

# Dynamic Choice of Information Sources

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Why do we learn?

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“

Physics is like sex: sure, it may give some practical results, but that's not why we do it.

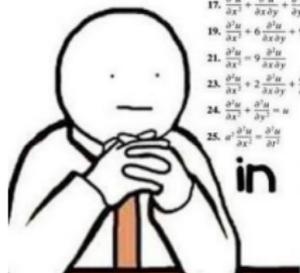
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Richard Feynman

# Why do we learn?

I'm still waiting for the day that I will actually use



17.  $\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial x \partial y} + \frac{\partial^2 u}{\partial y^2} = 0$       18.  $3 \frac{\partial^2 u}{\partial x^2} + 5 \frac{\partial^2 u}{\partial x \partial y} + \frac{\partial^2 u}{\partial y^2} = 0$   
19.  $\frac{\partial^2 u}{\partial x^2} + 6 \frac{\partial^2 u}{\partial x \partial y} + 9 \frac{\partial^2 u}{\partial y^2} = 0$       20.  $\frac{\partial^2 u}{\partial x^2} - \frac{\partial^2 u}{\partial x \partial y} - 3 \frac{\partial^2 u}{\partial y^2} = 0$   
21.  $\frac{\partial^2 u}{\partial x^2} = 0$       22.  $\frac{\partial^2 u}{\partial x \partial y} - \frac{\partial^2 u}{\partial y^2} + 2 \frac{\partial u}{\partial x} = 0$   
23.  $\frac{\partial^2 u}{\partial x^2} + 2 \frac{\partial^2 u}{\partial x \partial y} + \frac{\partial^2 u}{\partial y^2} + \frac{\partial u}{\partial y} + \frac{\partial u}{\partial x} - 6 \frac{\partial u}{\partial y} = 0$   
24.  $\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} = u$       25.  $a^2 \frac{\partial^2 u}{\partial x^2} - \frac{\partial^2 u}{\partial y^2}$   
26.  $k \frac{\partial^2 u}{\partial x^2} = \frac{\partial u}{\partial t}$ ,  $k > 0$

in real life

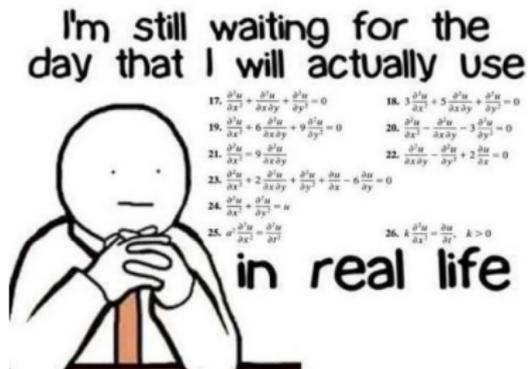
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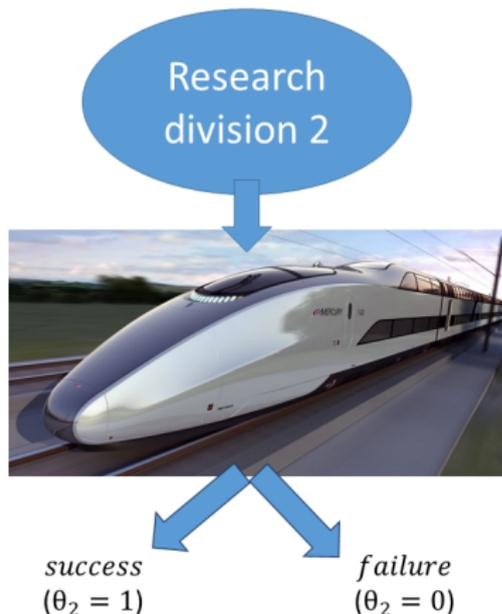
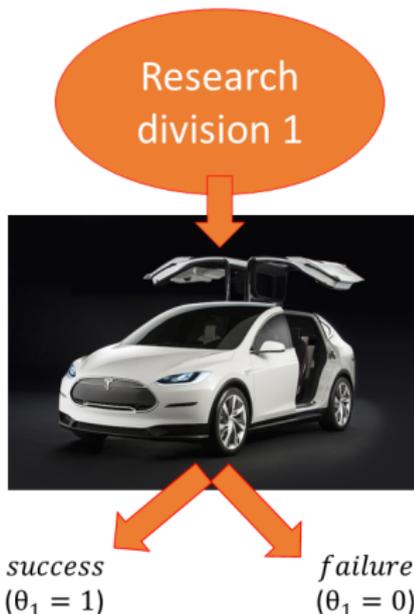
## Motivation

We have common sense understanding that knowledge is important, it will pay off. But often in a distant future, and **right now we might not know where and how we are going to use this knowledge.**

*How to choose what to learn if we don't know the goal?*

## Example

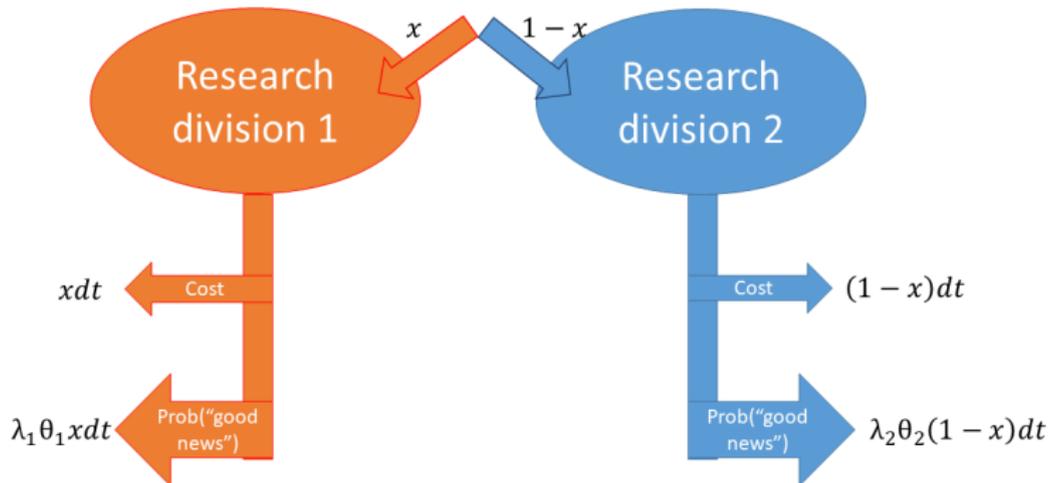
- ▶ A company has **two research divisions**
- ▶ Each division  $k = 1, 2$  investigates the profitability of a certain project, which can be either **success** ( $\theta_k = 1$ ) or **failure** ( $\theta_k = 0$ )
  - ▶  $\theta_1$  and  $\theta_2$  are not necessarily independent



## Example

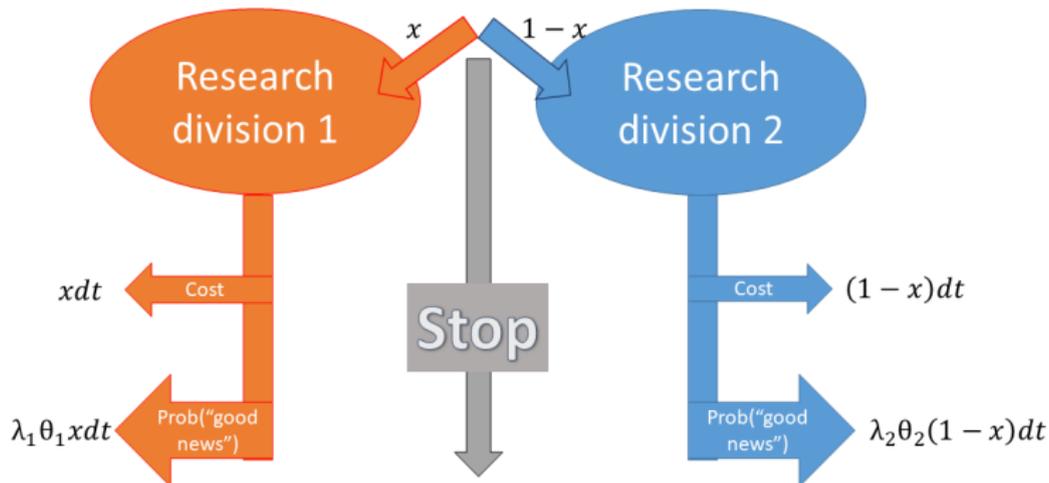
- ▶ At each instance of time, the company allocates a **unit of resources** between two divisions
- ▶ Each division  $k$  spends its resources  $x_k \in [0, 1]$  to **search for a proof** that its project is successful  $\theta_k = 1$

	$\theta_k = 1$	$\theta_k = 0$
Prob("good news")	$\lambda_k x_k dt$	0
Prob("no news")	$1 - \lambda_k x_k dt$	1



## Example

- ▶ The company decides when to stop research and make the decision



Which project(s) to invest in (if any)?

# General Framework

## Learning Stage

- ▶ four states of the world:  
 $(\theta_1, \theta_2) \in \{(1, 0), (0, 1), (1, 1), (0, 0)\}$
- ▶ two information sources:
  - ▶ source 1 = search for a proof that  $\theta_1 = 1$
  - ▶ source 2 = search for a proof that  $\theta_2 = 1$

## Decision Making Stage

- ▶  $\mathcal{A} = \{a_1, \dots, a_n\}$ : set of alternatives to choose from
- ▶  $u_i(a)$ : payoff from choosing alternative  $a$

	(1, 0)	(0, 1)	(1, 1)	(0, 0)
$a_1$	$u_1(a_1)$	$u_2(a_1)$	$u_3(a_1)$	$u_4(a_1)$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$a_n$	$u_1(a_n)$	$u_2(a_n)$	$u_3(a_n)$	$u_4(a_n)$

# General Framework

## Learning Stage *How to learn?*

- ▶ four states of the world:  
 $(\theta_1, \theta_2) \in \{(1, 0), (0, 1), (1, 1), (0, 0)\}$
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## Decision Making Stage *Why to learn?*

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$a_1$	$u_1(a_1)$	$u_2(a_1)$	$u_3(a_1)$	$u_4(a_1)$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$a_n$	$u_1(a_n)$	$u_2(a_n)$	$u_3(a_n)$	$u_4(a_n)$

# Contribution

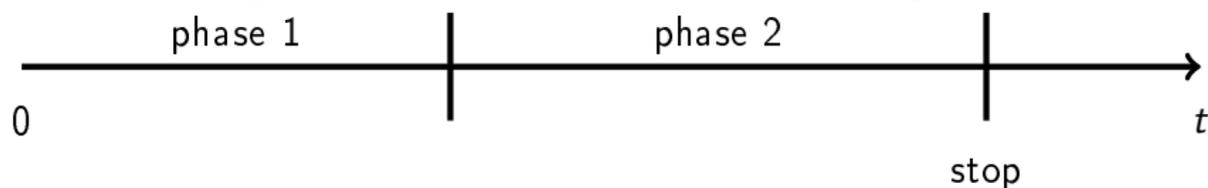
Optimal strategy balances the trade-off:

- ▶ *belief-based incentives*: use the source that leads to a higher  $\text{Prob}(\text{"good news"})$ 
  - ▶ depends on current **beliefs** and information **sources'** characteristics
- ▶ *payoff-based incentives*: learn about the project that leads to a higher profit if successful
  - ▶ depends on **payoff** matrix

## Contribution

This paper shows

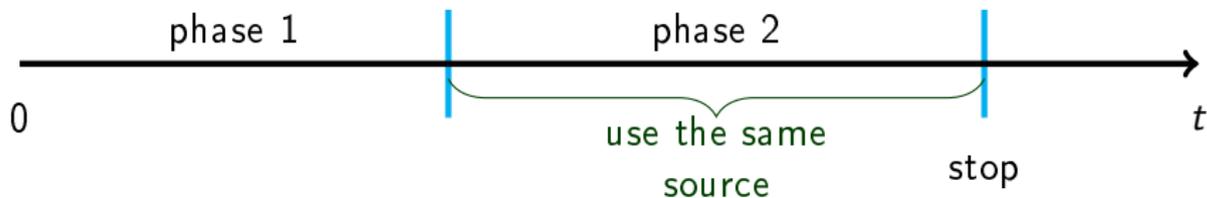
1. Optimal strategy has two phases: in the absence of “good news”



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1. Optimal strategy has two phases: in the absence of “good news”

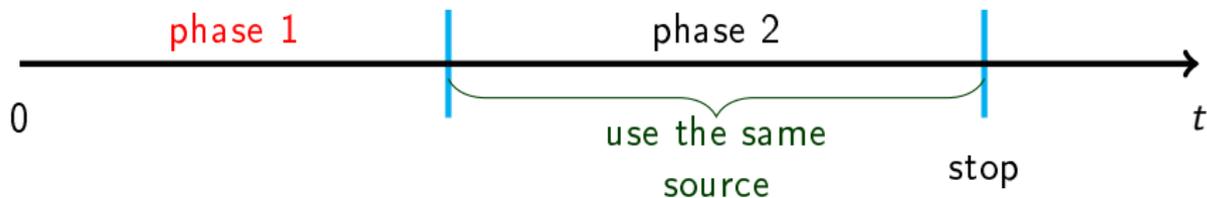


- ▶ phase 2 source depends on the *payoff matrix*
- ▶ thresholds depend on the *payoff matrix*

# Contribution

This paper shows

1. Optimal strategy has two phases: in the absence of “good news”



- ▶ phase 2 source depends on the *payoff matrix*
- ▶ thresholds depend on the *payoff matrix*

2. Phase 1 rule introduces the notion is a source *index*

use the source with the highest **index**

## Main Result

Expression for the index

## Properties of the index

### 1. It's (almost) independent of the payoff matrix

- ▶ independence of the payoff matrix makes the index *constant across all decision problems*
- ▶ the index is mainly a characteristic of the information source itself

## Properties of the index

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- ▶ the index is mainly a characteristic of the information source itself

#### *Examples:*

information sources = different diagnostic tests;

decision problem also specifies possible treatments

information sources = news topics in media;

decision problem also reflects individual characteristics, such as policy preferences

## Properties of the index

1. It's (almost) independent of the payoff matrix
2. When the index is independent of the payoff matrix, it is equal to

$$\text{Prob}(\text{"good news"}) = \lambda_k \cdot \underbrace{\mathbb{P}(\theta_k = 1)}_{\text{current beliefs}}$$

- ▶ the index of source  $k$  depends *only* on the characteristics of that source  $k$  (probability of receiving a positive signal from that source); it does *not* depend on neither the intensity of the other source, nor the correlation between the states
- ▶ similarity with the Gittins index

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$$\text{Prob}(\text{"good news"}) = \lambda_k \cdot \underbrace{\mathbb{P}(\theta_k = 1)}_{\text{current beliefs}}$$

3. When the index does depend on the payoff matrix, it depends only on the payoffs at state (1,1)

Example with two investment projects:

- ▶ in monopoly market, only the difference in payoffs in case of success matters

$$\underbrace{v_1}_{\text{payoff from successful project 1}} - \underbrace{v_2}_{\text{payoff from successful project 2}}$$

- ▶ when another firm can compete with the other project, only the payoffs when both projects are successful matter

	(1, 0)	(0, 1)	(1, 1)	(0, 0)
invest in project 1	$v_1$	0	$v_1 - d_1$	0
invest in project 2	0	$v_2$	$v_2 - d_2$	0

## Literature

Che&Mierendorff  
(2017, R&R in AER)

Nikandrova&Pancs  
(2018, TE)

This paper

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states	(1,0) and (0,1)	(1,0), (0,1), (1,1), (0,0)	
correlation	$\theta_1 + \theta_2 = 1$	$\theta_1 \perp \theta_2$	arbitrary
alternatives	2 ("match the state")	2 ("choose successful project")	any number
focus	on a given decision problem ↓ optimal strategy (including chosen alternative)		on the general form of the learning process ↓ index

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# Literature

## Existing literature: alternatives and states are tightly connected

- ▶ Drift-diffusion model: info about alternatives directly, not through a state of the world  
*Fudenberg, Strack, and Strzalecki (2015) and Ke, Shen, and Villas-Boas (2016): Brownian motion; Pancs and Nikandrova (2018): Poisson process*
- ▶ Multi-armed bandit problem: each source gives both the payoff and information about the payoff distribution
- ▶ Search problem
  - ▶ minimize cost of learning conditional on finding the state  
*Ahlswede&Wegener 1987*
  - ▶ or finding the state has a direct consequences to the payoff (treasure hunt)  
*Fershtman&Rubinstein 1997, Matros&Smirnov 2016*
- ▶ *Liang, Mu, and Syrgkanis (2017)* came to the “opposite” conclusion that myopic learning is (almost) optional
  - ▶ completely different structure of the decision problem; in particular, only one state component,  $\theta_1$ , is payoff relevant

# Outline

Introduction

Special Case:  $\theta_1 + \theta_2 \leq 1$

General Case

Conclusion

## Payoff Matrix and Beliefs

$\mathcal{A} = \{a_1, a_2, \dots, a_n\}$  — set of alternatives

State  $(\theta_1, \theta_2)$ :     $(1, 0)$      $(0, 1)$      $(0, 0)$



Alternative  $a_1$      $u_1(a_1)$      $u_2(a_1)$      $u_3(a_1)$

Alternative  $a_2$      $u_1(a_2)$      $u_2(a_2)$      $u_3(a_2)$

...

...

...

...

WLOG:  $u_1(a_1) = \max_{a \in \mathcal{A}} u_1(a)$ ,  $u_2(a_2) = \max_{a \in \mathcal{A}} u_2(a)$

## Payoff Matrix and Beliefs

$\mathcal{A} = \{a_1, a_2, \dots, a_n\}$  — set of alternatives

State $(\theta_1, \theta_2)$ :	$(1, 0)$	$(0, 1)$	$(0, 0)$
<i>Beliefs:</i>	$p_1$	$p_2$	$1 - p_1 - p_2$



Alternative $a_1$	$u_1(a_1)$	$u_2(a_1)$	$u_3(a_1)$
Alternative $a_2$	$u_1(a_2)$	$u_2(a_2)$	$u_3(a_2)$
...	...	...	...

WLOG:  $u_1(a_1) = \max_{a \in \mathcal{A}} u_1(a)$ ,  $u_2(a_2) = \max_{a \in \mathcal{A}} u_2(a)$

## Information Sources

- ▶ The decision maker can **stop** the learning process **at any moment**.
- ▶ At each moment of time **during** the learning process, the decision maker chooses how to split a **unit of attention** ( $dT_{t,1} + dT_{t,2} = dt$ ) between **two information sources**
- ▶ Information source  $k$  ( $k = 1, 2$ ):

$$X^{(k)} = \begin{cases} \text{Poisson process with intensity } \lambda_k > 0, & \theta_k = 1 \\ 0, & \theta_k = 0 \end{cases}$$

- ▶ Cost of source  $k$  is  $c_k > 0$

		(1,0)	(0,1)	(0,0)
source 1	pay $c_1 dT_{t,1}$	$\begin{cases} 1, & \text{w/pr } \lambda_1 dT_{t,1} \\ 0, & \text{o/w} \end{cases}$	0	0
source 2	pay $c_2 dT_{t,2}$	0	$\begin{cases} 1, & \text{w/pr } \lambda_2 dT_{t,2} \\ 0, & \text{o/w} \end{cases}$	0

# Optimization Problem

Strategy  $(T, \tau, \alpha)$ :

$T = (T_1, T_2)$  : attention allocation plan,  $T_{t,k}$  is the total amount of attention the agent paid to source  $k$  by time  $t$

$\tau \geq 0$  : stopping time

$\alpha$  : alternative chosen at  $\tau$  (*function: info by  $\tau \mapsto \mathcal{A}$* )

Total ex post payoff:

$u_j(\alpha) - c_1 T_{\tau,1} - c_2 T_{\tau,2}$ , where  $j$  corresponds to the true state

*Assumption: no discounting*

Optimization problem:

$$\sup_{(T, \tau, \alpha)} \mathbb{E} [u_j(\alpha) - c_1 T_{\tau,1} - c_2 T_{\tau,2}]$$

# Strategy

strategy  $(T, \tau, \alpha)$

$T$  — random

$\tau$  — random

$\alpha$  — function

contingency plan  $(T, \bar{\tau}, a)$

$T$  — deterministic:

*conditional on not finding the state*

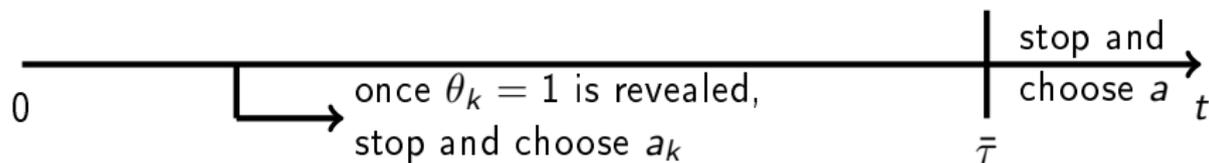
$\bar{\tau} = \sup \tau$  — deterministic:

*stopping time when state is not revealed by  $\tau$*

$a = \alpha(\tau = \bar{\tau}) \in \mathcal{A}$ :

*alternative chosen if state is not revealed by  $\tau$   
(define it as the **default alternative**)*

What to do if the state is not revealed?

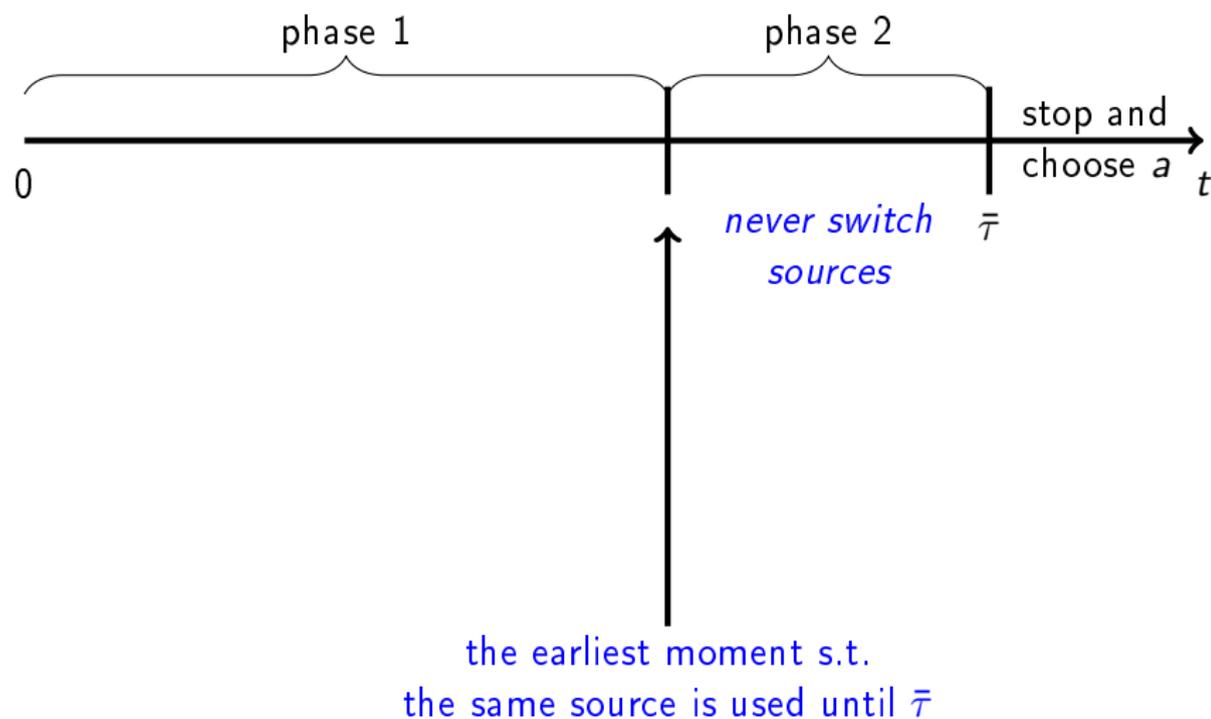


Denote

$p_{k,t}$  = belief at time  $t$  about  $\theta_k = 1$ , if the state is not revealed by  $t$

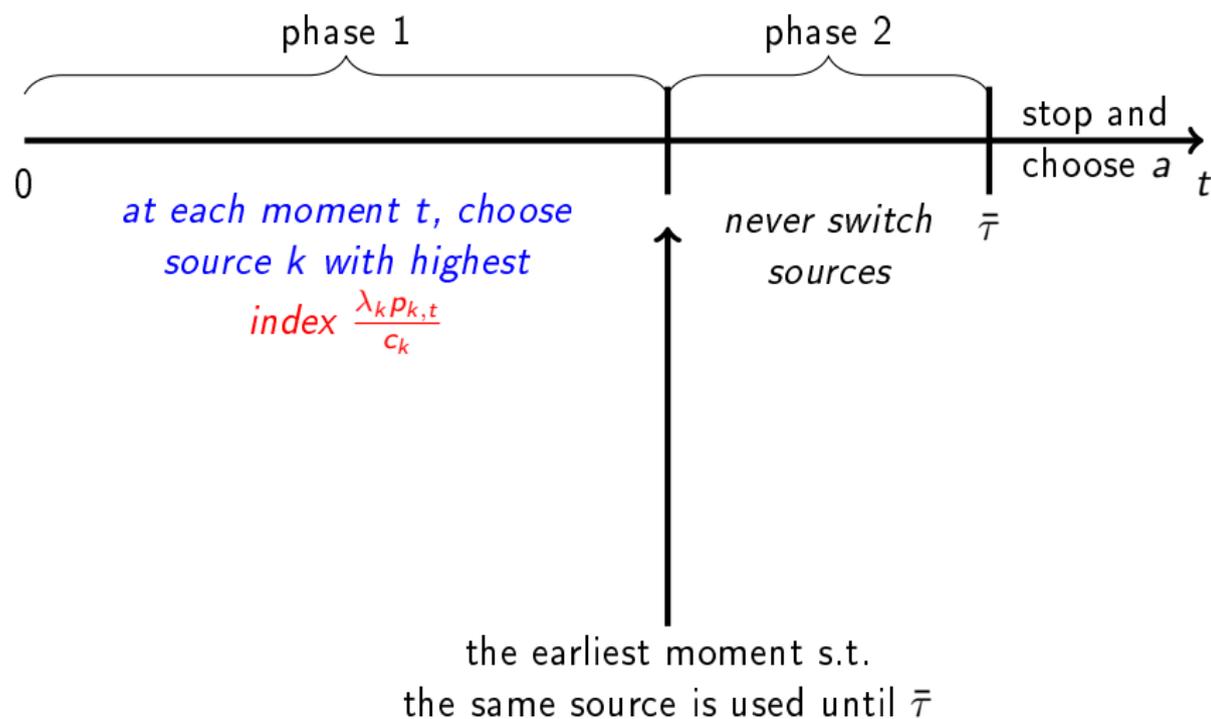
## Optimal Strategy

**Theorem:** The optimal contingency plan  $(T, \bar{\tau}, a)$  has two phases.



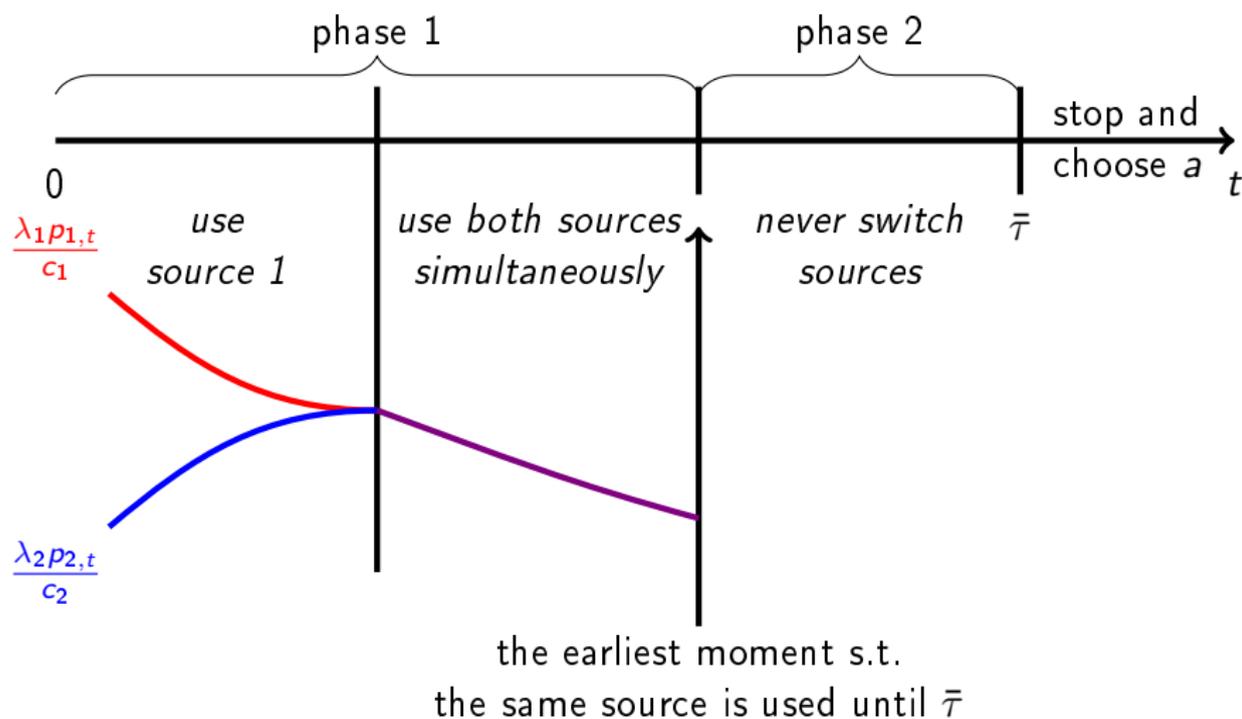
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## Optimal Strategy

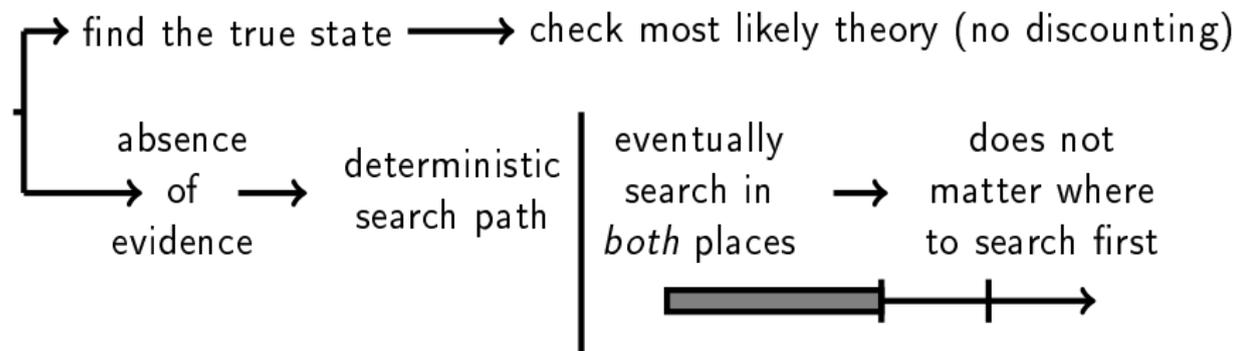
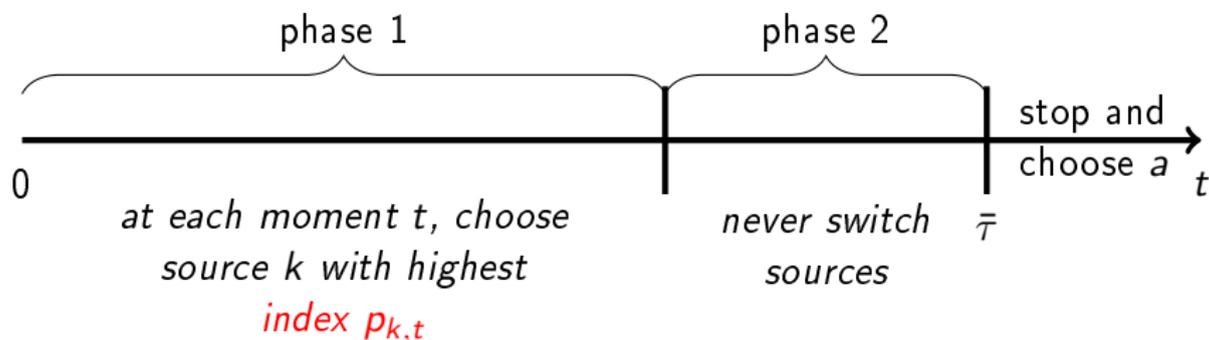
**Theorem:** The optimal contingency plan  $(T, \bar{\tau}, a)$  has two phases.



# Optimal Strategy

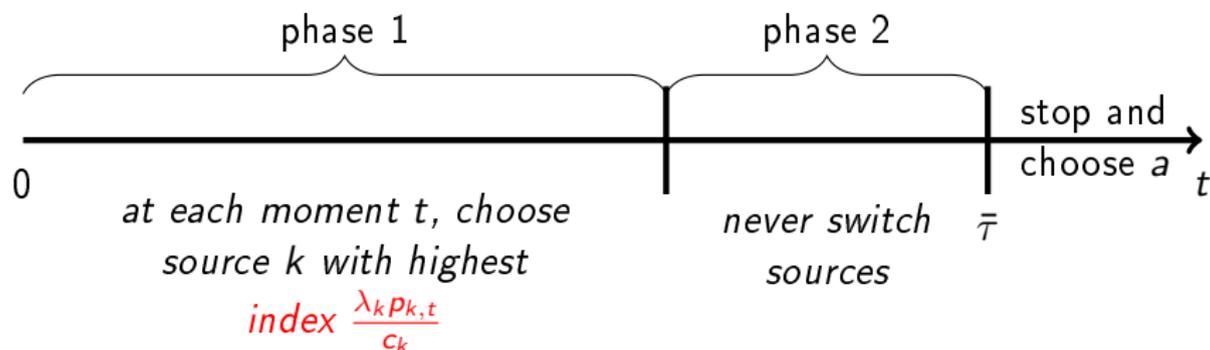
## Intuition

For simplicity, assume  $\lambda_1 = \lambda_2$ ,  $c_1 = c_2$



# Optimal Strategy

## Intuition



Source  $k$  is more efficient if

- ▶ intensity  $\lambda_k \uparrow$
- ▶ cost  $c_k \downarrow$

- ▶ We looked at the optimal strategy as a **function of time**
- ▶ Optimal strategy is Markovian: optimal action depends only on *current beliefs*  $(p_1, p_2) \Rightarrow$  let's look at the optimal strategy as a **function of beliefs**

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- ▶ Why do we need to do this?

function of **time**

function of **beliefs**

two-phase representation  
& introduction of **index**

specifies **thresholds**,  
**optimal default alternative**  
as long as the **index**



gives the full description

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gives the full description

- ▶ Why haven't we started with this?
  1. focus of the paper — **index**
    - ▶ the notion of index it is easier to present on the time line
  2. thresholds and optimal default alternatives depend on the **payoff matrix**  $\Rightarrow$  general case description of the optimal strategy on the belief triangle is **messy** (too many cases are possible)
    - $\Rightarrow$  I'll present only a few examples

# Optimal Strategy: Example

on belief triangle

Payoff matrix

state $(\theta_1, \theta_2)$	$(1,0)$	$(0,1)$	$(0,0)$
alternative $a_1$	1	0	0
alternative $a_2$	0	1	0
alternative $a_3$	0	0	1

Interpretation: get 1 if guess the state and 0 otherwise

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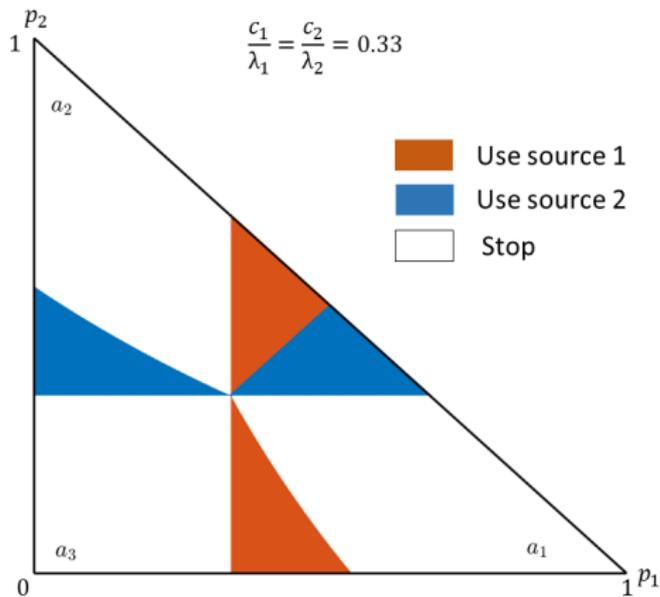
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- ▶ It turns out that the optimal strategy representation of the belief triangle depends on  $c_1$ ,  $c_2$ ,  $\lambda_1$  and  $\lambda_2$  only through the ratios  $\frac{c_1}{\lambda_1}$  and  $\frac{c_2}{\lambda_2}$
- ▶ Consider symmetric sources:

$$\frac{c_1}{\lambda_1} = \frac{c_2}{\lambda_2}$$

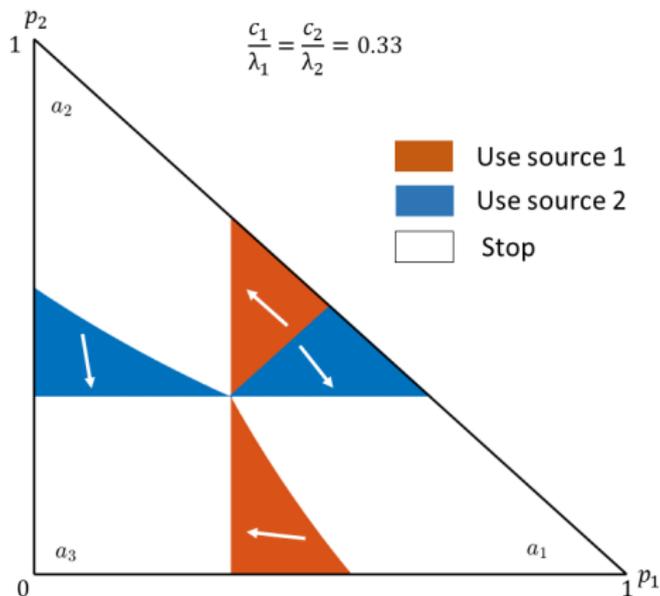
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# Optimal Strategy: Example

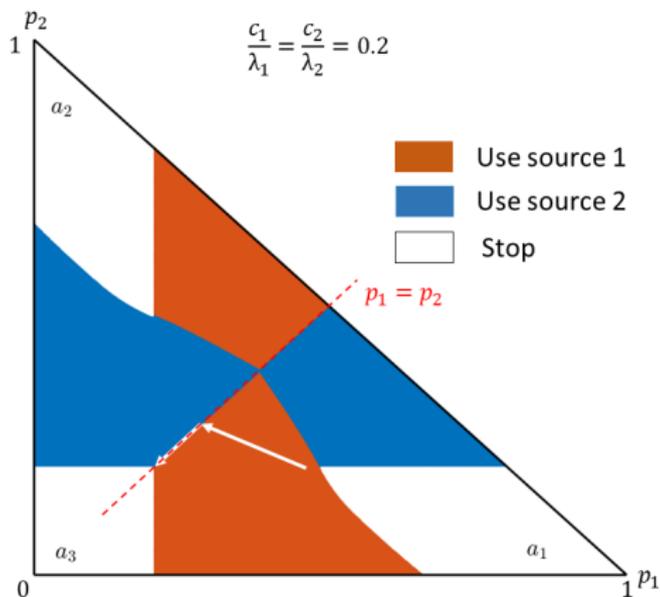
on belief triangle



At most one source is used  $\Rightarrow$  only **phase 2**

# Optimal Strategy: Example

on belief triangle



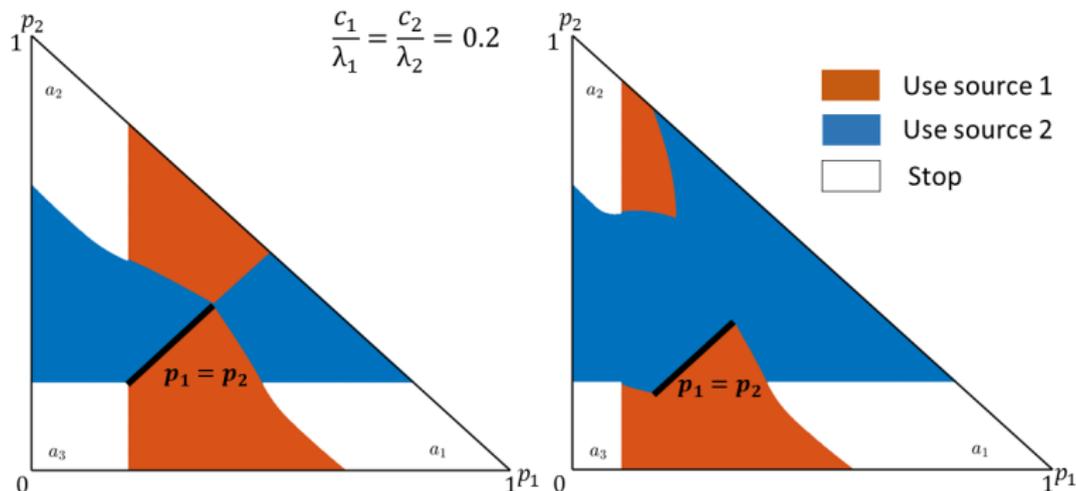
When uncertainty is the highest (middle of triangle), **phase 1** rule is optimal

# Optimal Strategy: Example

on belief triangle

	(1,0)	(0,1)	(0,0)
$a_1$	1	0	0
$a_2$	0	1	0
$a_3$	0	0	1

	(1,0)	(0,1)	(0,0)
$a_1$	2	0	0
$a_2$	0	1	0
$a_3$	0	0	1



Phase 1 rule is **independent** of the payoff matrix

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Special Case:  $\theta_1 + \theta_2 \leq 1$

General Case

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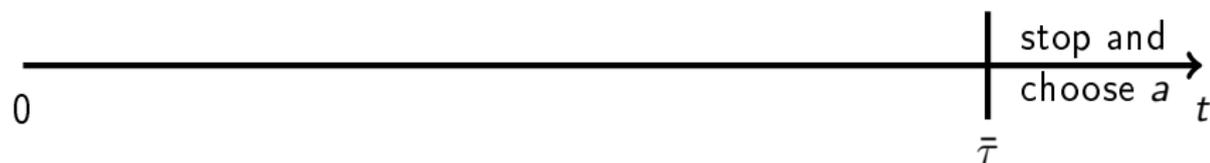
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<i>Beliefs:</i>	$p_1$	$p_2$	$p_3$	$1 - p_1 - p_2 - p_3$
Alternative $a_1$	$u_1(a_1)$	$u_2(a_1)$	$u_3(a_1)$	$u_4(a_1)$
Alternative $a_2$	$u_1(a_2)$	$u_2(a_2)$	$u_3(a_2)$	$u_4(a_2)$
...	...	...	...	...

## General Case vs Special Case: $\theta_1 + \theta_2 \leq 1$

In the absence of a positive signal, follow a **contingency plan**:

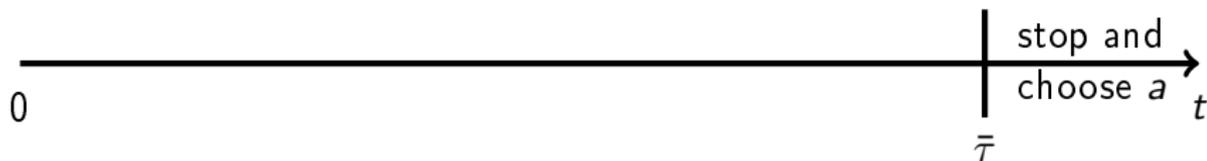


## General Case vs Special Case: $\theta_1 + \theta_2 \leq 1$

### Key difference

Once a positive signal is received (state  $\theta_k = 1$  is revealed), there might still be uncertainty about the state

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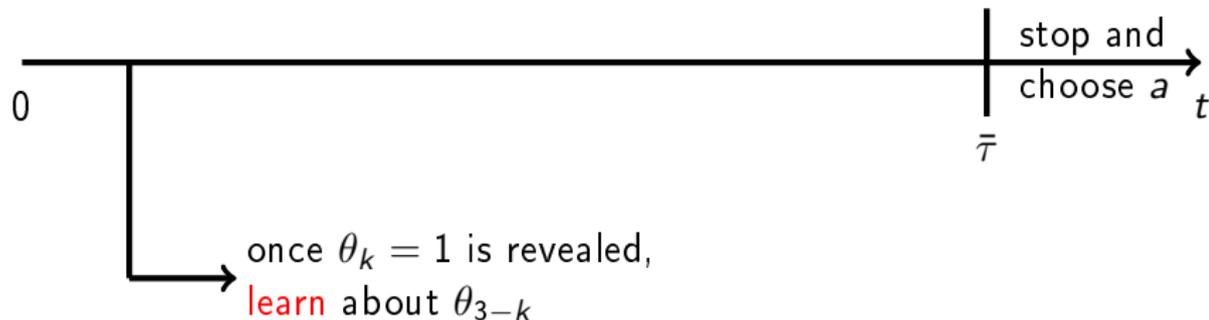
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⇒

1. It might be optimal to learn even after a positive signal

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## General Case vs Special Case: $\theta_1 + \theta_2 \leq 1$

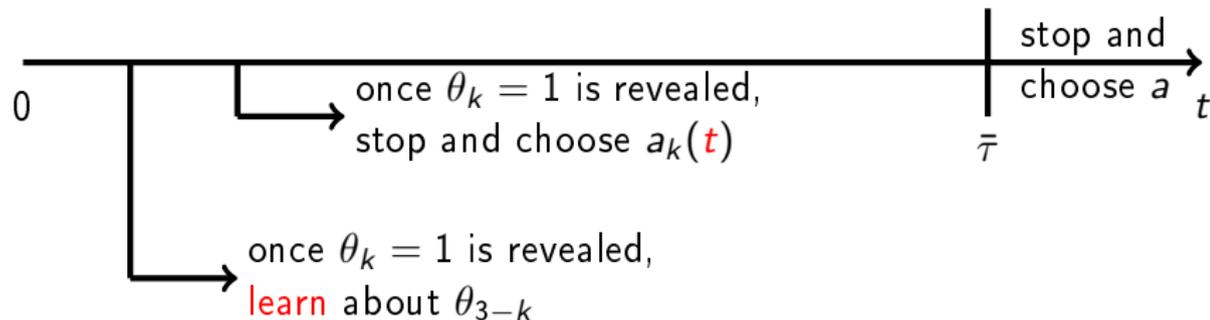
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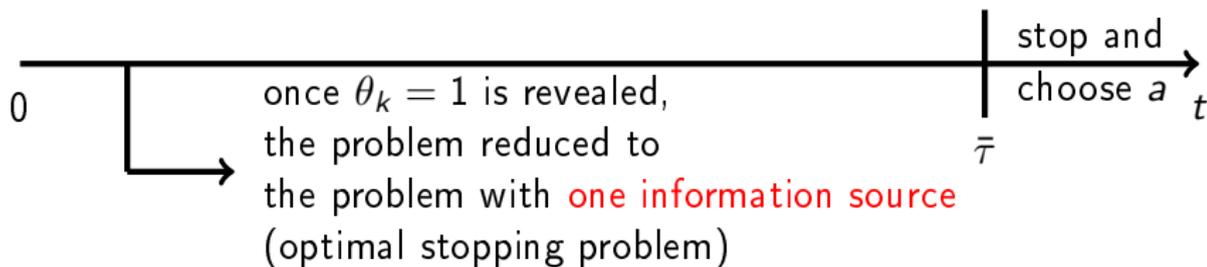
⇒

1. It might be optimal to learn even after a positive signal
2. Even if it is optimal to stop after receiving a positive signal, the optimal alternative after receiving a positive signal depends on beliefs

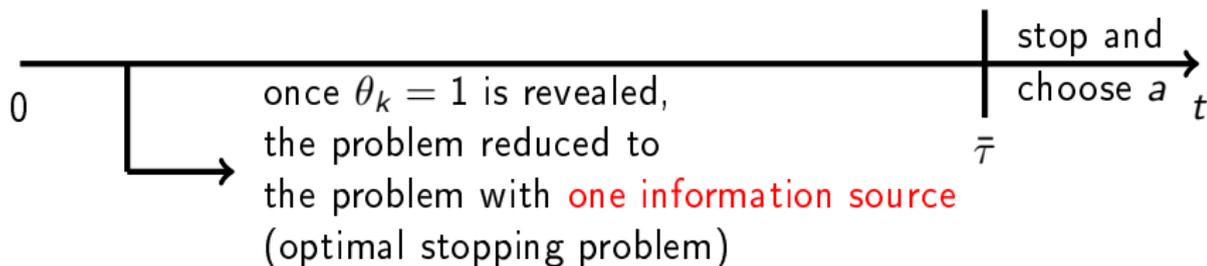
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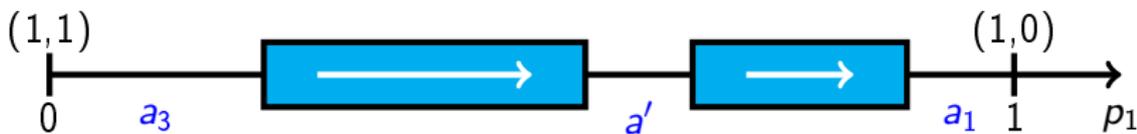
In the absence of a positive signal, follow a **contingency plan**:



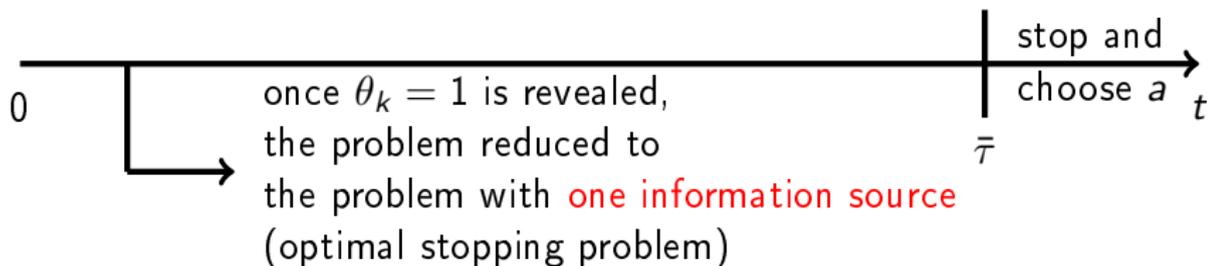
1. When  $\theta_1 = 1$  is revealed: only **source 2** might be used

$(1,0)$	<del><math>(0,1)</math></del>	$(1,1)$	<del><math>(0,0)</math></del>
$p_1$	$p_2$	$p_3$	$1 - p_1 - p_2 - p_3$
↓	↓	↓	↓
$p'_1 = \frac{p_1}{p_1 + p_3}$	0	$1 - p'_1 = \frac{p_3}{p_1 + p_3}$	0

For example:

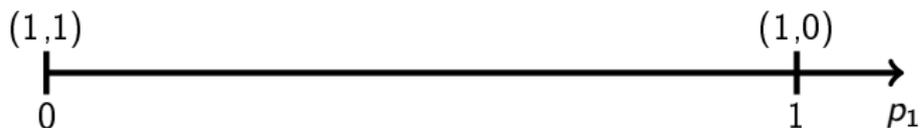


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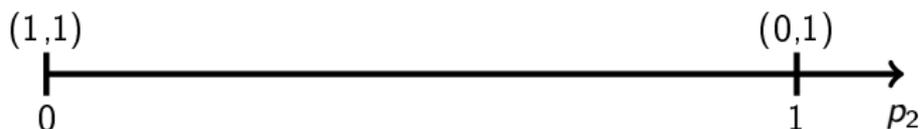
1. When  $\theta_1 = 1$  is revealed:

- ▶ problem with only **source 2**



2. When  $\theta_2 = 1$  is revealed:

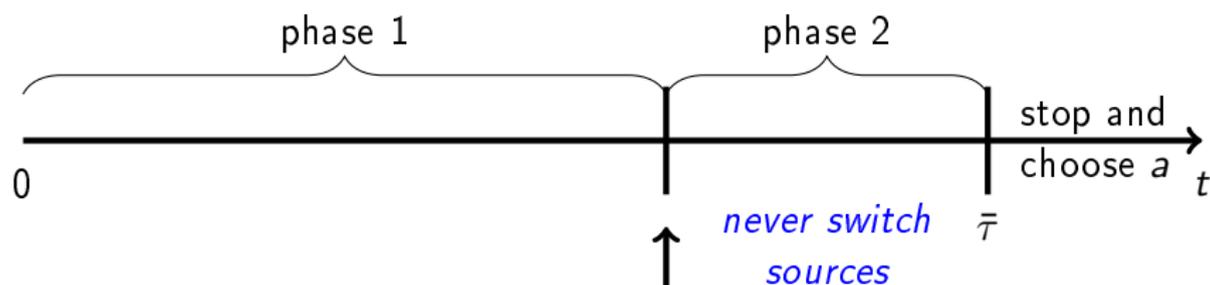
- ▶ problem with only **source 1**



To find the optimal strategy, it only remains to find the **optimal contingency plan**

## Optimal Strategy

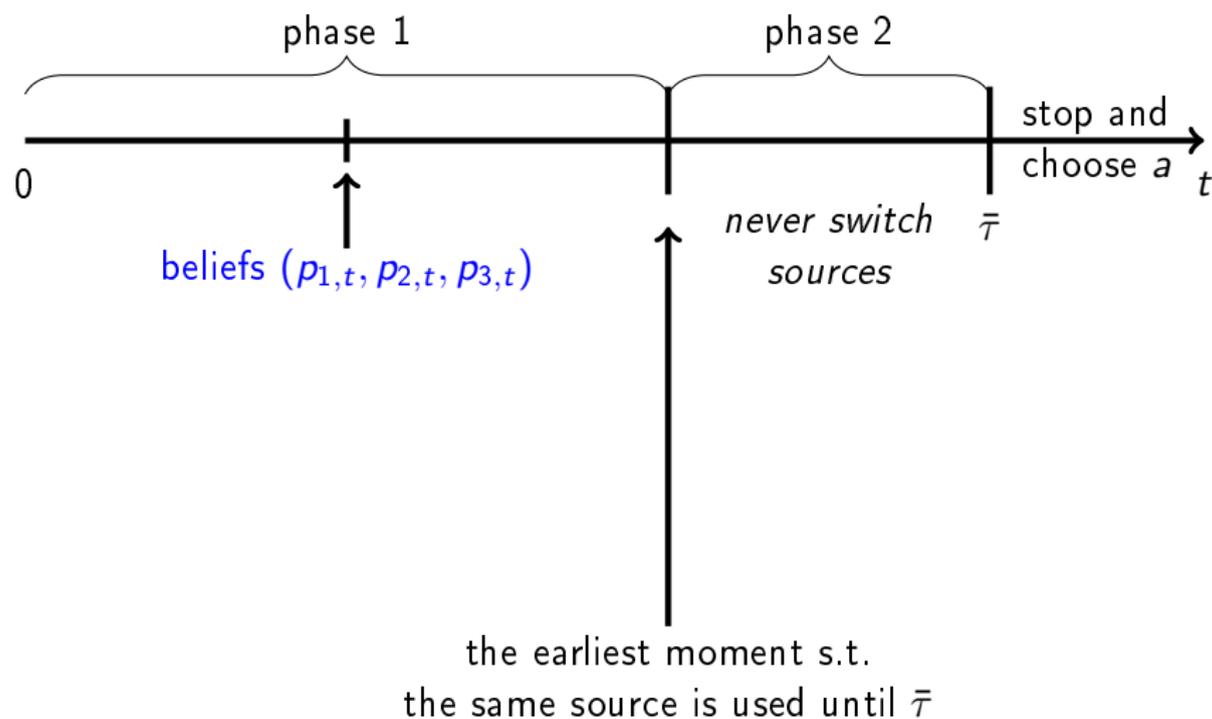
**Theorem:** The optimal contingency plan has two phases.



the earliest moment s.t.  
the same source is used until  $\bar{t}$

## Optimal Strategy

**Theorem:** The optimal contingency plan has two phases.



## Phase 1

Fix current beliefs  $(p_1, p_2, p_3)$ .

*If a positive signal occurs **now**, what is the optimal strategy?*

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Four possibilities:

1.  $\theta_1 = 1 \Rightarrow$  learn from source 2;  $\theta_2 = 1 \Rightarrow$  learn from source 1
2.  $\theta_1 = 1 \Rightarrow$  stop ;  $\theta_2 = 1 \Rightarrow$  learn from source 1
3.  $\theta_1 = 1 \Rightarrow$  learn from source 2;  $\theta_2 = 1 \Rightarrow$  stop
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▶ phase 1 rule: use the source with the highest index

## Phase 1: Index

### Assumption

$\theta_1 = 1 \Rightarrow$  stop and choose  $a_1$ ;  $\theta_2 = 1 \Rightarrow$  stop and choose  $a_2$

### Theorem

Phase 1 rule: use the source with the highest index

$$\frac{\lambda_k \mathbb{P}(\theta_k = 1)}{c_k}$$

if  $a_1 = a_2$

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$$\frac{\lambda_k(p_k + p_3)}{c_k} + p_3 \times \frac{\lambda_1 \lambda_2}{c_1 c_2} \times \underbrace{u_3(a_k)}_{\text{payoff in state (1,1)}}$$

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$$p_k + p_3 u_3(a_k)$$

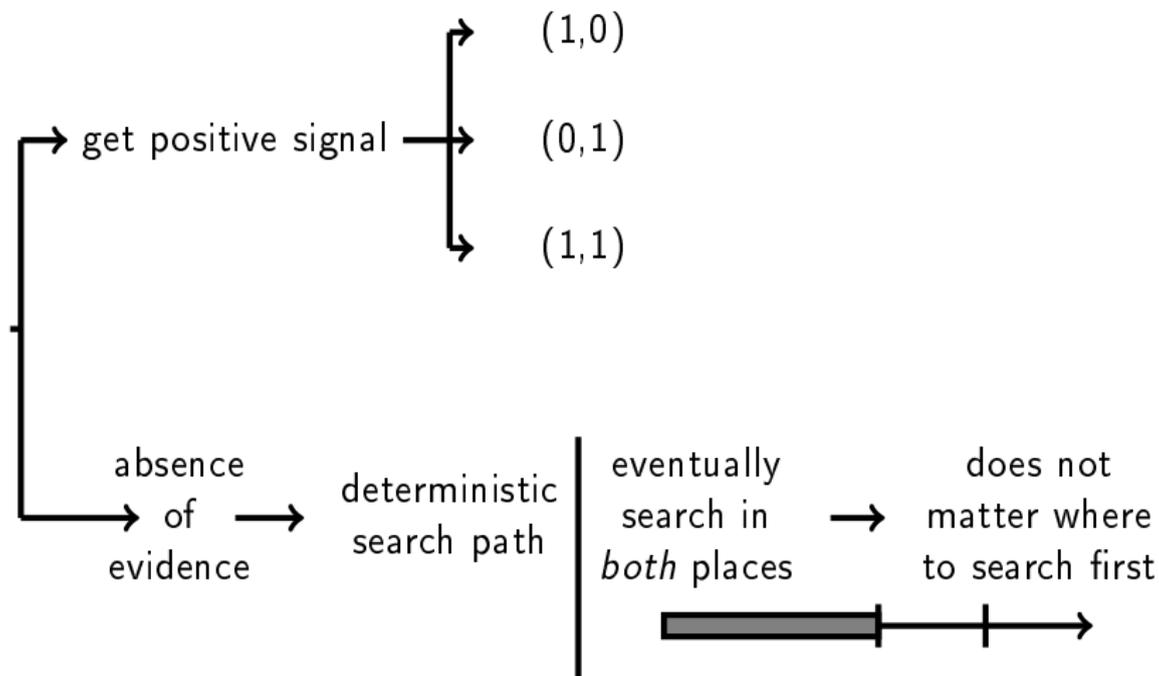
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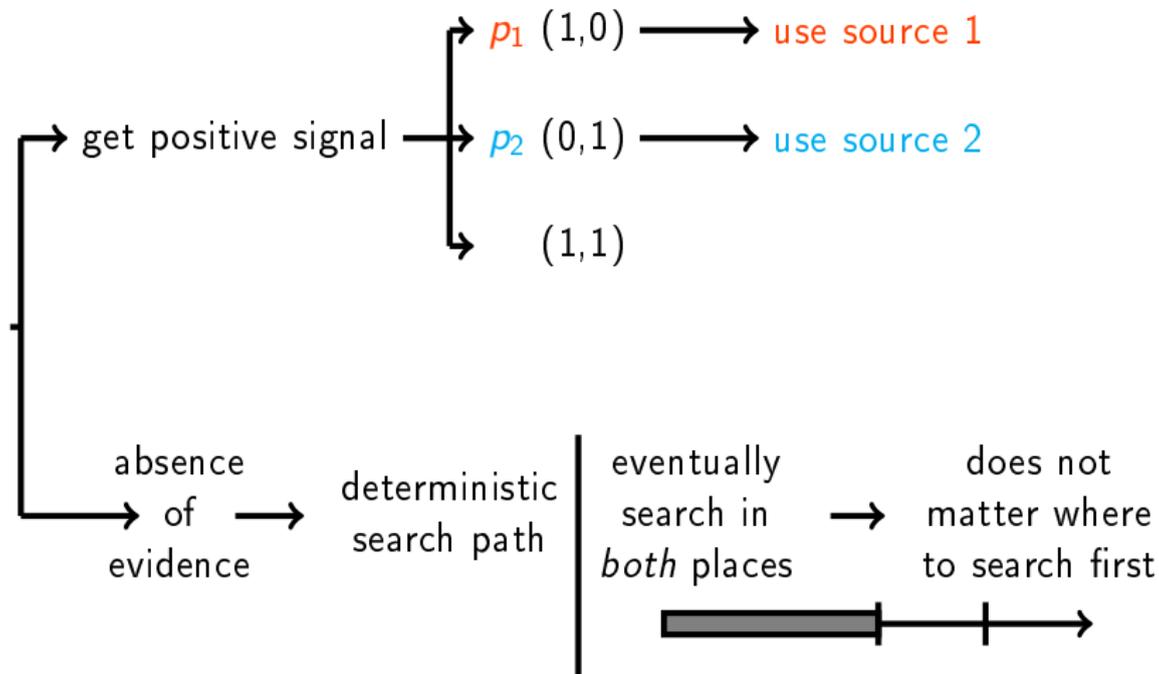
## Theorem

Phase 1 rule: use the source with the highest index

source 1:  $p_1$

source 2:  $p_2$

if  $c_1 = c_2 = 1$  and  $\lambda_1 = \lambda_2 = 1$

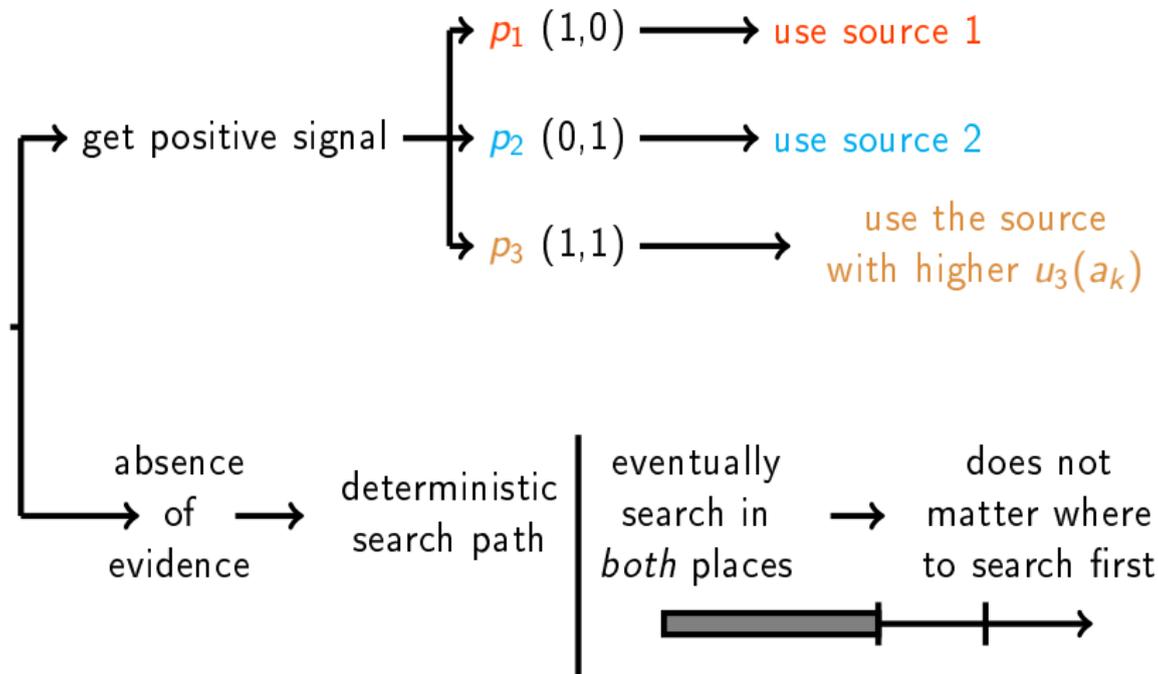


## Theorem

Phase 1 rule: use the source with the highest index

source 1:  $p_1 + p_3 u_3(a_1)$     source 2:  $p_2 + p_3 u_3(a_2)$

if  $c_1 = c_2 = 1$  and  $\lambda_1 = \lambda_2 = 1$



# Properties of the Index

## Theorem

Phase 1 rule: use the source with the highest index

$$\frac{\lambda_k \mathbb{P}(\theta_k = 1)}{c_k} + \mathbb{P}(\theta_1 = \theta_2 = 1) \frac{\lambda_1 \lambda_2}{c_1 c_2} u_3(a_k)$$

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- ▶ Payoffs in states (0,0), (1,0) and (0,1) do not matter
- ▶ As we increase the correlation between  $\theta_1$  and  $\theta_2$ , the difference  $u_3(a_1) - u_3(a_2)$  plays more important role

# Conclusion

## Question

How to choose the research direction **if we don't know the goal?**

## Answer

In a long-term research, **you don't have to know the goal *fully*** to behave optimally:

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In a long-term research, **you don't have to know the goal *fully*** to behave optimally: **search for the truth**

1. Current beliefs & difficulty of research

# Conclusion

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How to choose the research direction if **we don't know the goal**?

## Answer

In a long-term research, **you don't have to know the goal fully** to behave optimally: **search for the truth**, taking into account *lost opportunities*:

1. Current beliefs & difficulty of research
2. Lost opportunities:

	true state	
research direction 1	<input checked="" type="checkbox"/>	← how much you gain if another research direction was successful
research direction 2	<input checked="" type="checkbox"/>	← discover only this one