Title: Lecture - Causal Inference, PHYS 777

Speakers: Robert Spekkens

Collection/Series: Causal Inference (Elective), PHYS 777, March 31 - May 2, 2025

Subject: Quantum Foundations

Date: April 01, 2025 - 11:30 AM

URL: https://pirsa.org/25040036

Causal Inference: Classical and Quantum

Lecturer: Robert Spekkens
PSI fellow: Bindiya Arora
TA: Marina Maciel Ansanelli

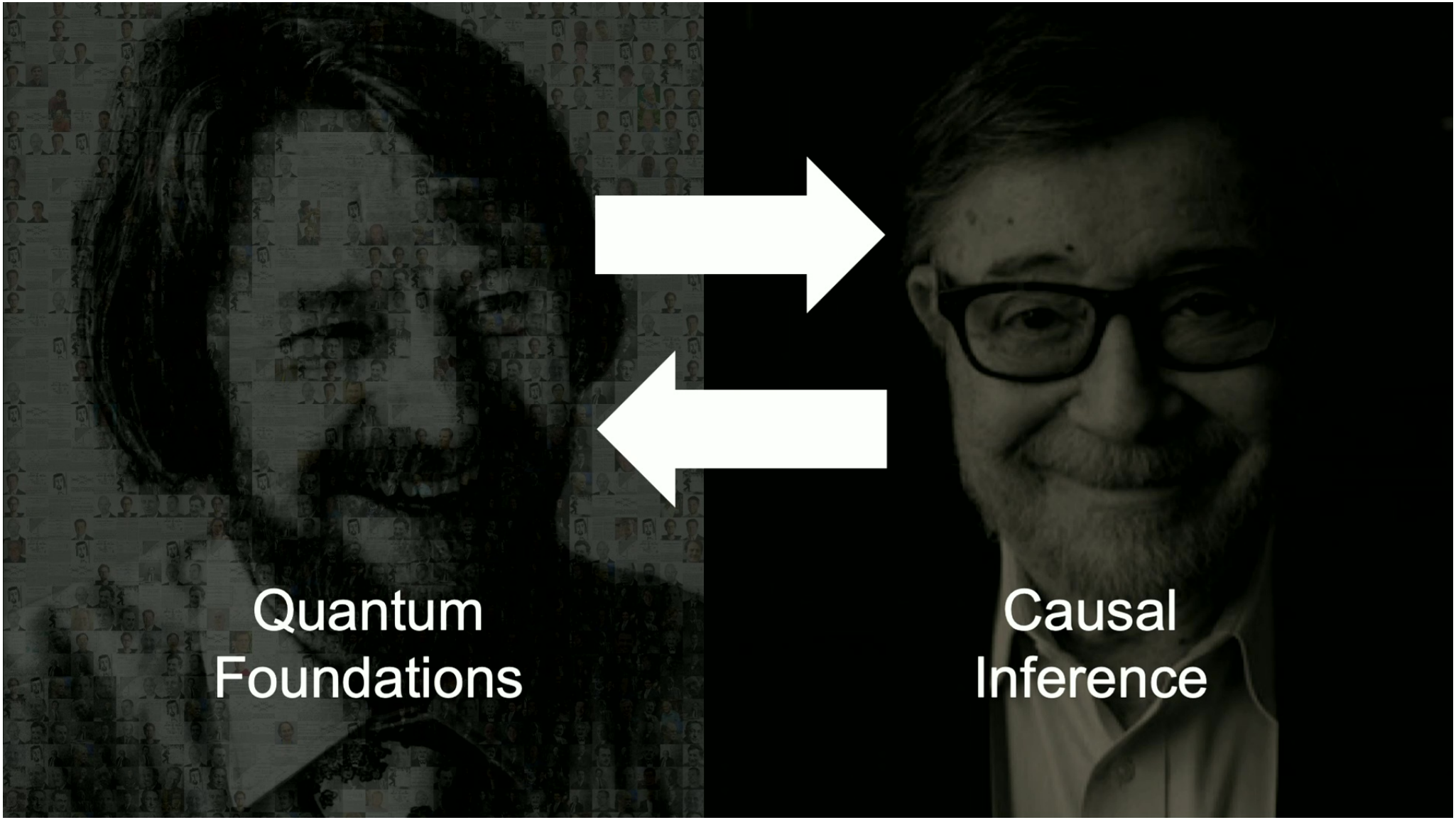
April 1, 2025

Causarum Investigatio
“Investigate the causes”


CAUSALITY
MODELS, REASONING, AND INFERENCE
JUDEA PEARL
Causation, Prediction, and Search
second edition
Peter Spirtes, Clark Glymour, and Richard Scheines
CAUSAL INFERENCE IN STATISTICS
A Primer
Judea Pearl
Madelyn Glymour
Nicholas P. Jewell
WILEY
Jonas Peters, Dominik Janzing, and Bernhard Schölkopf
Elements of Causal Inference
Foundations and Learning Algorithms
EXPLANATION IN CAUSAL INFERENCE
Methods for Mediation and Interaction
TYLER J. VANDERWEELE
OXFORD
CAUSAL INFERENCE
FOR
STATISTICS, SOCIAL, AND BIOMEDICAL SCIENCES
AN INTRODUCTION
GUIDO W. IMBENS
DONALD B. RUBIN
ICSA Book Series in Statistics
Hua He
Pan Wu
Ding-Geng (Din) Chen Editors
Statistical Causal Inferences and Their Applications in Public Health Research
Springer
ANALYTICAL METHODS FOR SOCIAL RESEARCH
Counterfactuals and Causal Inference
Methods and Principles for Social Research
SECOND EDITION
STEPHEN L. MORGAN
CHRISTOPHER WINSHIP

“statisticians are invariably motivated by causal questions but the peculiar nature of these questions is that they cannot be answered, or even articulated, in the traditional language of statistics.
[…]
causation is not merely an aspect of statistics; it is an addition to statistics, an enrichment that allows statistics to uncover workings of the world that traditional methods cannot”

From: J. Pearl, M. Glymour and N. Jewell, ‘Causal Inference in Statistics’


Quantum
Foundations
Causal
Inference

Simpson’s paradox in statistics and its causal resolution

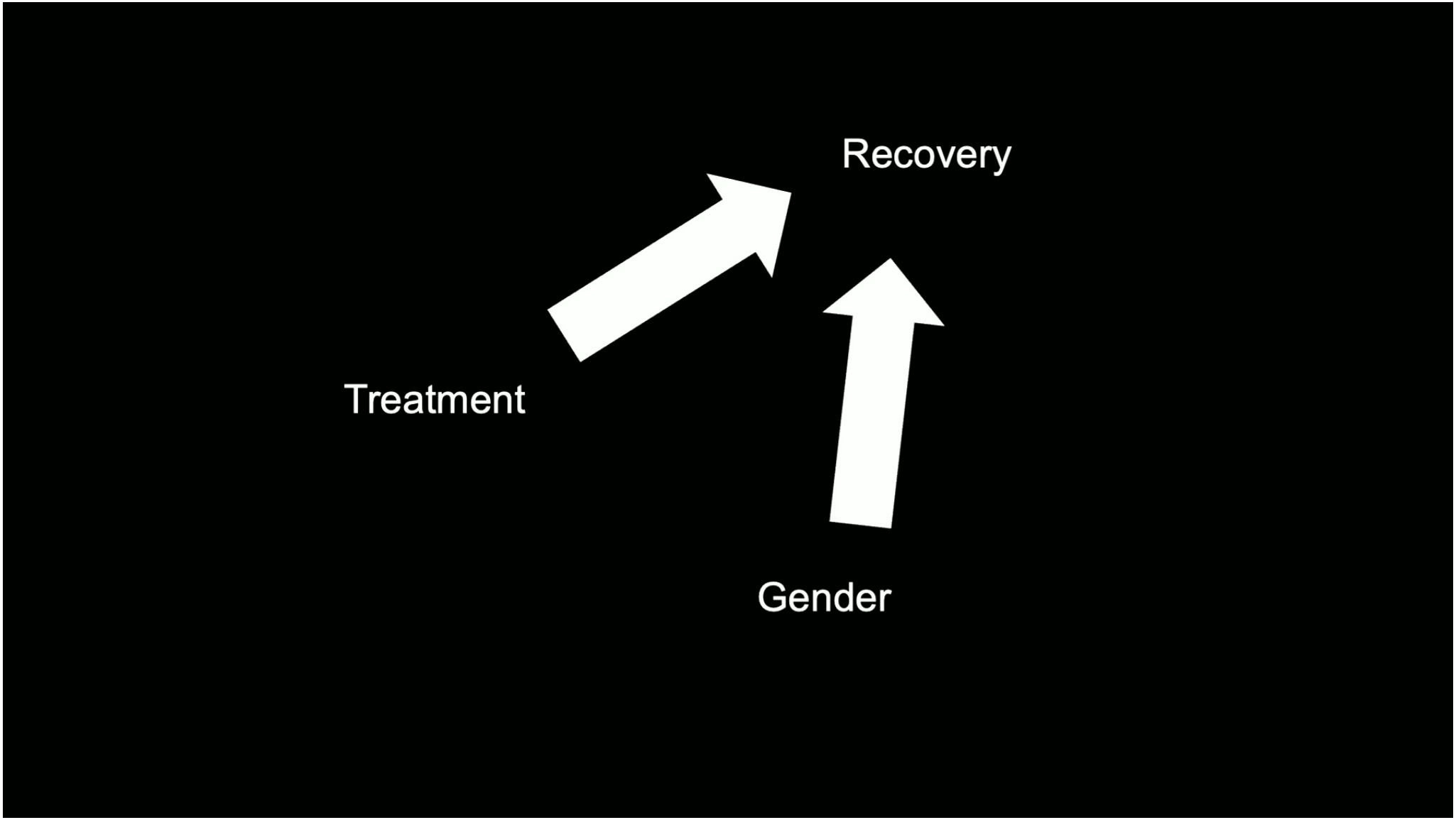
$$P(\text{recovery} \mid \text{drug}) > P(\text{recovery} \mid \text{no drug})$$

$$P(\text{recovery} \mid \text{drug, male}) < P(\text{recovery} \mid \text{no drug, male})$$

$$P(\text{recovery} \mid \text{drug, female}) < P(\text{recovery} \mid \text{no drug, female})$$

Recovery probability

	drug	no drug
male	180/300 = 60%	70/100 = 70%
female	20/100 = 20%	90/300 = 30%
combined	200/400 = 50%	160/400 = 40%


Recovery
Treatment
Gender

$$P(\text{recovery} \mid \text{drug}) > P(\text{recovery} \mid \text{no drug})$$

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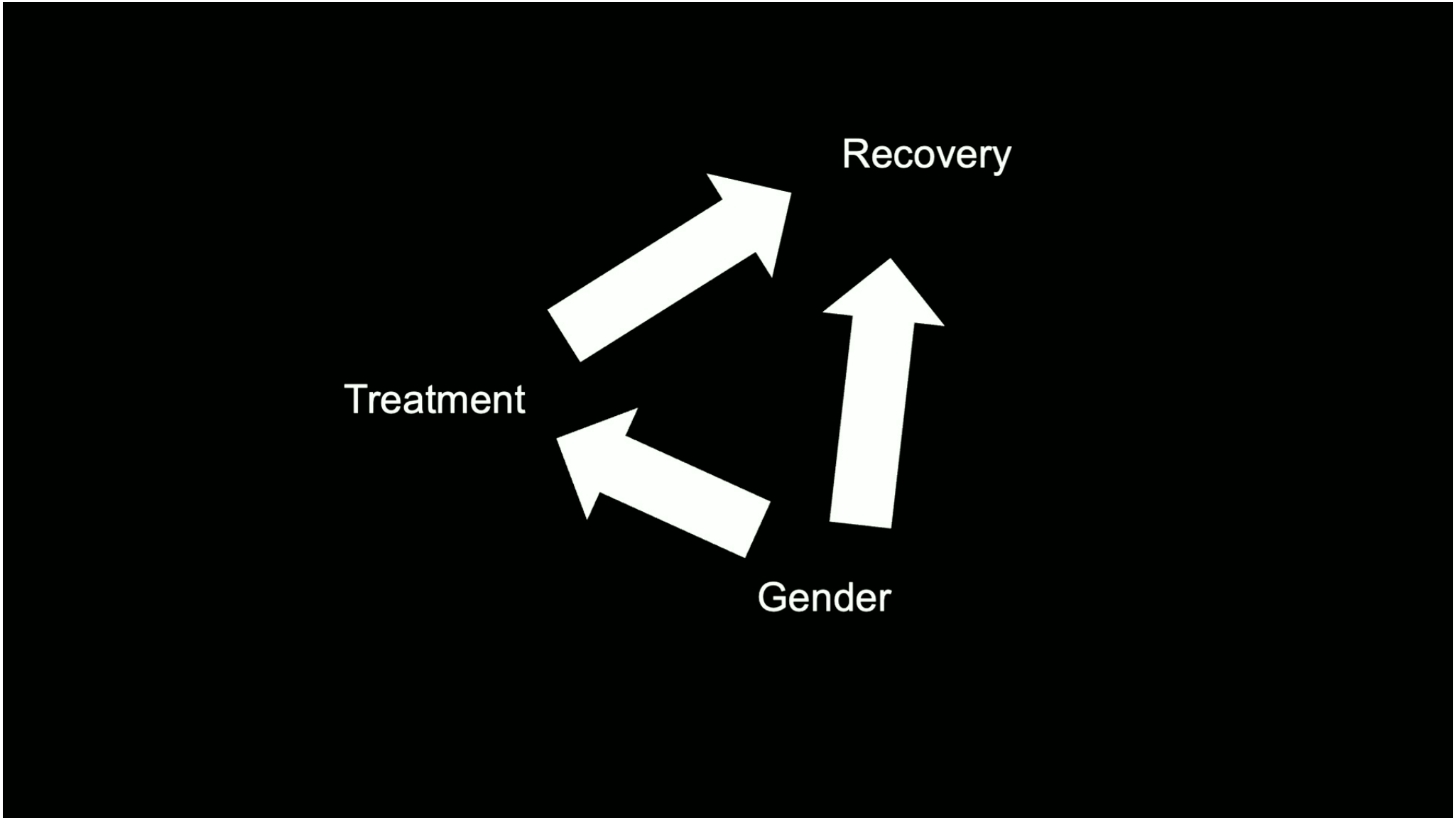
Recovery
Treatment
Gender

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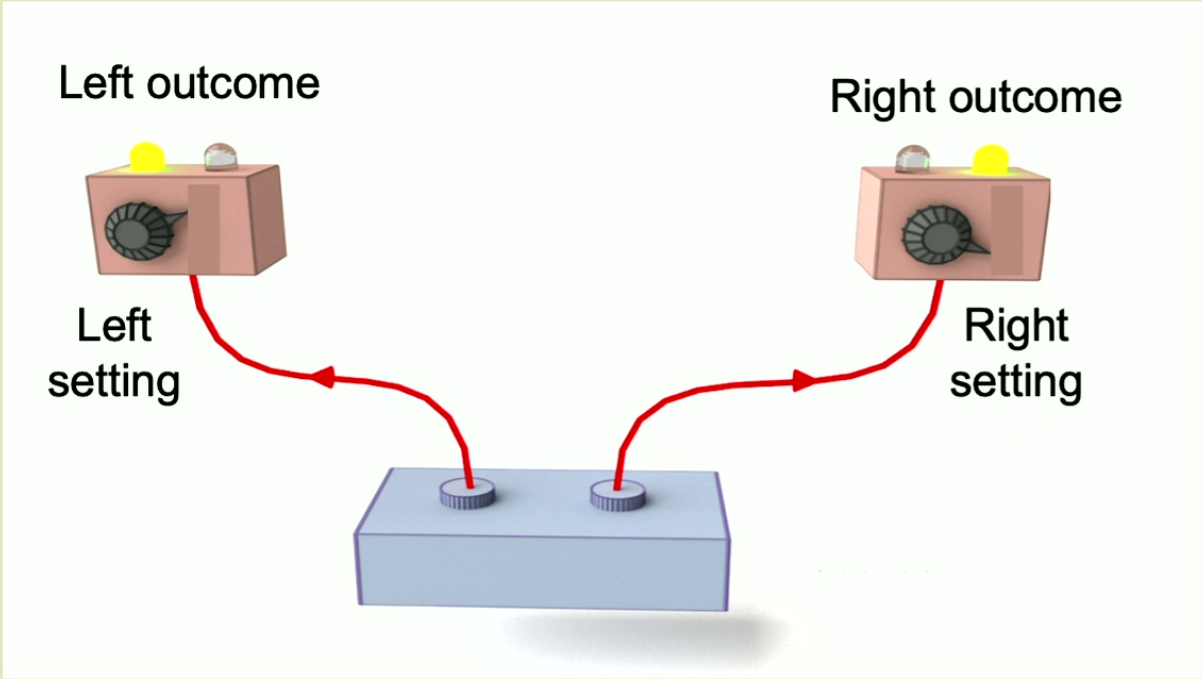
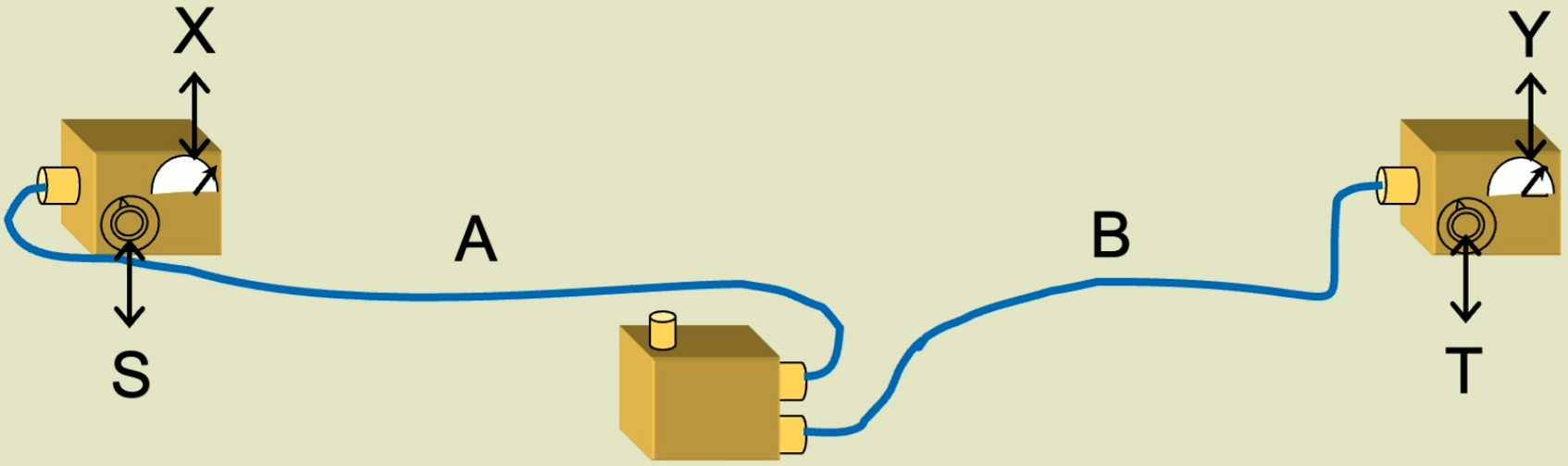
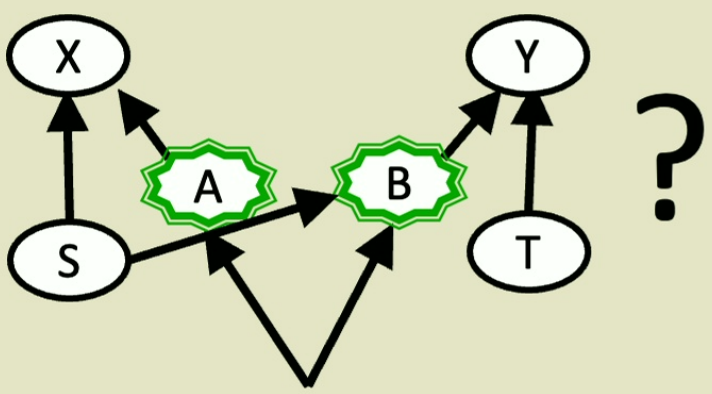
combined	200/400 = 50%	160/400 = 40%

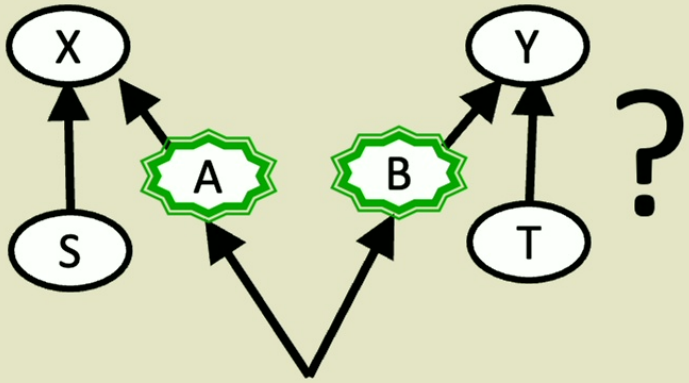
The Einstein-Podolsky-Rosen paradox in quantum theory


Left outcome
Right outcome
Left
setting
Right
setting

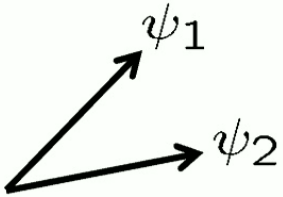
Left setting and Right setting	Left outcome and Right outcome: 0 and 0	0 and 1	1 and 0	1 and 1
0 and 0	50%	0%	0%	50%
0 and 1	25%	25%	25%	25%
1 and 0	25%	25%	25%	25%
1 and 1	50%	0%	0%	50%


X
Y
A
B
S
T


X
Y
A
B
S
T
?

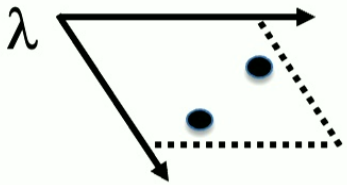

X
Y
A
B
S
T
?

ψ is ontic



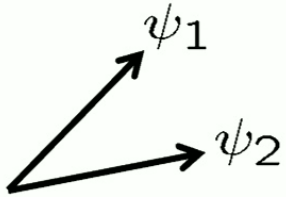
= two different ways the world could be

Example:



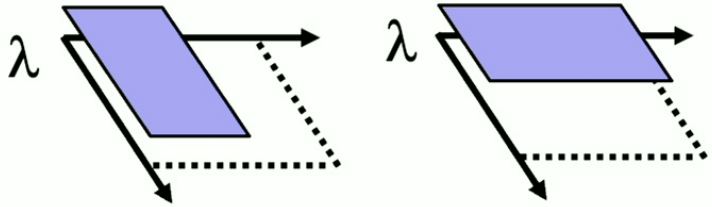
VS.

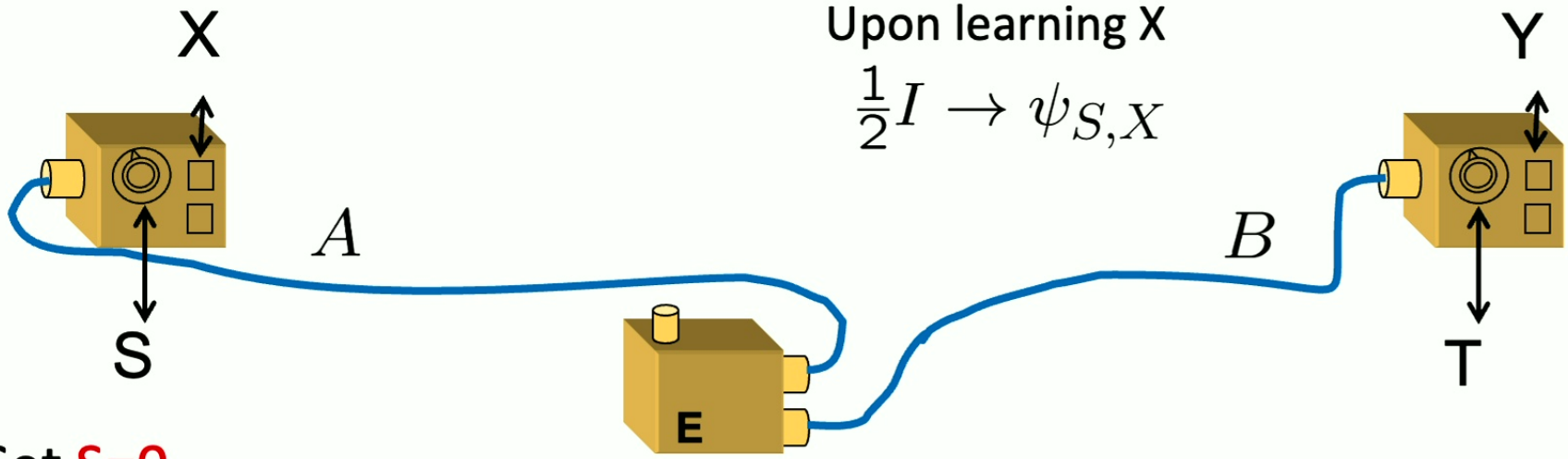
ψ is epistemic



= two different ways of having incomplete information about the world

Example:

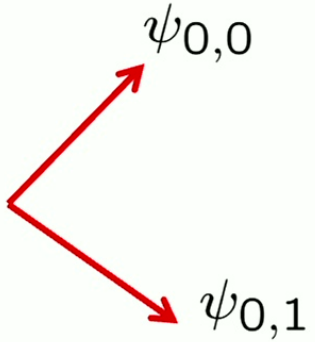




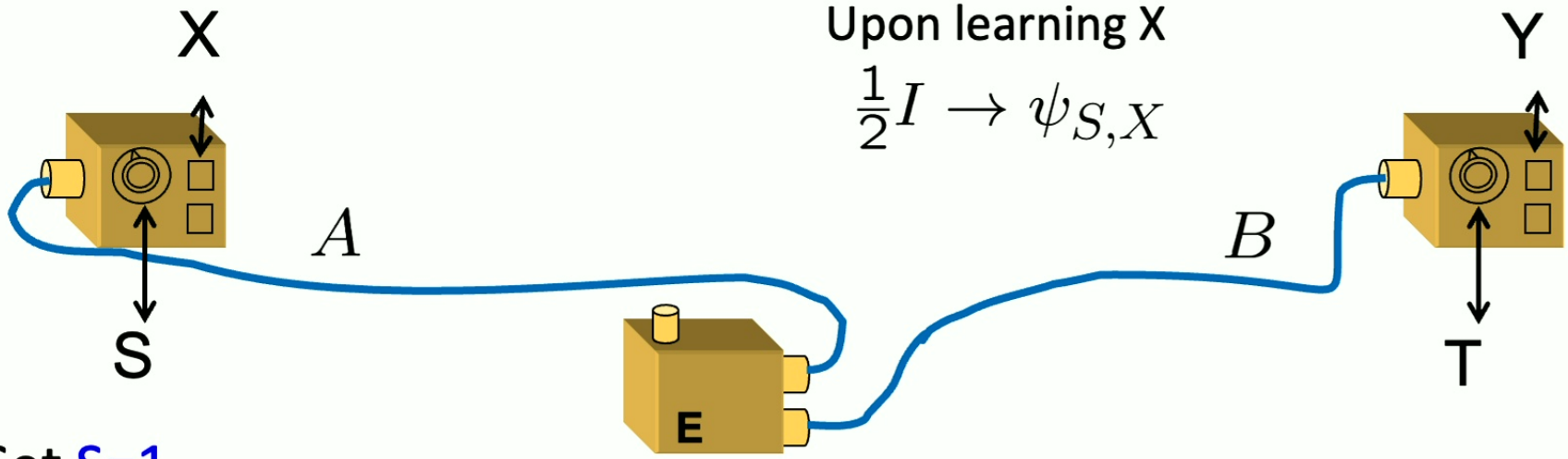
Set S=0

get X=0 $\quad \frac{1}{2}I \to \psi_{0,0}$

get X=1 $\quad \to \psi_{0,1}$



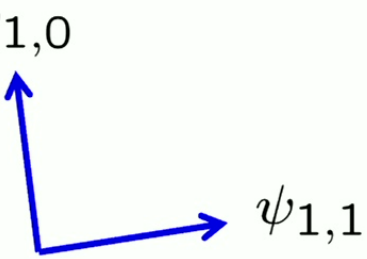
Pauli Z



Set S=1

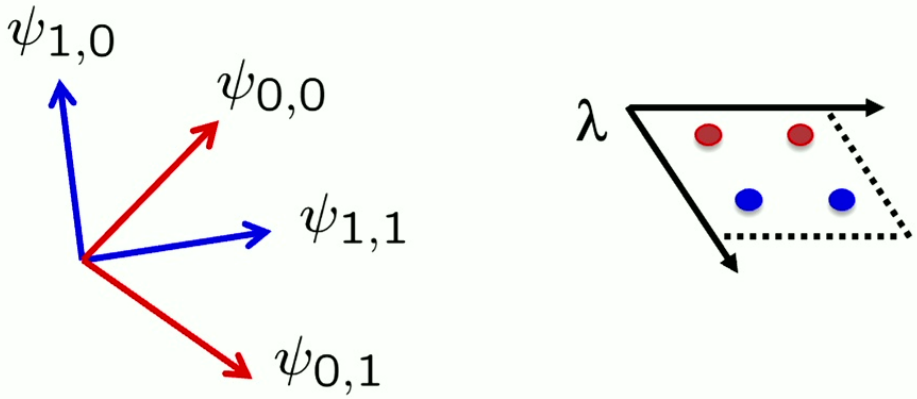
get X=0 $\quad \frac{1}{2}I \to \psi_{1,0}$

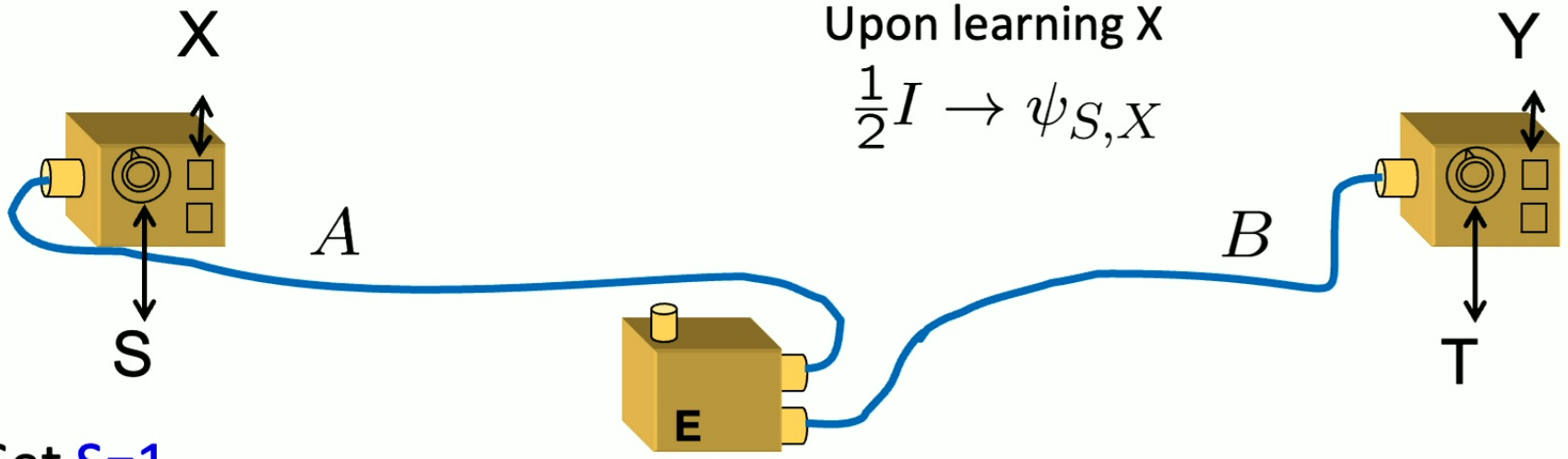
get X=1 $\quad \to \psi_{1,1}$



Pauli X

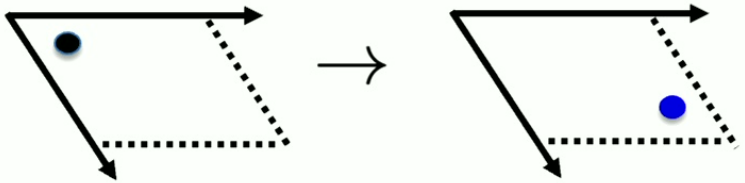
ψ is ontic



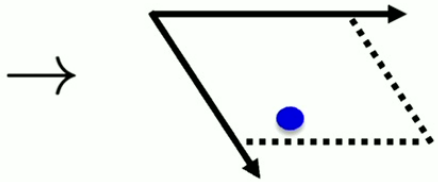


Set S=1

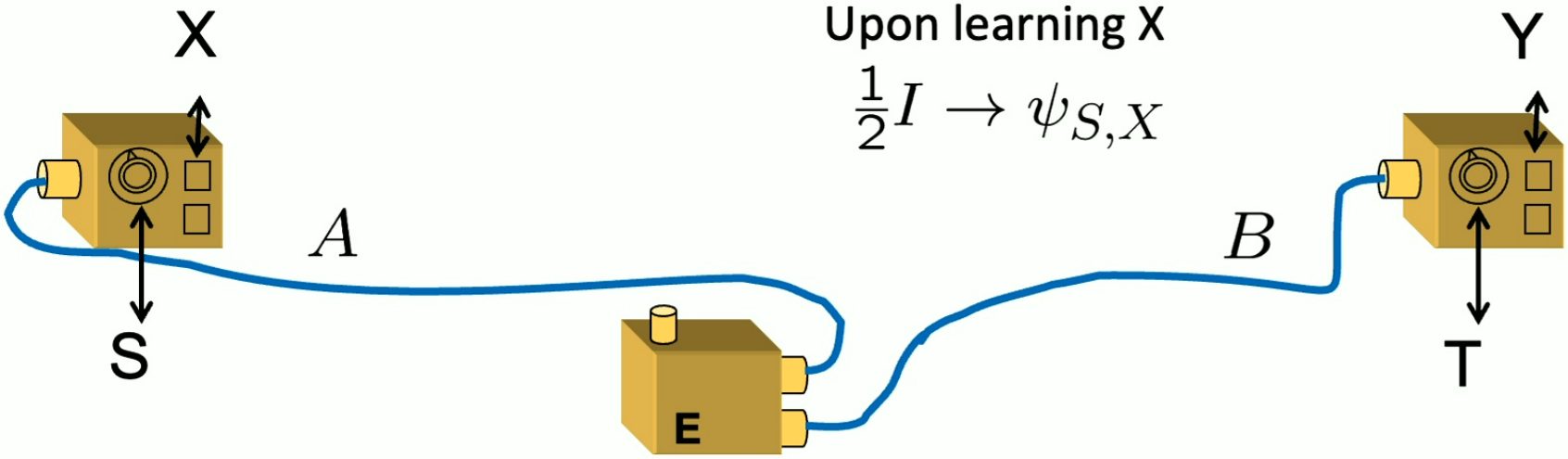
get X=0

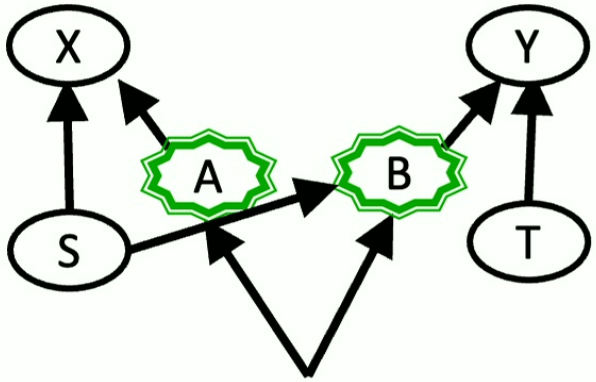


get X=1



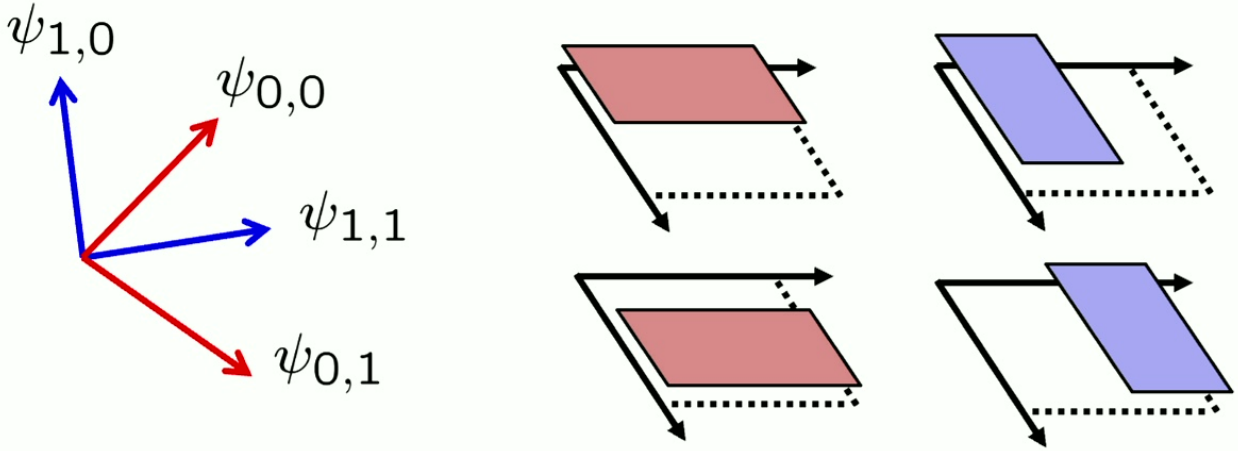
Like “treatment influences recovery”

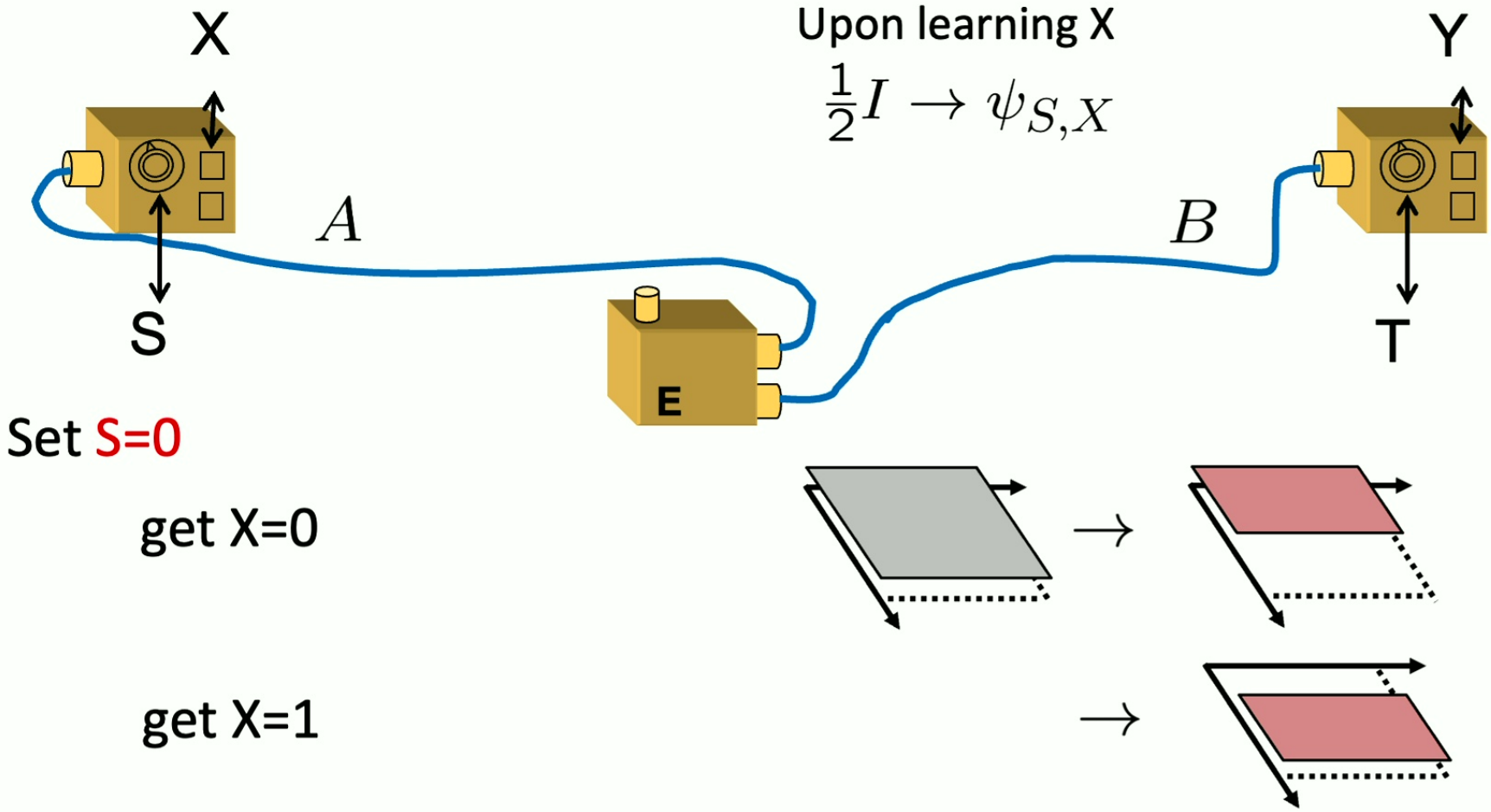


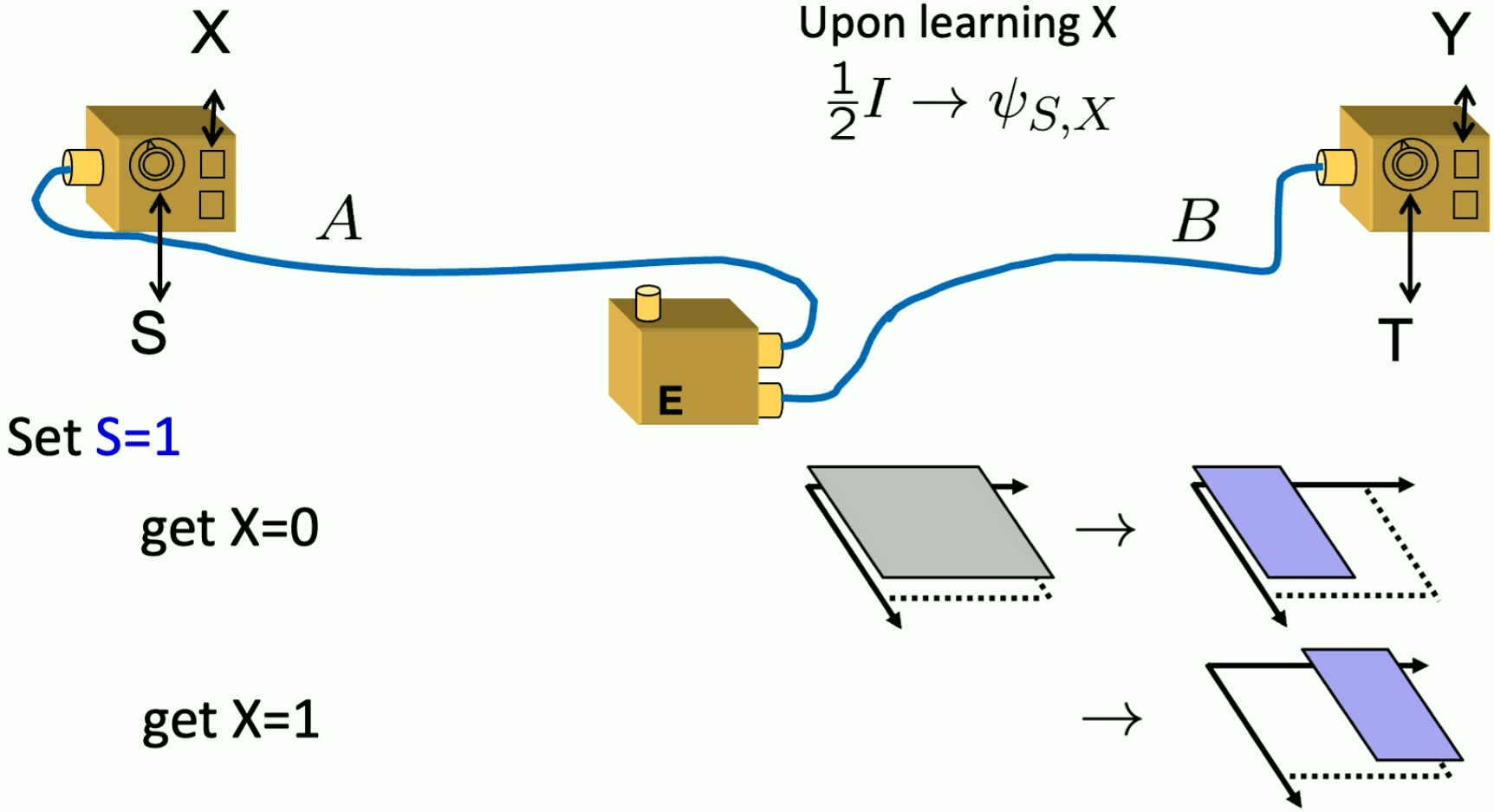


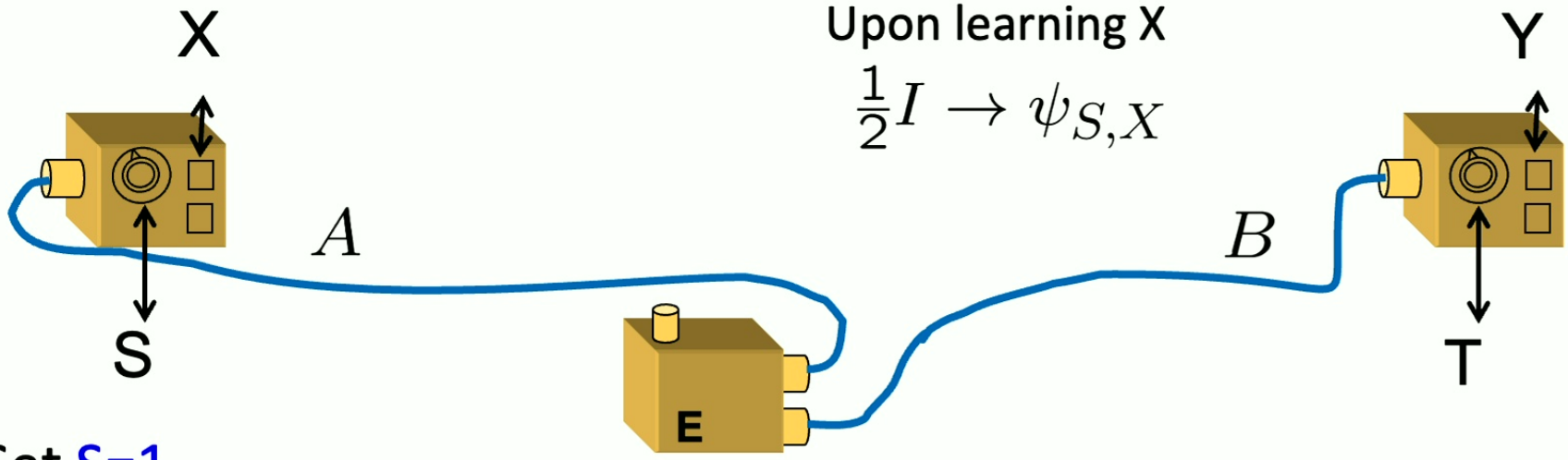
"Spooky action at a distance"

ψ is epistemic



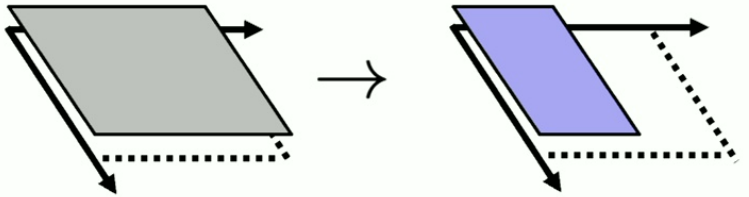

X
Upon learning X
$\frac{1}{2}I \to \psi_{S,X}$
Y
A
B
S
T
E
Set S=0
get X=0
get X=1


X
Upon learning X
$\frac{1}{2}I \rightarrow \psi_{S,X}$
Y
A
B
S
E
T
Set S=1
get X=0
get X=1

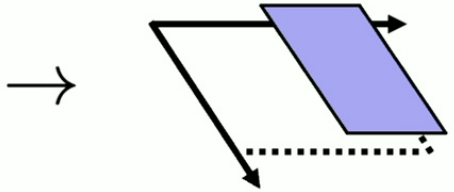


Set S=1

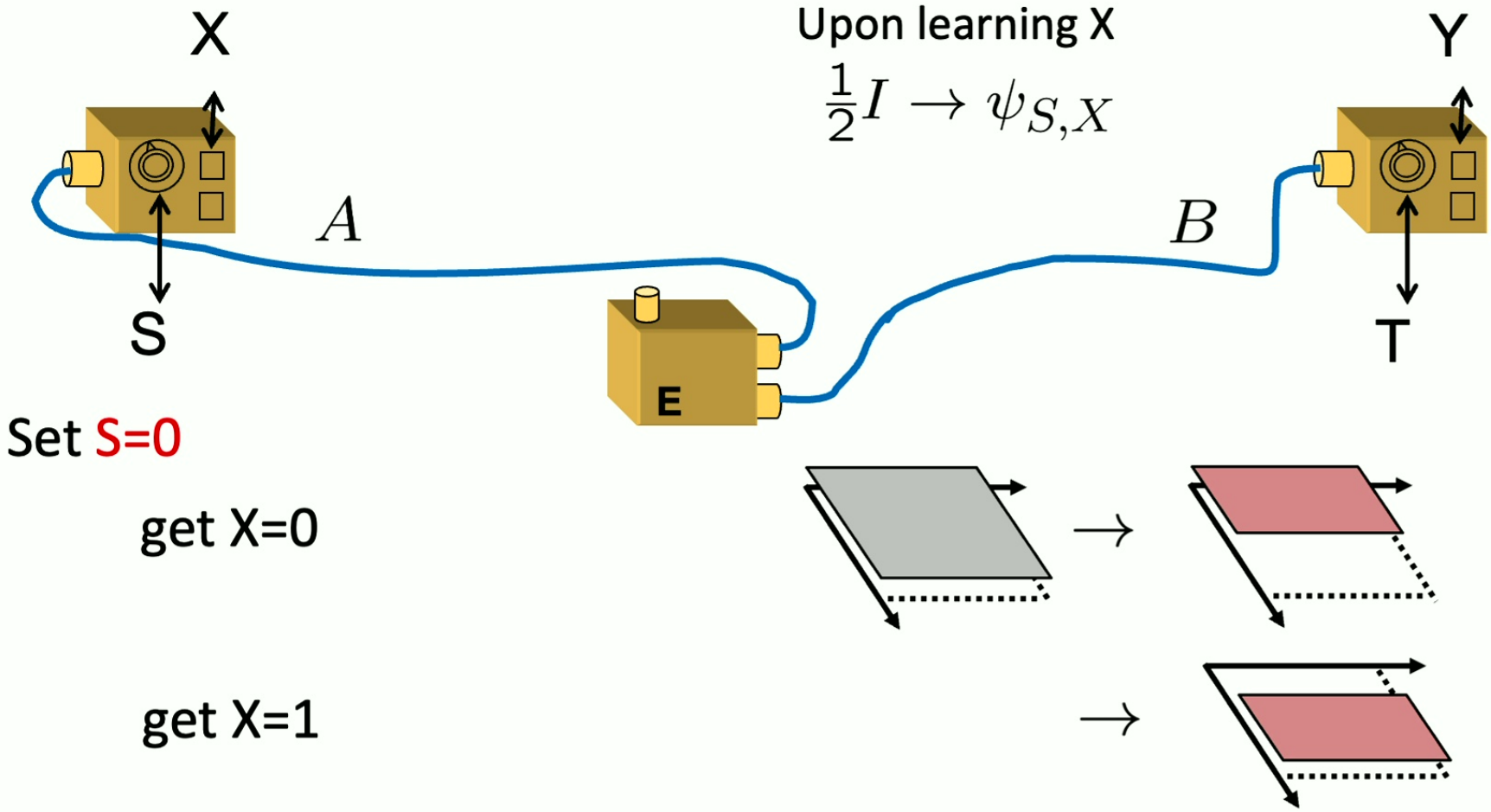
get X=0

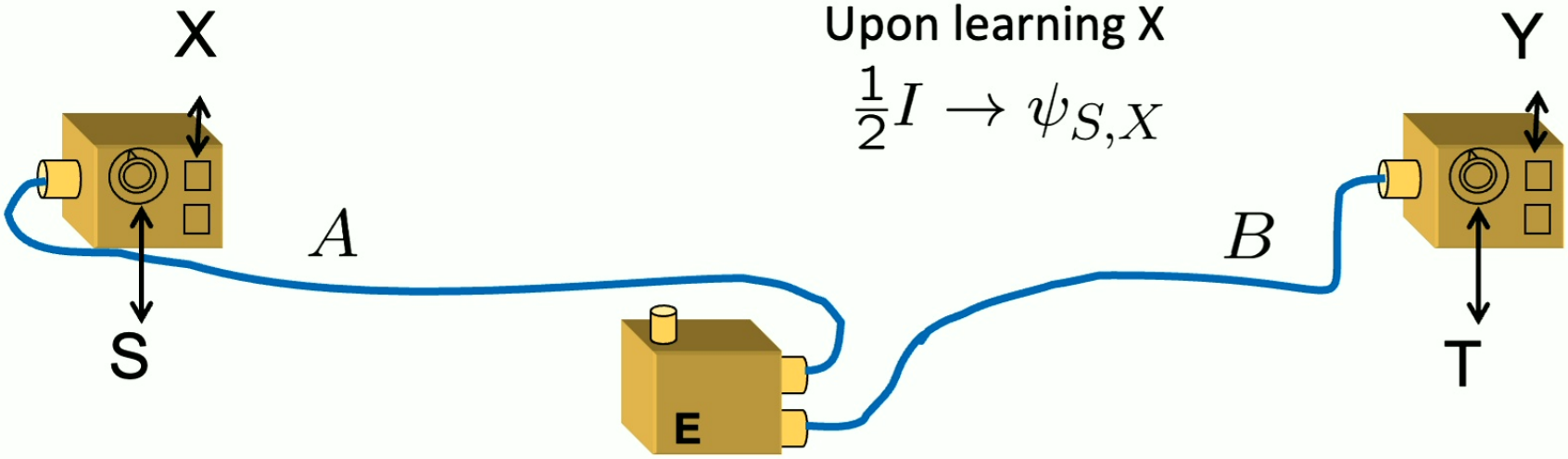


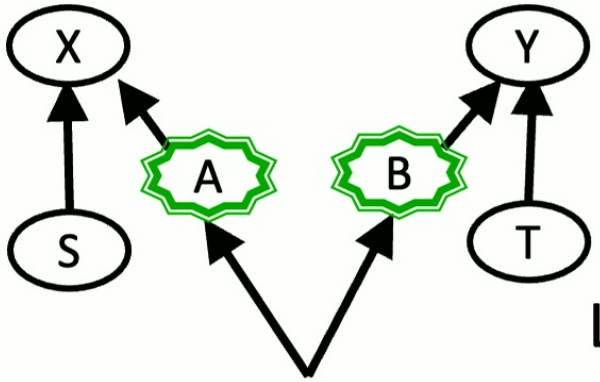
get X=1



Like “treatment informs us about recovery”


X
Upon learning X
$\frac{1}{2}I \to \psi_{S,X}$
Y
A
B
S
T
E
Set S=0
get X=0
get X=1





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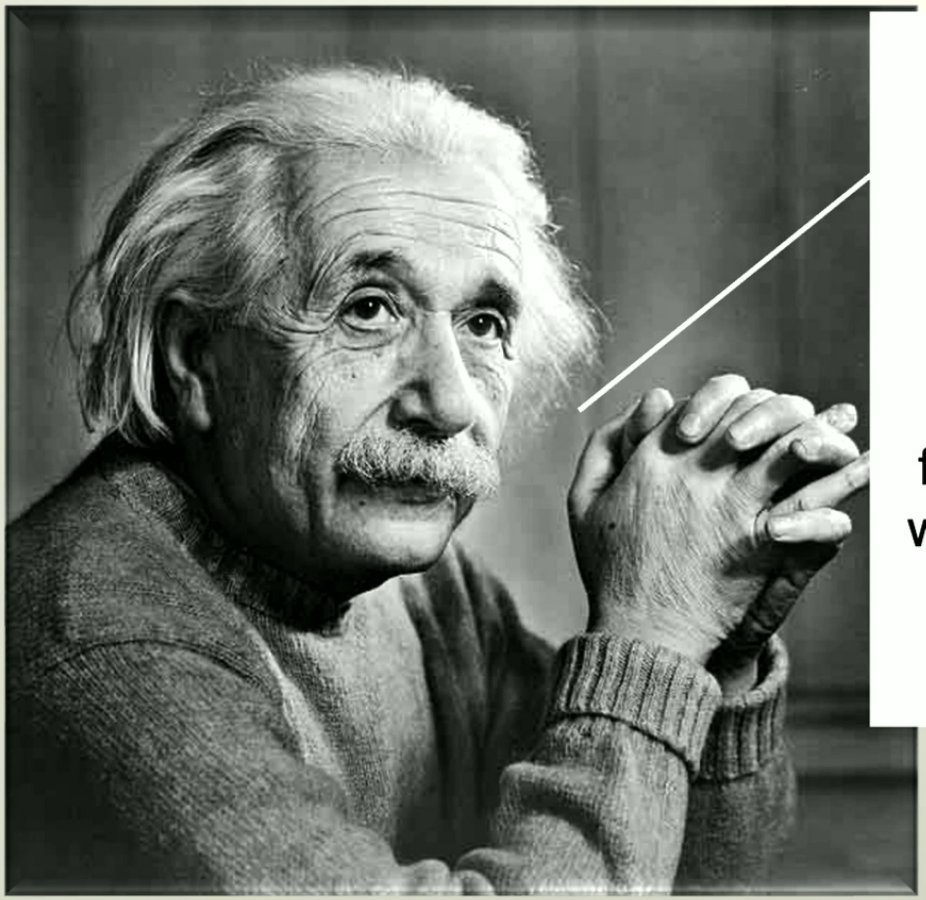
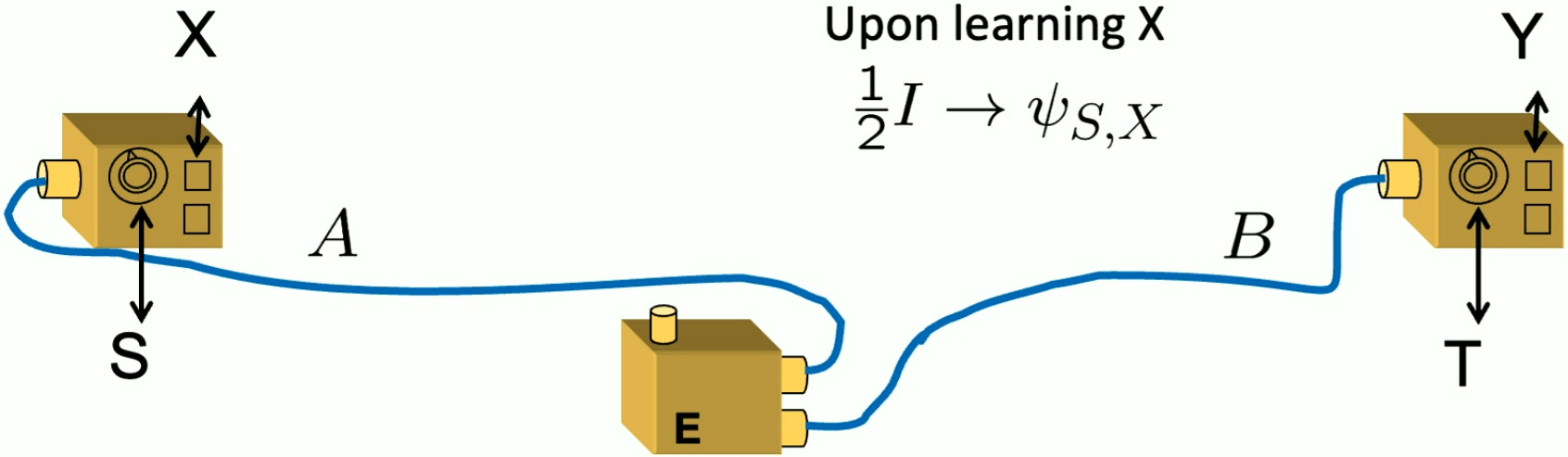
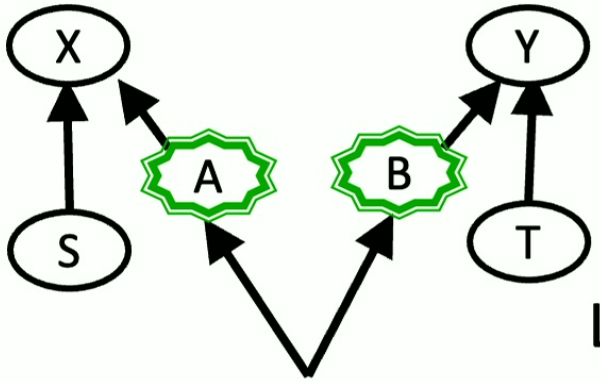


"ψ_2 does not describe the totality of what "really" pertains to the partial system 2, rather only what we know about it in this particular case."

"I incline to the opinion that the wave function does not (completely) describe what is real, but only a to-us-empirically-accessible maximal knowledge regarding that which really exists."





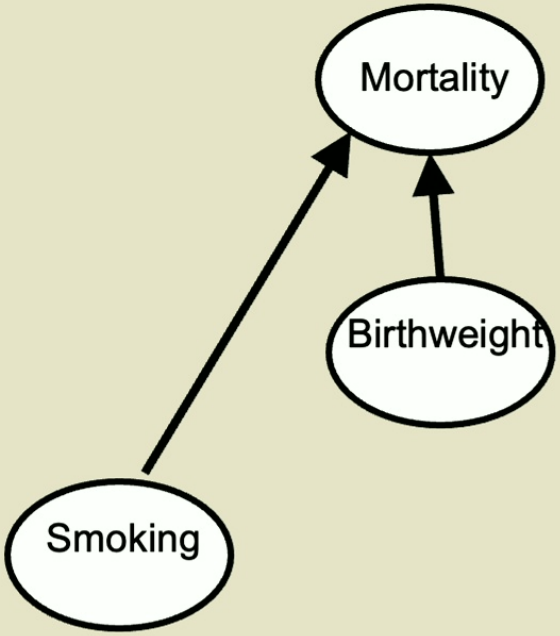
Like “treatment informs us about recovery”

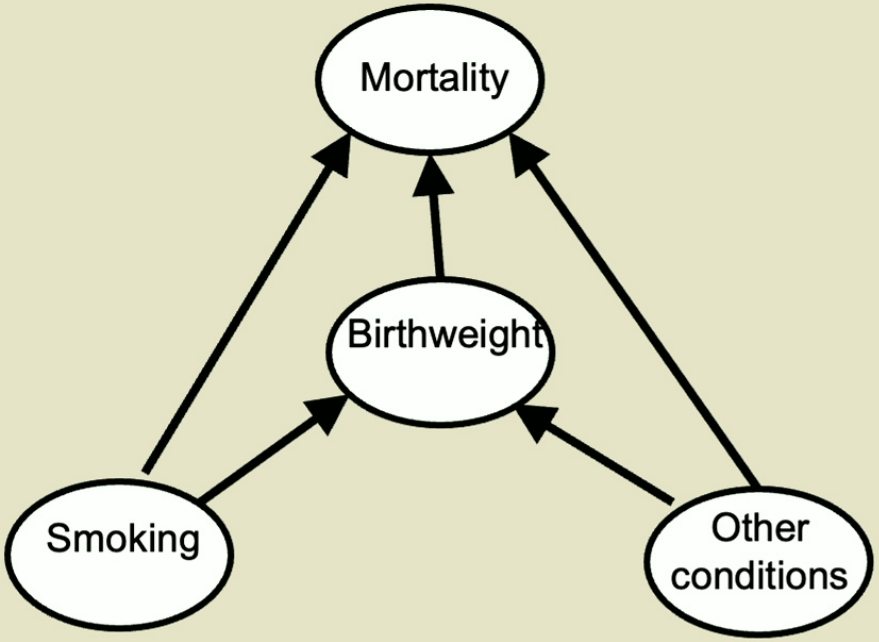
Birth weight paradox

P(mortality | born to smoker) > P(mortality | born to nonsmoker)

P(mortality | born to smoker, LBW) < P(mortality | born to nonsmoker, LBW)

Can a mother being a smoker really reduce the risk of mortality for low birth weight children?

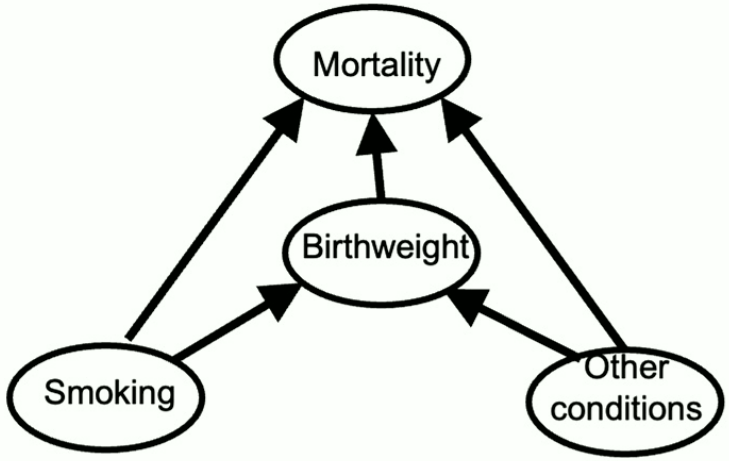

Mortality
Birthweight
Smoking


Mortality
Birthweight
Smoking
Other conditions

Birth weight paradox

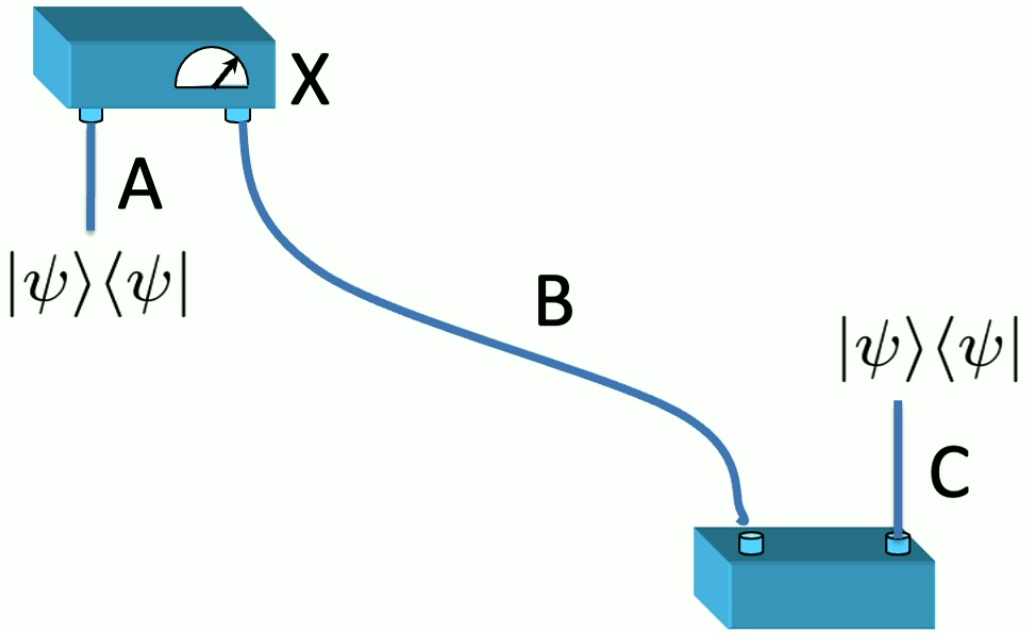
P(mortality | born to smoker) > P(mortality | born to nonsmoker) ✓

P(mortality | born to smoker, LBW) < P(mortality | born to nonsmoker, LBW)

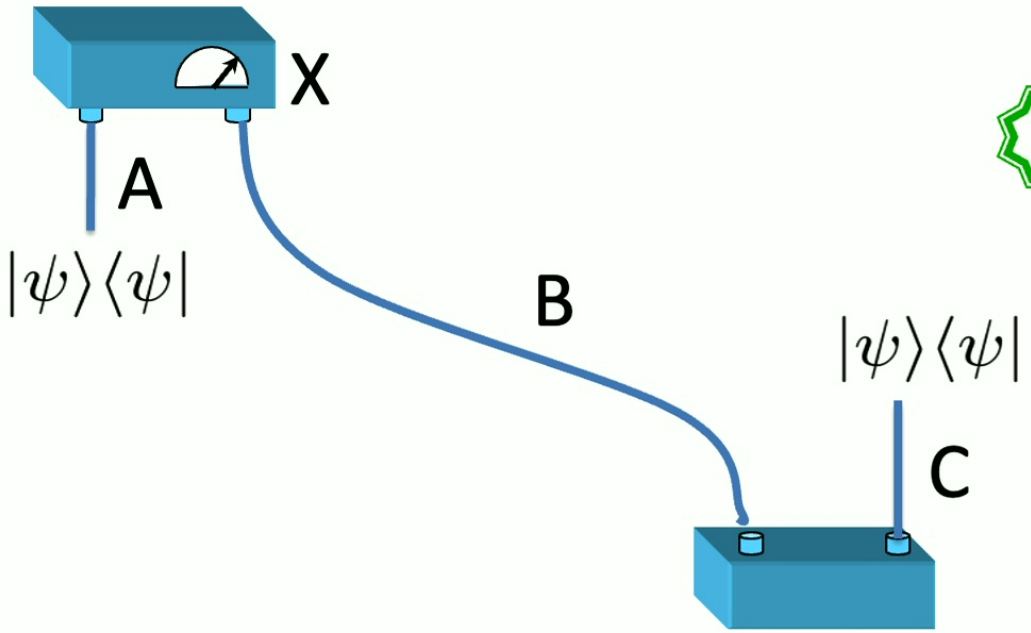


Therefore: *marginalize* over colliders on the "backdoor path"

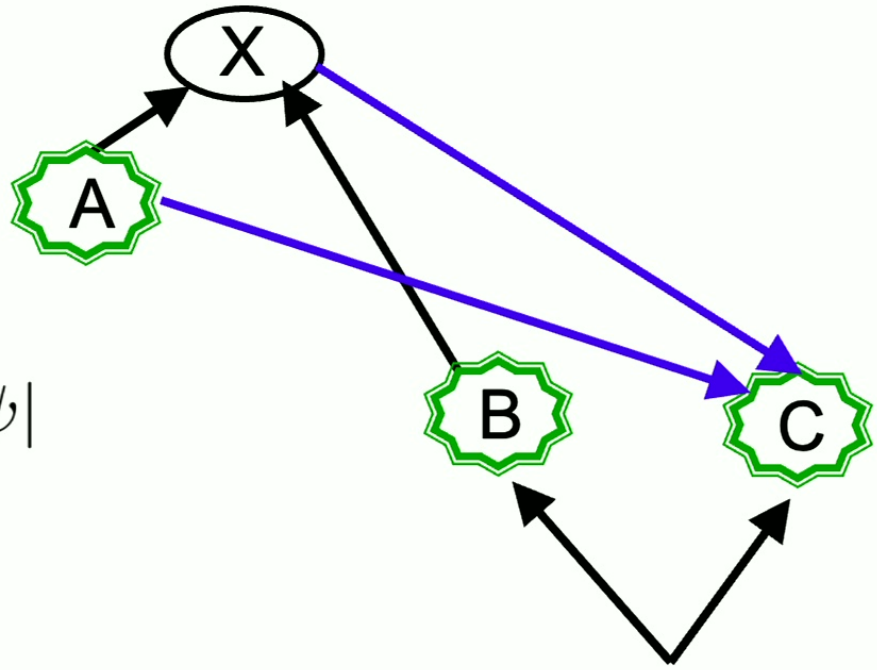
Post-select on outcome



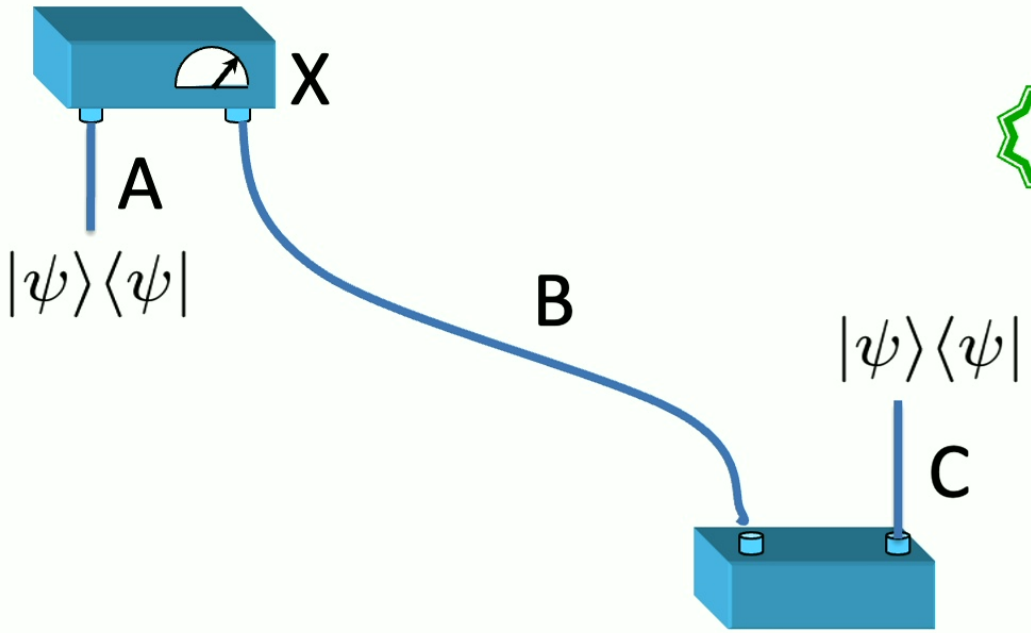
Post-select on outcome



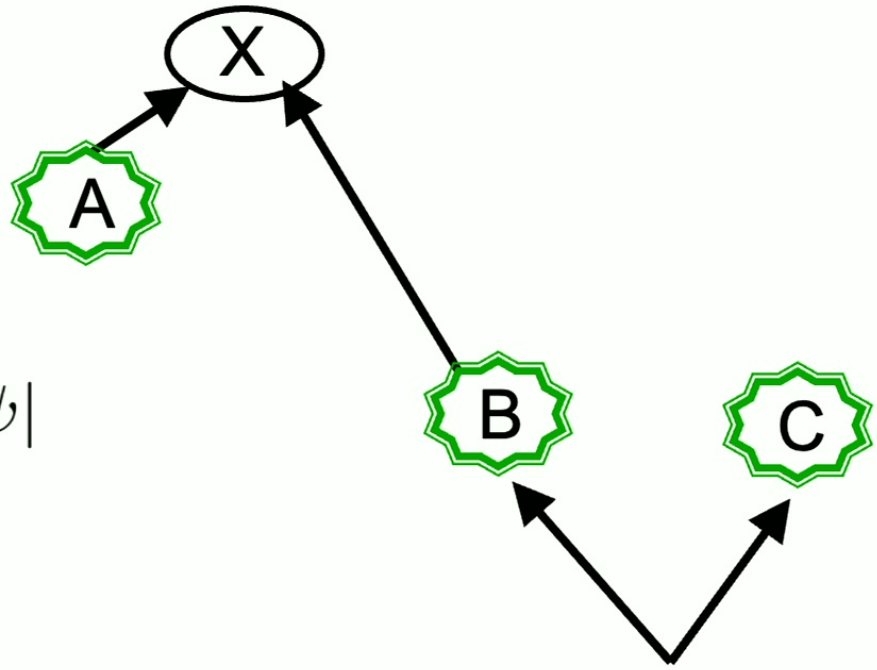
ψ is ontic



Post-select on outcome



ψ is epistemic

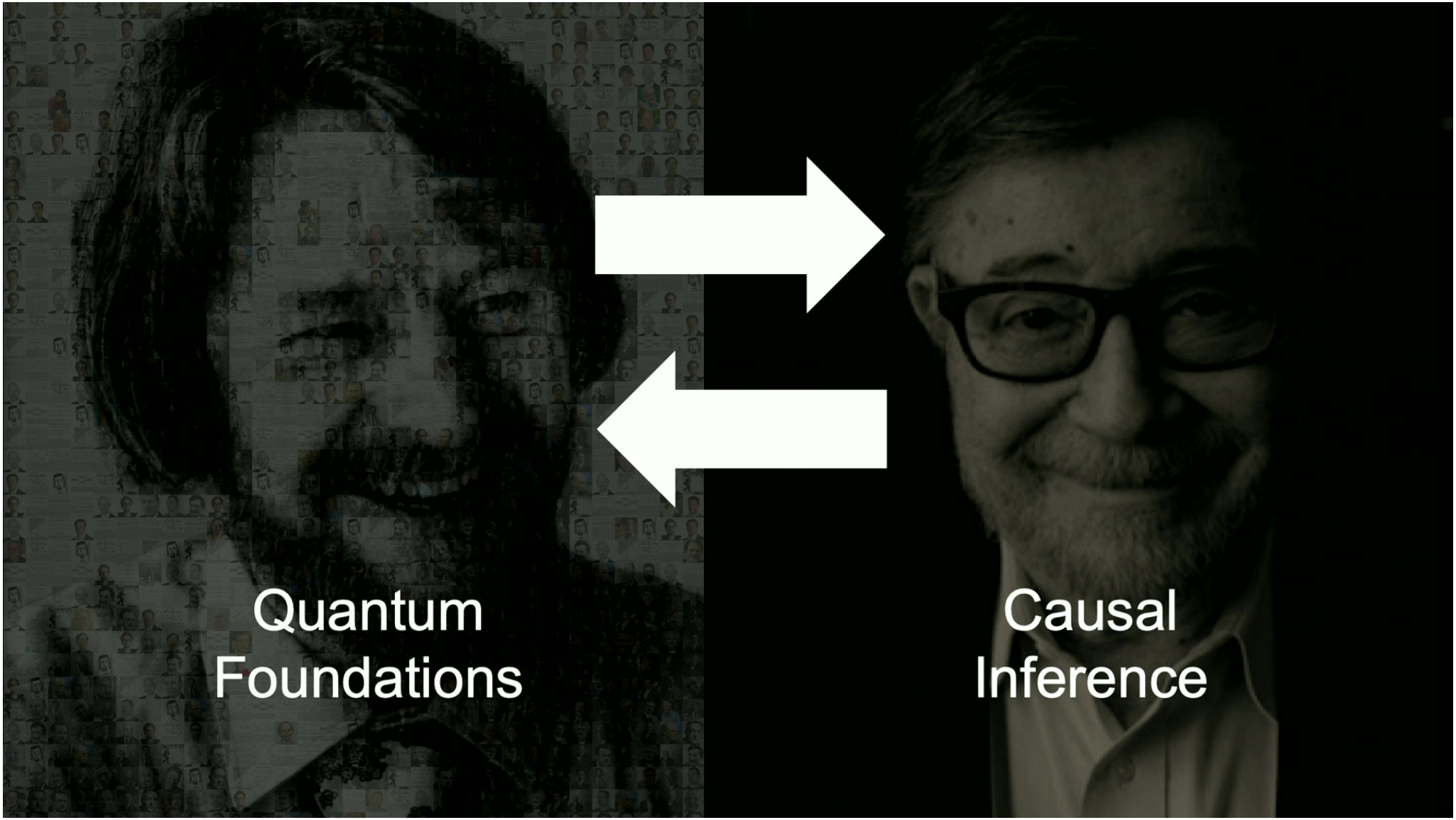


Given post-selection, your posterior about C tracks your prior about A

What hope do we have of making sense of quantum theory if we do not understand how to resolve Simpson's or Berkson's paradox?

"[...] our present Quantum Mechanical formalism [...] is a peculiar mixture describing in part realities of Nature, in part incomplete human information about Nature all scrambled up by Heisenberg and Bohr into an omelette that nobody has seen how to unscramble."

E.T. Jaynes, 1989


Quantum
Foundations
Causal
Inference