

Bridging the Rational and Behavioral Worlds: Rationally Inattentive Decision Making and Implications on Business Operations

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Abundance of Information

Toothbrush with 3 Replacement Brush Heads,...



4,017 customer reviews | 483 answered questions

Google

top mba program in vienna

Model Compare

Comparing the "2019 BMW X5", "2019 Porsche Cayenne" and "2019 Jaguar F-PACE"

Share



2019 BMW X5

2019 Porsche Cayenne

2019 Jaguar F-PACE

401,440 MSRP

Base MSRP

201,400 MSRP

Customize Your Comparison

Overview

MSRP

\$401,440

\$161,700

\$140,000



Attention Economy



How do we make decisions?

- Rational decision making

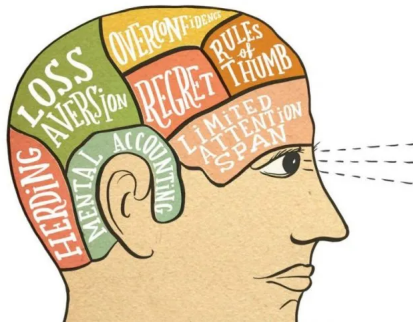


How do we make decisions?

- Rational decision making



- Boundedly rational (behavioral) decision making



An Example...



- Selection of brands, models
- Prices, features (resolution, zoom etc.) and performance (color reproduction, etc.)
- Past experience with brands and knowledge of features (priors)
- Actively acquire and process information about choice options
- Make final decision (with incomplete information)

Some Things You Learn...

Fast and with ease

Which cam is more expensive?



\$389



\$409

Slow and with difficulty

Which cam makes better pictures?



\$379

How Much You Learn...

What's at stake - relative gains and losses



\$ 379



\$ 55,000

My Broad Research Agenda

My Broad Research Agenda

Model decision-making /choice under limited time and attention

How much time and attention?

What information to acquire?

What choice to make?

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Implications on business operations and firm decisions

Pricing, assortment planning

Information provisioning

Service system design

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Human - AI collaboration

Judgement and decisions

Accuracy, rate of errors

Cognitive effort

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Service system design



Rational
Inattention
Theory

Human - AI collaboration

Judgement and decisions

Accuracy, rate of errors

Cognitive effort

Some Related Publications



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Pricing When Customers Have Limited Attention

Tamer Boyaci,* Yalçın Akçay*

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MANAGEMENT SCIENCE

Vol. 64, No. 7, July 2018, pp. 2995–3014
ISSN 0025-1909 (print), ISSN 1526-0343 (online)



<https://pubsonline.informaworld.com/journals/home>

CROSSCUTTING AREAS

Consumer Choice Under Limited Attention When Alternatives Have Different Information Costs

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<https://orcid.org/10.1002/9781118104014.ch141> (YA); <https://orcid.org/10.1002/9781118104014.ch141> (YA)

Received: October 3, 2016

Revised: February 9, 2018; September 25, 2018

Abstract. Consumers often do not have complete information about the choices they face and, therefore, have to spend time and effort acquiring information. Because information

OPERATIONS RESEARCH

Vol. 67, No. 3, May–June 2019, pp. 671–699
ISSN 0030-3616 (print), ISSN 1080-1344 (online)



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MANUFACTURING & SERVICE OPERATIONS MANAGEMENT

Vol. 25, No. 1, January 2023, pp. 266–287
ISSN 1053-6861 (print), ISSN 1080-1344 (online)

Queueing Systems with Rationally Inattentive Customers

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Published Online in Advance: November 1, 2022

<https://doi.org/10.1080/10536861.2021.1999999>

Abstract. Prevalent diffusion-based models of queueing systems with rational and irrational customers are shown to be inadequate for the analysis of queueing systems with rationally inattentive customers. In this sense, they are not able to fully address important characteristics. When inattentive customers provide delays and respond to capacity in a non-linear fashion, attention and cognitive capacity, which are all limited. On the other hand, people have different and non-homogeneous attention and cognitive capacity.

MANAGEMENT SCIENCE

Articles in Advance, pp. 1–38
ISSN 0025-1909 (print), ISSN 1526-0343 (online)



<https://pubsonline.informaworld.com/journals/home>

Human and Machine: The Impact of Machine Input on Decision Making Under Cognitive Limitations

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<https://orcid.org/10.1002/9781118104014.ch141> (TB); <https://orcid.org/10.1002/9781118104014.ch141> (CC); <https://orcid.org/10.1002/9781118104014.ch141> (FV)

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Abstract. The rapid adoption of artificial intelligence (AI) technology by many organizations has raised recent concerns that AI may eventually replace humans in some tasks. In fact, when used in collaboration, machines can significantly enhance the complementary strengths of humans. Indeed, because of their immense computing power, machines can perform specific tasks with incredible accuracy. In contrast, human decision makers (HDMs) are flexible and adaptive but constrained by their limited cognitive capacity. This paper investigates how machine-based predictions may affect the decision process and outcomes of a human DM. We study the impact of these predictions on decision accuracy, the propensity and nature of decision errors, and the DM's cognitive efforts. To account for both

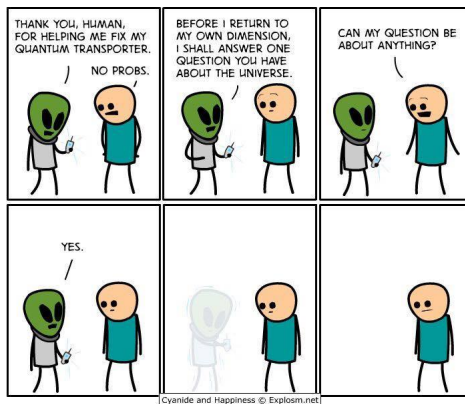
- T. Boyaci, Akçay, A. (2018) “Pricing When Customers Have Limited Attention”. *Management Science* 64 (7): 2995–3014.
- Huettner, F., T. Boyaci, Y. Akçay (2019) “Consumer Choice Under Limited Attention When Alternatives Have Different Information Costs”. *Operations Research*, 67 (3), 671–699.
- Canyakmaz, C., T. Boyaci (2023) “Queueing Systems with Rationally Inattentive Customers”. *Manufacturing & Service Operations Management*. 25(1), 266–287.
- T. Boyaci, C. Canyakmaz, F. de Vericourt “Human and Machine: The Impact of Machine Input on Human Decision Making Under Cognitive Limitations”. *Management Science*. Forthcoming.

Outline Going Forward

- A very quick intro to the theory of rational inattention (RI)
- Characterization of decisions under RI (with extensions)
- Impact on firm decisions and operations
 - Product choice and assortments
 - Pricing
- Human-AI collaboration
 - Impact of ML/AI input on decisions and accuracy
 - Cognitive effort

What is Rational Inattention?

- Pioneered by 2011 Nobel Laureate Christopher A. Sims
- DM allocates scarce attention wisely
- DM is free to ask about anything



Rationally Inattentive Decision Making / Choice

- DM **optimally** chooses type and quantity of information, trading off the benefit of better information and its acquisition cost
- Information is quantified as reduction in **Shannon Entropy (H)**:

$$H(X) = - \sum_i p_i \ln(p_i)$$

- Information costs are based on **Shannon Mutual Information**:
 - *Difference between entropy of X and entropy of X once Y is known:*

$$I(X, Y) = H(X) - H(X|Y)$$

- Information (Cognitive) Cost: $\lambda \cdot I$

Rationally Inattentive Decision Making / Choice

- $A = \{1, \dots, n\}$ set of alternatives
- State $\Omega = (\Omega_1 \times \dots \times \Omega_k \times \dots \times \Omega_n)$ taking values $\omega \in \mathbb{R}^n$.
- Choosing i in state ω yields $u(i, \omega) \in \mathbb{R}$.
- DM prior belief distribution $g \in \Delta(\Omega)$
- DM can ask questions to sharpen beliefs at unit cost λ
- Information strategy: Joint dist. $f \in \Delta(\Omega \times S)$ of states and signals
 - For any signal, DM chooses option with highest payoff $\rightarrow R(f)$
 - Elicited signal reduces entropy $\rightarrow C(f)$
- Optimization problem of DM: Find f to maximize $R(f) - C(f)$

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- **Optimization problem of DM:** Find f to maximize $R(f) - C(f)$

Rationally Inattentive Decision Making / Choice

- When the cost of information is the same $\lambda > 0$ for all options, the conditional probability $p(i | \omega)$ of choosing i follows the *Generalized MNL* formula (Matejka & McKay, AER 2015):

$$\text{(GMNL)} \quad p(i | \omega) = \frac{e^{\frac{u(i, \omega)}{\lambda}} p(i)}{\sum_{j \in A} e^{\frac{u(j, \omega)}{\lambda}} p(j)} \quad \text{almost surely,}$$

where $p(i) := \int p(i | \omega)$ are unconditional probabilities that capture the effects of prior beliefs

If $\lambda = 0$, highest payoff option is chosen with probability 1.

What does it tell us?

$$\text{(GMNL)} \quad p(i | \omega) = \frac{e^{\frac{u(i, \omega)}{\lambda}} p(i)}{\sum_{j \in A} e^{\frac{u(j, \omega)}{\lambda}} p(j)} \quad \text{almost surely,}$$

- The higher the pay-off $u(i, \omega)$, the more likely it will be selected
- An option that is a-priori attractive due to prior beliefs will be selected more (high $p(i)$)

Such an option can be selected even if its true value is low

- The higher the information cost λ , the less information will be processed and the more choices will be driven by prior beliefs.

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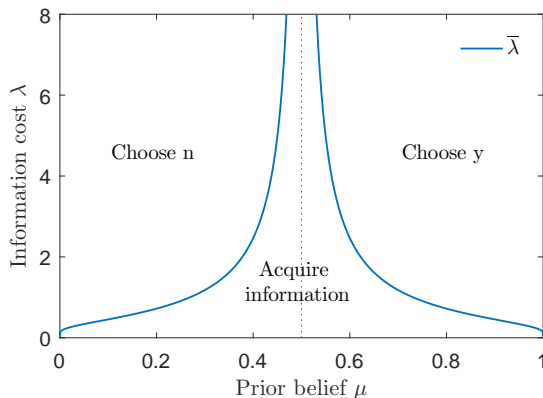
Example: Making The Right Decision (Accuracy)

- State of the world is $\omega \in \Omega = \{g, b\}$ representing “Good” and “Bad”
- DM’s prior belief that state is good is μ
- DM needs to choose one of two actions $a \in A = \{y, n\}$
- Immediate payoffs \Leftrightarrow decision accuracy

	$\omega = \mathbf{g}$	$\omega = \mathbf{b}$
$a = \mathbf{y}$	1	0
$a = \mathbf{n}$	0	1

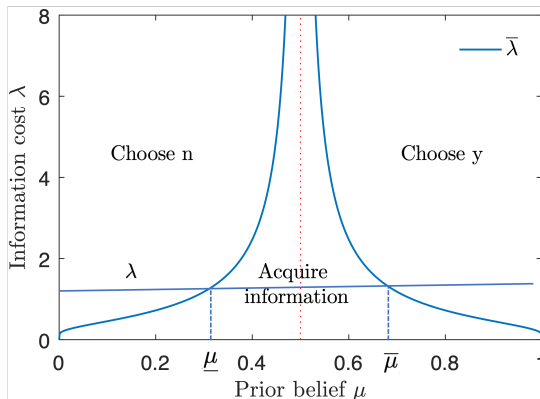
- DM may exert cognitive effort (λ) to refine her belief

Optimal Choice p^* - Cognitive Cost Threshold



- As the DM is more uncertain a-priori (μ is close to $1/2$), she is ready to tolerate high cognitive costs to learn more

Optimal Choice p^* - Belief Threshold



- DM processes information only in the range $(\underline{\mu}, \bar{\mu})$
- As the cognitive cost increases, DM relies more on her prior (μ)

Rationally Inattentive Choice When Information Costs Differ

- Let the alternatives be ordered such that $\lambda_1 \leq \lambda_2 \dots \leq \lambda_N$
- How would the DM allocate attention? What is the cost $C(f)$?
 - Distinguish *inferential (implied)* and *direct* information
 - Be efficient (prioritize cheaper channels)
- The information cost $C(f)$ is based on *conditional mutual information*
- **Theorem:** For any information cost $0 < \lambda_1 \leq \lambda_2 \dots \leq \lambda_n < \infty$, the optimal conditional choice probabilities satisfy

$$p(i | \omega) = \frac{e^{\frac{u(i, \omega)}{\lambda_n}} p(i)^{\frac{\lambda_1}{\lambda_n}} \prod_{k=1}^{n-1} p(i | \omega_{1..k})^{\frac{\lambda_{k+1} - \lambda_k}{\lambda_n}}}{\sum_{j \in A} e^{\frac{u(j, \omega)}{\lambda_n}} p(j)^{\frac{\lambda_1}{\lambda_n}} \prod_{k=1}^{n-1} p(j | \omega_{1..k})^{\frac{\lambda_{k+1} - \lambda_k}{\lambda_n}}}$$

- Choice probabilities are further adjusted based on what the DM learns (more) about the options with lower cost of information

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You study Canon camera and decide you don't like the digital zoom. You believe Sony camera is similar so ($p(\text{Sony}|\omega_{\text{Canon}})$ will be low)



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In reality, Sony camera's digital zoom is very good (ω_{Sony} is high)



Example: Strong Failure of Regularity

You are well informed about Nikon Sony
can be better or worse

	State 1	State 2
Nikon	1	1
Sony	0.6	1.2



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Hard to gain info on Sony ($\lambda = 1$) Sony
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An inferior Sony (e.g., no flash) is
included in choice set ($\lambda' = 0.2$)

	State 1	State 2
Sony Inferior	0.5	0.9



Example: Strong Failure of Regularity

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	State 1	State 2
Sony Inferior	0.5	0.9

Sony camera is chosen 29%
(Inferior Sony never selected)



Pricing for Rationally Inattentive Customers

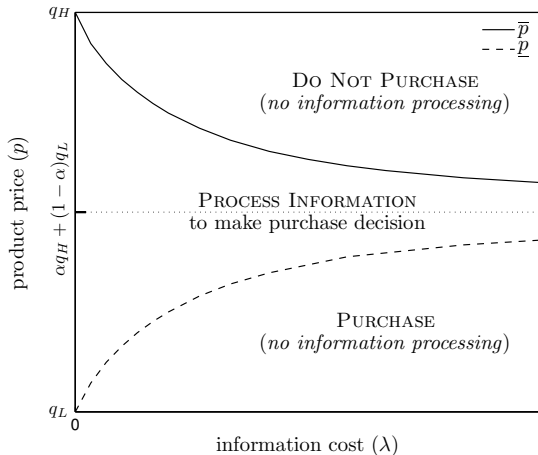


Buy or Not?

- Product price p (firm's decision; fully observed by customers)
- Customers not fully aware of the true quality (q) of the product
 - ⇒ $v = q - p$
 - ⇒ q : (High quality – q_H) or (Low quality – q_L)
- Customers' prior beliefs:
 - ⇒ q_H with probability μ and q_L with $1 - \mu$
- Rationally inattentive customers with cost of information λ
- No-purchase option $v = 0$

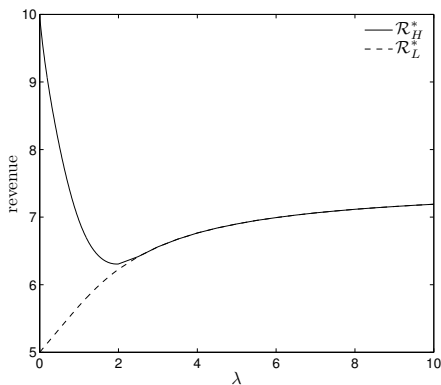
Pricing for Rationally Inattentive Customers

- Purchasing and information processing strategy



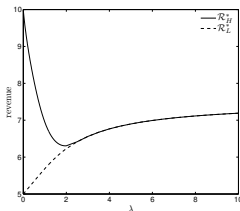
Impact of Costly Information (Too Little Time)

- Example: $q_H = 10$, $q_L = 5$, $\mu = 0.5$



- Information provision: search vs experience vs credence goods

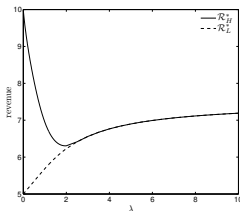
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What are the implications?

- Prices of highly experiential and credence goods should converge regardless of the quality
 - ⇒ Your mechanic/doctor should **overcharge** for simple procedures and **undercharge** for complicated procedures
 - ⇒ They should obscure, conceal, blur information
- Seller of search goods
 - ⇒ Low quality: Obscure, conceal, blur information
 - ⇒ High quality: Proactively reveal information

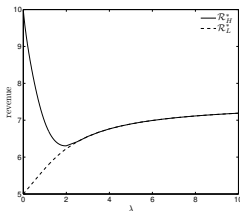
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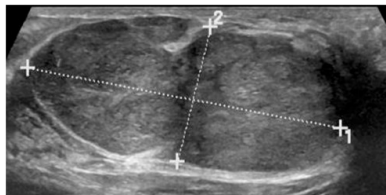


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Human - Machine/AI Collaboration

- Breast ultrasound - Detecting malignant tumors



Example of a true negative.

- The Human: MD
- The Machine: Deep learning image analysis

Humans and Machines Are Complementary

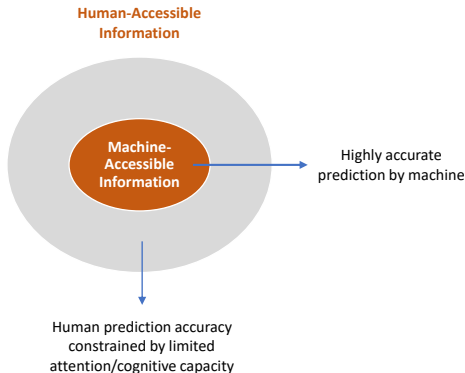


- Flexible - can assess any information
- Limited cognitive capacity



- Rigid - extract a limited subset of information
- Immense computing power

Fundamental Questions



- What is the impact of machine on human decisions?
- What is the impact of machine on accuracy & nature of errors?
- What is the impact of machine on cognitive effort spent?

The Task: Making The Right Decision (Accuracy)

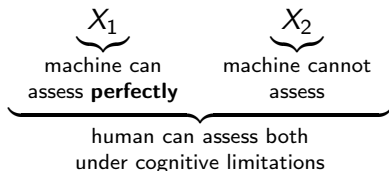
- State of the world is $\omega \in \Omega = \{g, b\}$ representing “Good” and “Bad”
- DM's prior belief that state is good is μ
- DM needs to choose one of two actions $a \in A = \{y, n\}$
- Baseline model: Immediate payoffs \Leftrightarrow decision accuracy

	$\omega = \mathbf{g}$	$\omega = \mathbf{b}$
$a = \mathbf{y}$	1	0
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- DM is rationally inattentive and may exert cognitive effort (λ) to refine her belief

Human Machine Collaboration

- Information sources are partitioned into two distinct subsets, $X_1, X_2 \in \{+, -\}$, one of which only human can assess

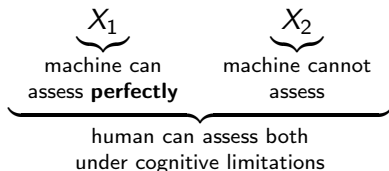


- True state is "good" only if both sources indicate a positive outcome
→ DM's prior belief that state is good is $\mu = Prob(x_1 = +, x_2 = +)$
- Given the machine's evaluation $x_1 \in \{-, +\}$, DM updates belief to μ^x :

$$\mu^- = 0 \text{ and } \mu^+ = \frac{\mu}{\mu + \pi(+, -)} > \mu.$$

Human Machine Collaboration

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Impact of Machine on Human Decision



- $A^*, V^*, C^*, p^*, \alpha^*, \beta^*$

- $A_m^*, V_m^*, C_m^*, p_m^*, \alpha_m^*, \beta_m^*$

A: Accuracy

V: Objective Value

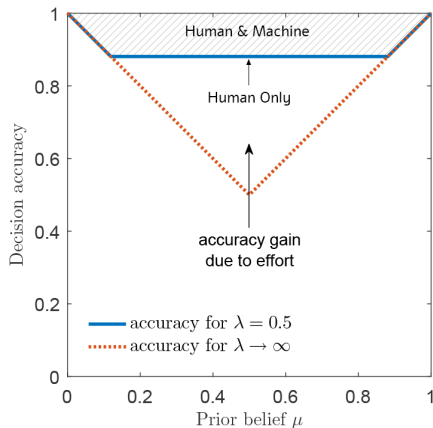
C: Cognitive Cost

p : Decision (Probability of choosing $a = y$)

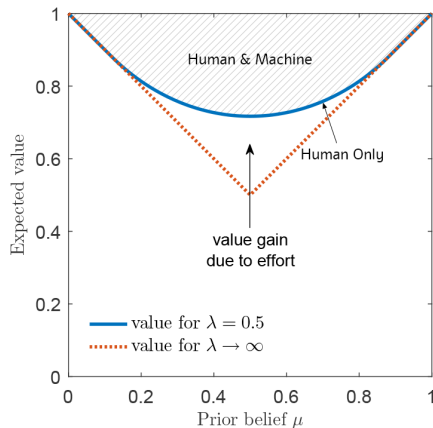
α : False positive rate

β : False negative rate

Impact on Accuracy and Value



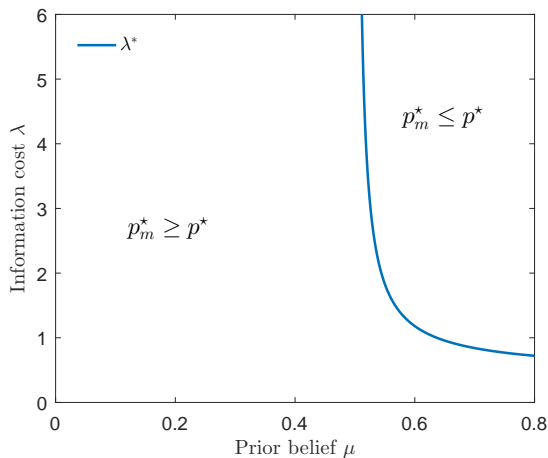
(a) Decision Accuracy



(b) Expected Value

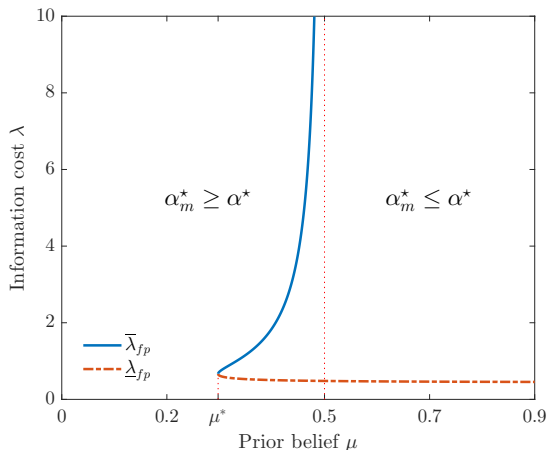
- DM's decision accuracy and expected utility **always increase** with machine

Impact on Choice Probability



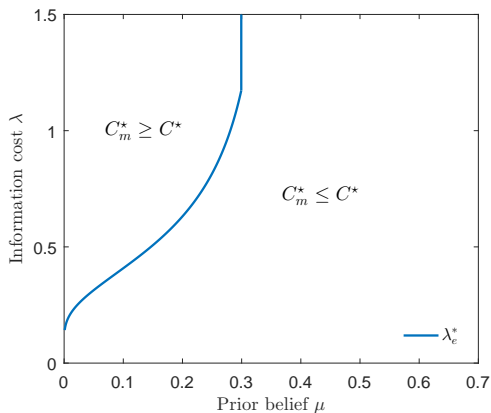
- The machine may increase the variability of the DM's decision

Impact on False Positive Errors



- When the DM sufficiently favors the bad state, a positive assessment may make her more uncertain or favor the good state

Impact on Cognitive Effort



- The machine can increase cognitive effort, especially when
 - The good state is less likely (low μ)
 - DM is cognitively constrained (high λ)

Human - Machine / AI Collaboration

- Overall accuracy is improved due to collaboration
- Collaboration most beneficial for identifying a relatively likely state
 - Errors are reduced
 - "Efficiency" of the DM is improved
- Collaboration less beneficial for identifying a relatively unlikely state, especially when the DM is cognitively constrained
 - False positive conclusions increase
 - "Efficiency" of the DM is reduced
- Results are robust
 - Generalized pay-off structures
 - Mistrust against the machine or the machine is imprecise

In Conclusion

- Rational inattention is a powerful theory for decision-making under
 - Limited time and attention
 - Limited information processing capacity
- Analytical characterizations of optimal decisions can be derived
- Empirical estimation and validation are developing
- Many academically and practically relevant applications
 - Assortment optimization
 - Pricing
 - Services ...
- Basis for modeling Human - AI collaboration
 - Impact on decisions and error rates
 - Impact on cognitive effort