

Title: Physical Limits of Inference

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URL: <http://pirsa.org/08110000>

Abstract: I show that physical devices that perform observation, prediction, or recollection share an underlying mathematical structure. I call devices with that structure "inference devices". I present a set of existence and impossibility results concerning inference devices. These results hold independent of the precise physical laws governing our universe. In a limited sense, the impossibility results establish that Laplace was wrong to claim that even in a classical, non-chaotic universe the future can be unerringly predicted, given sufficient knowledge of the present. Alternatively, these impossibility results can be viewed as a non-quantum mechanical "uncertainty principle". Next I explore the close connections between the mathematics of inference devices and of Turing Machines. I end by informally discussing the philosophical implications of these results, e.g., for whether the universe "is" a computer.

PHYSICAL LIMITS OF INFERENCE

David H. Wolpert

NASA Ames Research Center

David.H.Wolpert@nasa.gov

<http://ti.arc.nasa.gov/people/dhw/>

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ROADMAP

1) *Formalize observation, prediction, and memory*



2) *Extract what's in common: inference devices*



3) *Elementary properties of inference devices*

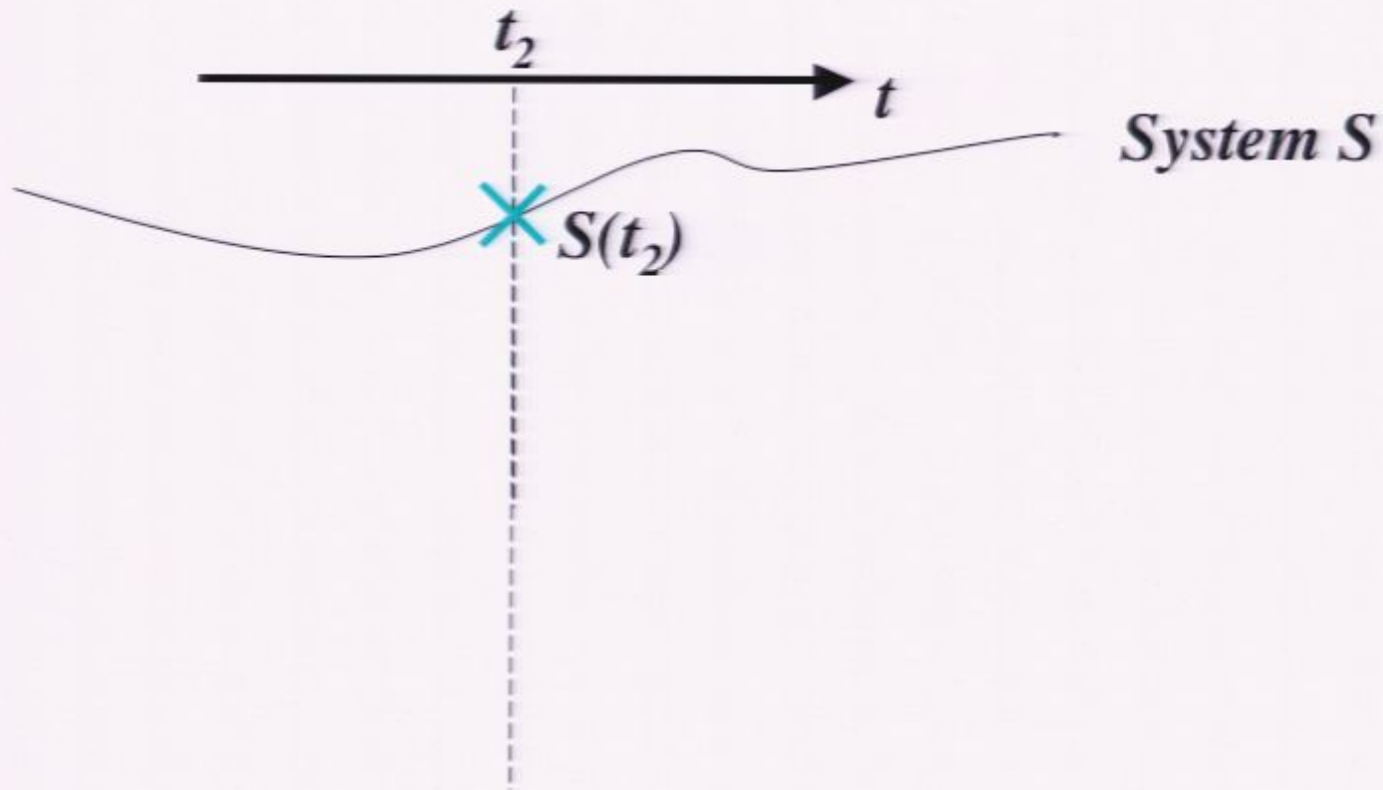


4) *Inference devices and Turing machine theory:
strong inference and inference complexity*



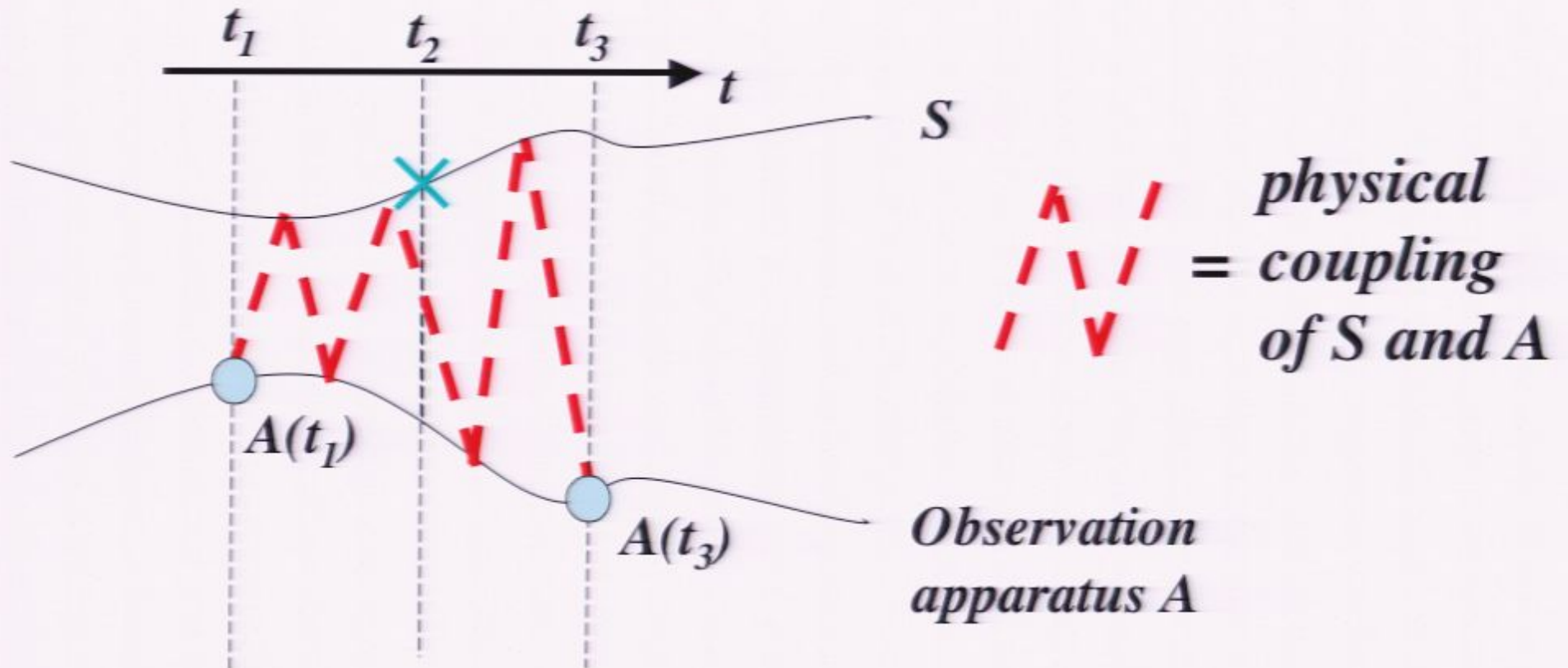
5) Stochastic inference

OBSERVATION



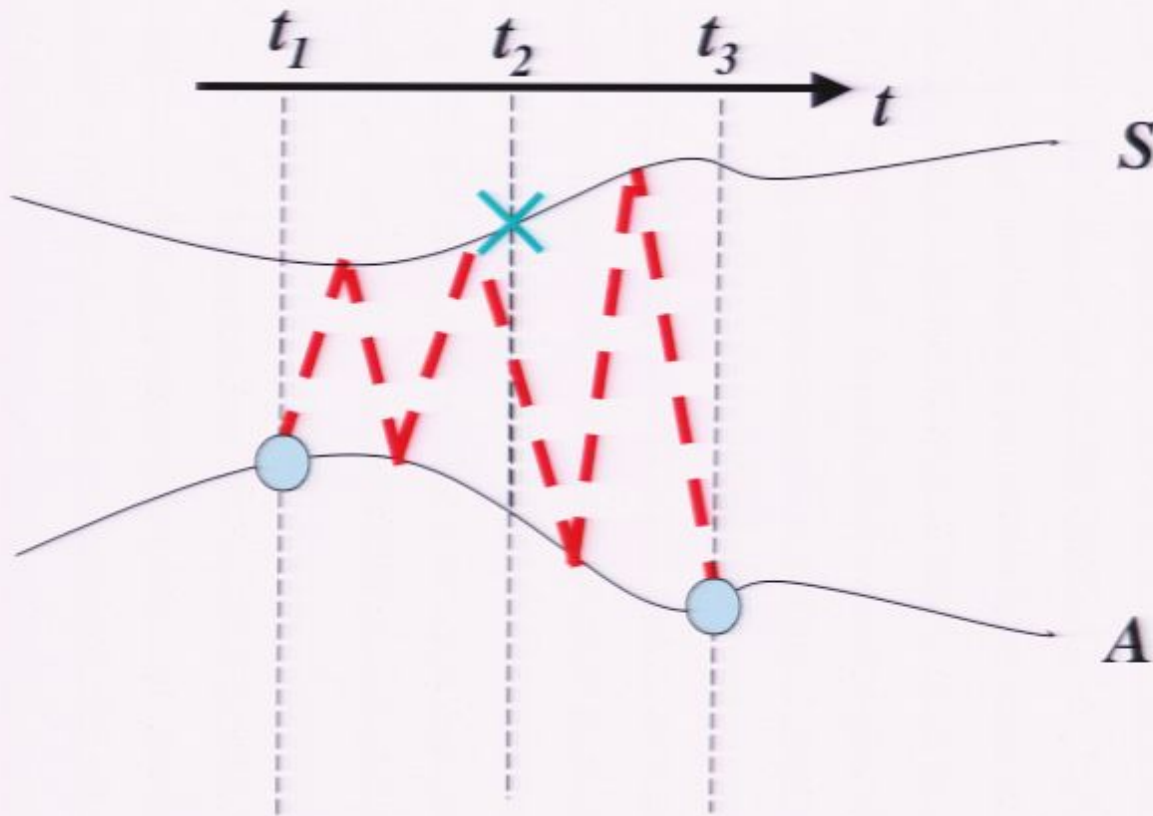
1) $S(t_2)$ is what we want to observe.

OBSERVATION



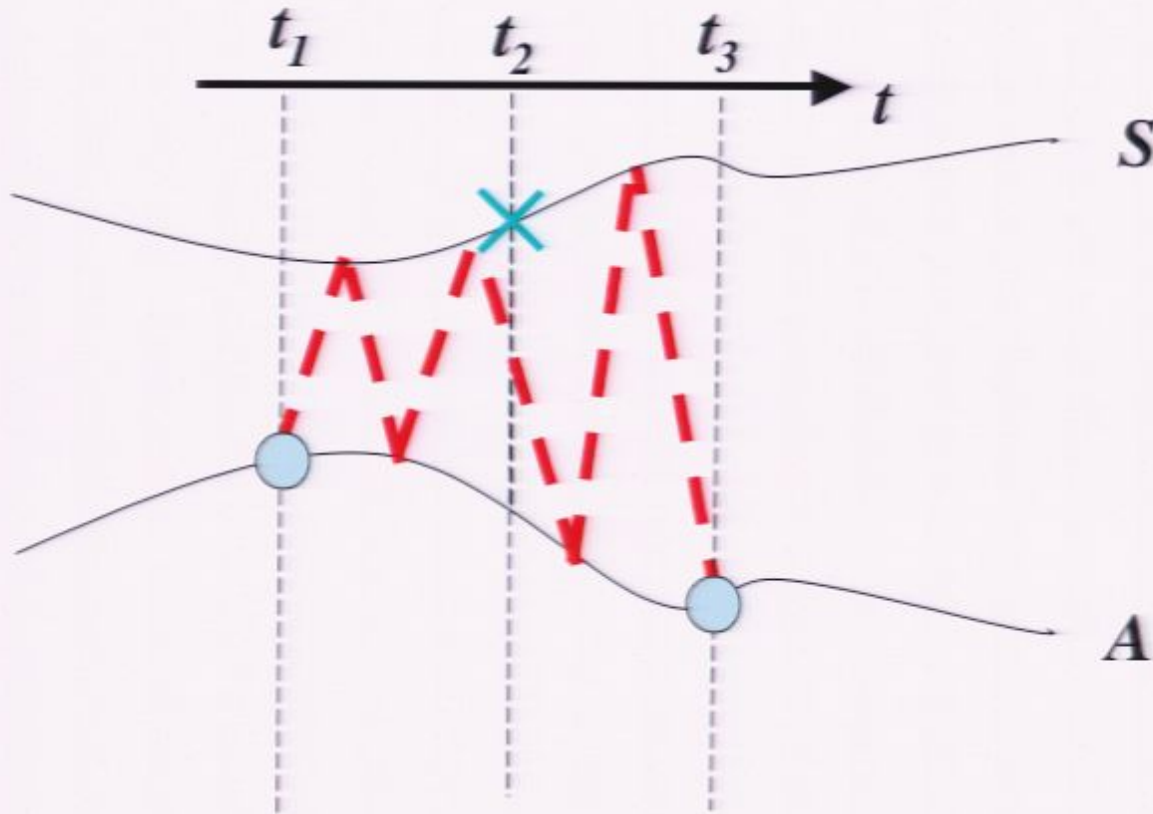
- 1) $S(t_2)$ is what we want to observe.
- 2) To do that we setup $A(t_1)$ appropriately.
- 3) The conclusion of the observation is $A(t_3)$.

OBSERVATION



- *Just having $A(t_3)$ and $S(t_2)$ correlated is NOT observation*
- *If a tree falls, but the camera aimed at it encrypts the image, the image on that camera is not an “observation”*
- *How imbue $A(t_3)$ with semantic meaning?*

OBSERVATION



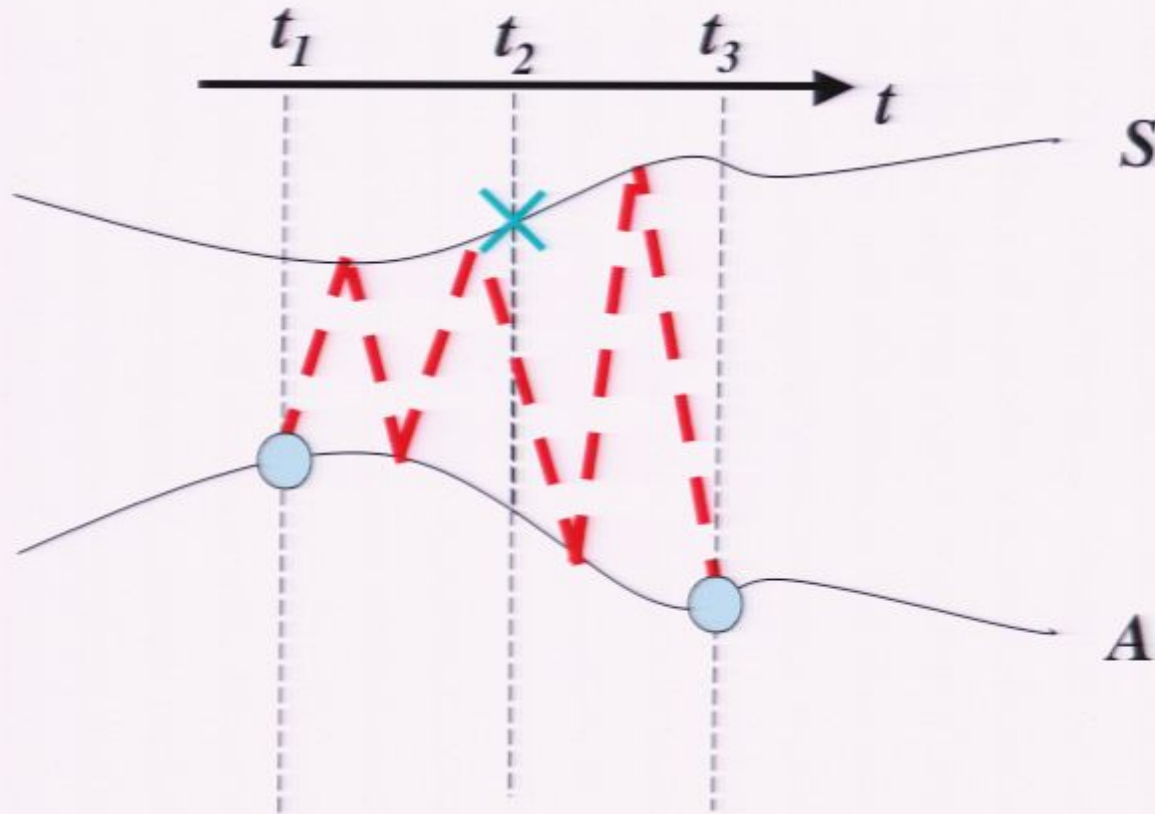
Suppose $A(t_3)$ says
 $S(t_2) = K$.

$S(t_2) = K?$



$A(t_3)$ says 'yes'

OBSERVATION



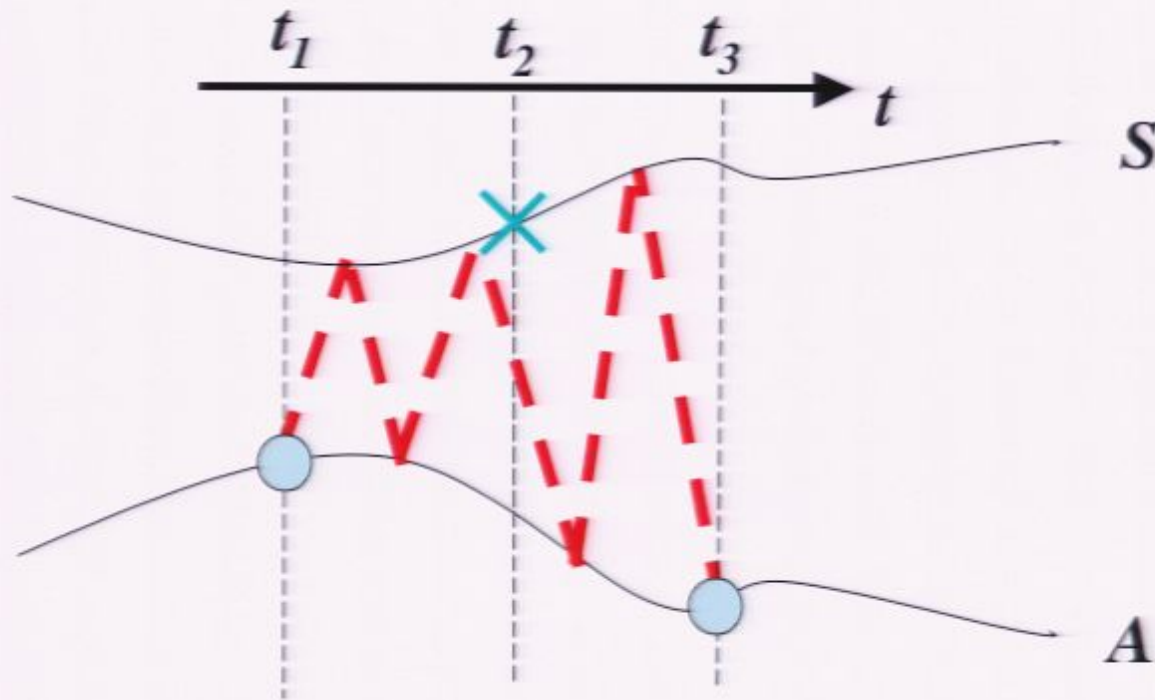
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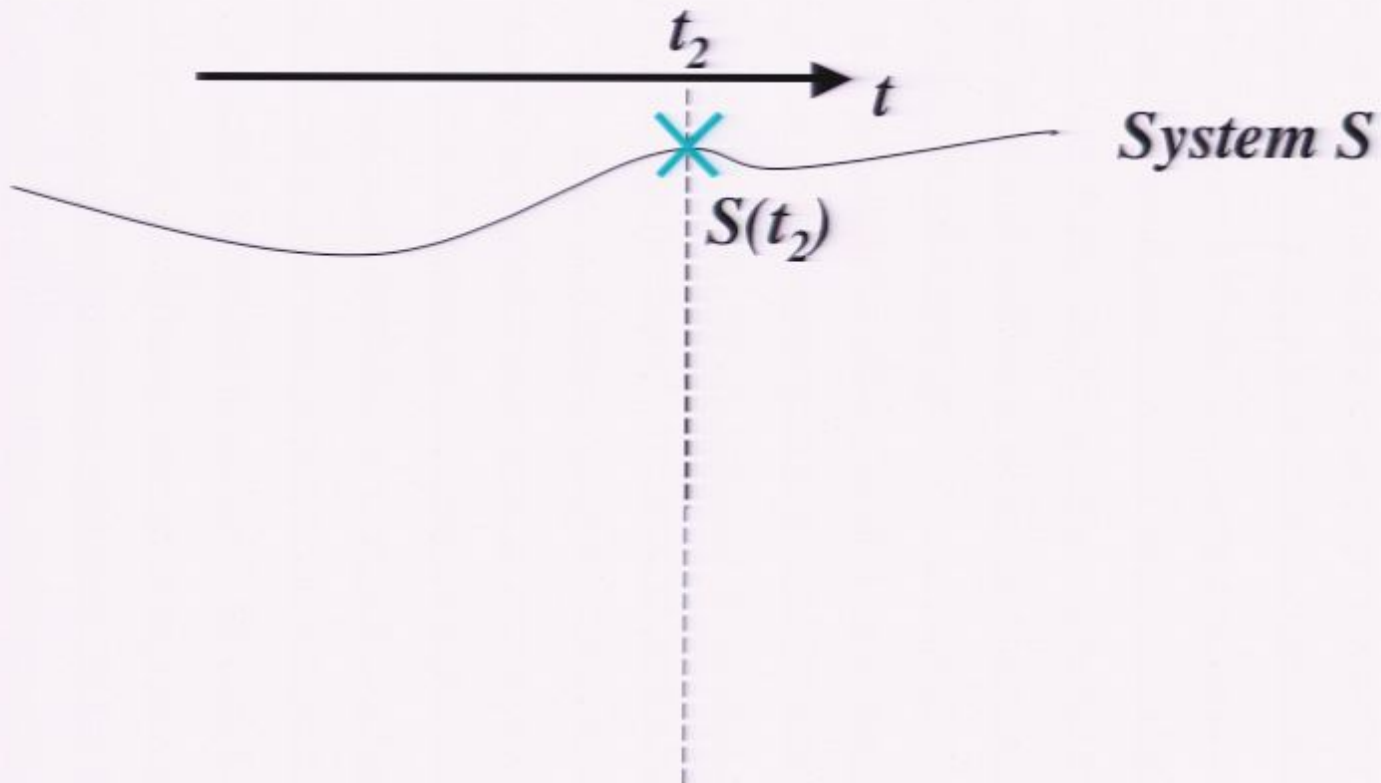
OBSERVATION



- 1) $A(t_3)$ has “semantic meaning” if there is a scientist who can read it to answer, “Does $S(t_2) = L?$ ” $\forall L$.
- 2) Successful observation is when the scientist’s answer to any such question is correct.

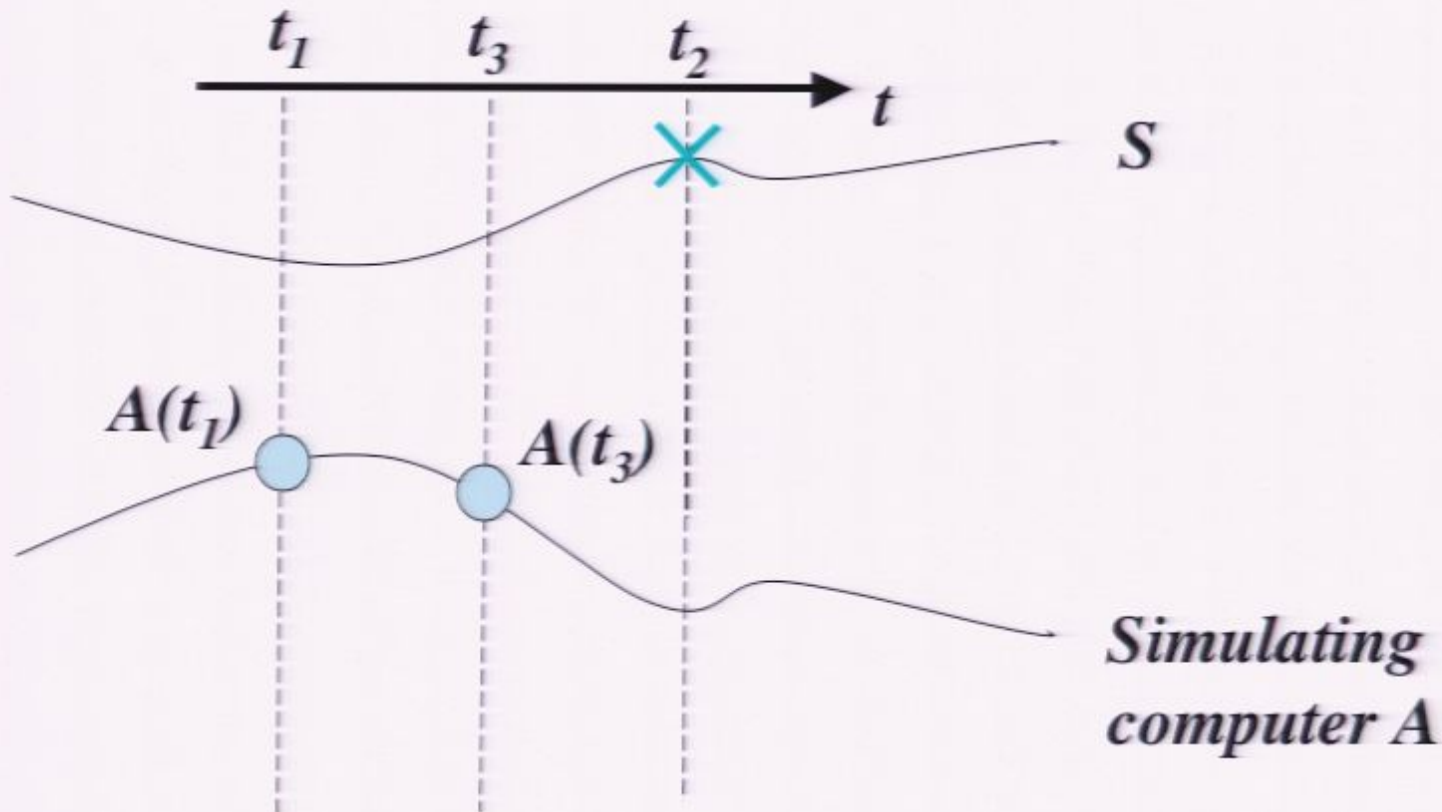


PREDICTION



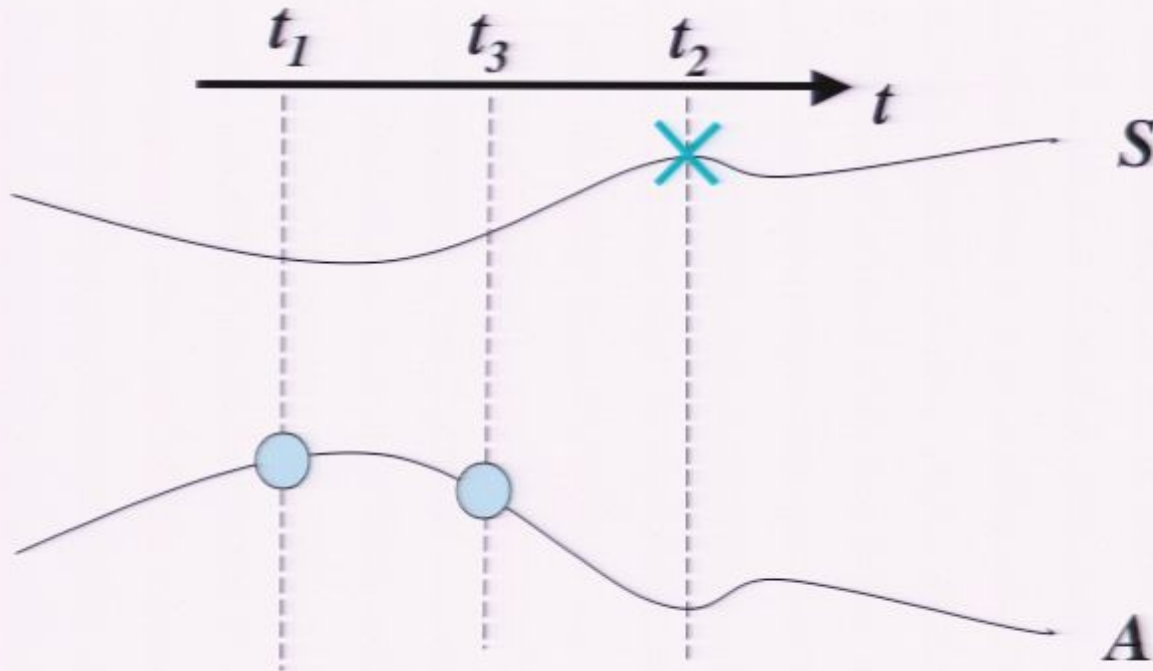
1) $S(t_2)$ is what we want to predict.

PREDICTION



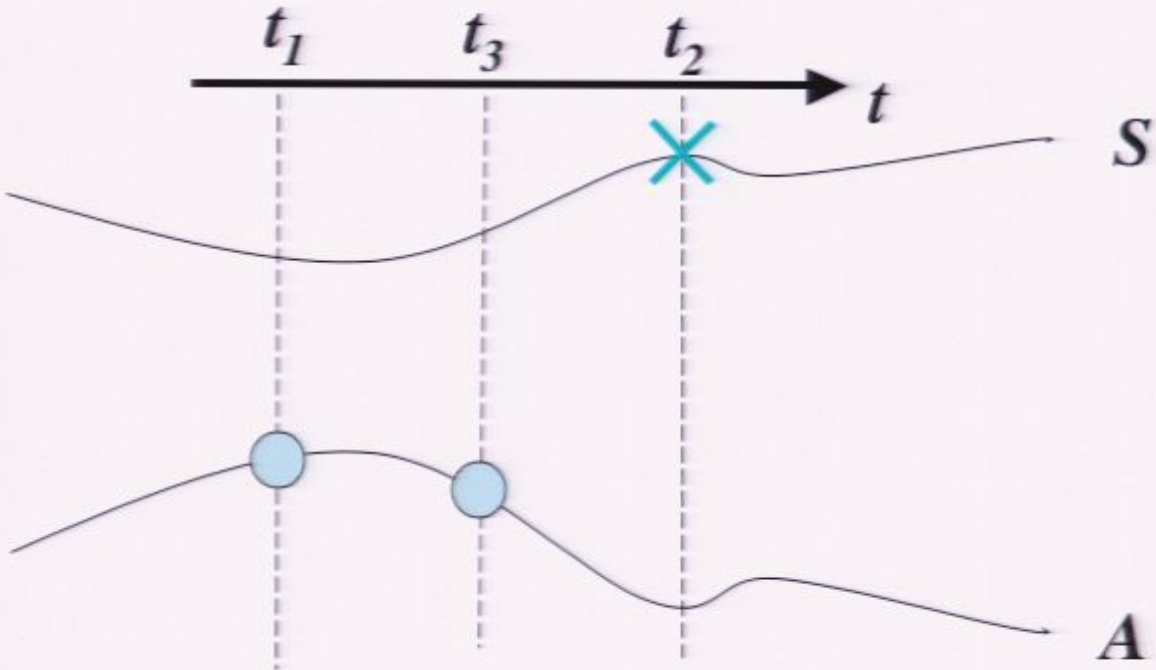
- 1) $S(t_2)$ is what we want to predict.
- 2) To do that we setup $A(t_1)$ appropriately.
- 3) The conclusion of the prediction is $A(t_3)$.

PREDICTION



- *Just having $A(t_3)$ and $S(t_2)$ correlated is NOT prediction*
- *If a tree will fall, but the results of a simulation of tree dynamics is encrypted, the results aren't a "prediction"*
- *How imbue $A(t_3)$ with semantic meaning?*

PREDICTION



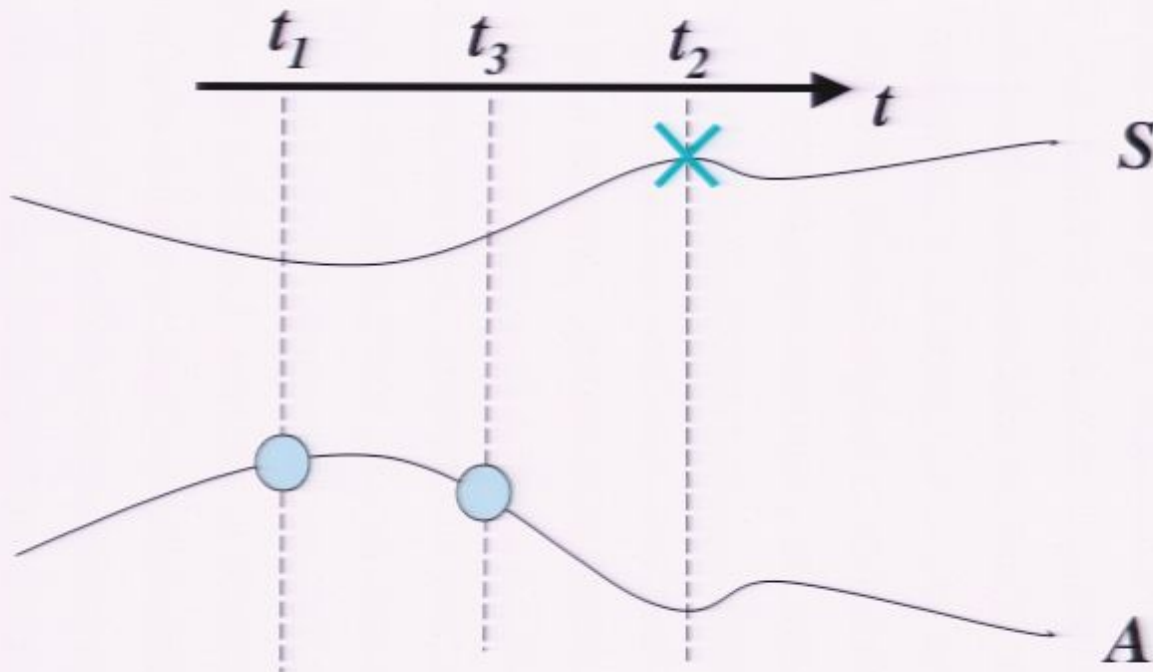
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$A(t_3)$ says 'yes'

PREDICTION

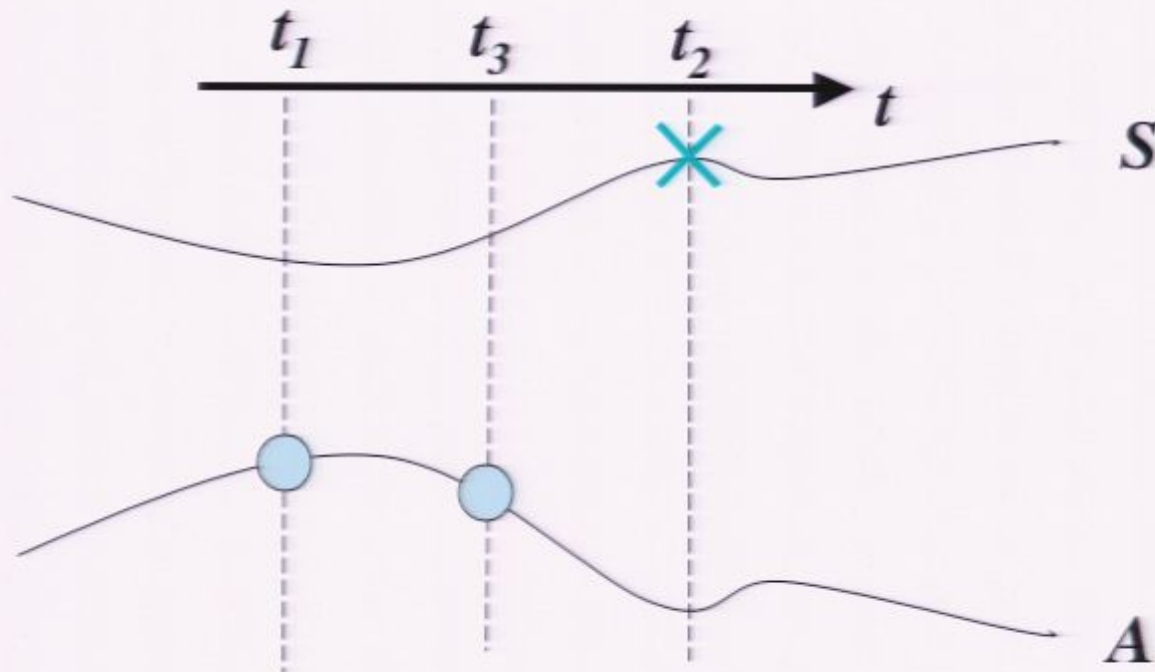


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PREDICTION

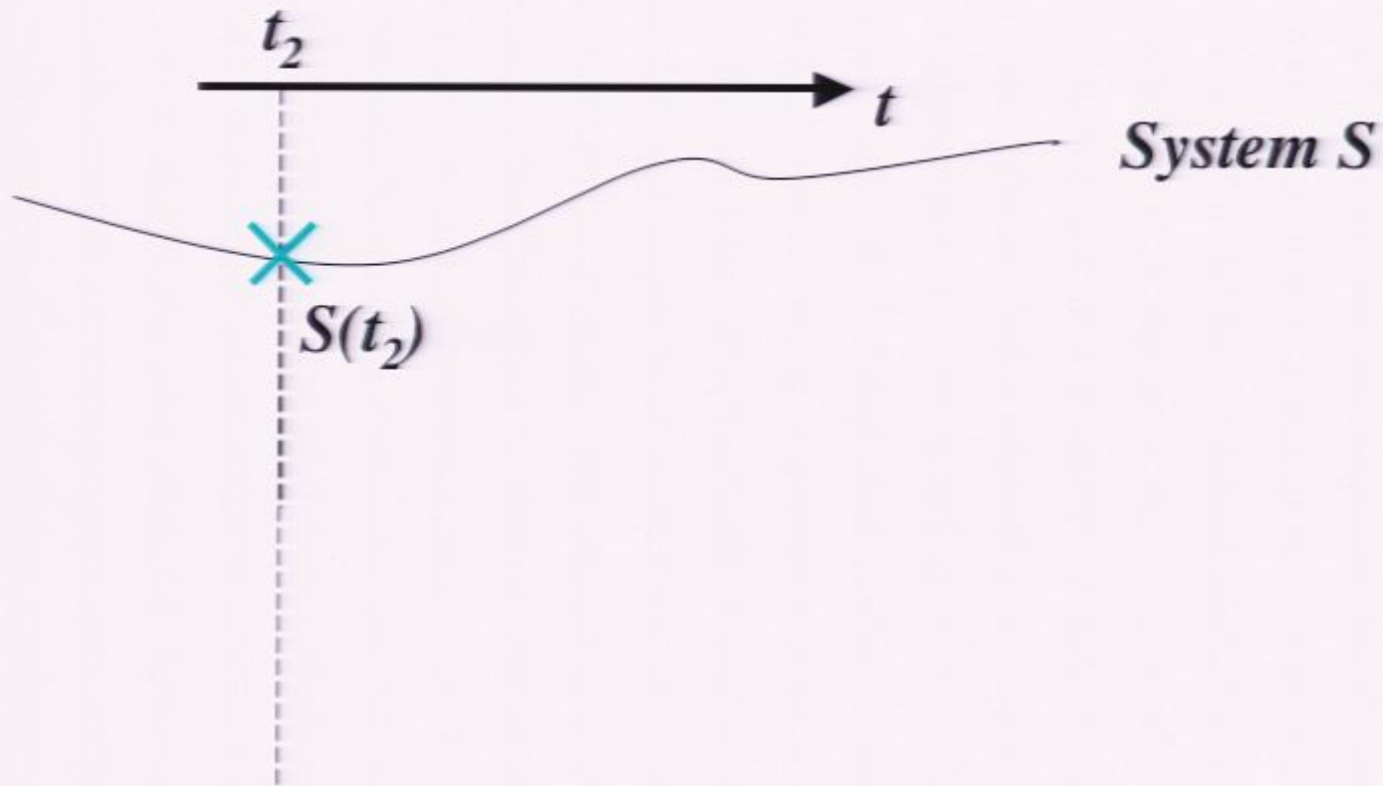


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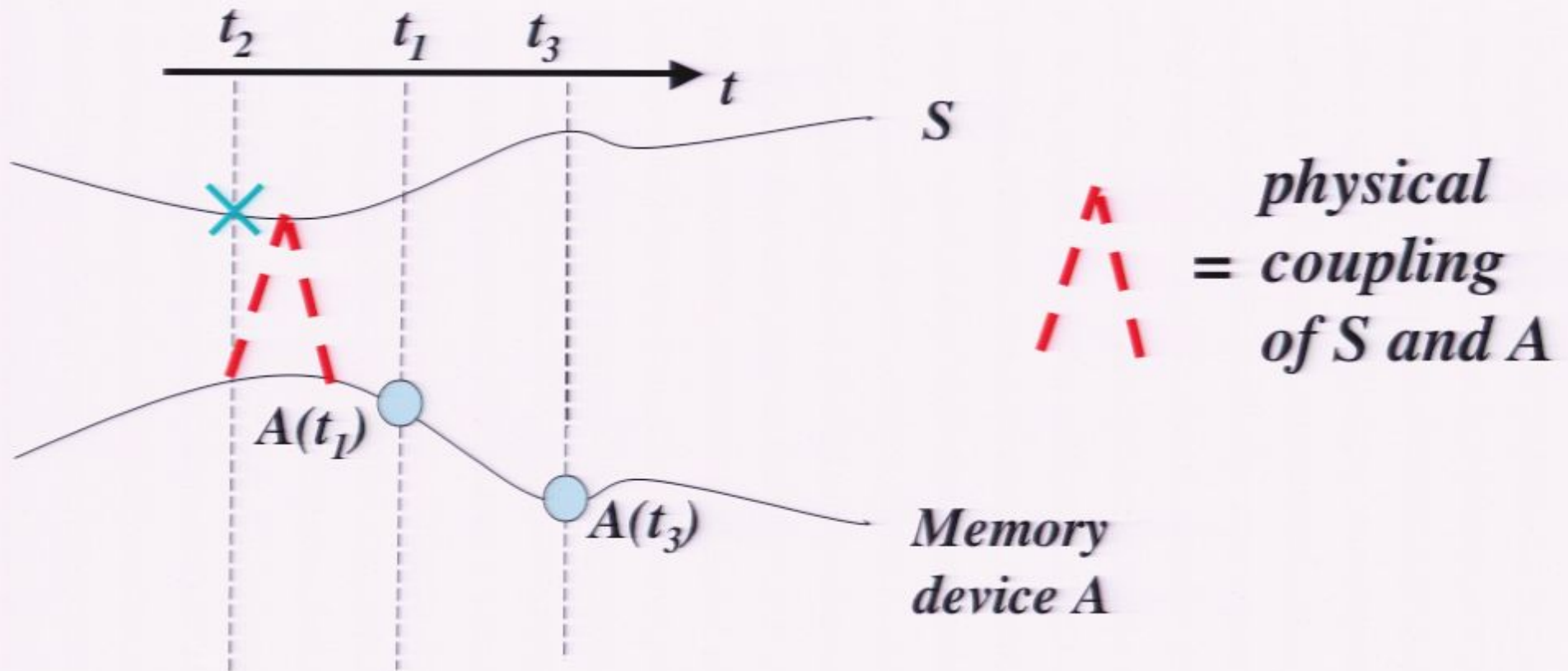


MEMORY



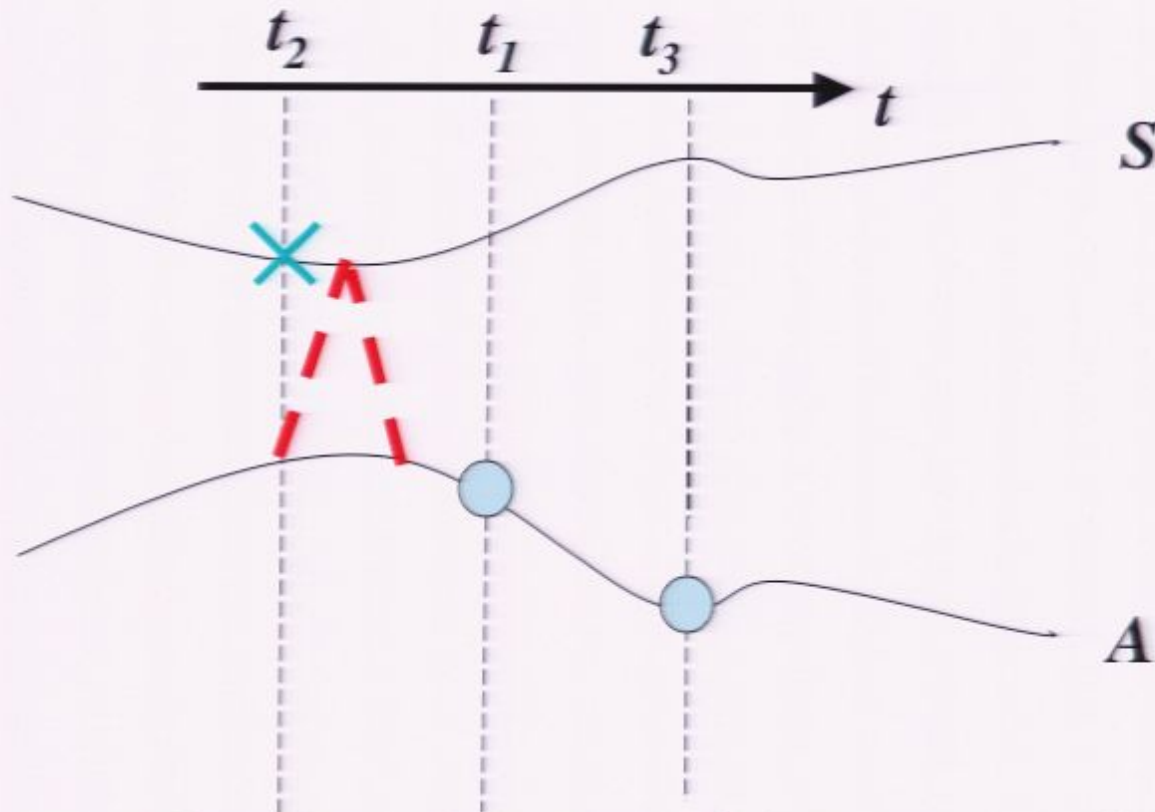
1) $S(t_2)$ is an event (out of many) we want to recollect.

MEMORY



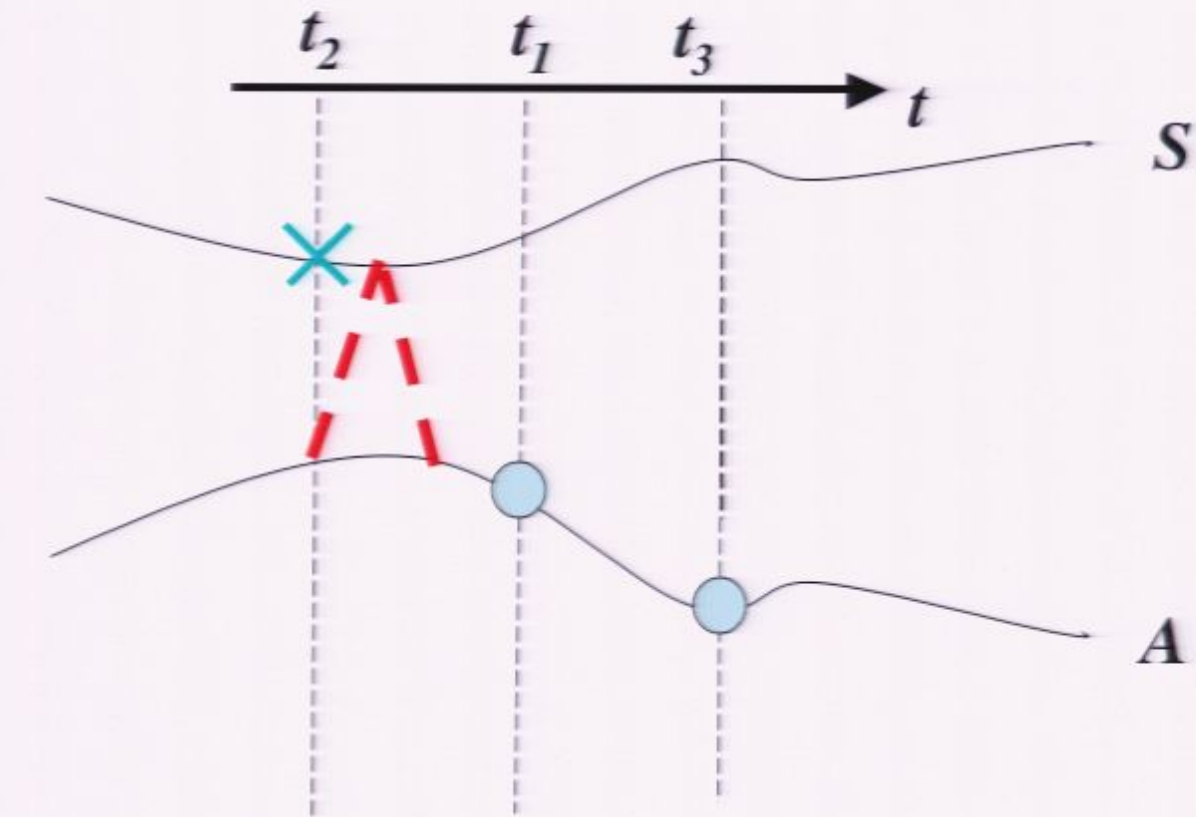
- 1) *$S(t_2)$ is an event (out of many) we want to recollect.*
- 2) *To do that we setup $A(t_1)$ appropriately.*
- 3) *The conclusion of our recollection request is $A(t_3)$.*

MEMORY



- *Just having $A(t_3)$ and $S(t_2)$ correlated is NOT memory*
- *If a tree fell, but the video of its fall is encrypted in our memory device, that video isn't a "memory"*
- *How imbue $A(t_3)$ with semantic meaning?*

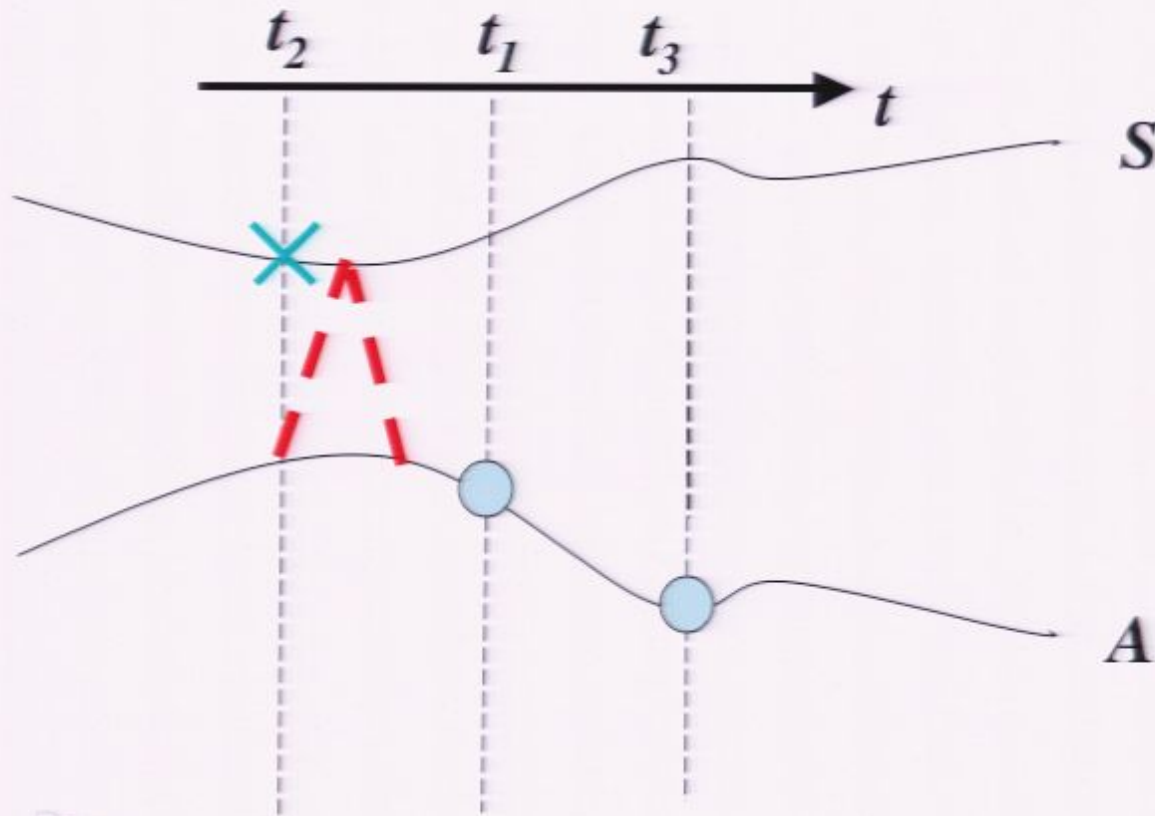
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MEMORY



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ROADMAP

1) *Formalize observation, prediction, and memory*



2) *Extract what's in common: inference devices*



3) *Elementary properties of inference devices*

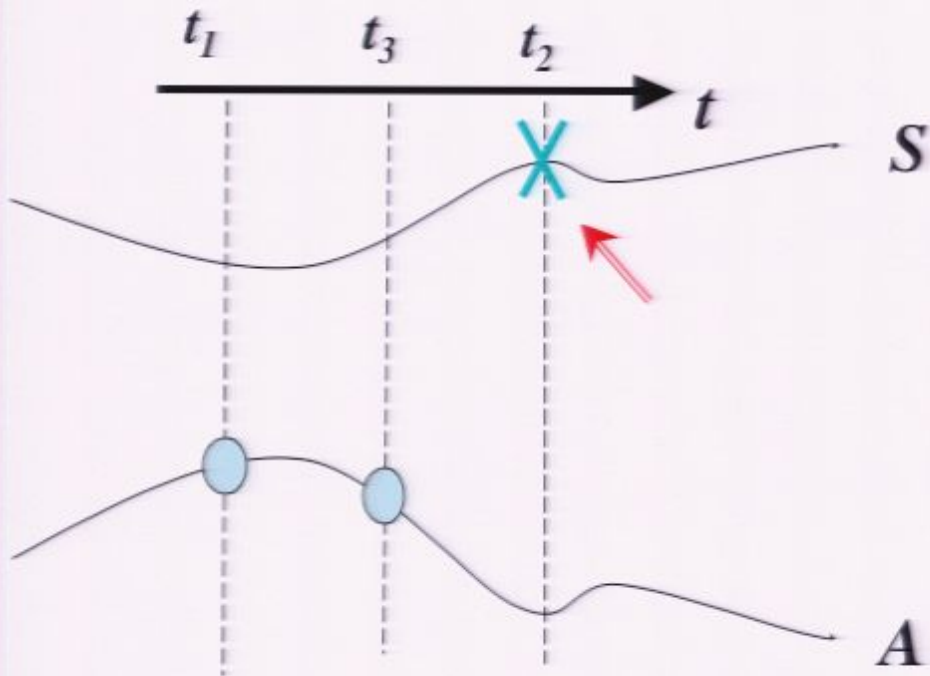


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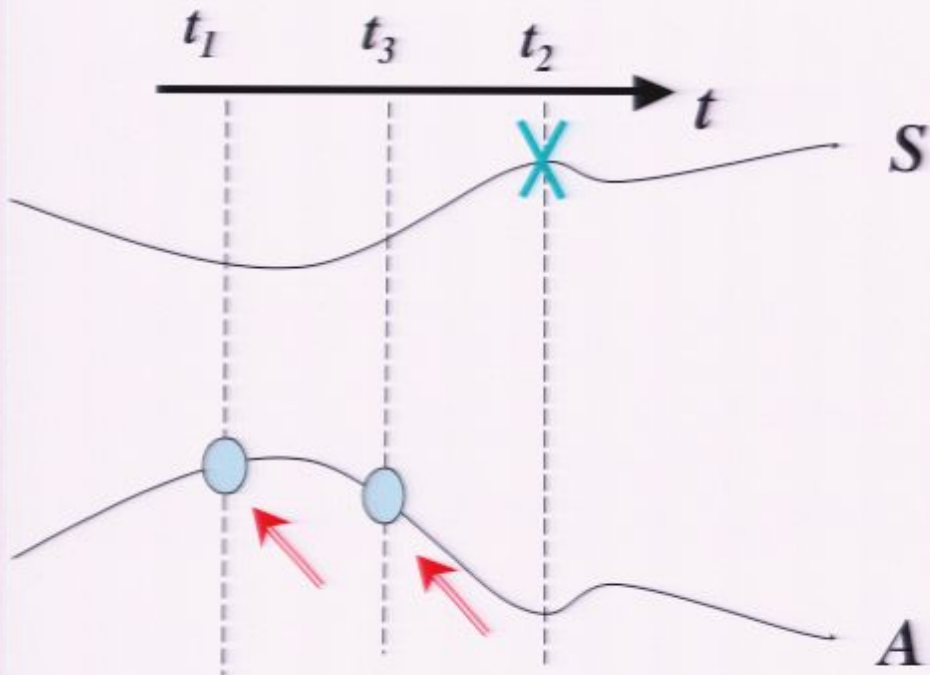
INFERENCE



- S exists in the physical universe
- So $S(t_2)$ is a function of u , the universe's worldline
- Write that function as $\Gamma(u)$



INFERENCE

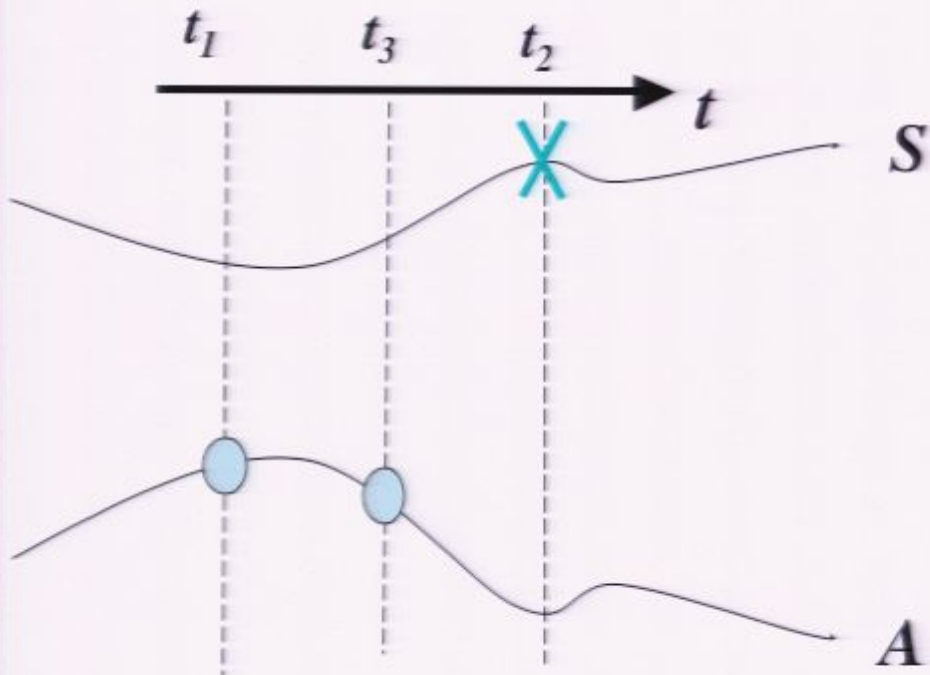


$$1) \Gamma(u) = S(t_2)$$

- *A exists in the physical universe*
- *So $A(t_1)$ and $A(t_3)$ are functions of u*
- *Write them as $\zeta(u)$ and $\chi(u)$*



INFERENCE



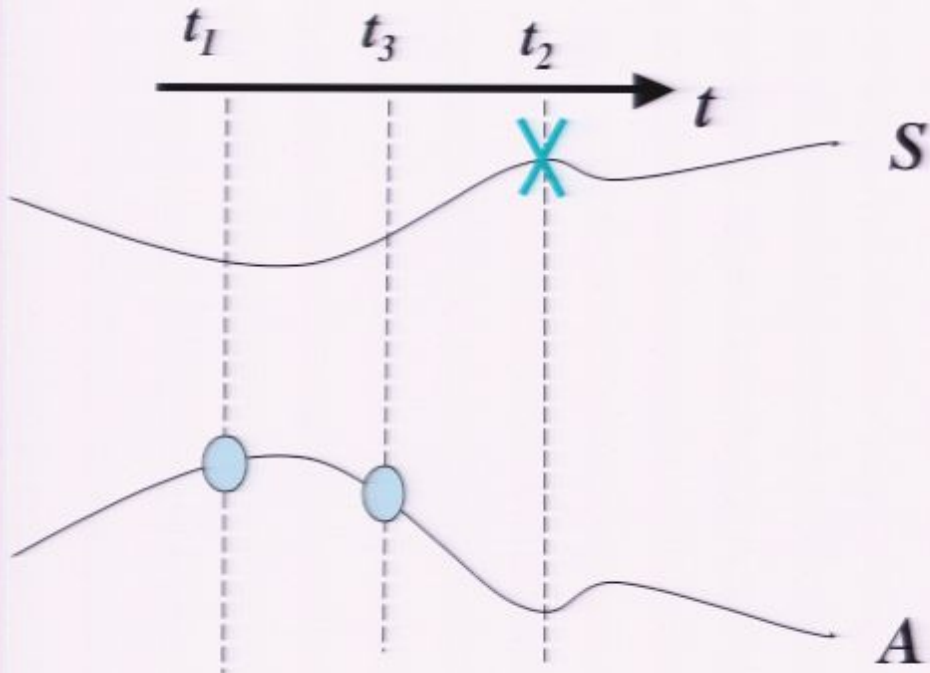
1) $\Gamma(u) = S(t_2)$

2) $\chi(u) = A(t_1), \zeta(u) = A(t_3)$

- For every L , “ $S(t_2) = L?$ ” is a binary-valued function of $S(t_2)$.
- Write that function as q_L



INFERENCE



1) $\Gamma(u) = S(t_2)$

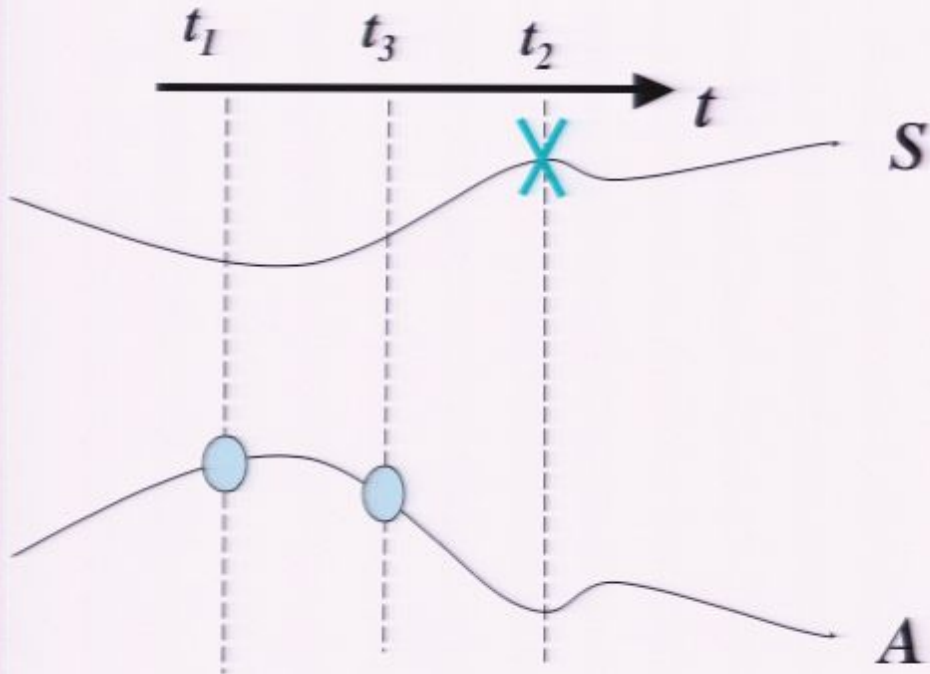
2) $\chi(u) = A(t_1), \zeta(u) = A(t_3)$

3) $q_L(\gamma) = 1$ iff $\gamma = L$

- *The scientist exists in the physical universe*
- *So which question they are asking is a function of u*
- *Write that function as $Q(u)$*



INFERENCE



1) $\Gamma(u) = S(t_2)$

2) $\chi(u) = A(t_1), \zeta(u) = A(t_3)$

3) $q_L(\gamma) = 1$ iff $\gamma = L$

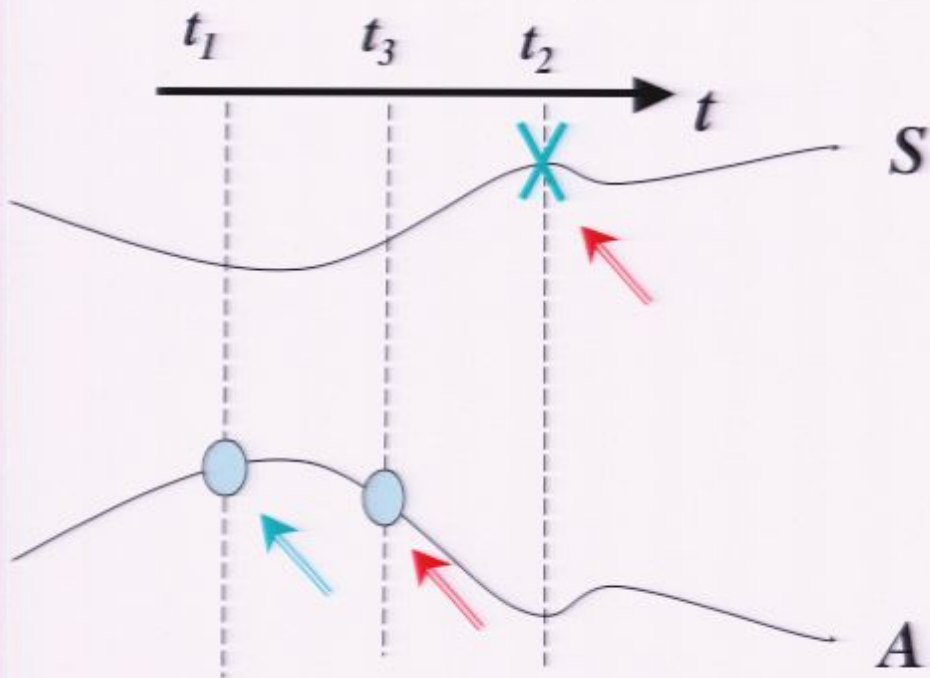
4) $Q(u)$

- *The scientist exists in the physical universe*
- *So what answer for Q they read from $\zeta(u)$ is a function of u*
- *Write that function as $Y(u)$*

$S(t_2) = L?$

$A(t_3)$ says ...

INFERENCE



- 1) $\Gamma(u) = S(t_2)$
- 2) $\chi(u) = A(t_1), \zeta(u) = A(t_3)$
- 3) $q_L(\gamma) = 1$ iff $\gamma = L$
- 4) $Q(u)$
- 5) $Y(u)$

Successful inference: $\forall q_L,$

$\exists a, b$ such that

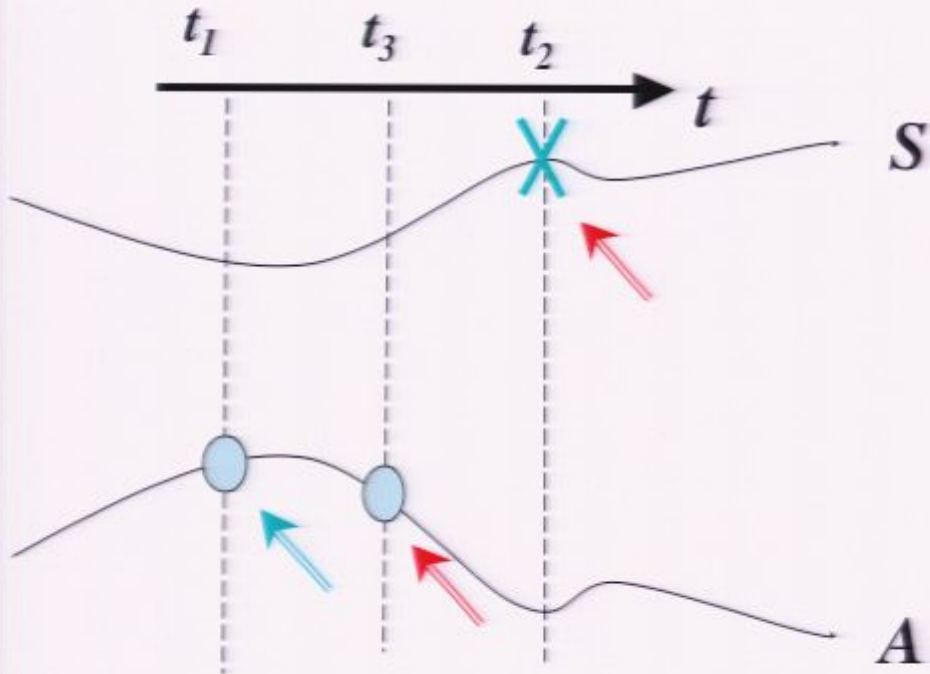
$$(Q(u), \chi(u)) = (a, b)$$

\Rightarrow

$$Y(u) = q_L(\Gamma(u))$$



INFERENCE



Successful inference: $\forall q_L,$

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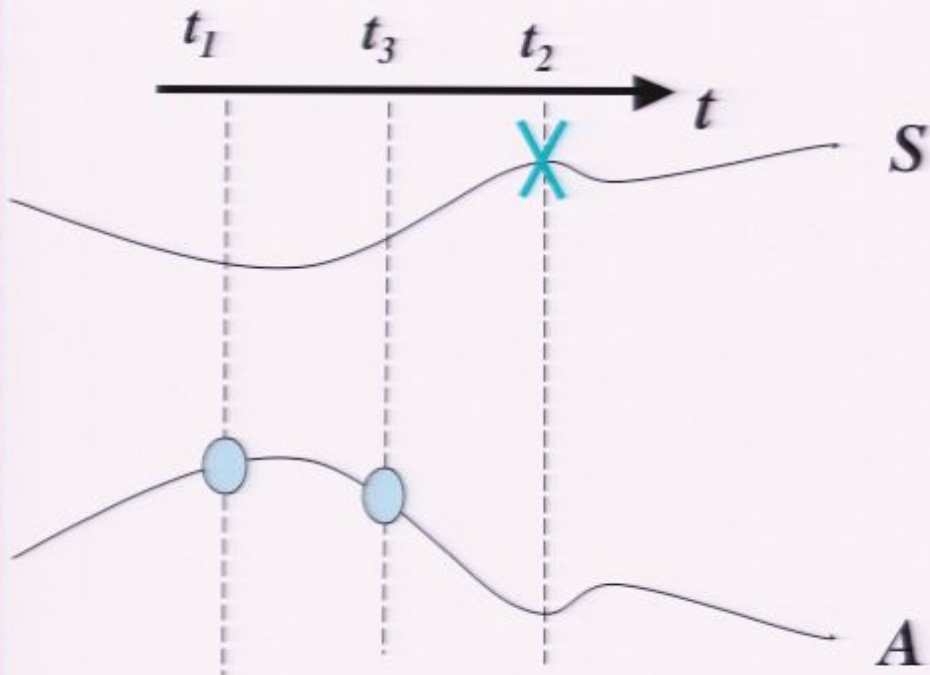
$$(Q(\mathbf{u}), \chi(\mathbf{u})) = (a, b)$$

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- 1) *Don't even require $a = q_L$*
- 2) *Allow any b ; even $b = q_L(\Gamma(\mathbf{u}))$*
- 3) *No restrictions on power of A , or power of the scientist*
- 4) *No restrictions on coupling between S and A*

INFERENCE SIMPLIFIED



- 1) $\Gamma(u) = S(t_2)$
- 2) $X(u) = (\chi(u), Q(u))$
- 3) $q_L(\gamma) = 1$ iff $\gamma = L$
- 4) $Y(u)$

$\forall q_L, \exists x : \forall u \in U,$

$$X(u) = x$$

$$\Rightarrow$$

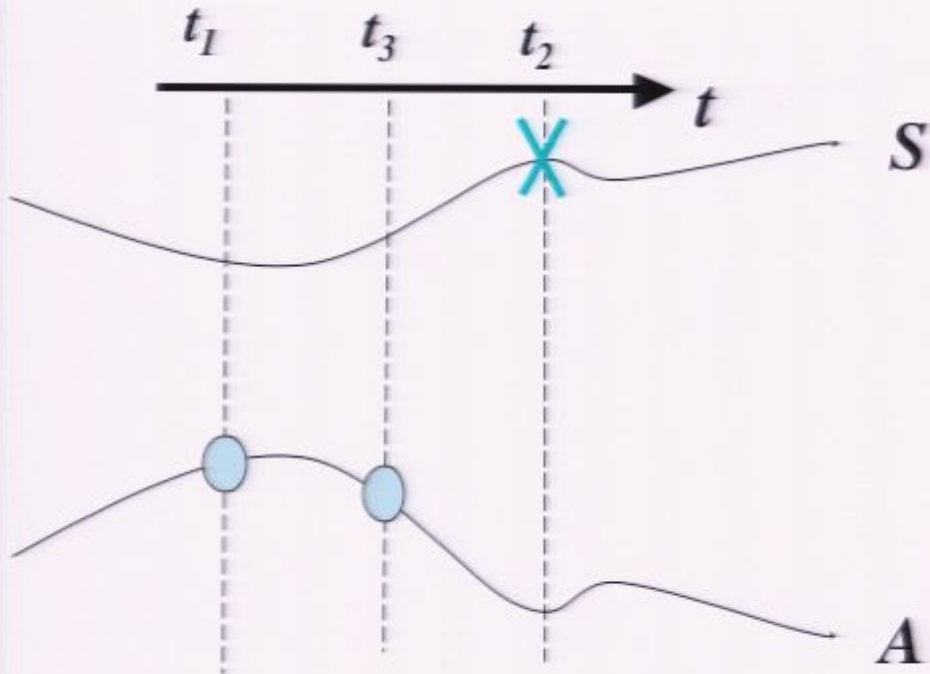
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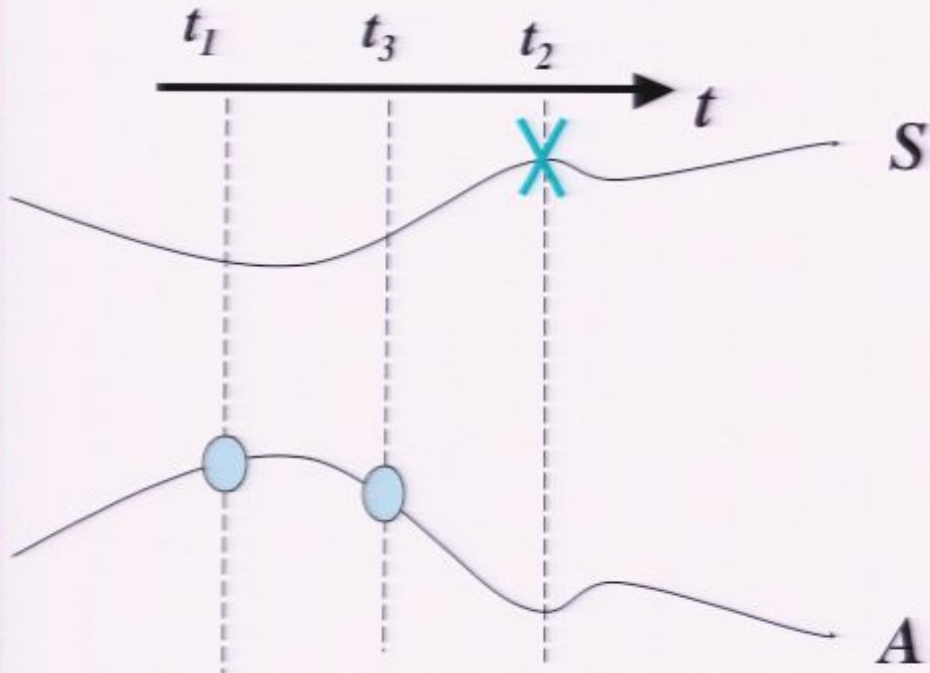
3) $q_L(\gamma) = I$ iff $\gamma = L$

4) $Q(u)$

- *The scientist exists in the physical universe*
- *So what answer for Q they read from $\zeta(u)$ is a function of u*
- *Write that function as $Y(u)$*



INFERENCE



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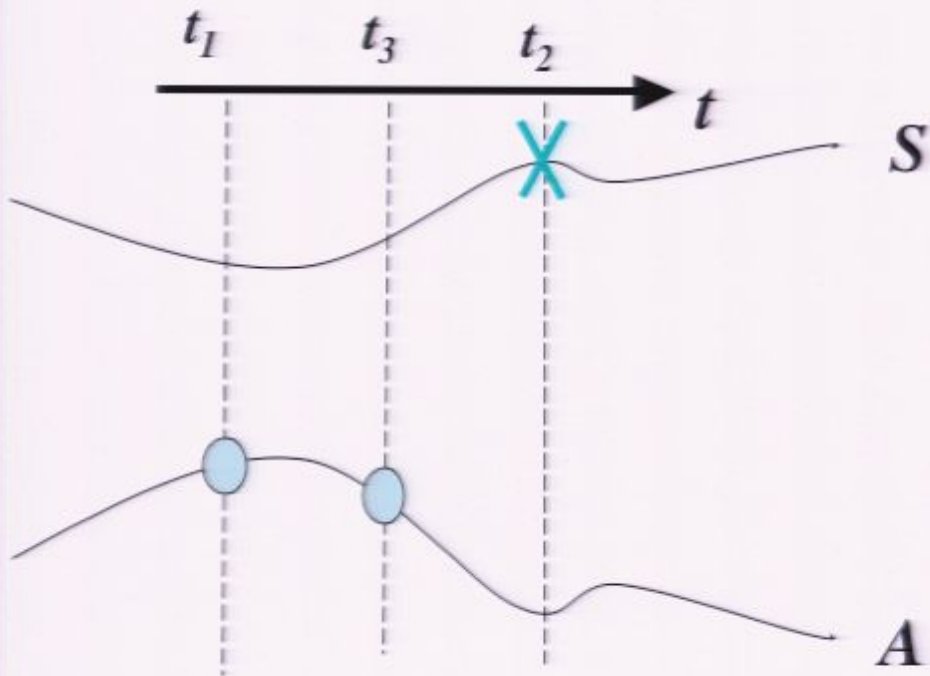
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INFERENCE



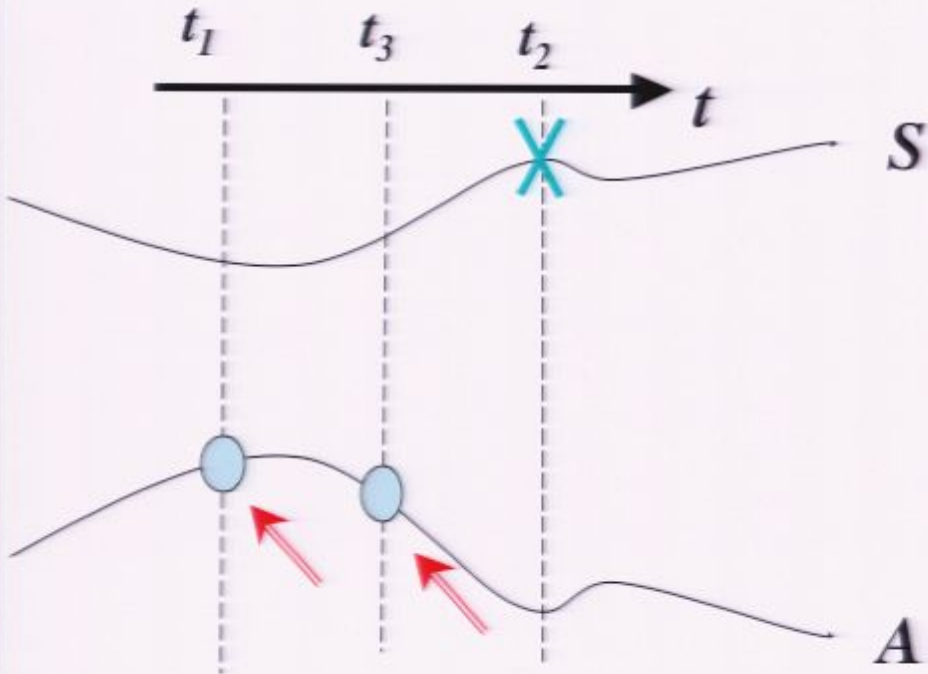
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INFERENCE

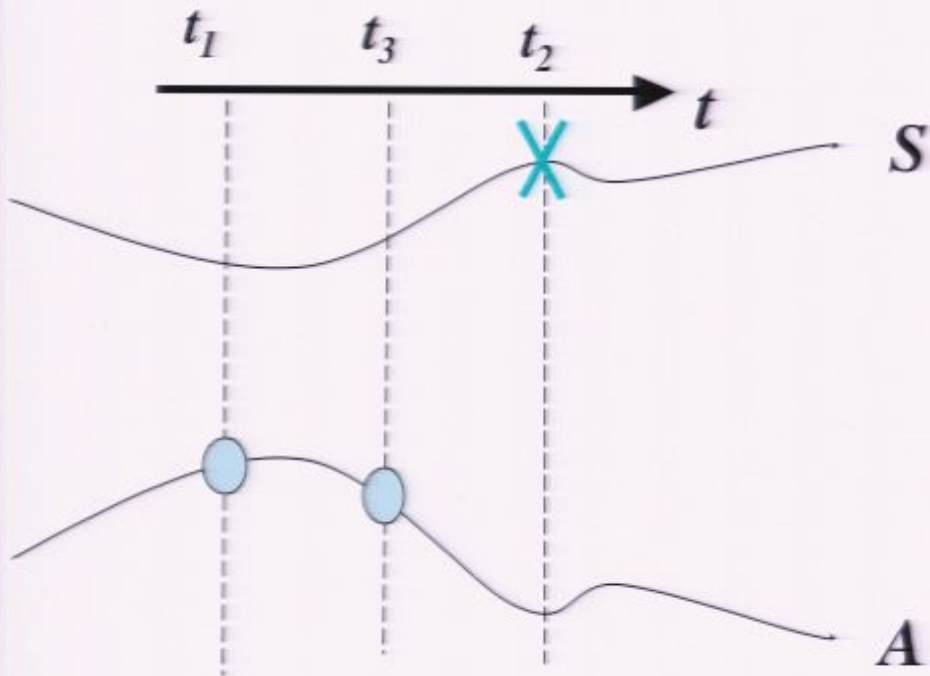


$$1) \Gamma(u) = S(t_2)$$

- *A exists in the physical universe*
- *So $A(t_1)$ and $A(t_3)$ are functions of u*
- *Write them as $\zeta(u)$ and $\chi(u)$*



INFERENCE



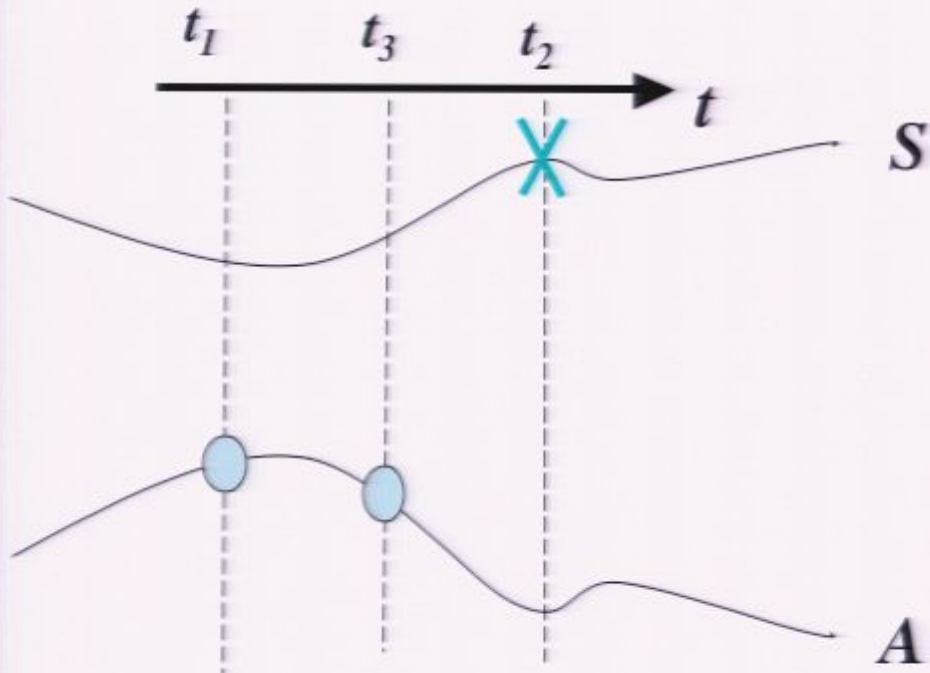
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INFERENCE



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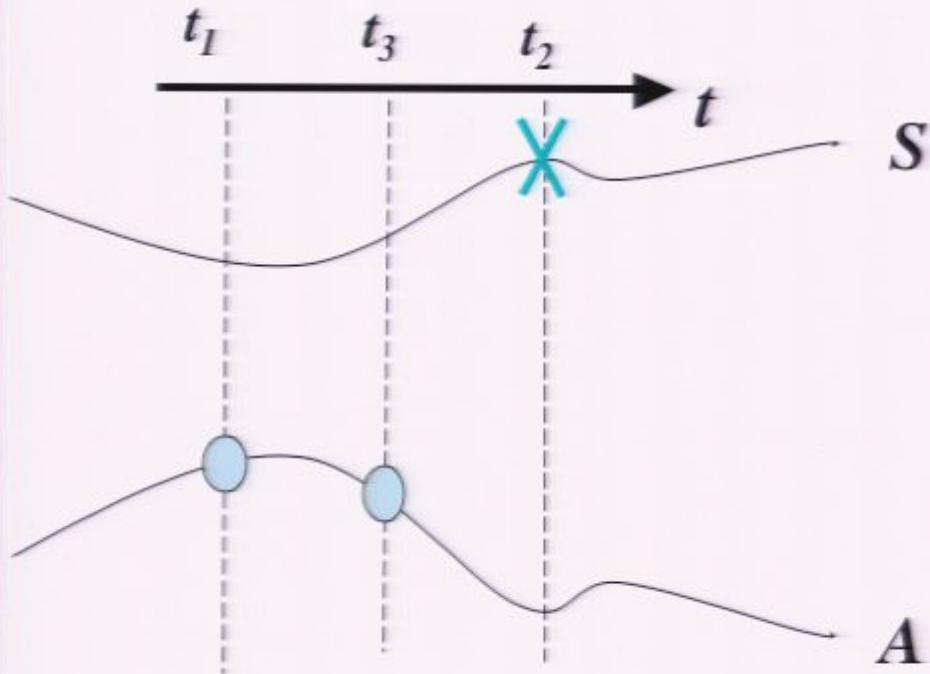
3) $q_L(\gamma) = 1$ iff $\gamma = L$

- *The scientist exists in the physical universe*
- *So which question they are asking is a function of u*
- *Write that function as $Q(u)$*

$S(t_2) = L?$

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INFERENCE



1) $\Gamma(u) = S(t_2)$

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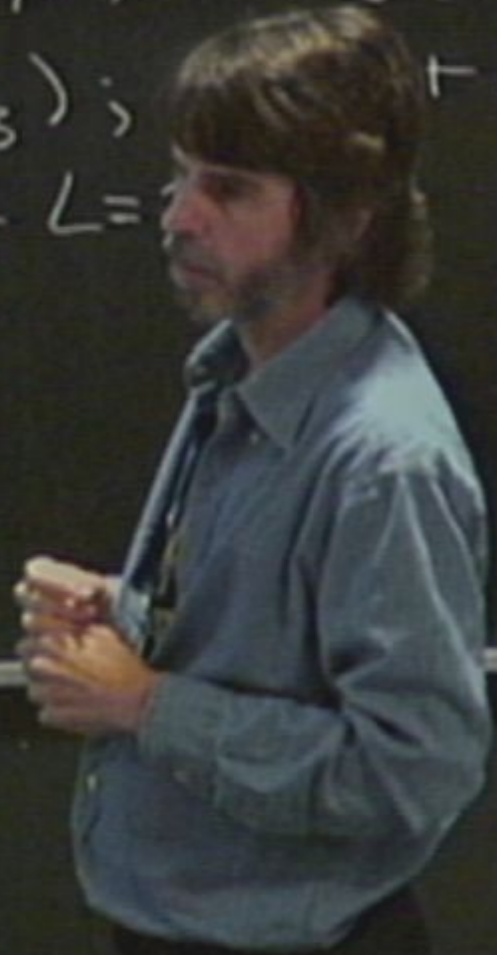
- *The scientist exists in the physical universe*
- *So what answer for Q they read from $\zeta(u)$ is a function of u*
- *Write that function as $Y(u)$*

$\Gamma(u) = S(t_2)$; what want to know

$\chi(u) = A(t_1)$; how device initialized

$S(u) = A(t_3)$; t of device

$g_{\delta L}(\gamma) = 1$ iff $L = \gamma$



$\Gamma(u) = S(t_2)$; what want to know

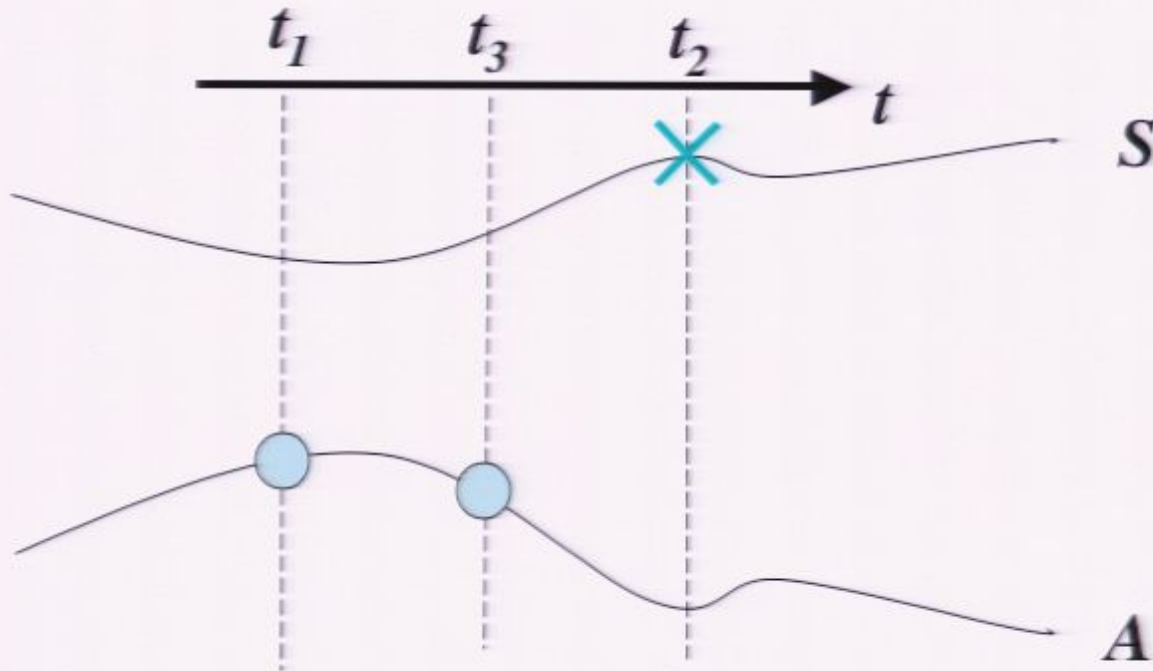
$\chi(u) = A(t_1)$; how device initialized

$S(u) = A(t_3)$; output of device

$g_{\gamma}(\gamma) = 1$ iff $L = \gamma$

$Q(u) =$

PREDICTION



Suppose $A(t_3)$ says
 $S(t_2) = K$.

- 1) $A(t_3)$ has “semantic meaning” if there is a scientist who can read it to answer, “Does $S(t_2) = L$?” $\forall L$.
- 2) Successful prediction is when the scientist’s answer to any such question is correct.



$\Gamma(u) = S(t_2)$; what want to know

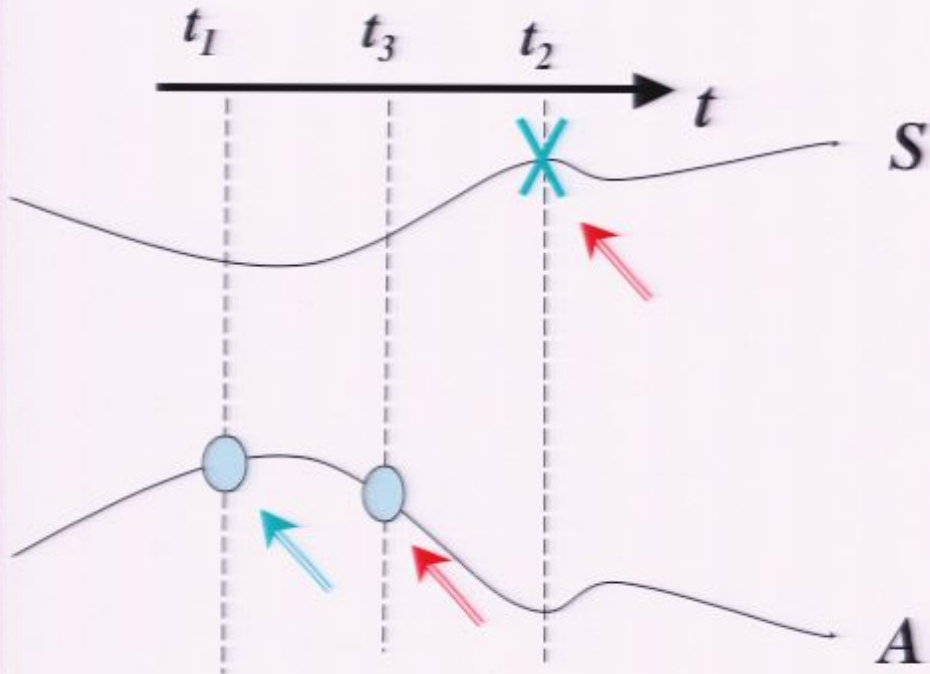
$\chi(u) = A(t_1)$; how device initialized

$S(u) = A(t_3)$; output of device

$q_{\mathcal{L}}(\gamma) = 1$ iff $\mathcal{L} = \gamma$

$Q(u) = \text{Scientist's question}$

INFERENCE



- 1) $\Gamma(u) = S(t_2)$
- 2) $\chi(u) = A(t_1), \zeta(u) = A(t_3)$
- 3) $q_L(\gamma) = 1$ iff $\gamma = L$
- 4) $Q(u)$
- 5) $Y(u)$

Successful inference: $\forall q_L,$

$\exists a, b$ such that

$$(Q(u), \chi(u)) = (a, b)$$

\Rightarrow

$$Y(u) = q_L(\Gamma(u))$$



$\Gamma(u) = S(t_2)$; what want to know

$\chi(u) = A(t_1)$; how device initialized

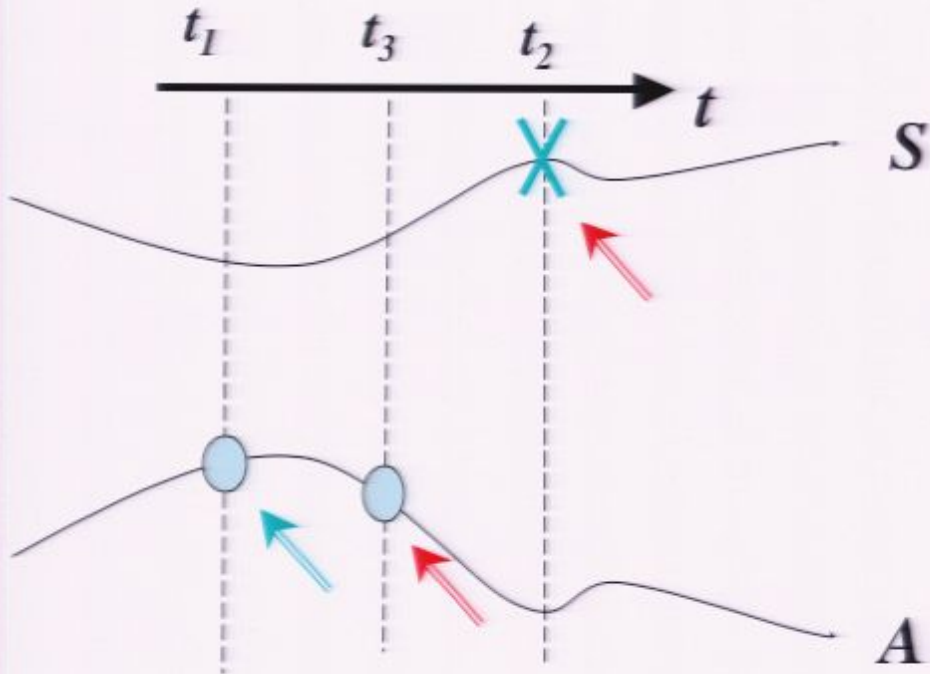
$S(u) = A(t_3)$; output of device

$g_{\beta L}(r) = 1$ iff $L = r$

$Q(u) =$ Scientist's question

$Y(u) =$ " answer

INFERENCE



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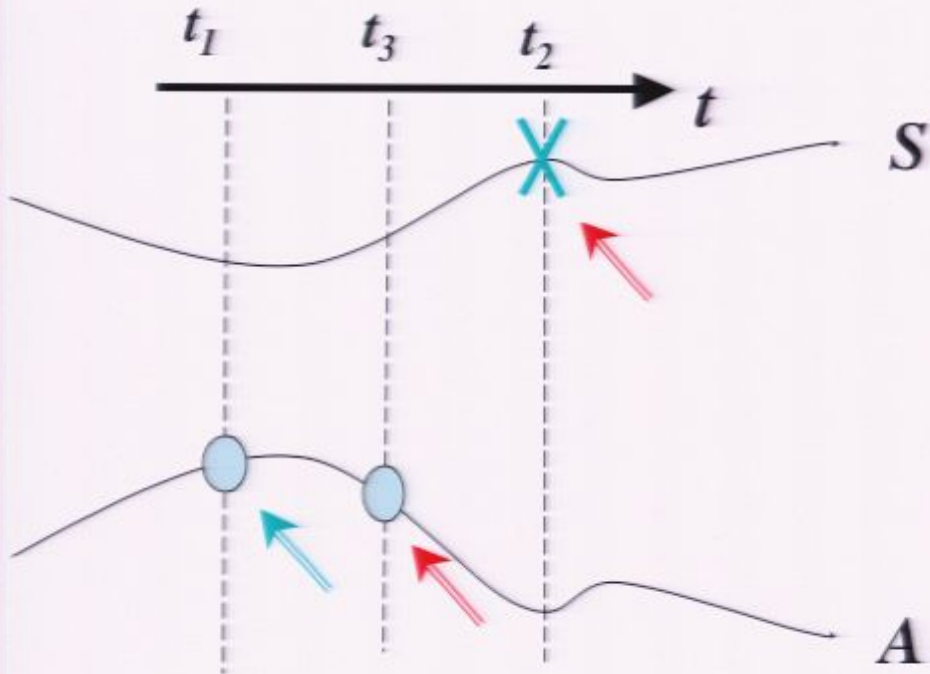
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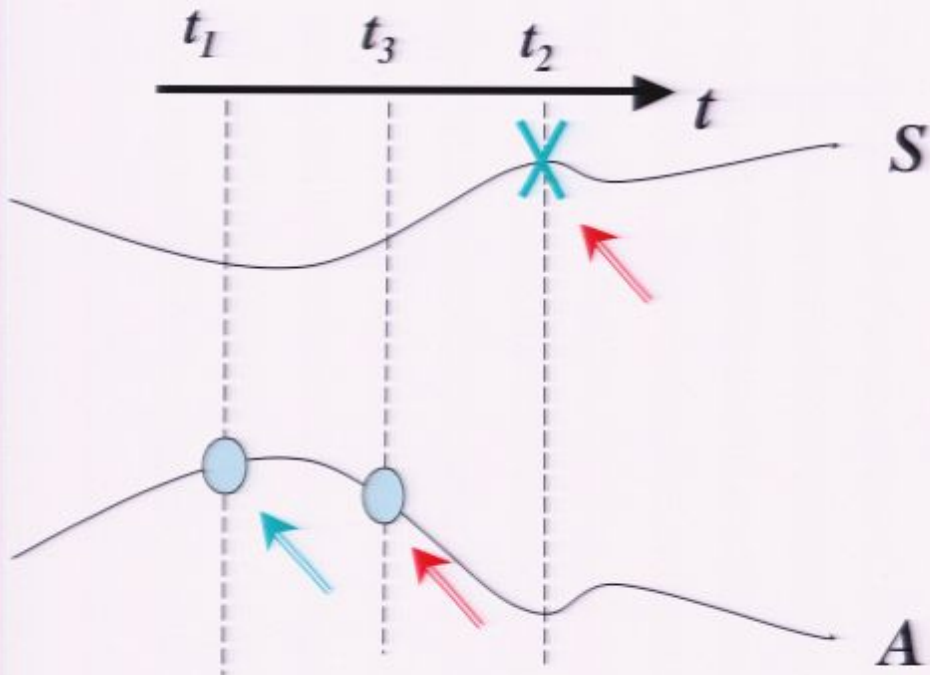
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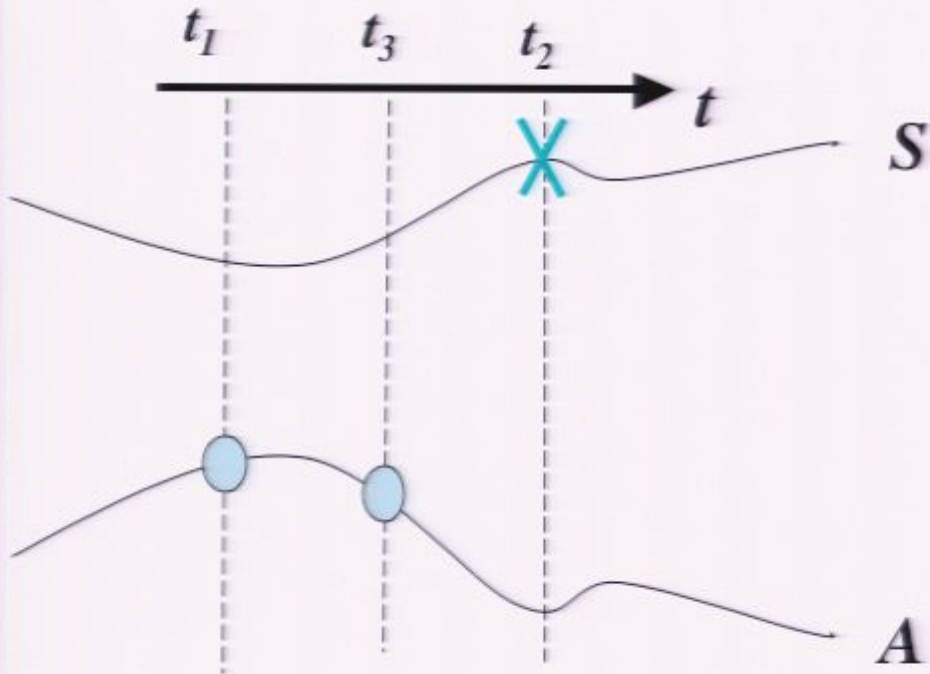
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INFERENCE SIMPLIFIED



- 1) $\Gamma(u) = S(t_2)$
- 2) $X(u) = (\chi(u), Q(u))$
- 3) $q_L(\gamma) = 1$ iff $\gamma = L$
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$\forall q_L, \exists x : \forall u \in U,$

$$X(u) = x$$

\Rightarrow

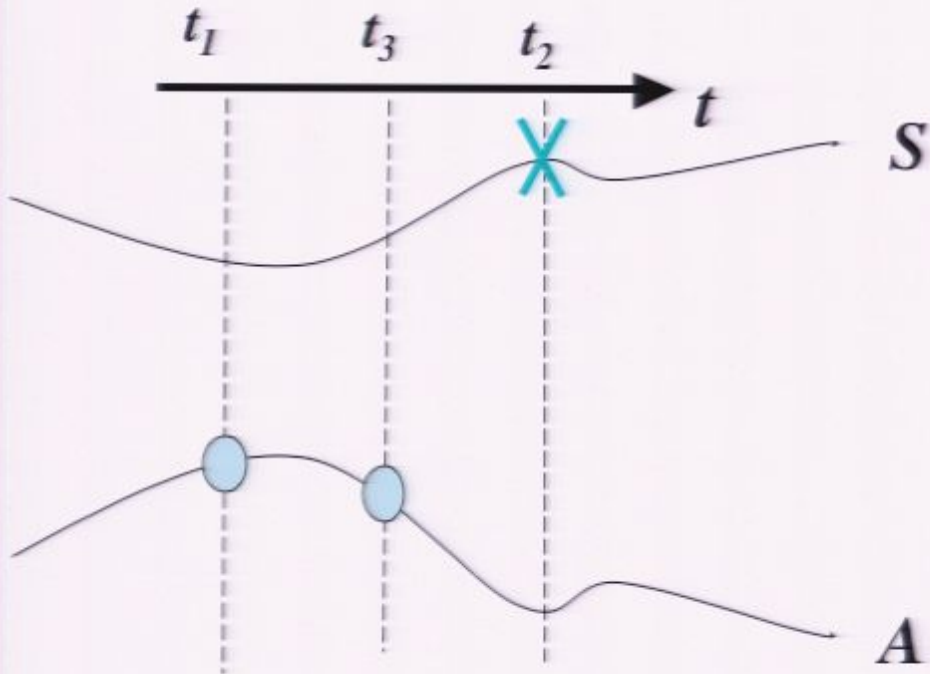
$$Y(u) = q_L(\Gamma(u))$$

$S(t_2) = L?$



$A(t_3)$ says ...

WEAK INFERENCE



- 1) $\Gamma(u) = S(t_2)$
- 2) $X(u) = (\chi(u), Q(u))$
- 3) $q_L(\gamma) = 1$ if $\gamma = L$, else $= -1$
- 4) $Y(u)$

An Inference Device is
a pair of functions $C = (X(u), Y(u))$
where Y is binary-valued

C Weakly infers Γ (“ $C > \Gamma$ ”) iff

$\forall q_L, \exists x$ such that

$$X(u) = x$$

\Rightarrow

$$Y(u) = q_L(\Gamma(u))$$



ROADMAP

1) *Formalize observation, prediction, and memory*



2) *Extract what's in common: inference devices*



3) *Elementary properties of inference devices*



4) *Inference devices and Turing machine theory:
strong inference and inference complexity*



5) Stochastic inference

ELEMENTARY PROPERTIES OF INFERENCE

- 1) For any Γ , \exists a device that infers Γ .**
- 2) For any device, \exists a Γ it does not infer. (Impossibility result.)**
- 3) Inference need not be transitive:**
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ENGINEERING IMPLICATIONS OF IMPOSSIBILITY RESULT

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 - *Laplace was wrong.*

- 2) *For any recording apparatus, there is always a past event that cannot be guaranteed to have been correctly recorded.*

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BREADTH OF IMPOSSIBILITY RESULT

- 1) *No requirement that x specify the question being asked.*
- 2) *No restriction on information fed into the device via x .*
 - *Can even have correct answer specified in x .*
- *No restriction on coupling between a simulator and the “rest of the universe” while it is computing the simulation.*
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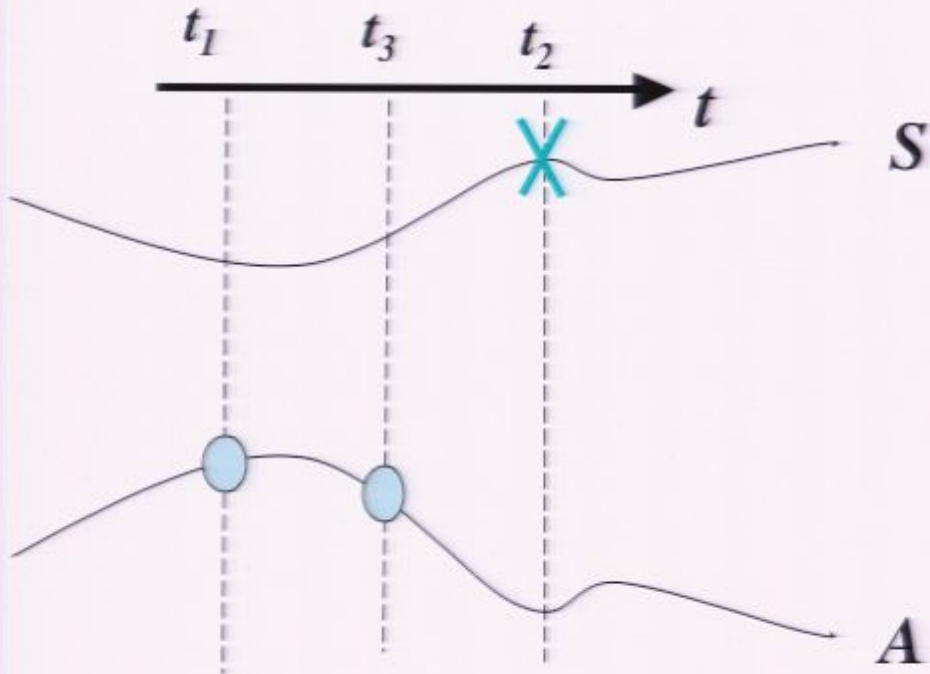
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WEAK INFERENCE



- 1) $\Gamma(u) = S(t_2)$
- 2) $X(u) = (\chi(u), Q(u))$
- 3) $q_L(\gamma) = 1$ if $\gamma = L$, else $= -1$
- 4) $Y(u)$

An Inference Device is a pair of functions $C = (X(u), Y(u))$ where Y is binary-valued

C Weakly infers Γ (“ $C > \Gamma$ ”) iff

$\forall q_L, \exists x$ such that

$$X(u) = x$$

\Rightarrow

$$Y(u) = q_L(\Gamma(u))$$

$S(t_2) = L?$

$A(t_3)$ says ...



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INFERENCE RELATIONS BETWEEN DEVICES

- Often not interested in inference of arbitrary functions, but rather inference relation among a set of devices.

1) Two devices (X, Y) , (X', Y') are pairwise distinguishable iff
any pair (x, x') can occur

2) A set of devices $\{(X_i, Y_i)\}$ is mutually distinguishable iff
any tuple (x_1, x_2, \dots) can occur

1) No device is distinguishable from itself.

2) Pairwise distinguishability may not be transitive.

INFERENCE RELATIONS BETWEEN DEVICES -2

- 3) If all pairs of devices from $\{C_i\}$ are pairwise distinguishable, \exists at most one $k : C_k > C_j \forall j \neq k$. “Monotheism” theorem.
(N.b., control is a special type of inference.)**

- 4) If all pairs of devices from $\{C_i\}$ are pairwise distinguishable, can have $C_1 > C_2 > \dots C_1$.**

- 5) If the set of devices $\{C_i\}$ is mutually distinguishable, *cannot* have $C_1 > C_2 > \dots C_1$.**

ROADMAP

1) *Formalize observation, prediction, and memory*



2) *Extract what's in common: inference devices*



3) *Elementary properties of inference devices*



4) *Inference devices and Turing machine theory:
strong inference and inference complexity*



5) Stochastic inference

STRONG INFERENCE

- A universal Turing Machine T can emulate any other one, T'
- T does that by having its input be the program and input of T'

The analog with inference devices:

$C = (X, Y)$ *strongly infers* $C' = (X', Y')$ iff:

\forall probe functions q_L of $Y'(U)$, $\forall x'$,

$\exists x$ s.t.

$$X(u) = x \Rightarrow Y(u) = q_L(Y'[u]), X'(u) = x'$$

- “ $C_1 \gg C_2$ ” means C_1 strongly infers C_2

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PROPERTIES OF STRONG INFERENCE

- 1) $C_1 \gg C_2$ and $C_2 > \Gamma \Rightarrow C_1 > \Gamma$
 - Just like with UTM's and TM's (contrast weak inference)

- 2) $C_1 \gg C_2$ and $C_2 \gg C_3 \Rightarrow C_1 \gg C_3$
 - Just like with UTM's (contrast weak inference)

- 3) For any C_1 , $\exists C_2$ that C_1 does not strongly infer

- 4) If $\forall x_1, |X_1^{-1}(x_1)| > 2$, then $\exists C_2$ such that $C_2 \gg C_1$

- 5) No two devices can strongly infer each other
 - Distinguishability irrelevant (contrast weak inference)
 - Even if C_1 and C_2 are same system at different moments in time: “intelligent design theorem”.

PROPERTIES OF STRONG INFERENCE - 3

6) Cannot have $C_1 \gg C_2 \gg \dots C_1$.

7) Let D be a finite set of devices, where:

- The associated digraph G of strong inferences among the devices in D is weakly connected;**
- Any pair of devices (nodes) in G not connected by an edge is pairwise distinguishable**

Then G has exactly one root.

PROPERTIES OF STRONG INFERENCE - 3

9) Let C_1 and C_2 be copies, i.e., implement the same logical mapping from X to Y .

E.g., same system at different moments in time.

i) Can have $C_1 > C_2$, even if $X_1(U)$, $X_2(U)$ are finite

ii) Can have $C_1 \gg C_2$, but only if $X_1(U)$, $X_2(U)$ are infinite

(ii) says “intelligent design requires an infinite god”.

INFERENCE COMPLEXITY

- 1) Kolmogorov complexity of a string s with respect to TM T is smallest input string to T needed for T to produce s .**
- 2) Inference complexity of Γ with respect to device (X, Y) is smallest set of setup values $x \in X$ needed for C to infer Γ .**
 - Size measured with $-\ln$ of phase space volume.**
- 3) We write that inference complexity as $\Omega(\Gamma | C)$.**

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INFERENCE COMPLEXITY

- 1) There is a bound on “translation” Kolmogorov complexity added in going from UTM T_1 to UTM T_2 ;
- 2) There is a bound on “translation” inference complexity added in going from C_1 to C_2 :

- Given a finite function Γ and two devices C_1 and $C_2 : C_1 \gg C_2$,

$$\Omega(\Gamma | C_1) - \Omega(\Gamma | C_2) \leq$$

$$|\Gamma(U)| \left(\max_{x_2} \min_{x_1 : X_1 = x_1 \Rightarrow X_2 = x_2, Y_1 = Y_2} \ln \left[\frac{X_2^{-1}(x_2)}{X_1^{-1}(x_1)} \right] \right)$$

- The RHS is non-negative, and independent of volume units

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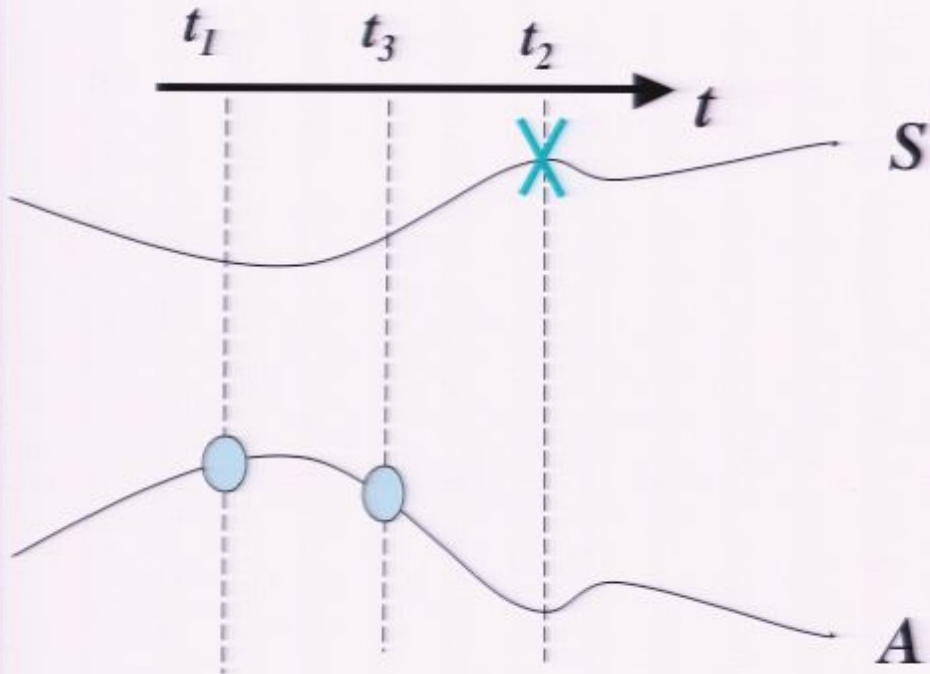
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INFERENCE SIMPLIFIED



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- 2) $X(u) = (\chi(u), Q(u))$
- 3) $q_L(\gamma) = 1$ iff $\gamma = L$
- 4) $Y(u)$

$\forall q_L, \exists x : \forall u \in U,$

$$X(u) = x$$

\Rightarrow

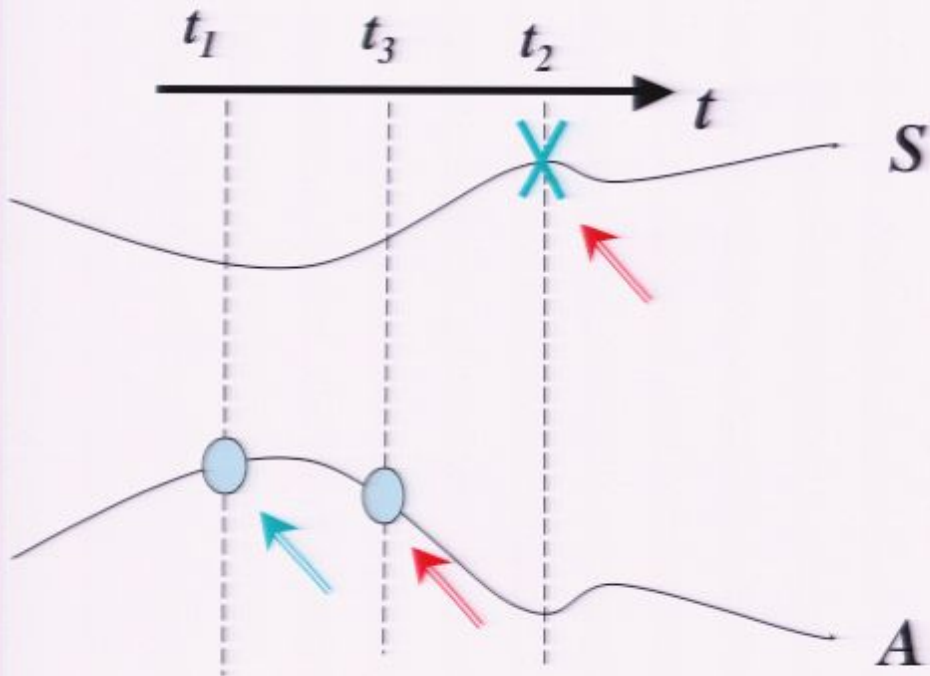
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INFERENCE



Successful inference: $\forall q_L,$

$\exists a, b$ such that

$$(Q(\mathbf{u}), \chi(\mathbf{u})) = (a, b)$$

\Rightarrow

$$Y(\mathbf{u}) = q_L(\Gamma(\mathbf{u}))$$

- 1) *Don't even require $a = q_L$*
- 2) *Allow any b ; even $b = q_L(\Gamma(\mathbf{u}))$*
- 3) *No restrictions on power of A, or power of the scientist*
- 4) *No restrictions on coupling between S and A*



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PHYSICAL LIMITS OF INFERENCE

David H. Wolpert

NASA Ames Research Center
David.H.Wolpert@[nasa.gov](mailto:David.H.Wolpert@nasa.gov)
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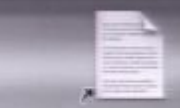
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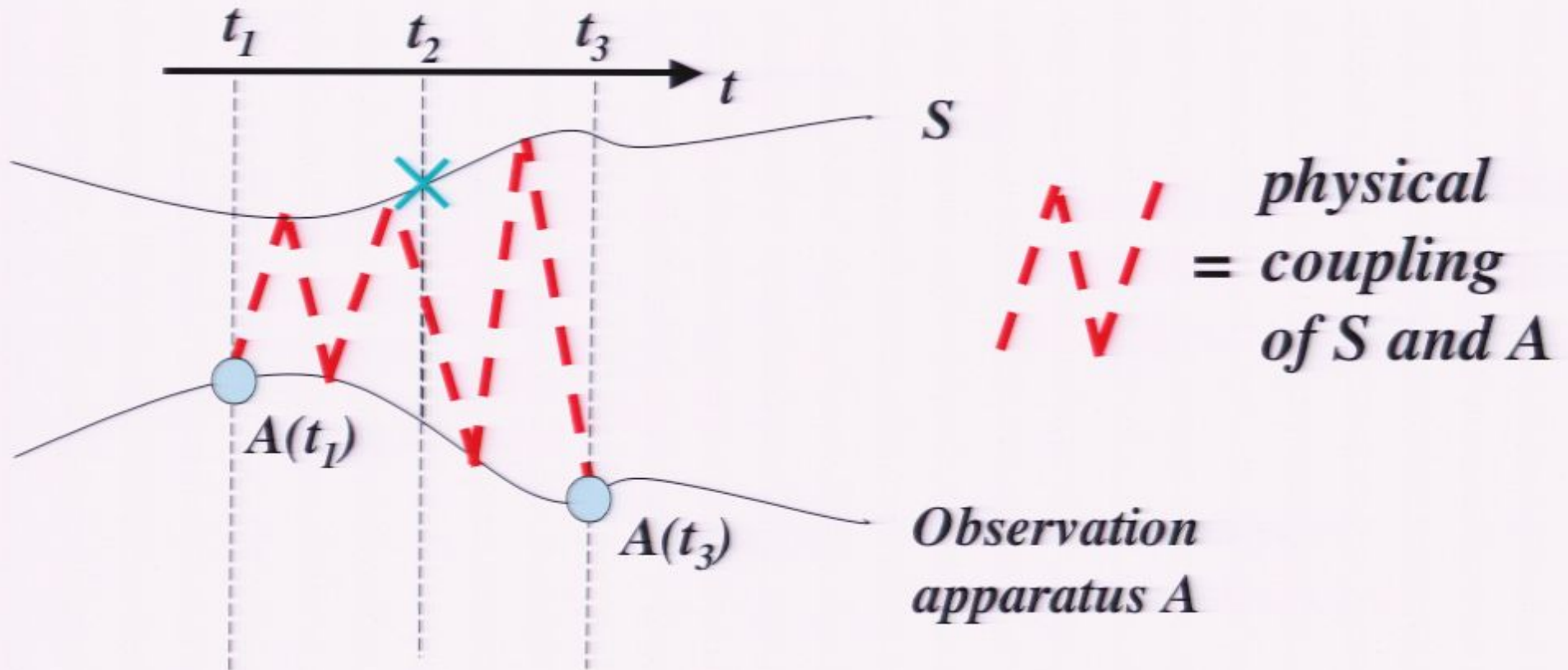
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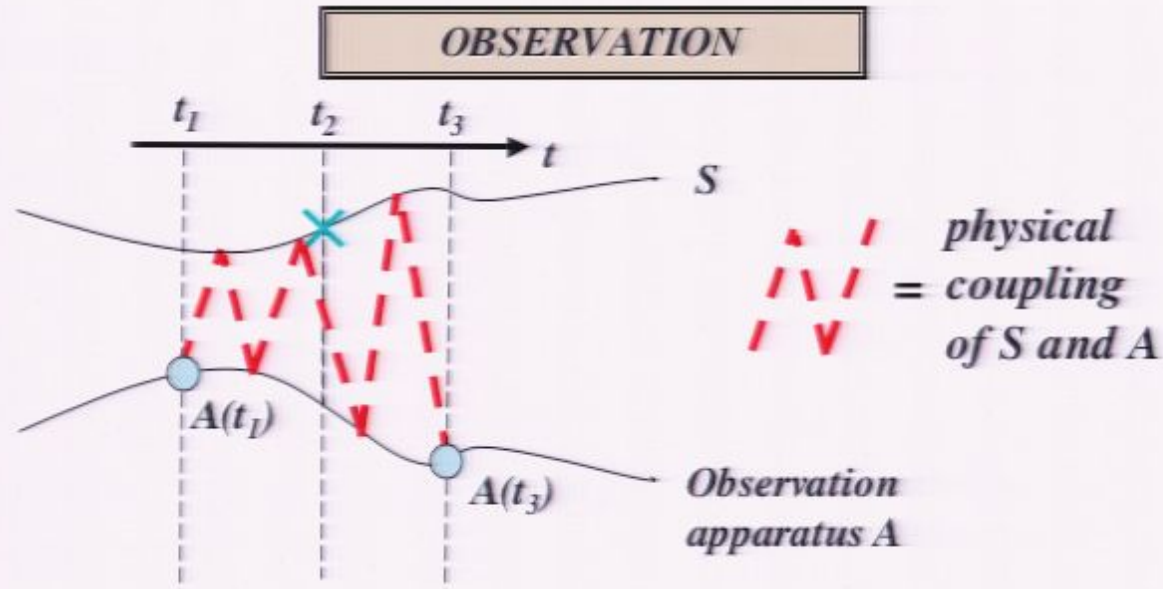
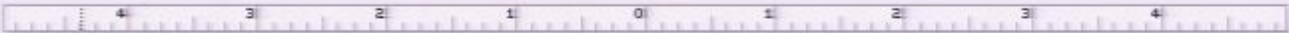
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OBSERVATION

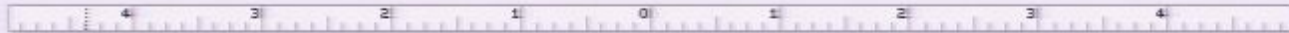


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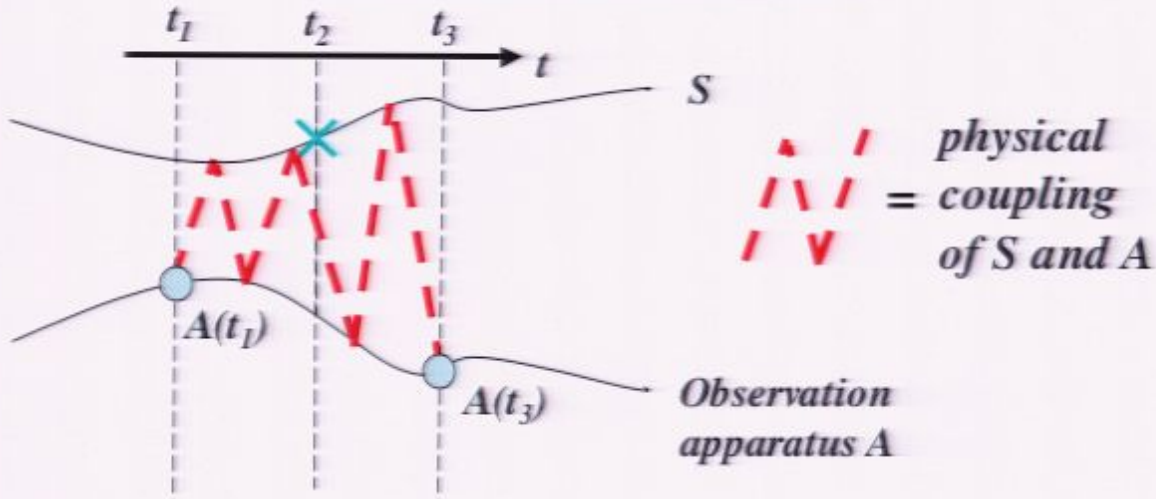


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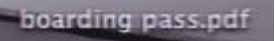
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Click to add notes

The image displays a grid of 25 PowerPoint slides, numbered 1 through 25. Each slide contains technical diagrams and text. Slide 4 is highlighted with a black border. The diagrams include flowcharts and circuit-like structures with labels like 'DYNAMIC', 'STATIC', and 'INTEGRATION'. Some slides have callouts with text like 'Dynamically Defect'. The slides are arranged in a 5x5 grid.



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31 32 33 34 35

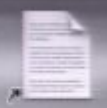
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STOCHASTIC INFERENCE

- What changes if there is probability measure P over U ?

- 1) Given a function Γ and device $C = (X, Y)$, C infers Γ with covariance accuracy

$$\varepsilon = \frac{\sum q_L \max_x [E_P(Yq_L(\Gamma) | x)]}{|\Gamma(U)|}$$

- 2) Can't use mutual information instead; it only captures syntactic content of distributions, not semantic content.
- 3) However can use mutual information to define stochastic distinguishability.

Click to add notes

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EXAMPLE OF STOCHASTIC INFERENCE RESULT

- 1) Let C_1 and C_2 be two devices, where:
 - i) Both $X_1(U)$ and $X_2(U)$ are the binaries;
 - ii) $C_1 > C_2$ with accuracy ε_1 , and $C_2 > C_1$ with accuracy ε_2 .
 - iii) $P(X_1 = -1) = \alpha$, and $P(X_2 = -1) = \beta$

- 2) Define H as the four-dimensional unit open hypercube, and
 - i) $\forall z \in H, k(z) = z_1 + z_4 - z_2 - z_3$;
 - ii) $\forall z \in H, m(z) = z_2 - z_4$;
 - iii) $\forall z \in H, n(z) = z_3 - z_4$.

- 3) $\varepsilon_1 \varepsilon_2 \leq \max_{z \in H} |\alpha \beta [k(z)]^2 + ak(z)m(z) + bk(z)n(z) + m(z)n(z)|$

- 4) E.g., for $\alpha = \beta = 1/2$, $\varepsilon_1 \varepsilon_2 \leq 1/4$.