{tensor product}$$

$$\text{Tr}_{\mathbb{H}}[R] = R * I_{\mathbb{H}} \quad \text{partial trace}$$

Circuits Architecture Optimization

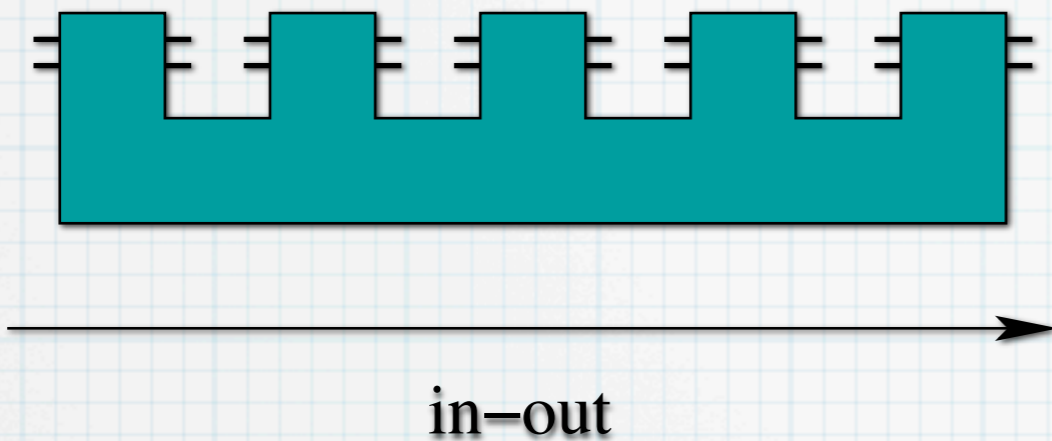


Circuits Architecture Optimization



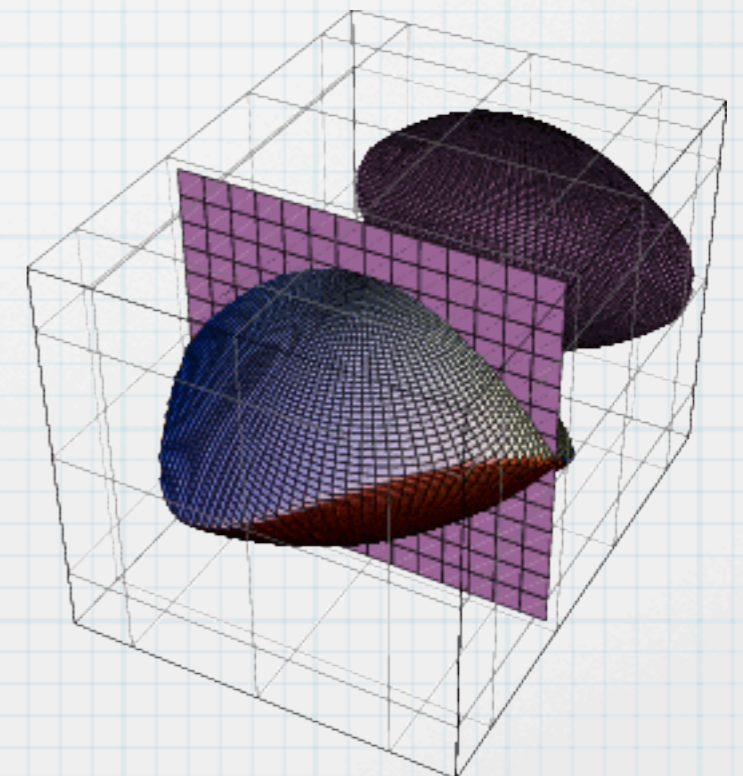
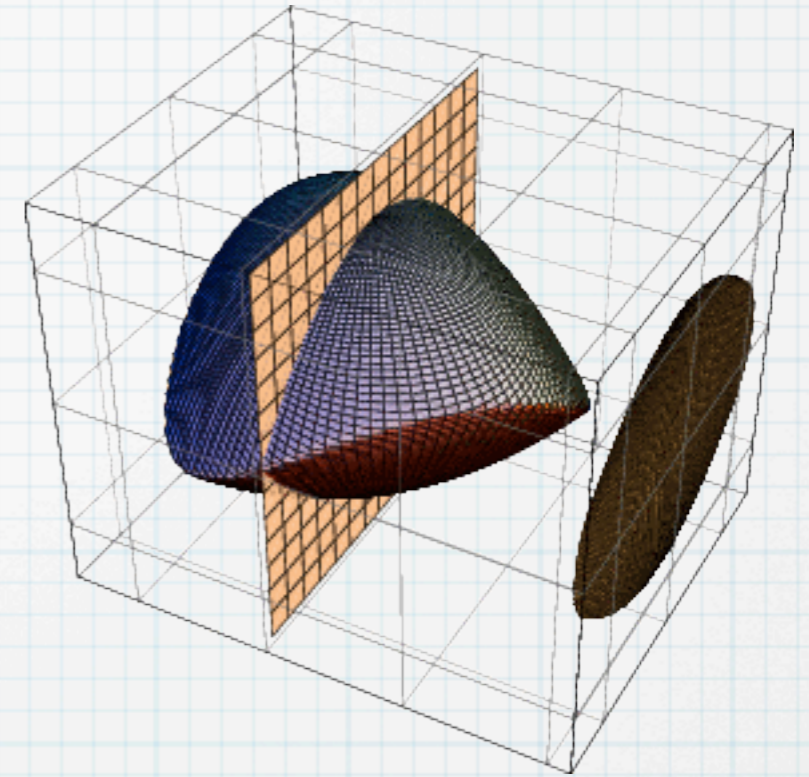
- The Choi operators of a fixed input-output comb structure make a **convex set**

Circuits Architecture Optimization



- The Choi operators of a fixed input-output comb structure make a **convex set**
- **Causality constraints** correspond to a hyperplane section of the convex
- Group-covariance gives another linear constraint:

$$[R, V_g] = 0 \implies R = \bigoplus_j R_j \otimes \mathbb{1}_{m_j}$$

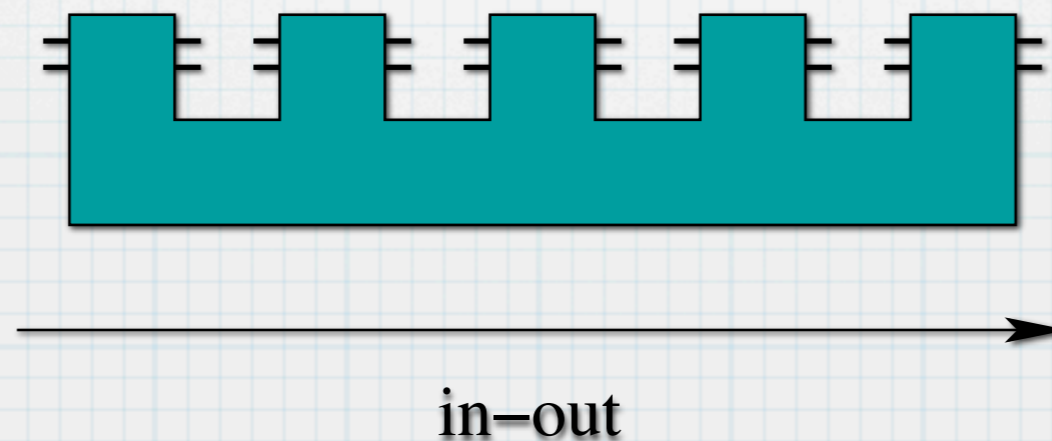
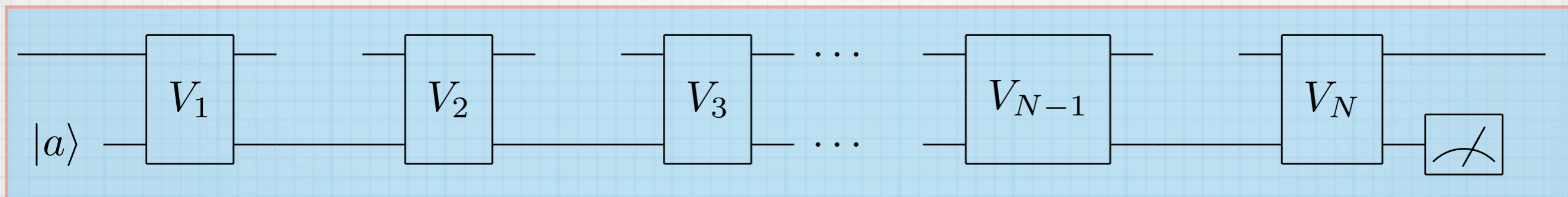


The mathematical
formulation is reduced to
a convex problem!

Realization theorem

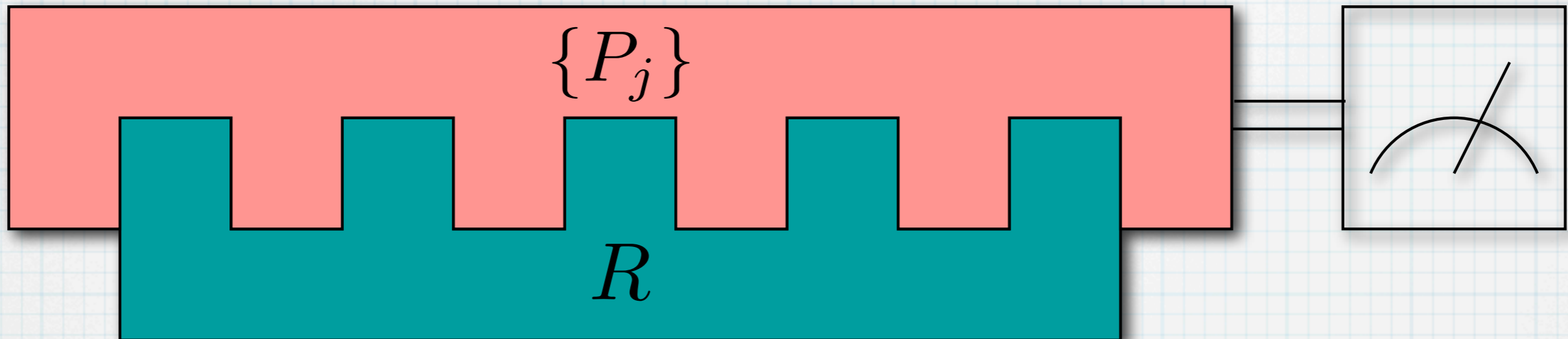
Chiribella, D'Ariano, Perinotti, PRL **101** 060401 (2008) EL **83** 30004 (2008)

Theorem: Every Choi operator on given input-output spaces and satisfying given causality conditions is realized by the comb of isometries



For realization of isometries see: Buscemi, D'Ariano, and Sacchi, PRA 68 042113 (2003)

Quantum board testers



Tester

Born rule:

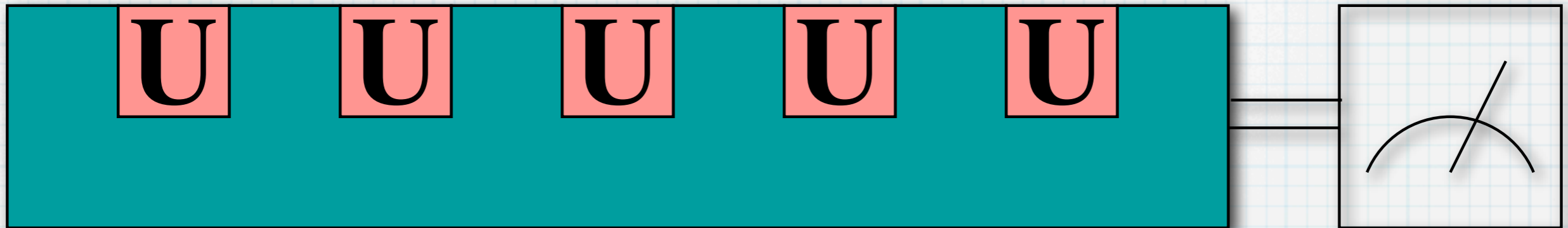
$$\text{Tr}[P_j R] = p_j, \quad \sum_j P_j = \Xi$$

causality constraints:

$$\text{Tr}_{2n+1}[\Xi^{(n)}] = I_{2n} \otimes \Xi^{(n-1)}, \quad n = 0, 1, \dots, N$$

$$\Xi^{(N)} \equiv \Xi, \quad \text{Tr}_1[\Xi^{(0)}] = 1$$

Estimating tester



Tester

Born rule:

$$\text{Tr}[P_j R] = p_j, \quad \sum_j P_j = \Xi$$

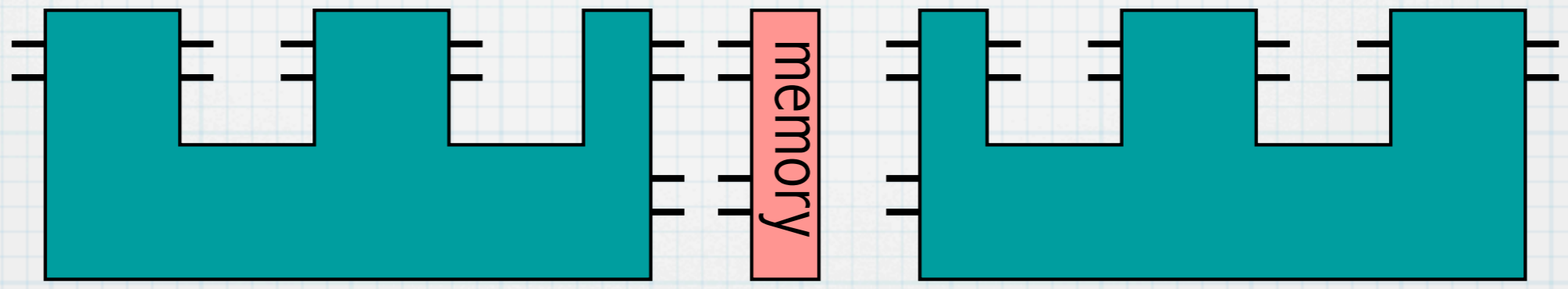
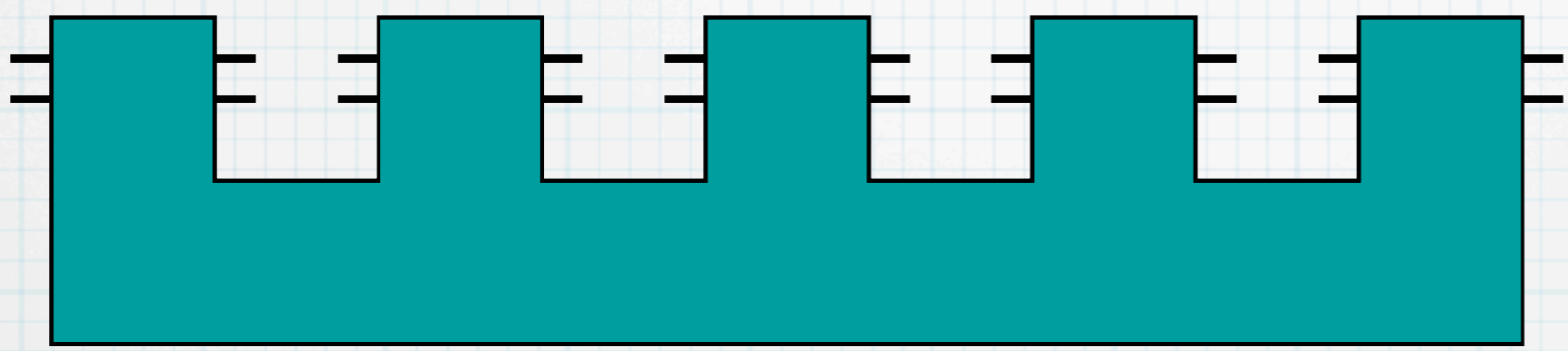
causality constraints:

$$\text{Tr}_{2n+1}[\Xi^{(n)}] = I_{2n} \otimes \Xi^{(n-1)}, \quad n = 0, 1, \dots, N$$

$$\Xi^{(N)} \equiv \Xi, \quad \text{Tr}_1[\Xi^{(0)}] = 1$$

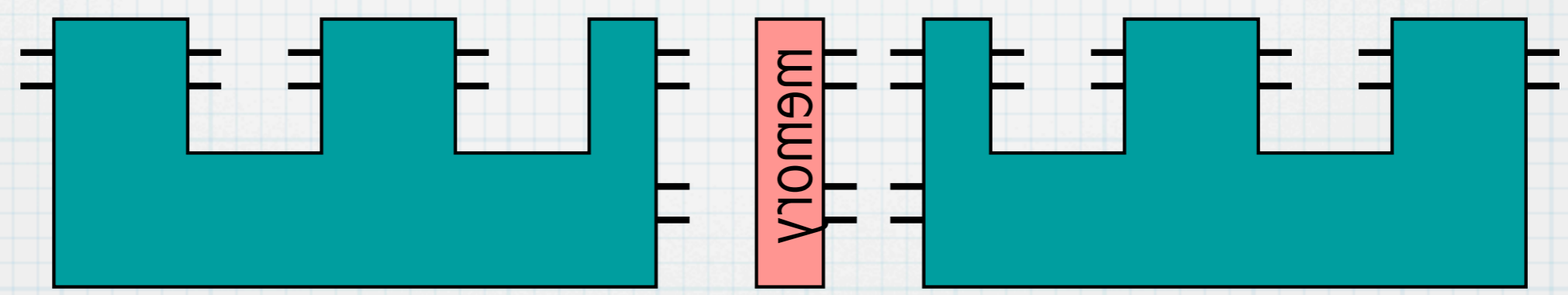
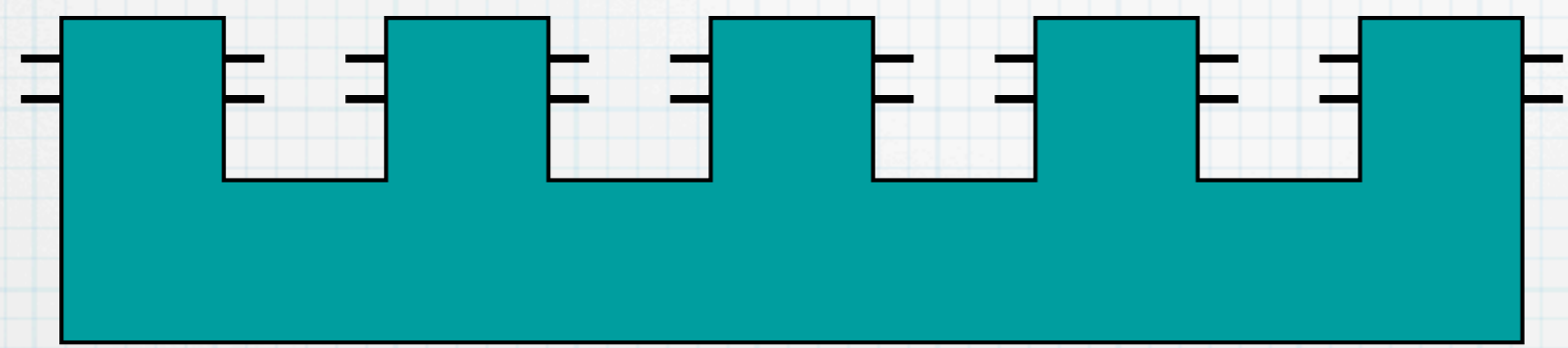
Using quantum memory

delay the use of subcircuits by breaking the comb into subcombs + quantum memory



Using quantum memory

delay the use of subcircuits by breaking the comb into subcombs + quantum memory



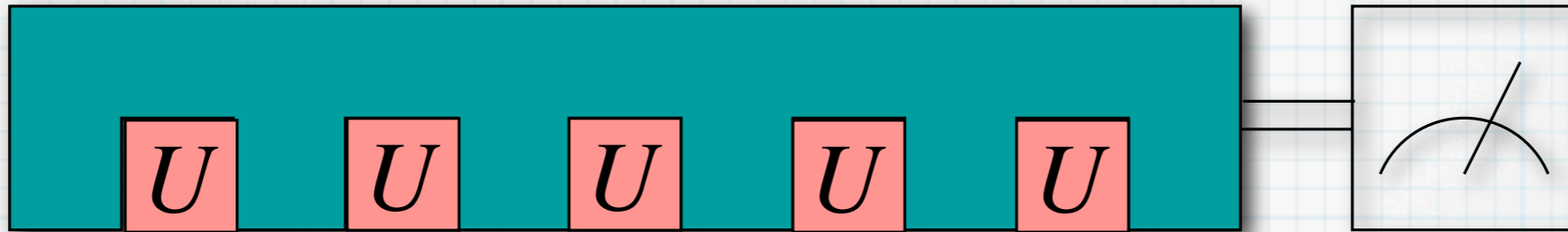
Applications

Application 1: discrimination and estimation of unitaries (optimal oracle-calling quantum algorithms)

Discrimination of unitaries

Chiribella, D'Ariano, Perinotti, PRL 101 180501 (2008)

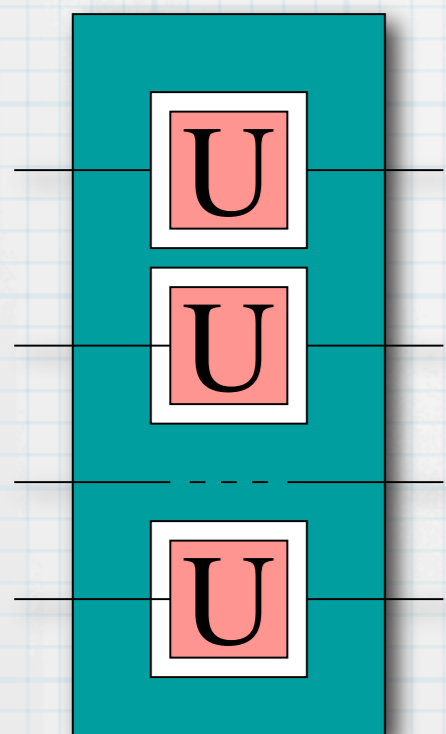
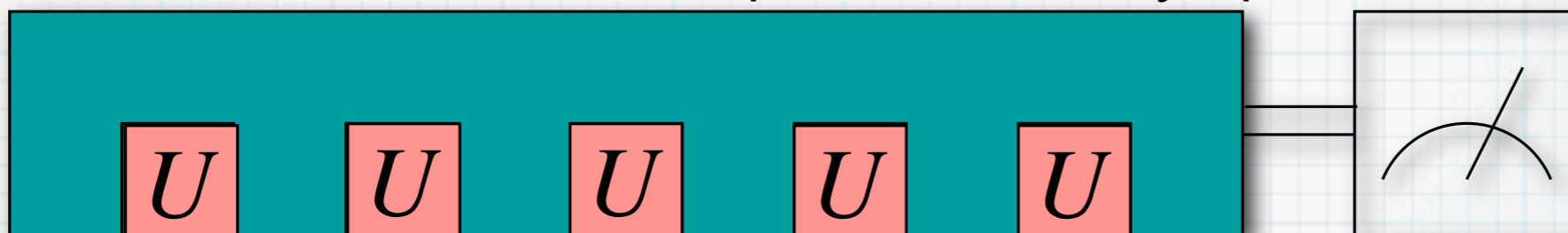
Optimal discrimination between two possible unitary operators U_1 U_2



Discrimination of unitaries

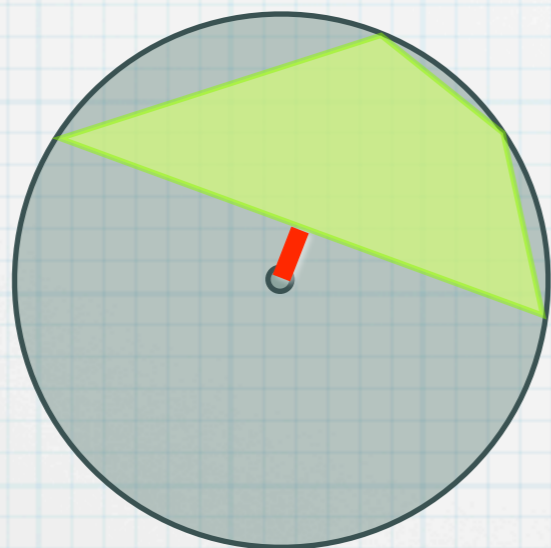
Chiribella, D'Ariano, Perinotti, PRL 101 180501 (2008)

Optimal discrimination between two possible unitary operators U_1 U_2



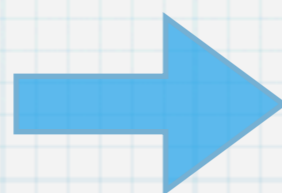
$$V = U_1^\dagger U_2$$

G. M. D'Ariano, P. Lo Presti, M. G. A. Paris, PRL 87, 270404 (2001);
A. Acín, PRL 87, 177901(2001).



angular spread $\Delta(U)$

$$\Delta(U \otimes V) = \Delta(U) + \Delta(V)$$

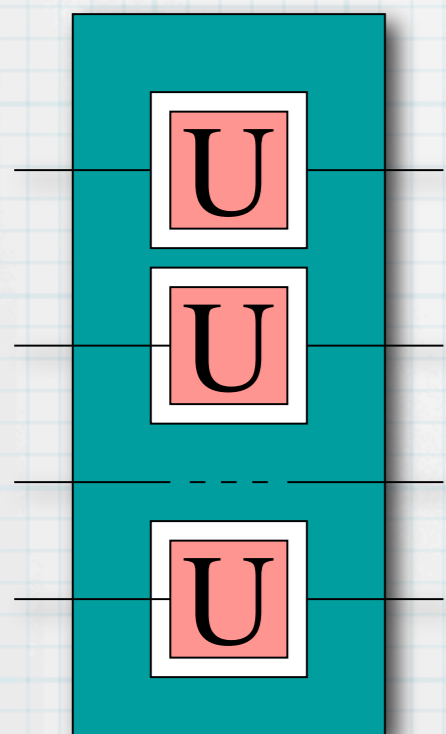
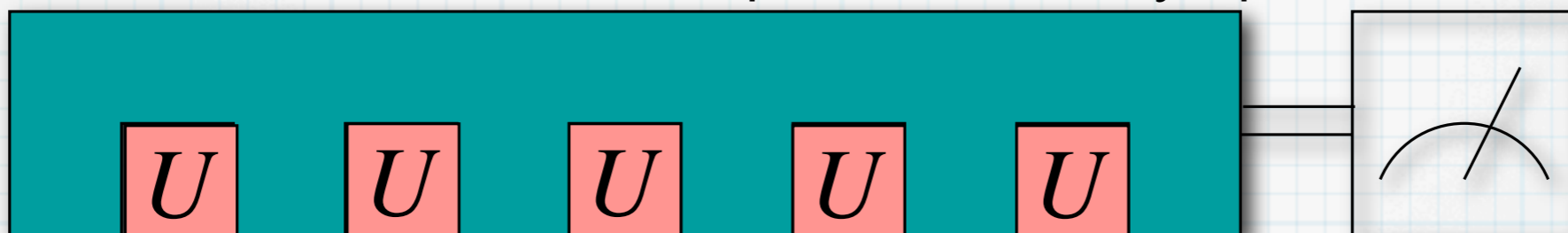


$$N = \left\lceil \frac{\pi}{\Delta\phi} \right\rceil$$

Discrimination of unitaries

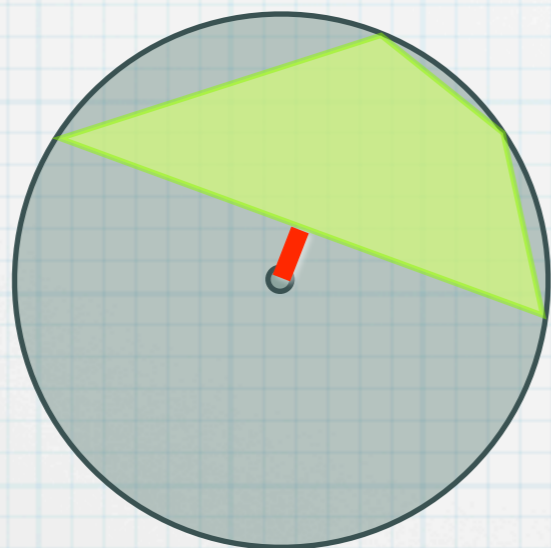
Chiribella, D'Ariano, Perinotti, PRL 101 180501 (2008)

Optimal discrimination between two possible unitary operators U_1 U_2



$$V = U_1^\dagger U_2$$

G. M. D'Ariano, P. Lo Presti, M. G. A. Paris, PRL 87, 270404 (2001);
A. Acín, PRL 87, 177901(2001).

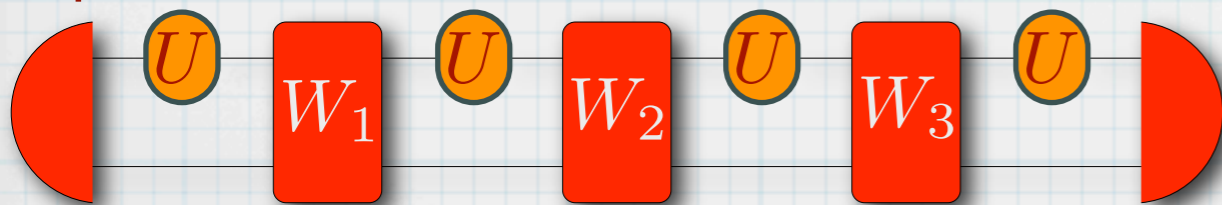


angular spread $\Delta(U)$

$$\Delta(U \otimes V) = \Delta(U) + \Delta(V)$$

$$N = \left\lceil \frac{\pi}{\Delta\phi} \right\rceil$$

spread lemma: $\Delta(AB) \leq \Delta(A) + \Delta(B)$ A M Childs, J Preskill, and J Renes, JMO 47, 155-176 (2000).



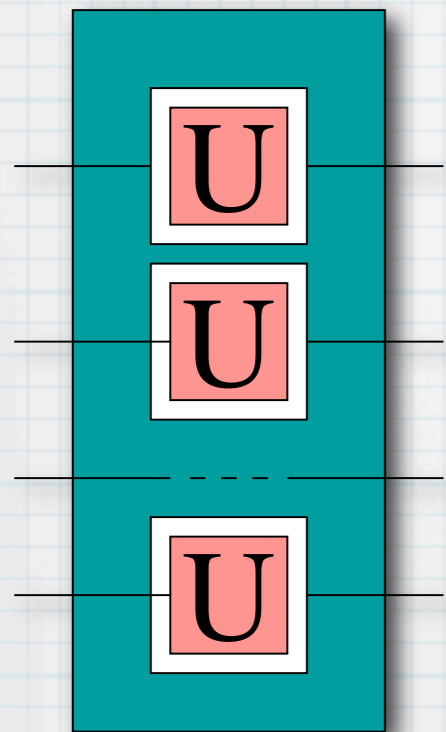
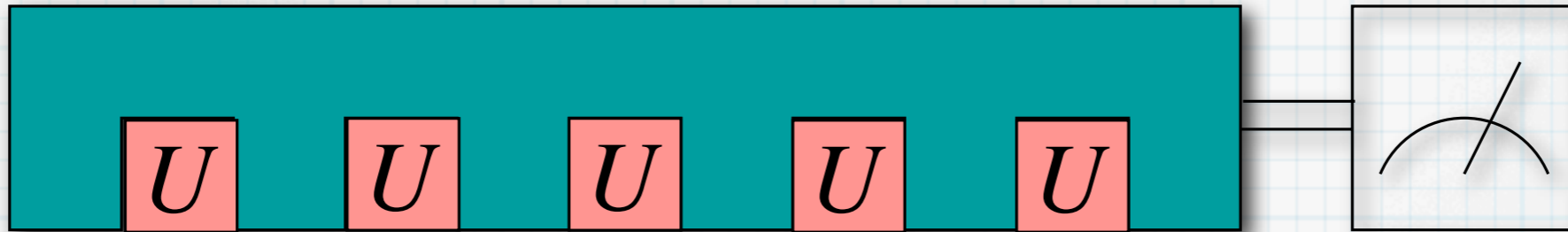
$$\Delta[W(U \otimes I)W^\dagger(U \otimes I)] \leq \Delta(U^{\otimes 2})$$

The spread of the tester is not larger than that of $U^{\otimes N}$ and U^N

Discrimination of unitaries

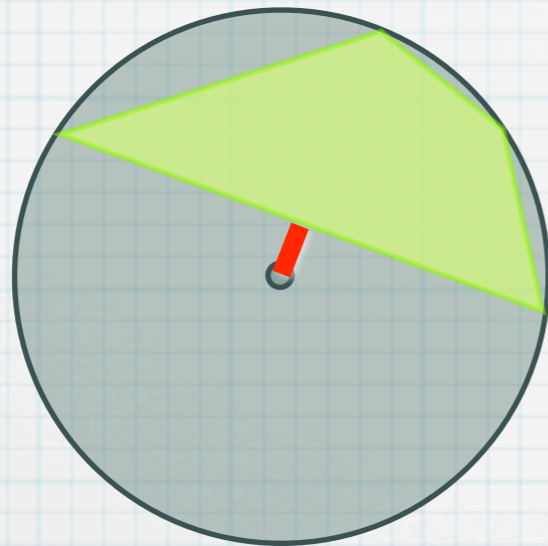
Chiribella, D'Ariano, Perinotti, PRL 101 180501 (2008)

Optimal discrimination between two possible unitary operators $U_1 U_2$



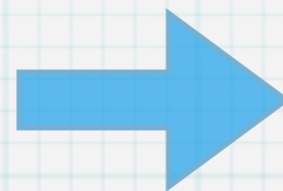
$$V = U_1^\dagger U_2$$

G. M. D'Ariano, P. Lo Presti, M. G. A. Paris, PRL 87, 270404 (2001);
A. Acín, PRL 87, 177901 (2001).



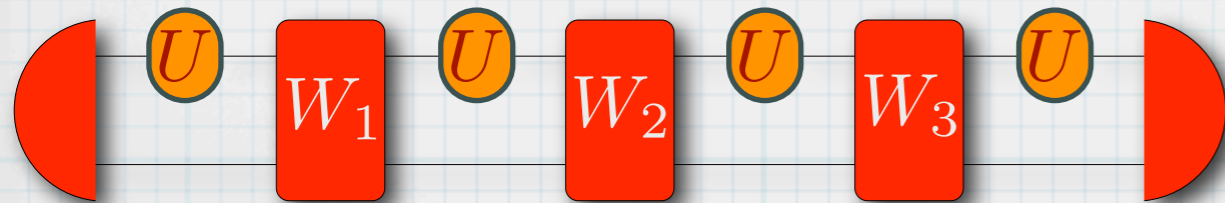
angular spread $\Delta(U)$

$$\Delta(U \otimes V) = \Delta(U) + \Delta(V)$$



$$N = \left\lceil \frac{\pi}{\Delta\phi} \right\rceil$$

spread lemma: $\Delta(AB) \leq \Delta(A) + \Delta(B)$ A M Childs, J Preskill, and J Renes, JMO 47, 155-176 (2000).

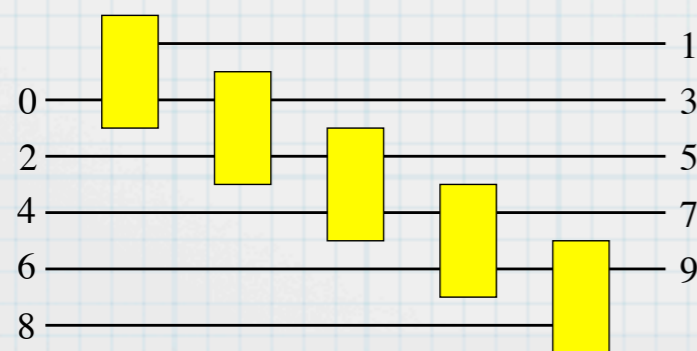
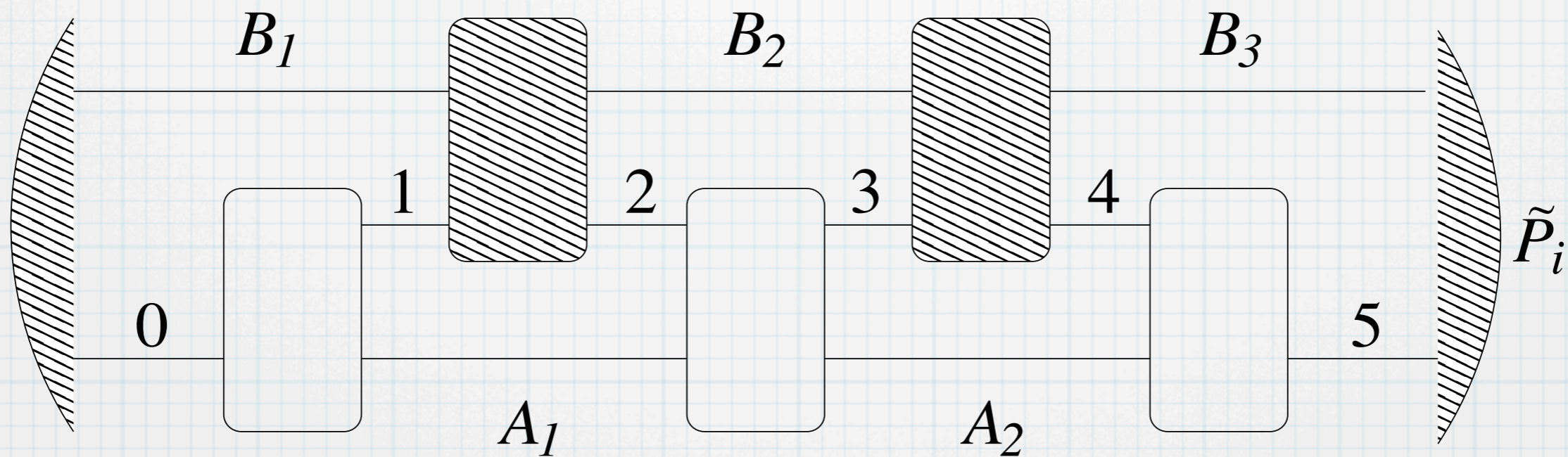


$$\Delta[W(U \otimes I)W^\dagger(U \otimes I)] \leq \Delta(U^{\otimes 2})$$

The spread of the tester is not larger than that of $U^{\otimes N}$ and U^N

The parallel disposition is already optimal

There are memory channels that can be discriminated perfectly with a single use by a quantum tester, and not conventionally

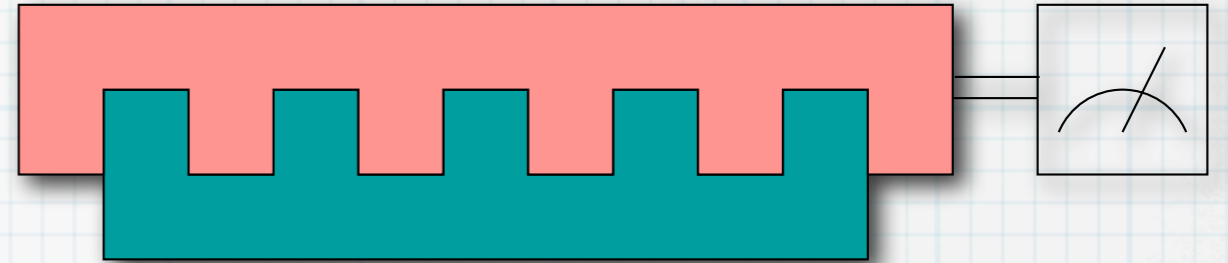


Discrimination of memory channels

Chiribella, D'Ariano, Perinotti, (unpublished)

Tester Born rule:

$$\text{Tr}[P_j R] = p_j, \quad \sum_j P_j = \Xi$$



Perfect discrimination for:

$$R_1 (I \otimes \Xi) R_2 = 0$$

Discrimination of unitaries

- What happens for more than two unitaries?
- What happens for non-unitary channels?

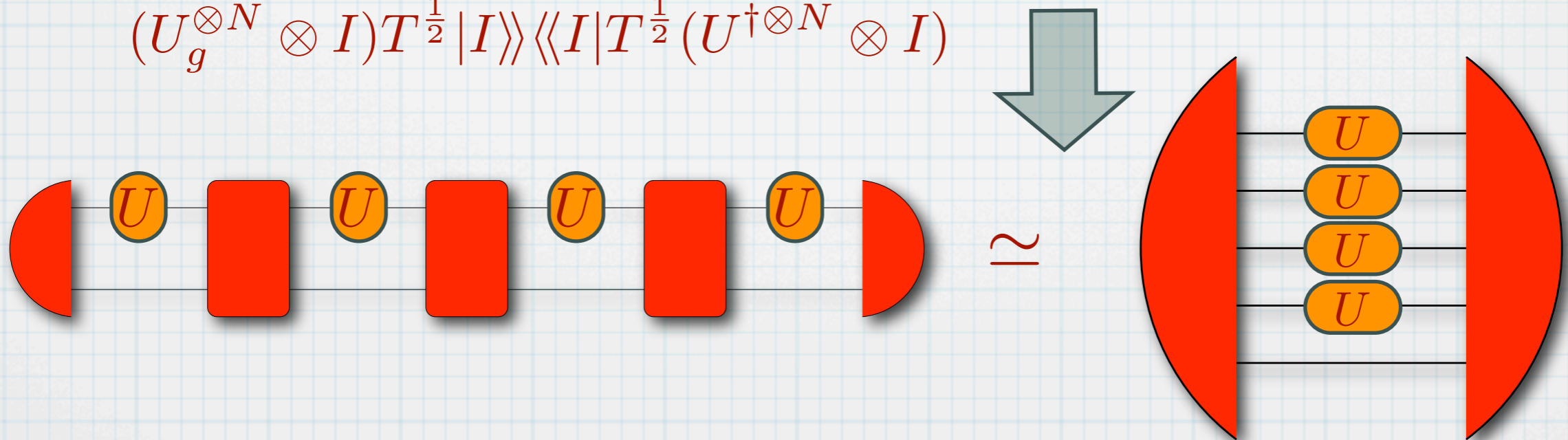
Covariant estimation of unitaries

- Covariant unitary estimation problem (group of unitaries, Haar-distributed)
- Problem: find the optimal tester for estimating the group element

One can prove that the optimal tester is covariant:

$$T = \int_G dg T_g \quad T_h = (U_h^{\otimes N} \otimes I) \Theta (U_h^{\dagger \otimes N} \otimes I) \Rightarrow [T, U_h^{\otimes N} \otimes I] = 0$$

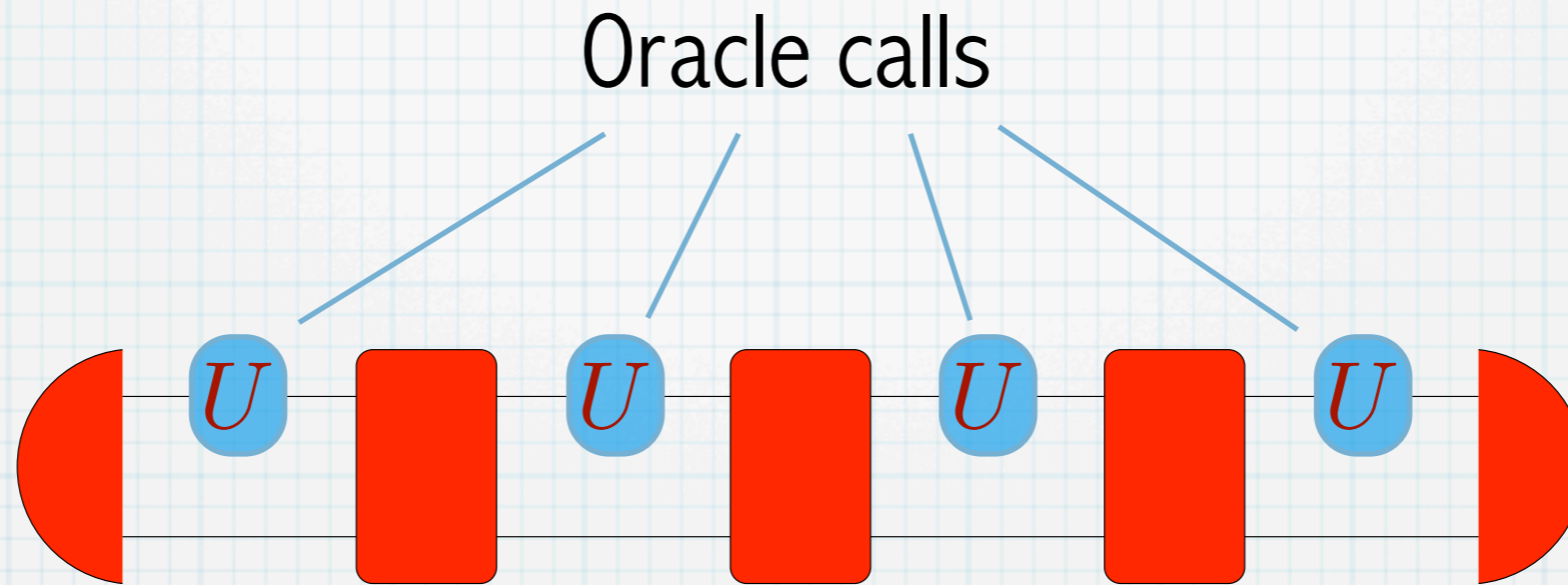
$$\text{Then: } T^{\frac{1}{2}} (|U_g\rangle\rangle \langle\langle U_g|)^{\otimes N} T^{\frac{1}{2}} = T^{\frac{1}{2}} (U_g^{\otimes N} \otimes I) |I\rangle\rangle \langle\langle I| (U^{\dagger \otimes N} \otimes I) T^{\frac{1}{2}} = \\ (U_g^{\otimes N} \otimes I) T^{\frac{1}{2}} |I\rangle\rangle \langle\langle I| T^{\frac{1}{2}} (U^{\dagger \otimes N} \otimes I)$$



Any covariant tester is equivalent to a parallel scheme

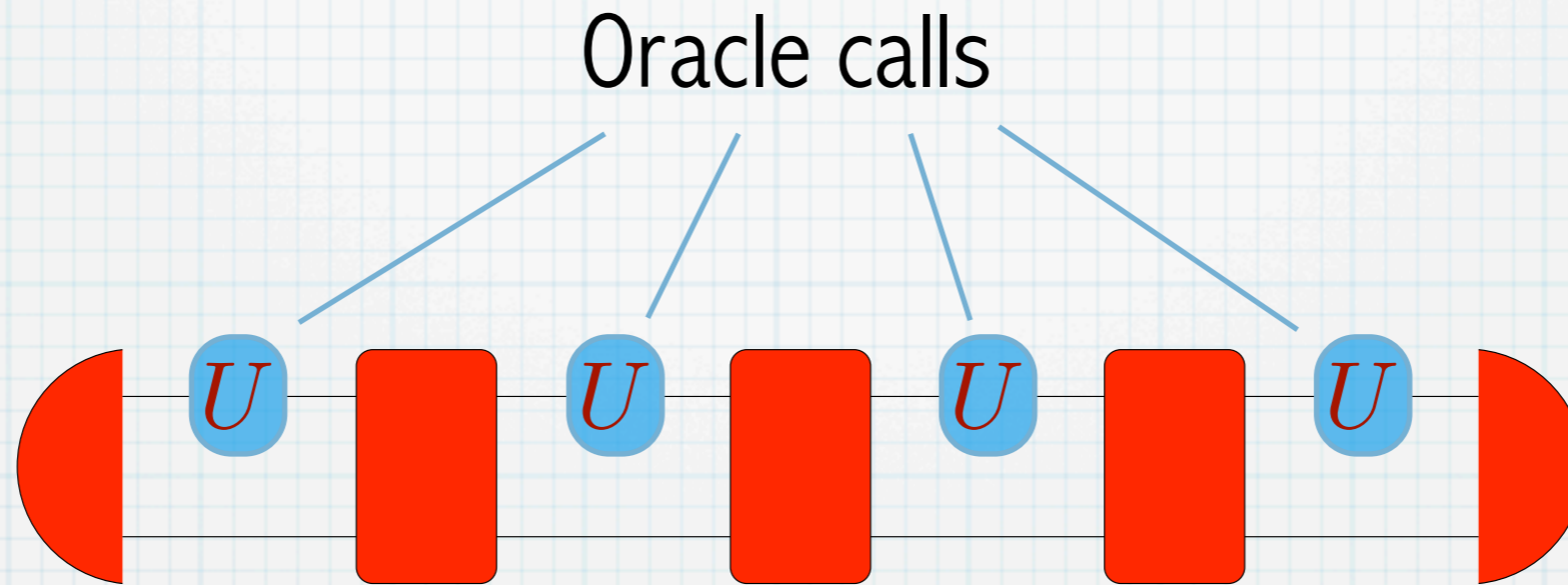
Discrimination of unitaries

Oracle-calling quantum algorithm as optimal discrimination of unitaries



Discrimination of unitaries

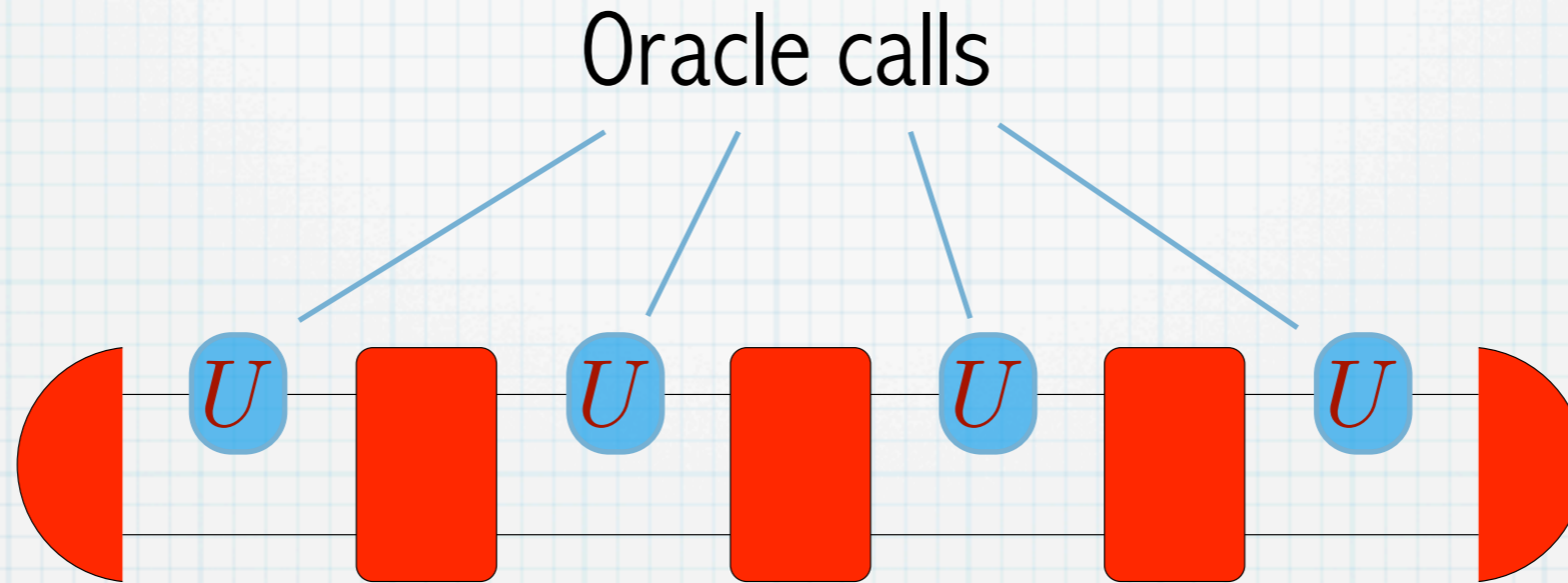
Oracle-calling quantum algorithm as optimal discrimination of unitaries



Hidden-subgroup algorithms (Deutsch-Jozsa, Simon, etc): parallel calls are optimal

Discrimination of unitaries

Oracle-calling quantum algorithm as optimal discrimination of unitaries

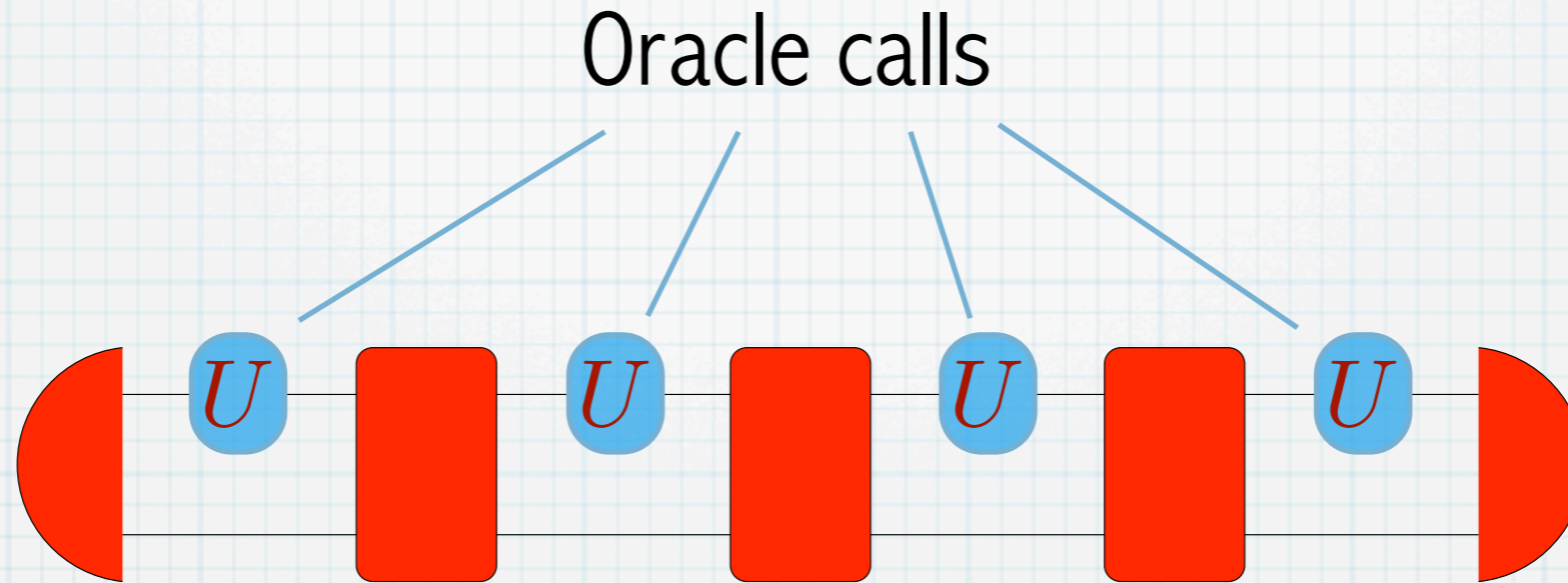


Hidden-subgroup algorithms (Deutsch-Jozsa, Simon, etc): parallel calls are optimal

Algorithms with no hidden subgroup (e.g. Grover) need a comb [C. Zalka, PRA 60, 2746 (1999)]

Discrimination of unitaries

Oracle-calling quantum algorithm as optimal discrimination of unitaries



Hidden-subgroup algorithms (Deutsch-Jozsa, Simon, etc): parallel calls are optimal

Algorithms with no hidden subgroup (e.g. Grover) need a comb [C. Zalka, PRA 60, 2746 (1999)]

Q-combs: systematic method to determine optimal oracle-calling algorithms

Discrimination of unitaries

When do we need a tester (not just a parallel discrimination):

Discrimination of unitaries

When do we need a tester (not just a parallel discrimination):

- For discrimination of non-unitary channels
- For discrimination within non-covariant sets
- For discrimination of memory channels

Operational network distance

PRL **101** 180501 (2008)

Existence of optimal non parallel optimal discrimination schemes

Operational network distance

PRL **101** 180501 (2008)

Existence of optimal non parallel optimal discrimination schemes



The proper distance for memory channels must be defined in terms of optimal discriminating testers

$$D(\mathcal{C}^{(N)}, \mathcal{D}^{(N)}) := \max_{\Xi^{(N)}} \left\| \left(I \otimes \Xi^{(N)\frac{1}{2}} \right) \Delta \left(I \otimes \Xi^{(N)\frac{1}{2}} \right) \right\|_1$$

$$\Delta := C - D$$

Operational network distance

PRL **101** 180501 (2008)

Existence of optimal non parallel optimal discrimination schemes



The proper distance for memory channels must be defined in terms of optimal discriminating testers

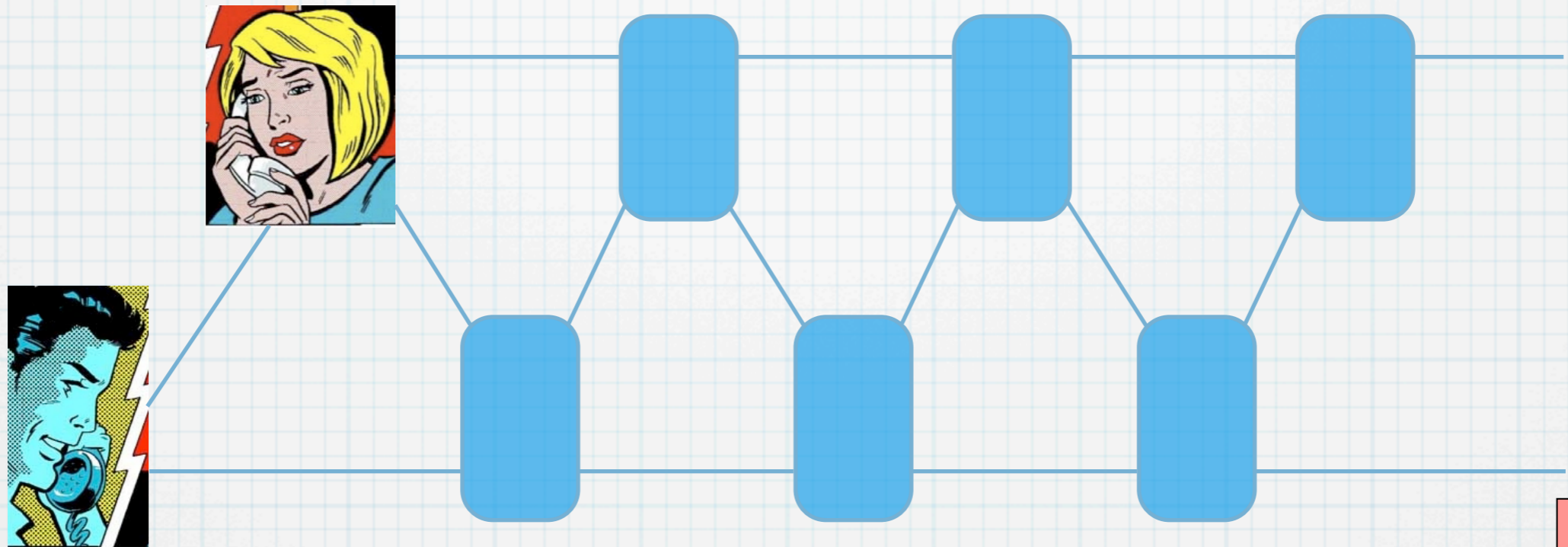
$$D(\mathcal{C}^{(N)}, \mathcal{D}^{(N)}) := \max_{\Xi^{(N)}} \left\| \left(I \otimes \Xi^{(N)\frac{1}{2}} \right) \Delta \left(I \otimes \Xi^{(N)\frac{1}{2}} \right) \right\|_1$$

$$\Delta := C - D$$

CB-norm distance only accounts for parallel discrimination schemes

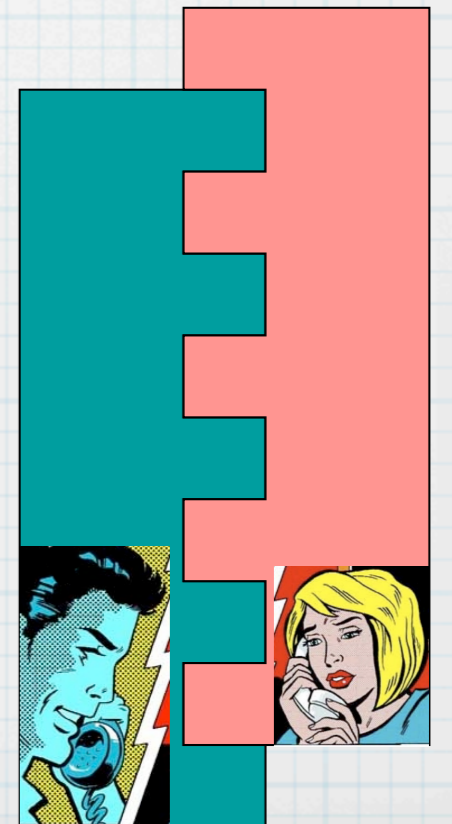
Application 2: quantum protocols (cryptography, game-theory)

Quantum protocols

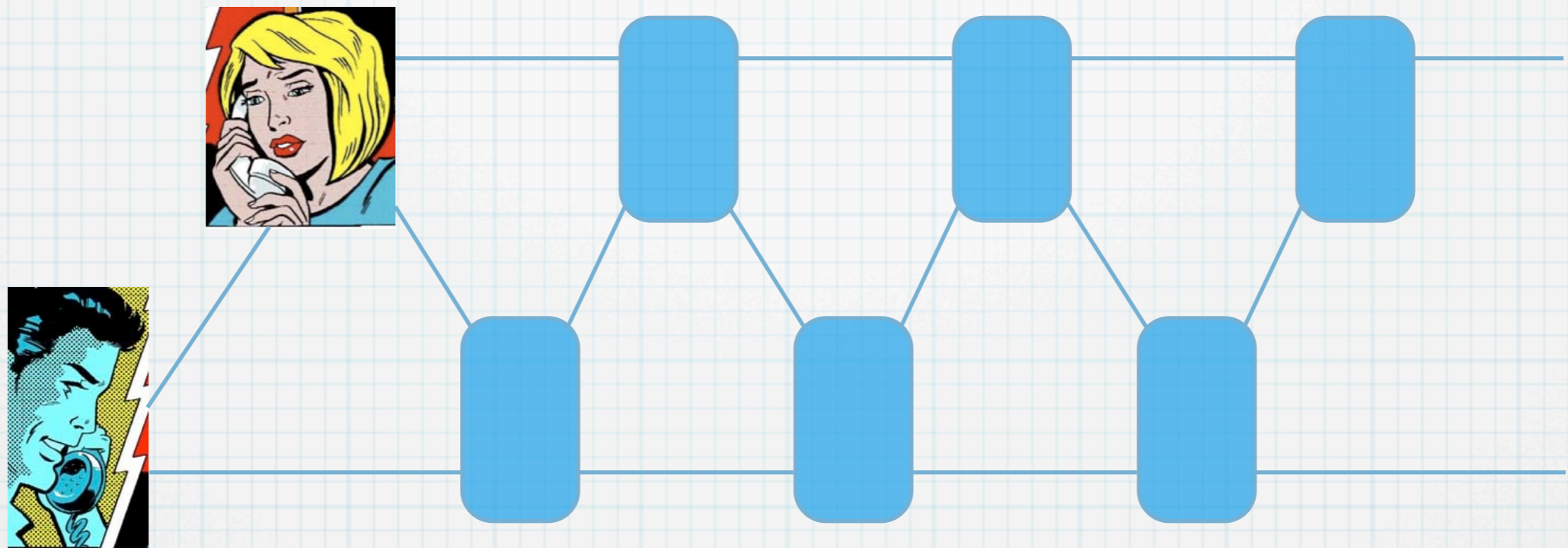


Quantum combs describe the most general strategies
in multi-party protocols and games

G. Gutoski and J. Watrous, Proc. STOC, 565-574, (2007)



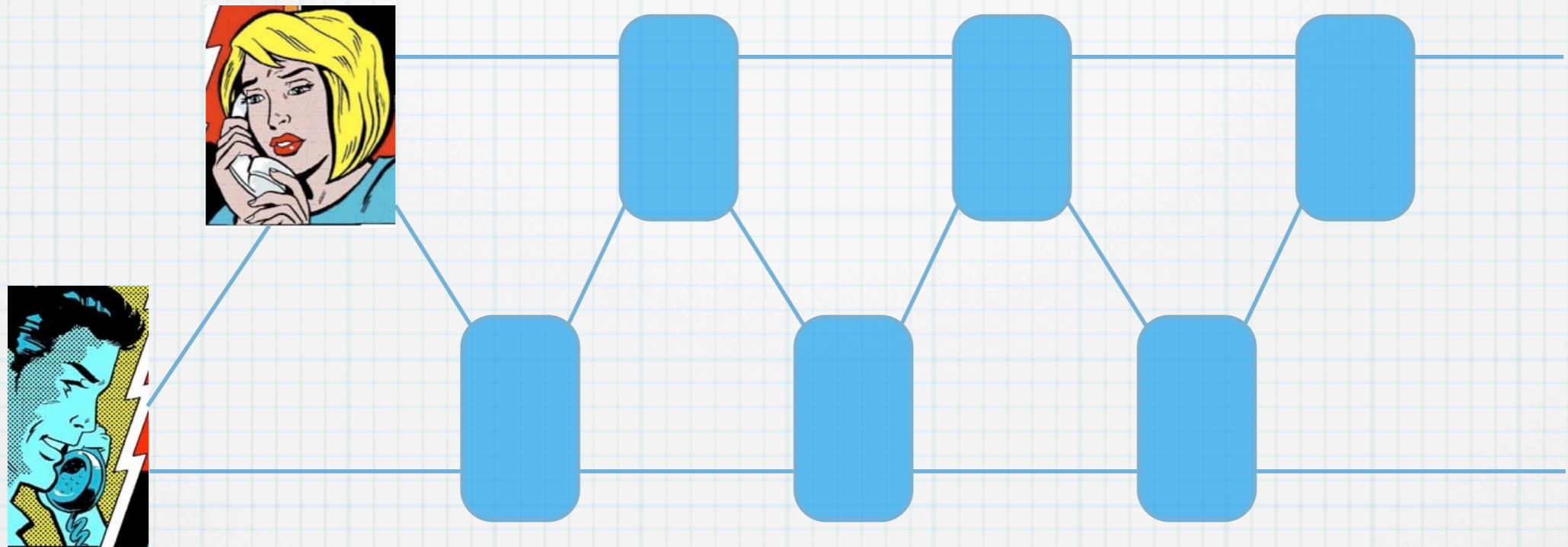
Quantum bit commitment



Quantum combs is the most suitable mathematical formulation of Alice and Bob's strategies in a quantum bit commitment protocol

Sketch of impossibility proof

Chiribella, D'Ariano, Perinotti, Schlingemann, and Werner (in preparation)



Thm: a QBC concealing protocol cannot be binding

Proof: continuity of the comb-Stinespring versus the operational distance between strategies

Application 3: Quantum-algorithm learning

Quantum-algorithm learning

Problem: run an unknown unitary that is available today on a quantum state that will be available tomorrow

Quantum-algorithm learning

Problem: run an unknown unitary that is available today on a quantum state that will be available tomorrow



Quantum-algorithm learning

Problem: run an unknown unitary that is available today on a quantum state that will be available tomorrow



- Alice owns quantum circuit that performs a very valuable algorithm U that she wants to keep undisclosed.



Quantum-algorithm learning

Problem: run an unknown unitary that is available today on a quantum state that will be available tomorrow



- Alice owns quantum circuit that performs a very valuable algorithm U that she wants to keep undisclosed.
- Bob needs to run Alice's algorithm on an input state that will be available tomorrow, but he can borrow the circuit from Alice only today for just a limited number of uses N , and with the circuit sealed.



Quantum algorithm learning

Problem: run an unknown unitary that is available today on a quantum state that will be available tomorrow



Quantum algorithm learning

Problem: run an unknown unitary that is available today on a quantum state that will be available tomorrow



The only thing that Bob can do today, with the circuit available, is to use it on a input state known to him.



Quantum algorithm learning

Problem: run an unknown unitary that is available today on a quantum state that will be available tomorrow



- The only thing that Bob can do today, with the circuit available, is to use it on a input state known to him.
- After that the only thing that remains available to Bob for tomorrow is the output state, which Bob can store on a quantum memory.



Quantum algorithm learning

Problem: run an unknown unitary that is available today on a quantum state that will be available tomorrow



The only thing that Bob can do today, with the circuit available, is to use it on a input state known to him.

After that the only thing that remains available to Bob for tomorrow is the output state, which Bob can store on a quantum memory.

Therefore, Bob needs a quantum device that is capable of retrieving from the output state, namely recovering U and then running it on a new unknown state.



Quantum algorithm learning

Problem: run an unknown unitary that is available today on a quantum state that will be available tomorrow



Quantum algorithm learning

Problem: run an unknown unitary that is available today on a quantum state that will be available tomorrow

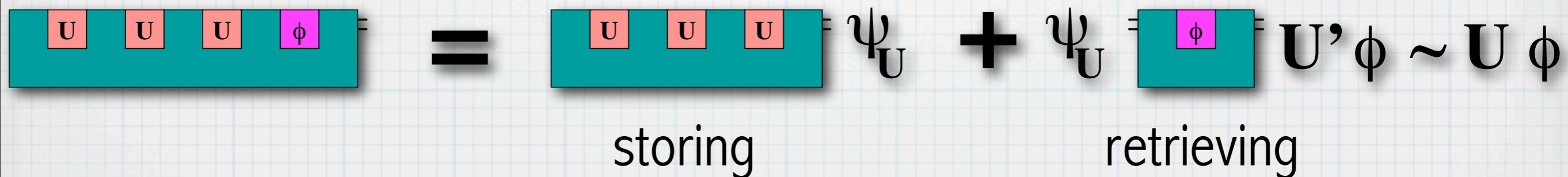
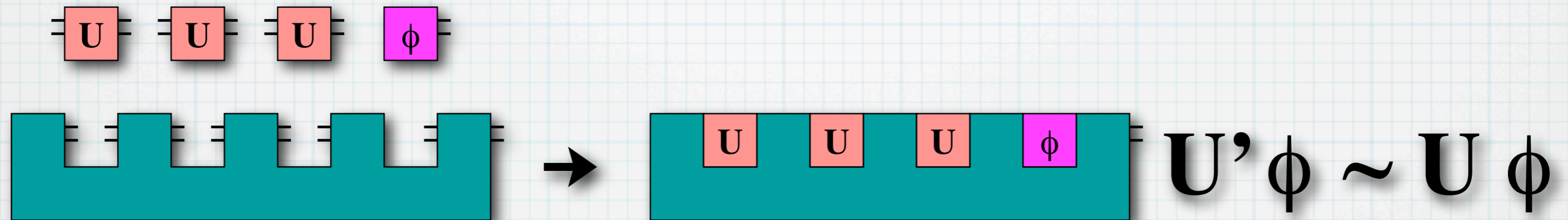


- Exact storing of quantum states is possible
(quantum memory is a technological problem)
- Perfect storing of undisclosed unitaries over a quantum state is impossible even in-principle
(Nielsen-Chuang no-programming theorem)



Quantum algorithm learning

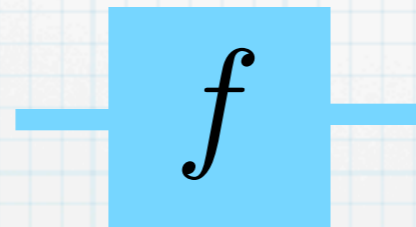
Problem: run an unknown unitary that is available today on a quantum state that will be available tomorrow



Quantum algorithm learning

Problem: a black box computes an unknown function $y = f(x)$

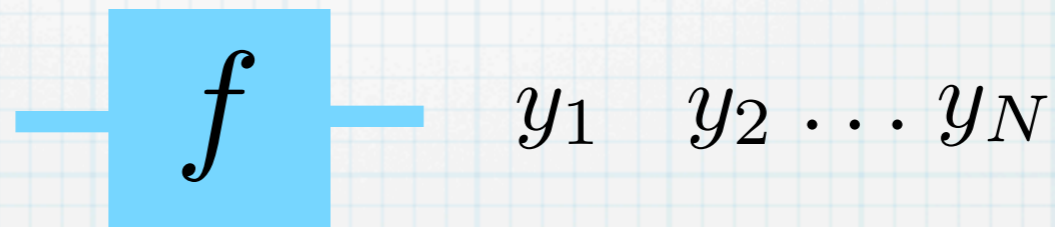
We can evaluate f on a finite set of points x_1, \dots, x_N
getting outcomes y_1, \dots, y_N



Quantum algorithm learning

Problem: a black box computes an unknown function $y = f(x)$

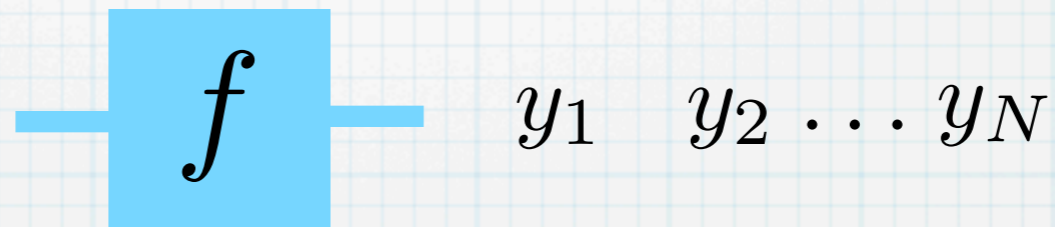
We can evaluate f on a finite set of points x_1, \dots, x_N
getting outcomes y_1, \dots, y_N



Quantum algorithm learning

Problem: a black box computes an unknown function $y = f(x)$

We can evaluate f on a finite set of points x_1, \dots, x_N
getting outcomes y_1, \dots, y_N

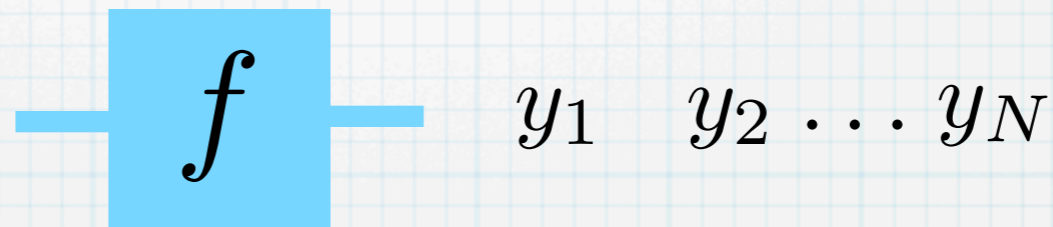


Subsequently, we are asked to compute f on a new point x ,
without using the black box $f(x) = ?$

Quantum algorithm learning

Problem: a black box computes an unknown function $y = f(x)$

We can evaluate f on a finite set of points x_1, \dots, x_N
getting outcomes y_1, \dots, y_N



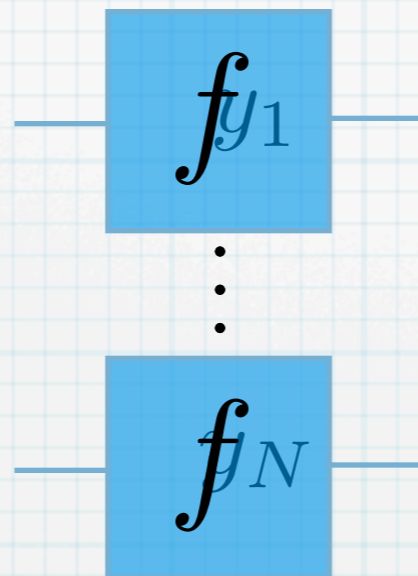
Subsequently, we are asked to compute f on a new point x ,
without using the black box $f(x) = ?$

In classical computer science, **statistical learning** provides
a method to solve this problem

Quantum algorithm learning

classical networks for learning:

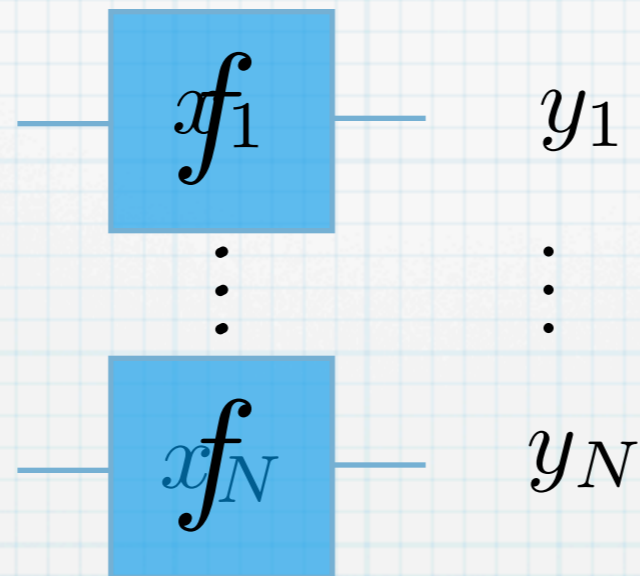
Comparing x with $f(x)$ for N times is not the only possibility:
this just corresponds to the parallel configuration



Quantum algorithm learning

classical networks for learning:

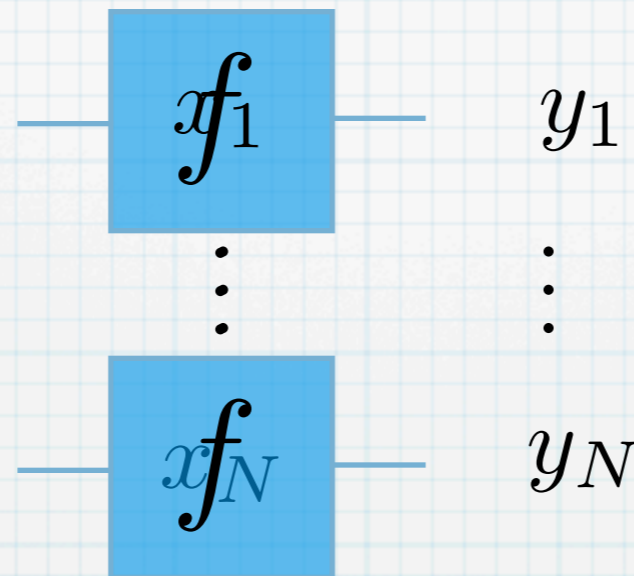
Comparing x with $f(x)$ for N times is not the only possibility:
this just corresponds to the parallel configuration



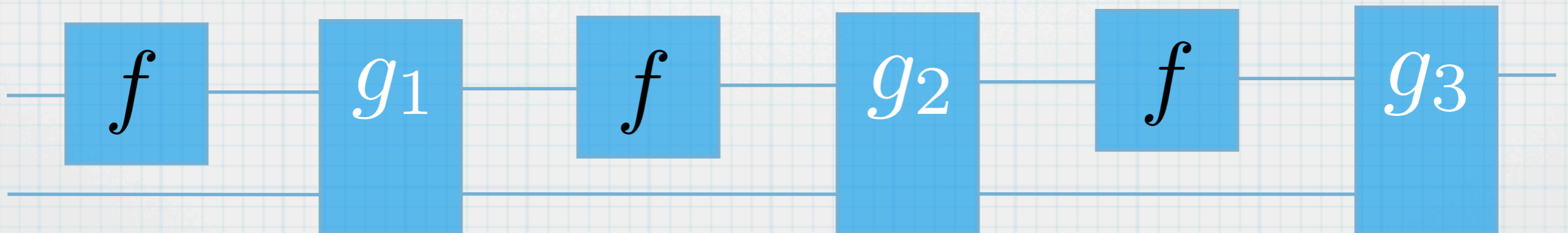
Quantum algorithm learning

classical networks for learning:

Comparing x with $f(x)$ for N times is not the only possibility:
this just corresponds to the parallel configuration



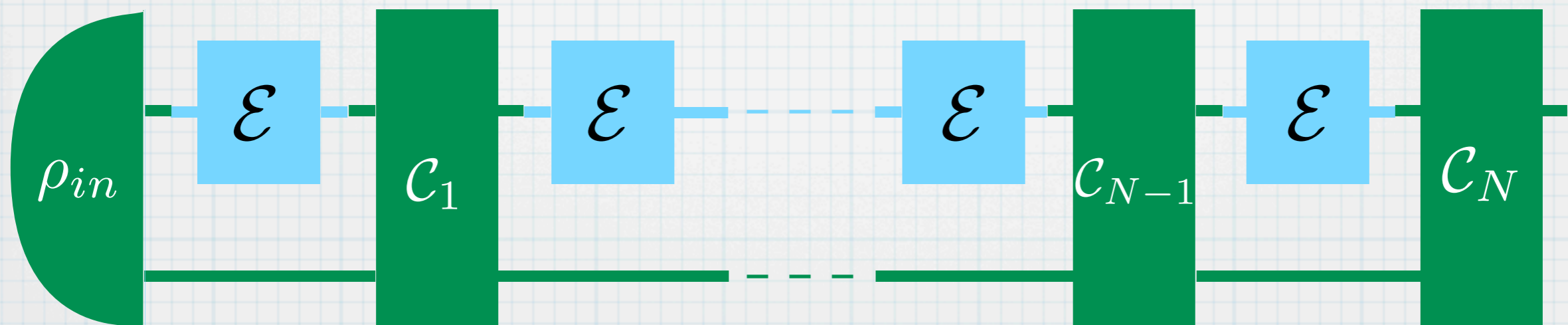
To learn better, one could use a sequential network:



where g_1, g_2, \dots, g_N are known functions

Quantum algorithm learning

- Unknown function $f \longrightarrow$ unknown quantum channel \mathcal{E}
- Classical program \longrightarrow quantum network
- Input $X \longrightarrow$ quantum state ρ_{in}
- Output $Y \longrightarrow$ quantum state ρ_{out}



Quantum algorithm learning

- Classical guess

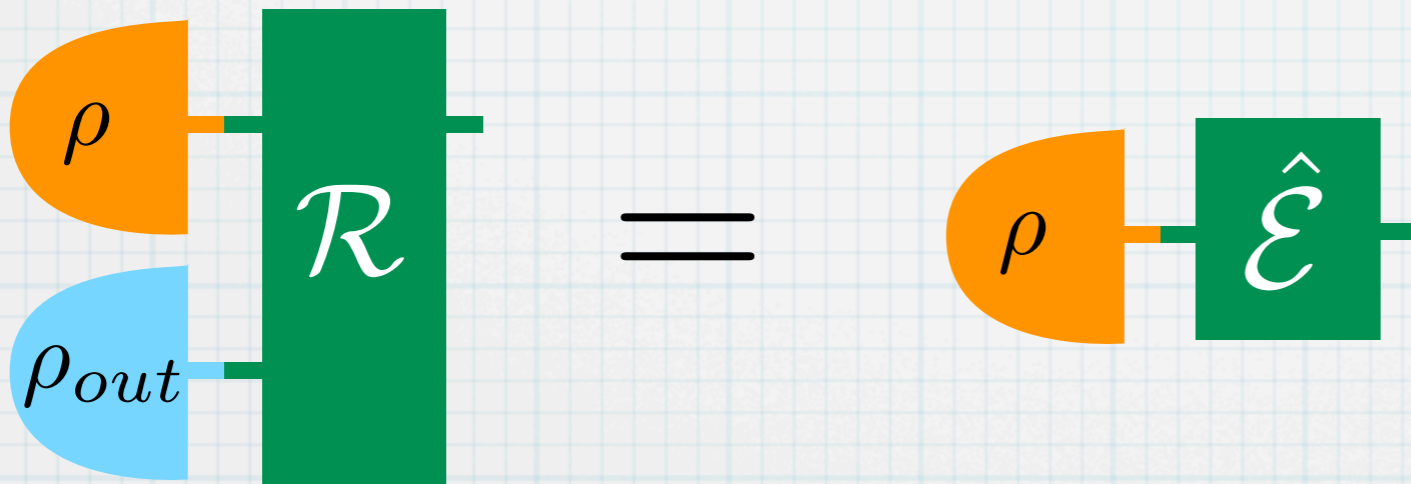
Quantum “guess”

$$Y \rightarrow \hat{f} \quad \longrightarrow \quad \rho_{out} \rightarrow \hat{\mathcal{E}}$$

Physical implementation of the quantum guess:

retrieving channel \mathcal{R}

It retrieves the unknown transformation from the output state ρ_{out} and performs it on a new state ρ



Quantum algorithm learning

- Classical guess

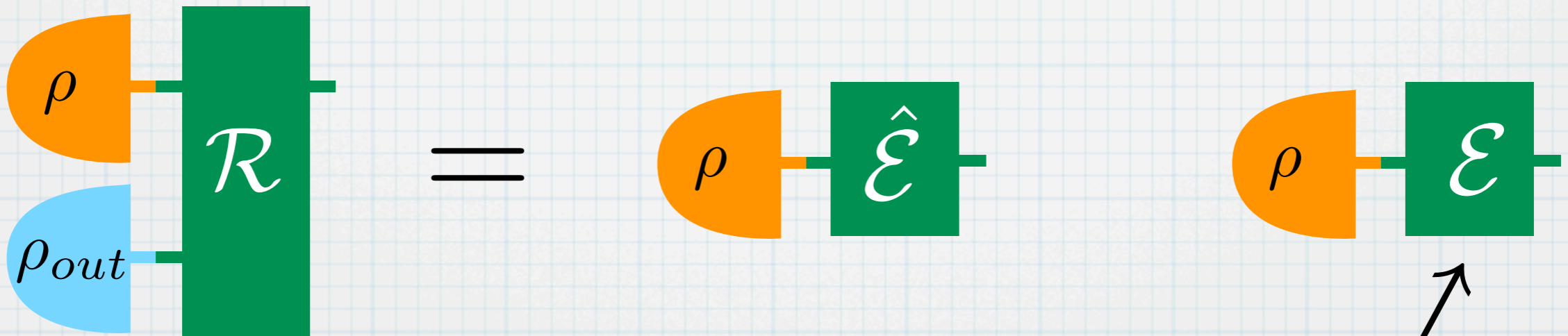
Quantum "guess"

$$Y \rightarrow \hat{f} \quad \longrightarrow \quad \rho_{out} \rightarrow \hat{\mathcal{E}}$$

Physical implementation of the quantum guess:

retrieving channel \mathcal{R}

It retrieves the unknown transformation from the output state ρ_{out} and performs it on a new state ρ



Target: implementing the unknown channel with maximum fidelity

Quantum algorithm learning

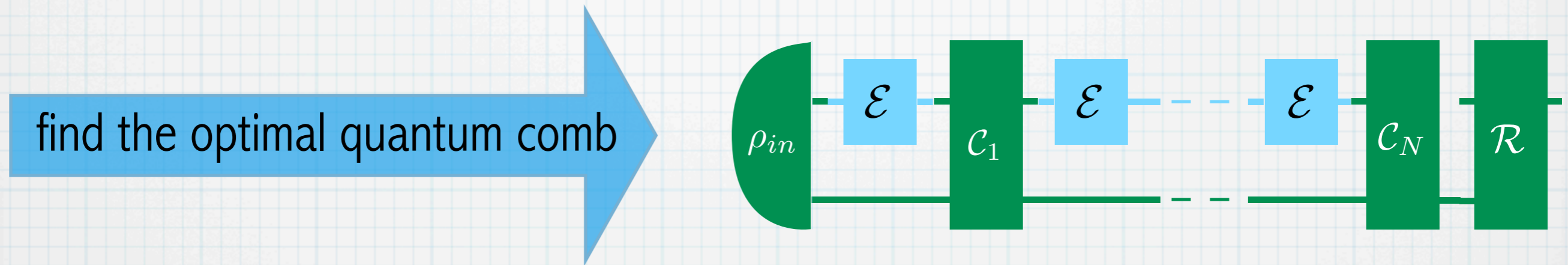
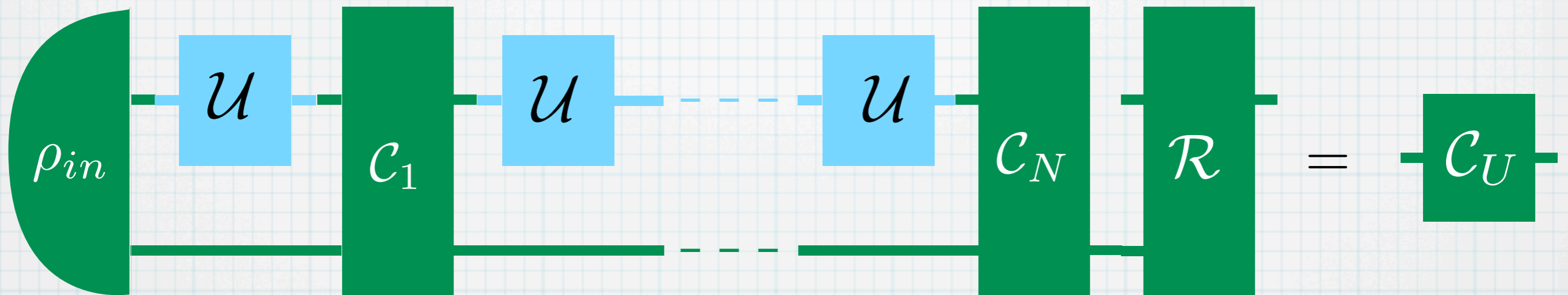


Figure of merit: input-output fidelity

$$F(\mathcal{E}, \hat{\mathcal{E}}) = \int d\varphi F(\mathcal{E}(\varphi), \hat{\mathcal{E}}(\varphi)) \quad F(\rho, \sigma) = \text{Tr} \left[(\rho^{\frac{1}{2}} \sigma \rho^{\frac{1}{2}})^{\frac{1}{2}} \right]$$

Quantum algorithm learning

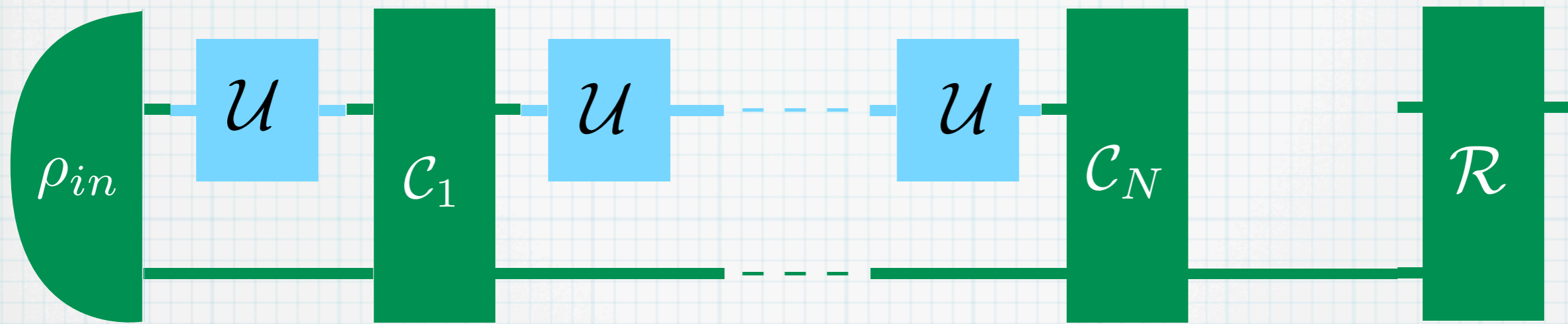
Consider the case where the set of channels is a **group of unitary transformations**.



Assuming a uniform prior for the unknown unitaries, we have the average fidelity

$$F = \int dU \ F(U, \mathcal{C}_U)$$

Quantum algorithm learning



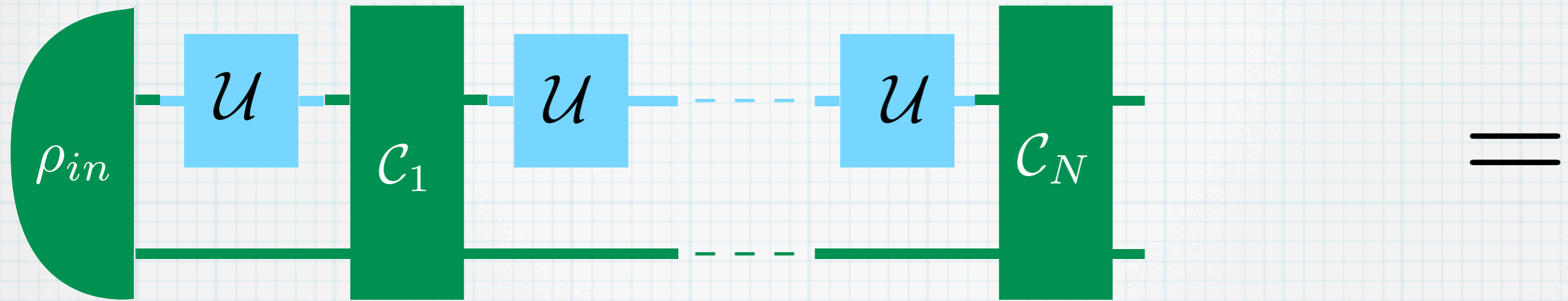
Comb of the learning network: $L = R * C_N * \dots * C_2 * C_1 * \rho_{in}$

Fidelity: $F = \frac{1}{d^2} \int dU \langle\langle U | \langle\langle U^* |^{\otimes N} | L | U \rangle\rangle | U^* \rangle\rangle^{\otimes N}$

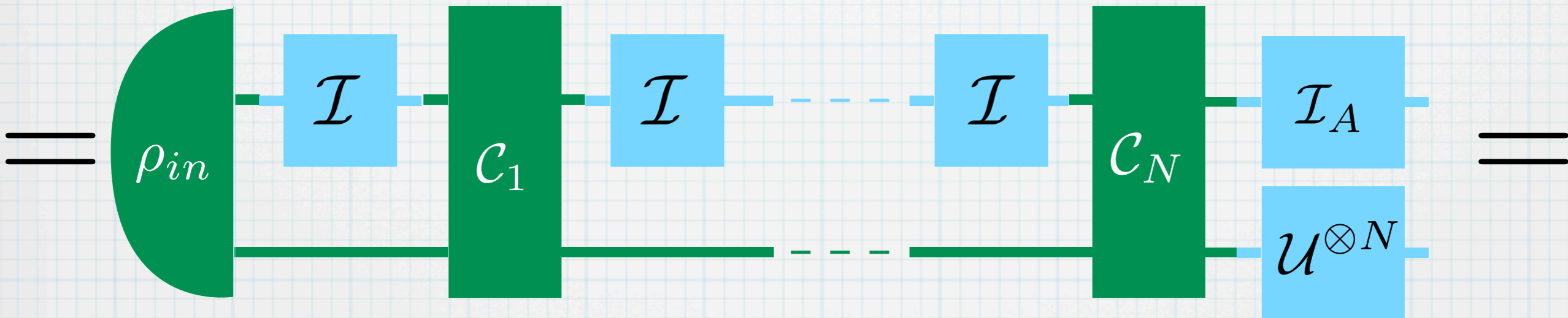
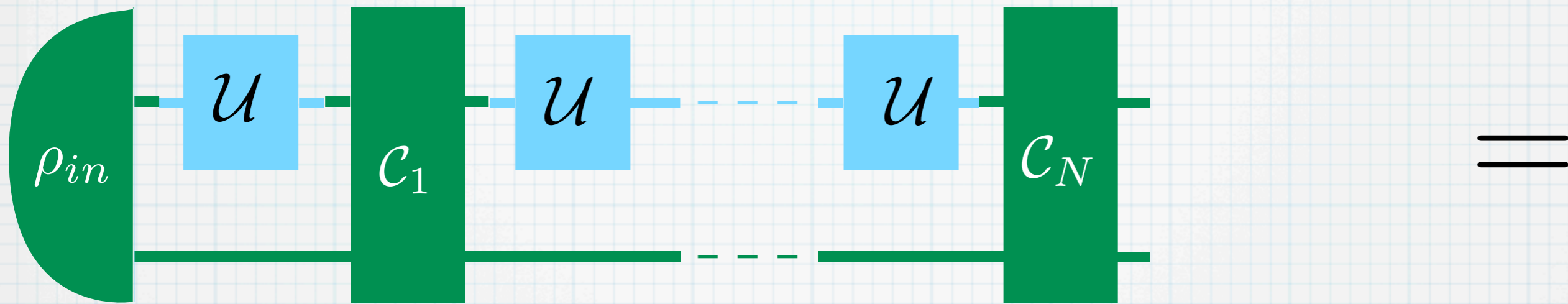
We can always optimize over **covariant combs**:

$$[L, U \otimes V^* \otimes U^{*\otimes N} \otimes V^{\otimes N}] = 0 \quad \forall U, V$$

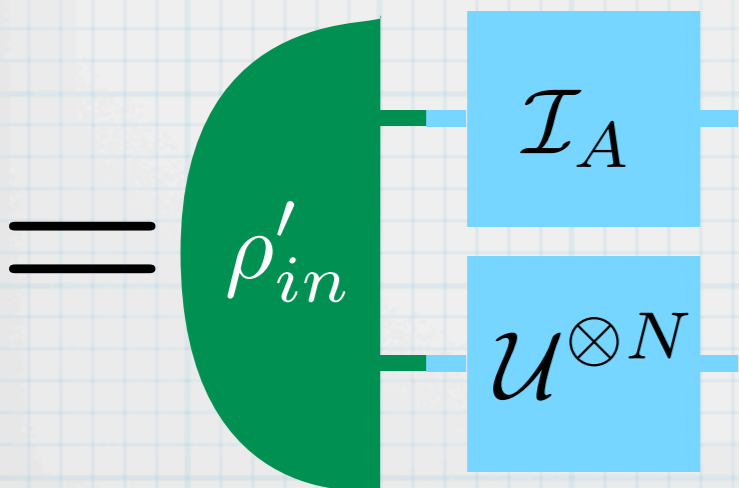
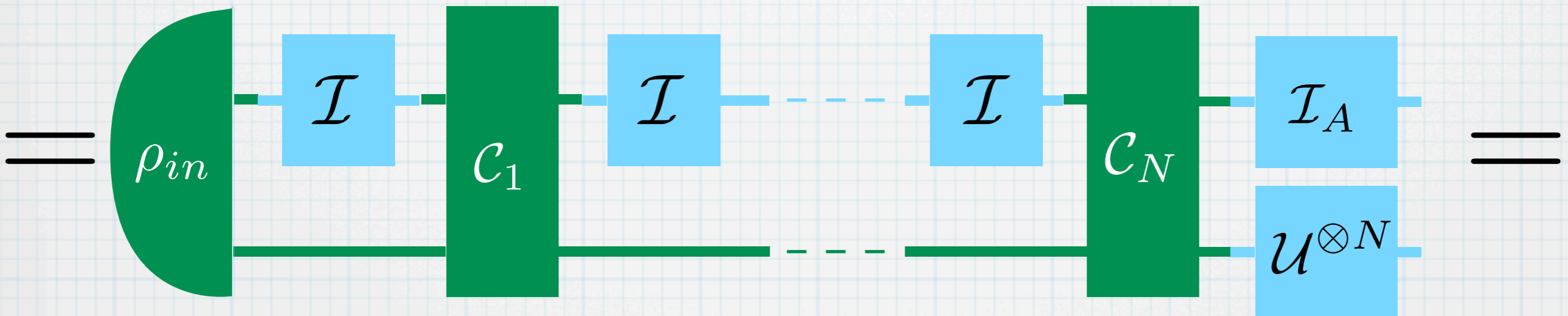
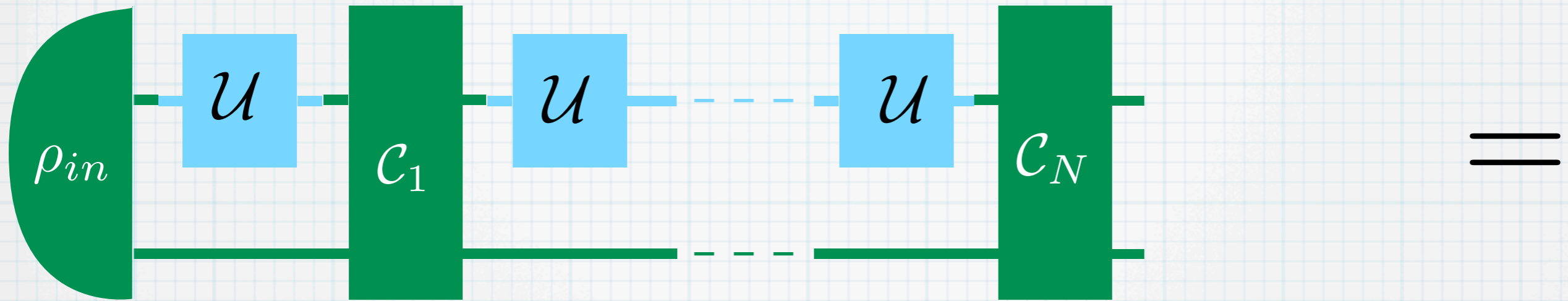
Quantum algorithm learning



Quantum algorithm learning



Quantum algorithm learning



Any covariant network is equivalent to a parallel scheme with ancilla!

Learning can be parallelized, in the same way as estimation

Quantum algorithm learning

Decomposing the unitaries as
$$U^{\otimes N} \otimes I_A = \bigoplus_J (U_J \otimes I_{m_J})$$

one can prove that the optimal input states have the form

$$|\psi\rangle = \bigoplus_J a_J \frac{|I_J\rangle\rangle}{\sqrt{d_J}} \quad a_J \geq 0$$

where $|I_J\rangle\rangle \in \mathcal{H}_J^{\otimes 2}$ is a maximally entangled state

This is the same form of the optimal states for
estimation of the unknown unitary U with N copies

G Chiribella, G M D'Ariano, and M F Sacchi, Phys. Rev. A 72, 043448 (2005).

Quantum algorithm learning

Bisio, Chiribella, D'Ariano, Facchini, Perinotti (unpublished)

Theorem: for any group of unitaries, for an input state of the optimal form

$$|\psi\rangle = \bigoplus_J a_J \frac{|I_J\rangle\rangle}{\sqrt{d_J}} \quad a_J \geq 0$$

the optimal retrieving channel to extract U from the states

$$(U^{\otimes N} \otimes I_A) |\psi\rangle = \bigoplus_J a_J \frac{|U_J\rangle\rangle}{\sqrt{d_J}} \quad a_J \geq 0$$

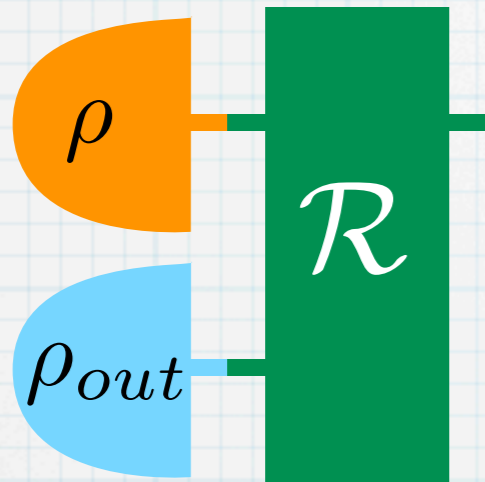
is achieved by a “measure-and-prepare” scheme.

(estimation of the unknown unitary U :

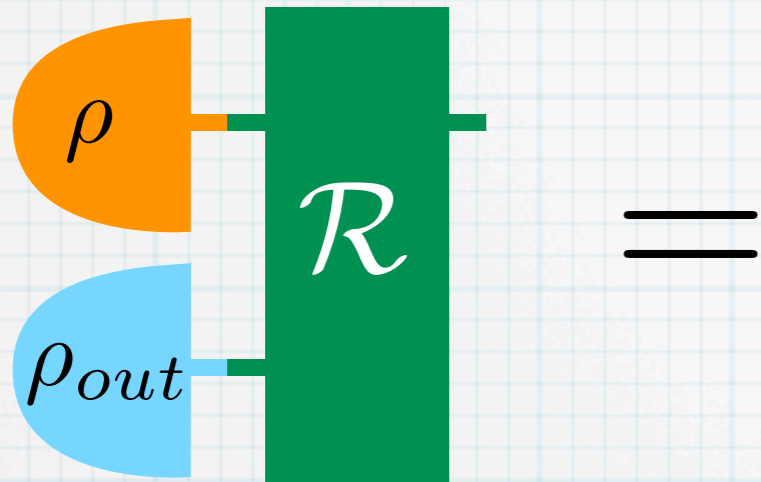
for outcome \hat{U} , just perform the unitary \hat{U})

Quantum algorithm learning

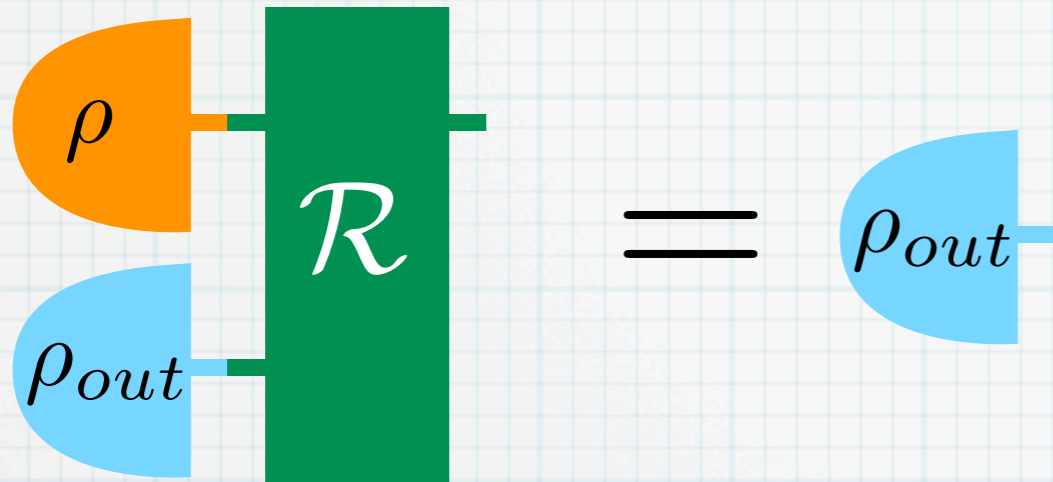
Quantum algorithm learning



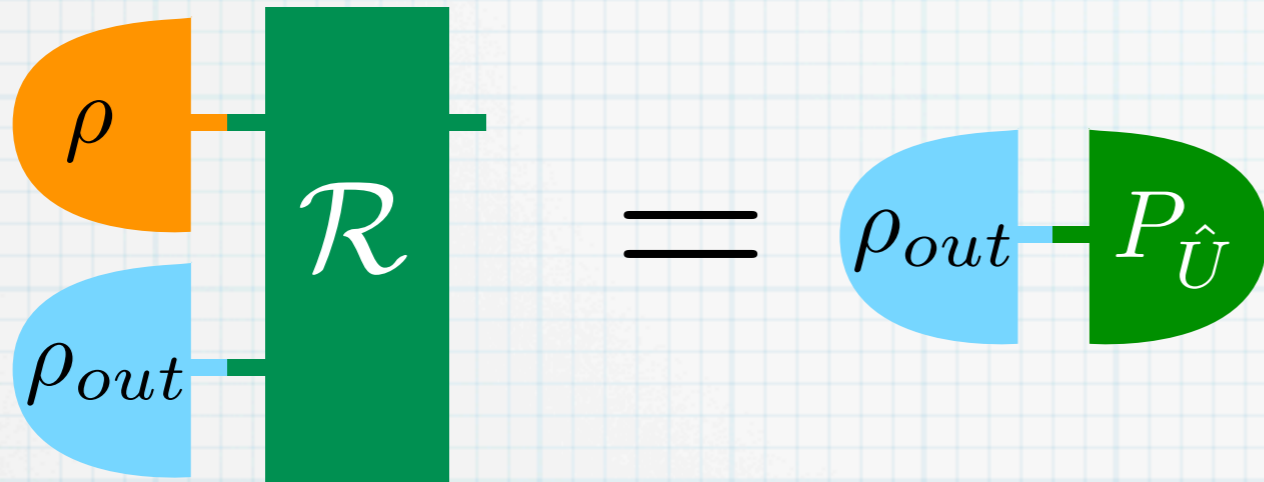
Quantum algorithm learning



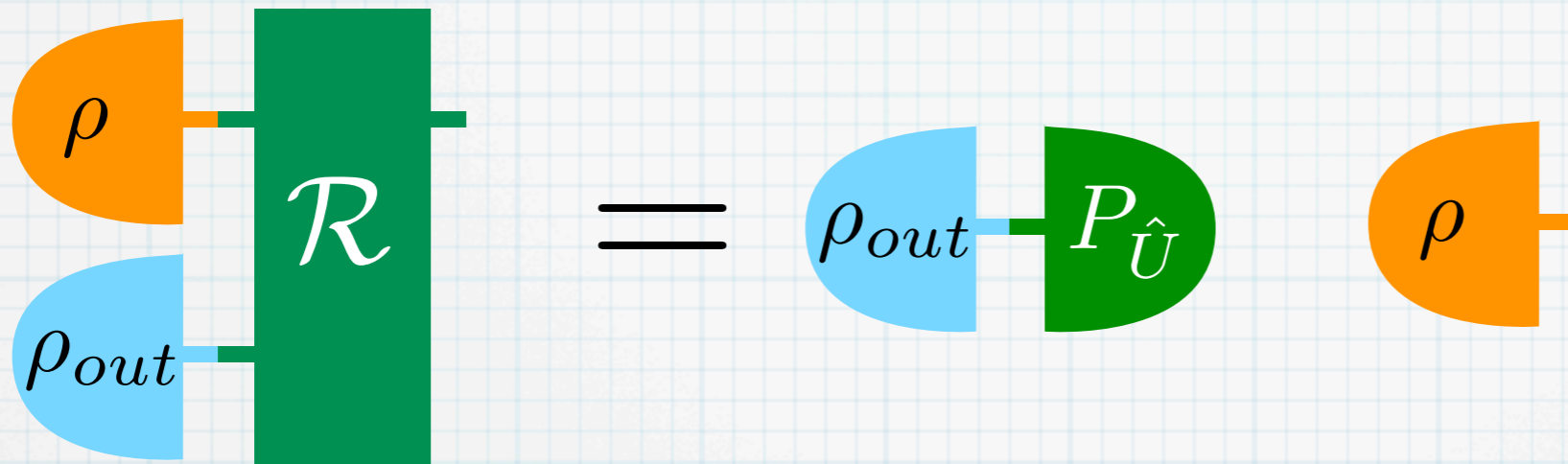
Quantum algorithm learning



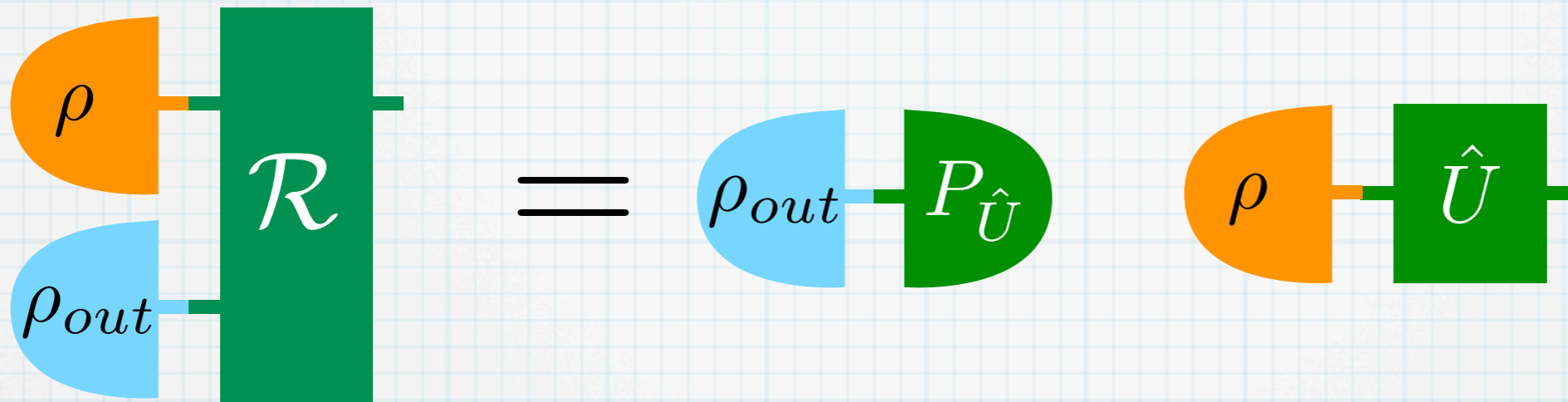
Quantum algorithm learning



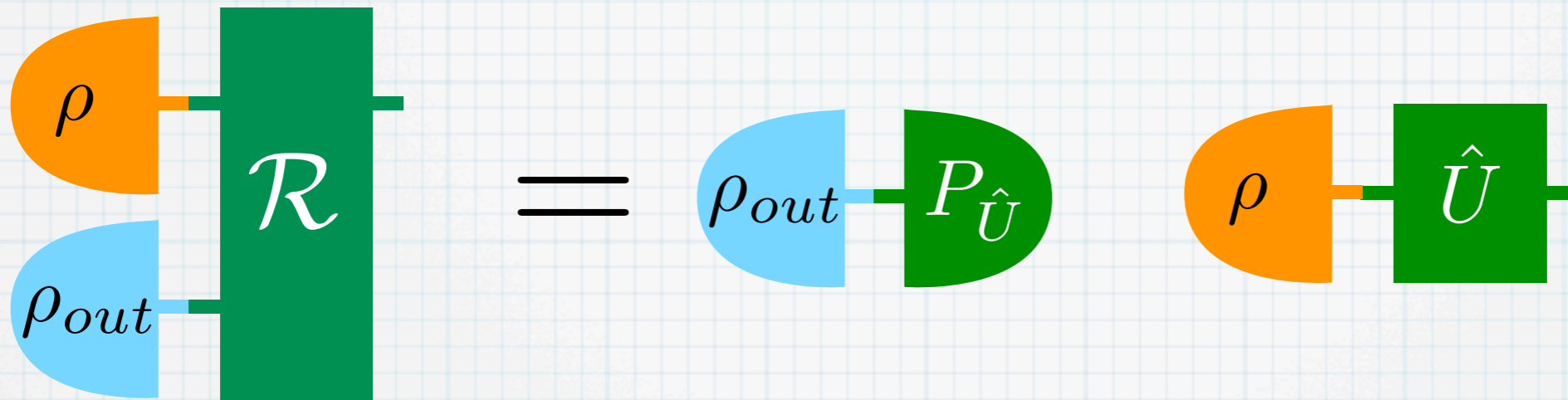
Quantum algorithm learning



Quantum algorithm learning



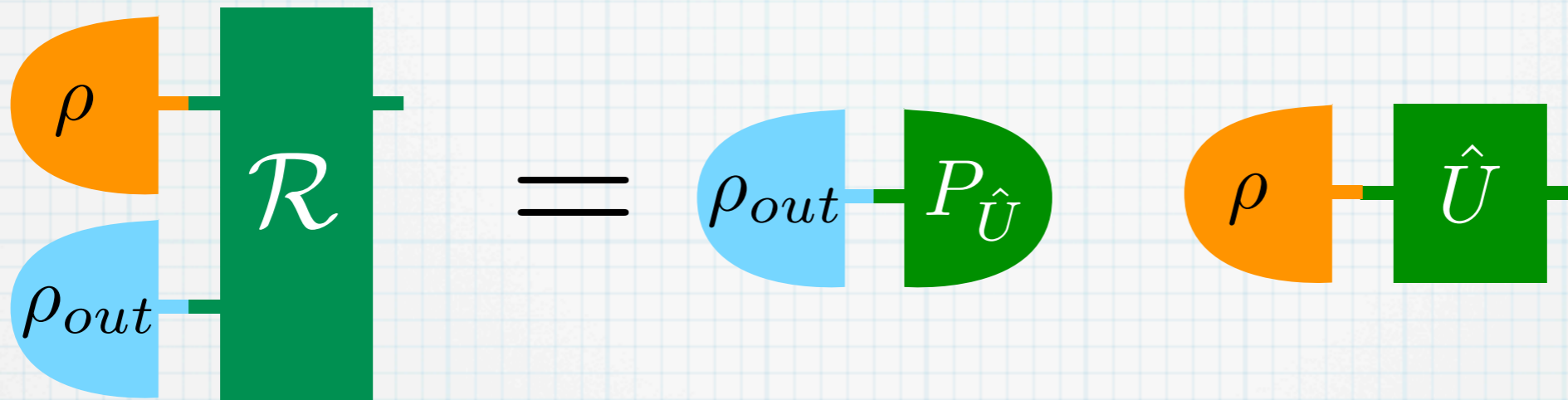
Quantum algorithm learning



Optimal retrieving is “measure-and-prepare”: **no need for quantum memory**. We **can measure** immediately after applying U , and store the outcome \hat{U} in a classical memory.

We can make **as many copies as we want** (a quantum memory is degraded at every access).

Quantum algorithm learning



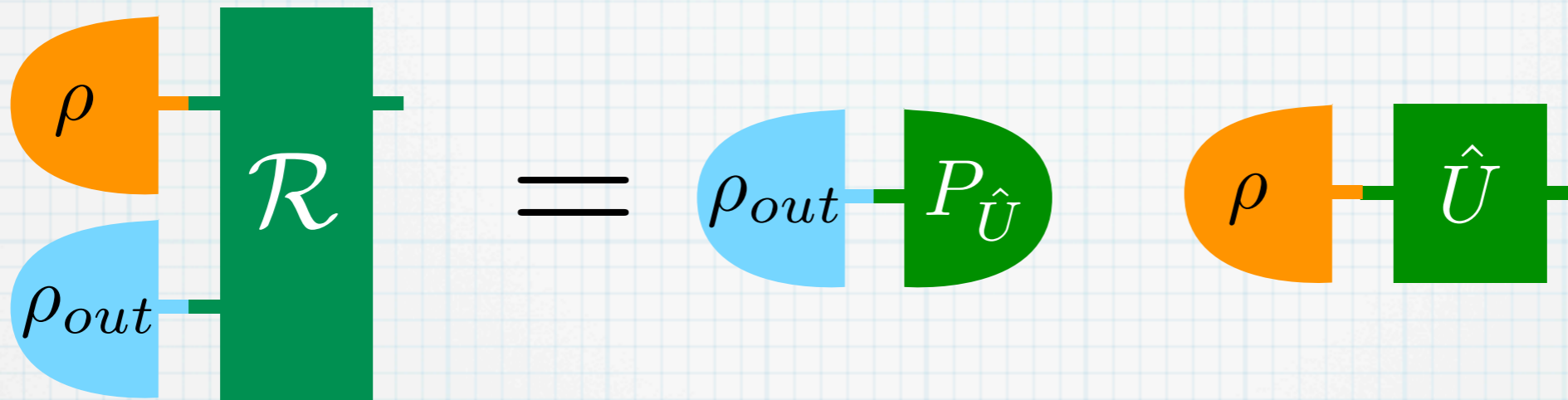
Optimal retrieving is “measure-and-prepare”: **no need for quantum memory**. We **can measure** immediately after applying U , and store the outcome \hat{U} in a classical memory.

We can make **as many copies as we want** (a quantum memory is degraded at every access).

Parallel scheme + measure&reprepare still optimal for:

- N non-identical input unitaries (and/or non-identical target unitaries)
- perform the inverse of U : target U^\dagger (error correction with correlated noise)

Quantum algorithm learning



Optimal retrieving is “measure-and-prepare”: **no need for quantum memory**. We **can measure** immediately after applying U , and store the outcome \hat{U} in a classical memory.

We can make **as many copies as we want** (a quantum memory is degraded at every access).

Parallel scheme + measure&reprepare still optimal for:

- N non-identical input unitaries (and/or non-identical target unitaries)
- perform the inverse of U : target U^\dagger (error correction with correlated noise)

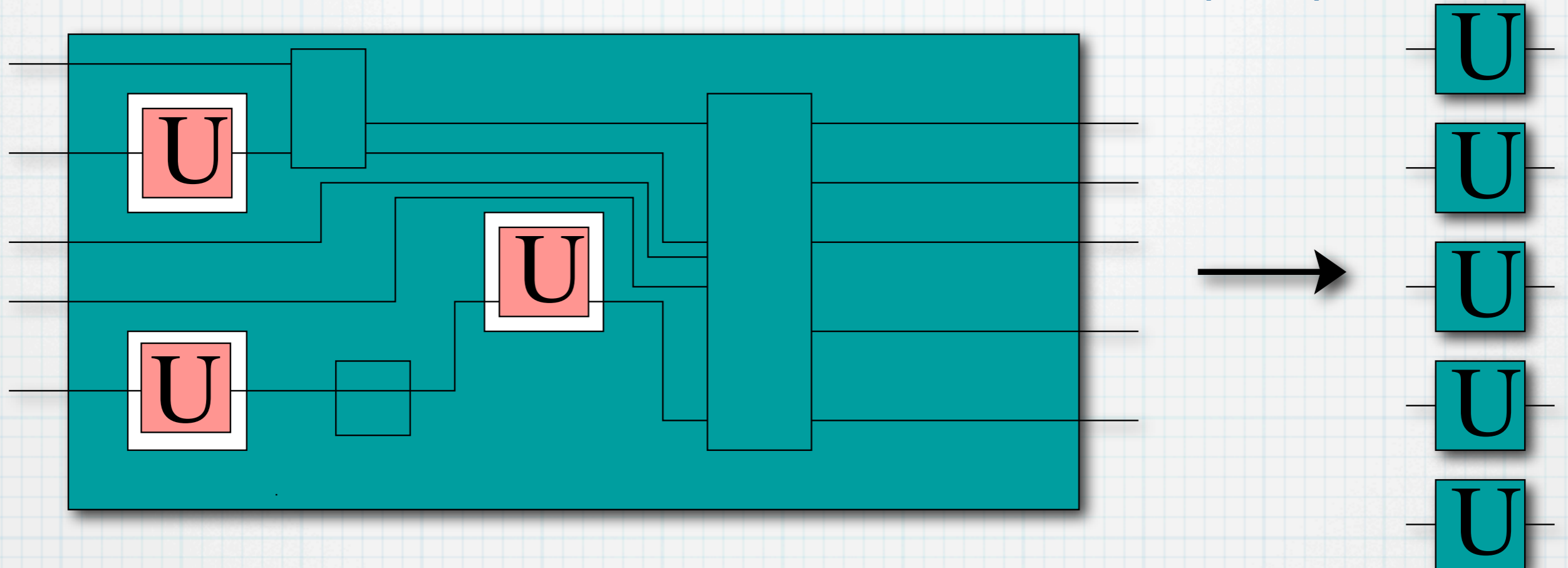
not necessarily optimal for

- learning general channels
- learning unitaries that do not form a group
- learning with restrictions on the available input states (entanglement)

Application 4: Optimal cloning of unitaries

Cloning of unitaries

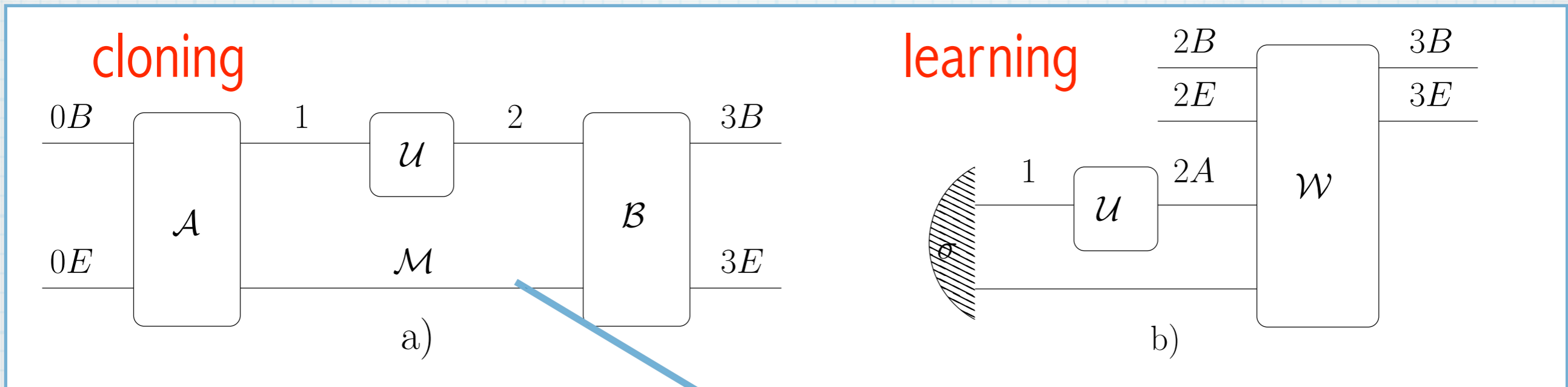
G. Chiribella, G. M. D'Ariano, P. Perinotti PRL **101** 180504 (2008)



$$F = \int dU F(\mathcal{T}_U^{(N)}, \mathcal{T}_U^{\otimes N}) \quad (\text{channel fidelity})$$

Cloning of unitaries

Chiribella, D'Ariano, Perinotti, PRL **101** 180504 (2008)



1-to-2 cloning

$$F = \frac{d + \sqrt{d^2 - 1}}{d^3} > F_{est} = \frac{6}{d^4} \quad (d \neq 2)$$

(same for learning)

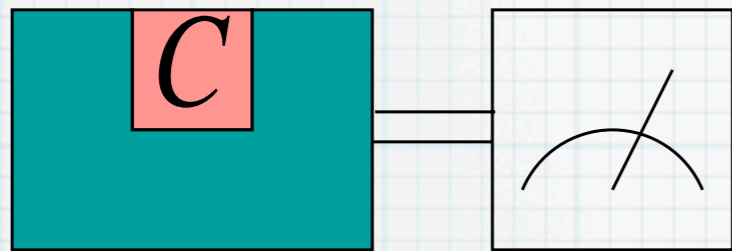
Much better than cloning states $(I \otimes U)|I\rangle\rangle \longrightarrow$ q-learning

Applying U to a state “degrades” U

Cloning unitaries is harder than cloning states (cryptography with information encoded on transformations is more secure)

Application 5: Optimal quantum tomography

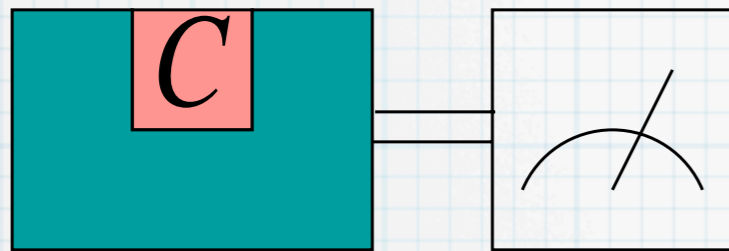
Optimal tomographers



(d^4 outcomes)

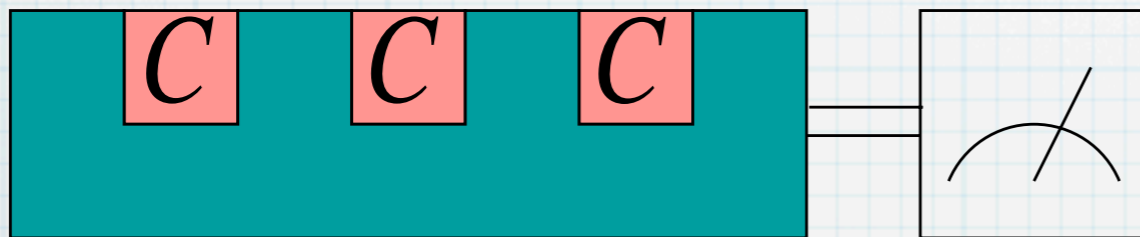
Informationally
complete tester

Optimal tomographers



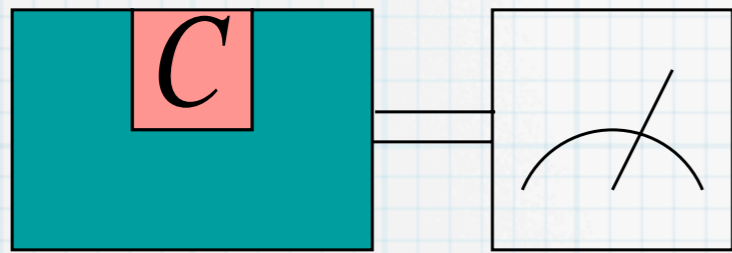
(d^4 outcomes)

Informationally
complete tester



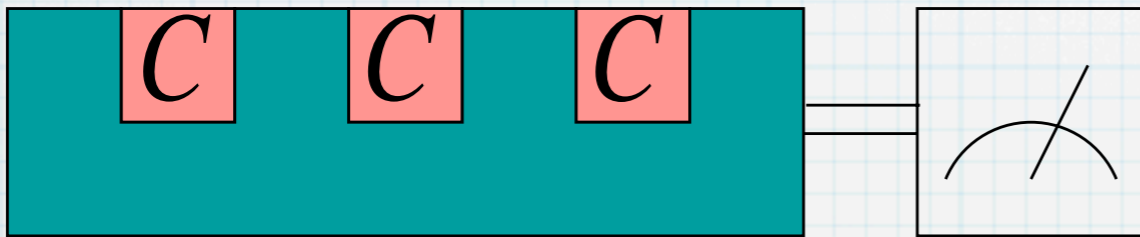
multiple uses

Optimal tomographers

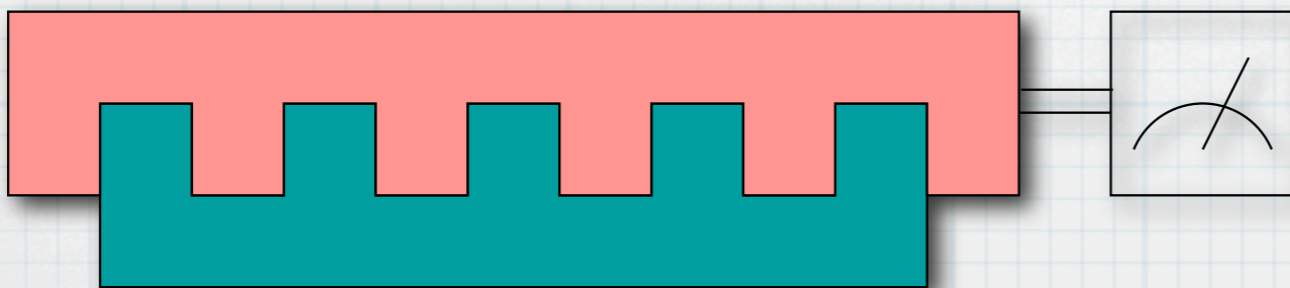


(d^4 outcomes)

Informationally
complete tester



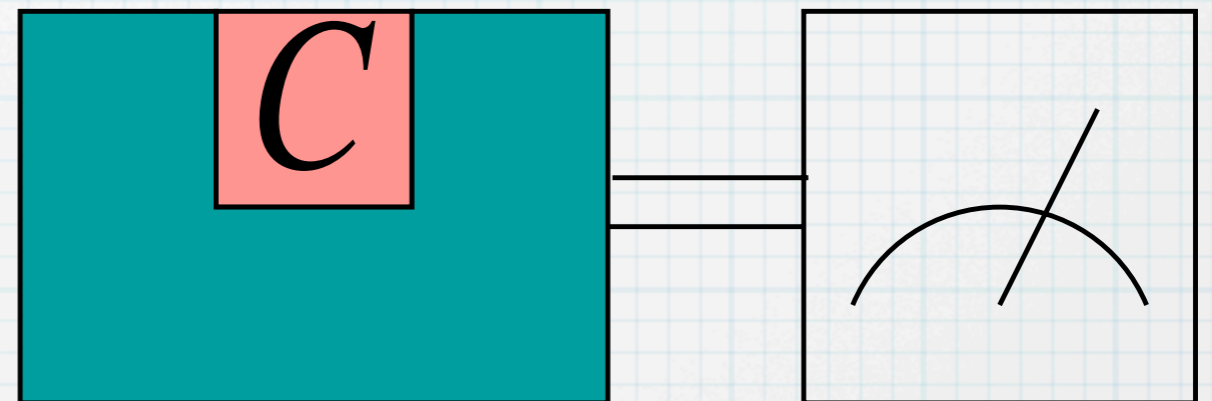
multiple uses



circuit board tomographer

Optimal tomography

Use **different in and out dimensions** to unify: states, channels, and POVMs



A. Bisio, G. Chiribella, G. M. D'Ariano, S. Facchini, P. Perinotti PRL 102 010404 (2009)

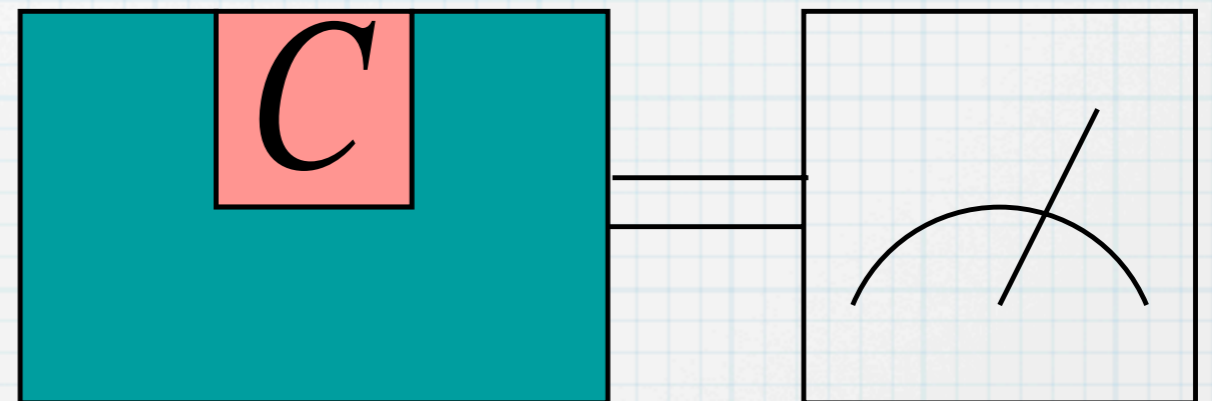
Optimal tomography

🔊 **Prior distribution** of channels corresponding to the depolarizing average channel

🔊 **Cost function** = representation, (equally weighted orthonormal set of operators)

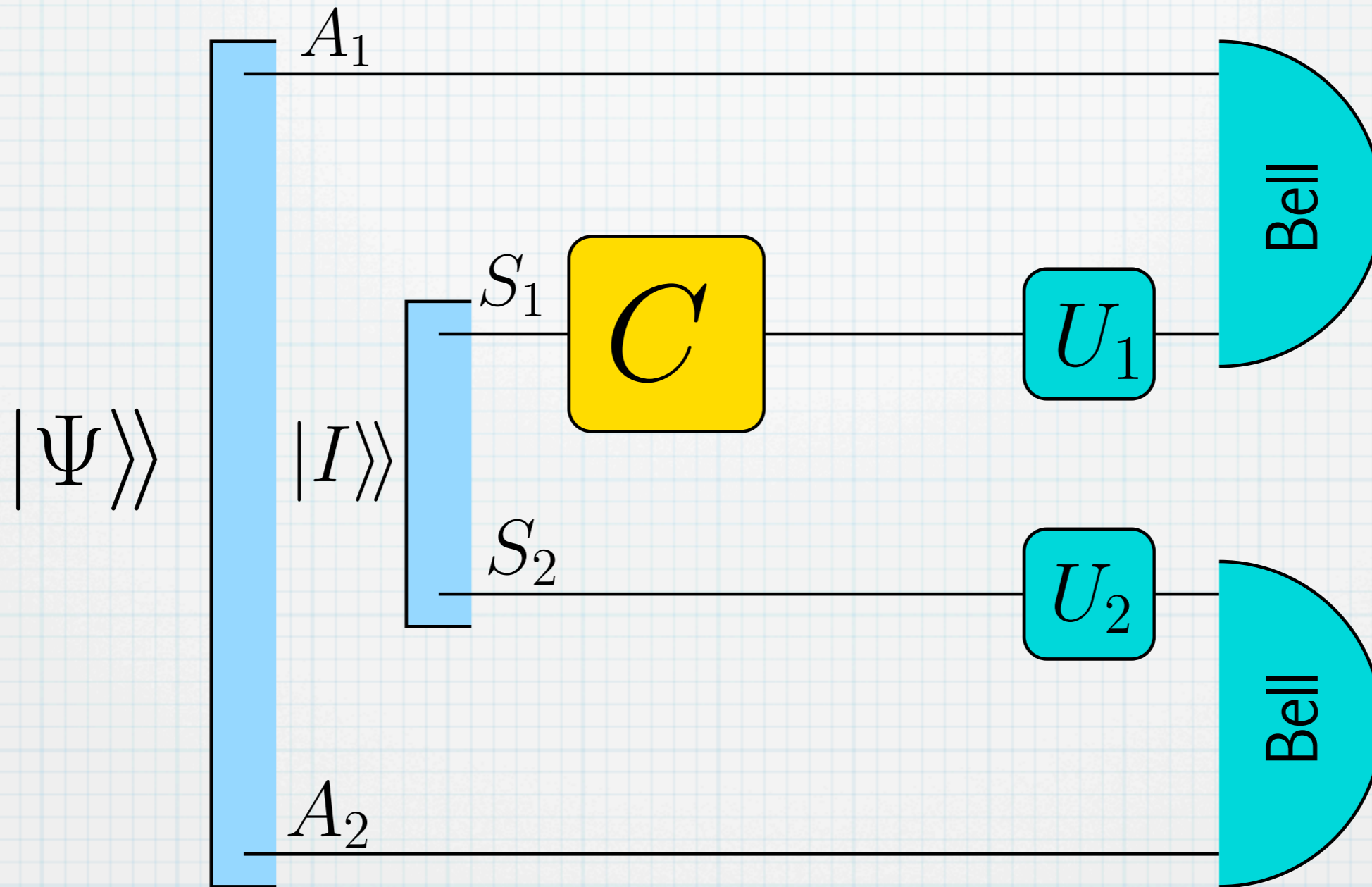
🔊 Further selection:
1) quantum operations,
2) channels,
3) unital channels

Use **different in and out dimensions** to unify: states, channels, and POVMs



A. Bisio, G. Chiribella, G. M. D'Ariano, S. Facchini, P. Perinotti PRL 102 010404 (2009)

Optimal tomography



$$\Psi = [d^{-1}(1 - \beta)I + \beta |\psi\rangle \langle \psi|]^{\frac{1}{2}}$$

$\beta = \sqrt{(d+1)/(d^2+1)}$ quantum operations

$\beta = [(d-1)(2 + \sqrt{2}(d^2-1))]^{-1/2}$ channels


$\beta = 0$ unital channels


Conclusions


PRL **101** 060401 (2008)
PRL **101** 180501 (2008)
PRL **101** 180504 (2008)
PRL **102** 010404 (2009)
EL **83** 30004 (2008)

Conclusions

PRL **101** 060401 (2008)
 PRL **101** 180501 (2008)
 PRL **101** 180504 (2008)
 PRL **102** 010404 (2009)
 EL **83** 30004 (2008)


- 
 New Quantum Estimation Theory, with multiple copies, and optimization of the setup \rightarrow optimization of quantum circuits architecture, engineering high-precision operations

- 
 Quantum circuit board = **quantum comb** = supermap


- 
 Comb algebra (link-product)

- 
Convex optimization method


- 
 Applications:

- 
 discrimination/estimation of unitaries and memory channels (optimal quantum oracle-calling algorithms)

- 
 quantum protocols

- 
 quantum-algorithm learning = storing undisclosable unitaries

- 
 cloning undisclosable unitaries

- 
 process tomography