

Cognitive Biases and Information Retrieval

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A Concept Learning Task



A Concept Learning Task



Chair: four legs,
brown color

A Concept Learning Task



A Concept Learning Task



Chair: four legs,
brown color



?



?

A Concept Learning Task



- Economical: We quickly (from few examples) learn to identify many chairs.
- Deficit in precision: We classify non-chairs as chairs.
- Deficit in recall: We cannot identify all chairs.

Outline

- ① Meanings of Bias
- ② Addressing Cognitive Biases with IR
- ③ Related Research @ Webis

CONFIRMATION BIAS



"AHA! I KNEW IT!"

Meanings of Bias

“Bias” has Acquired a Derogatory Definition

A leaning of the mind; inclination; prepossession; propensity towards an object, not leaving the mind indifferent; as, education gives a bias to the mind.

[Webster's Dictionary 1913: bias]

An inclination of temperament or outlook especially; a personal and sometimes unreasoned judgment; prejudice

[Merriam-Webster 2022: bias]

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[Merriam-Webster 2022: bias]

Synonyms [Merriam-Webster 2022] :

Bias, Nonobjectivity, Prejudice, One-Sidedness, Tendentiousness

Synonyms [e.g. Kahneman et al. 1982, Gigerenzer et al. 2000, Roberts 2022] :

Heuristic, Rule-of thumb, Cognitive Bias

Meanings of Bias

Bias: Two Camps of Interpretation

Based on the following (and other) authorities . . .

- H. Simon (1955). A behavioral model of rational choice.
- A. Tversky, D. Kahneman (1974). Judgment under uncertainty: Heuristics and biases.
- D. Kahneman, P. Slovic, A. Tversky (1982). Judgment under uncertainty: Heuristics and biases.
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- G. Gigerenzer, R. Hertwig, T. Pachur (2011). Heuristics: The foundation of adaptive behavior.

. . . Cleotilde Gonzalez defines:

Heuristics are the “shortcuts” that humans use to reduce task complexity in judgment and choice, and biases are the resulting gaps between normative behavior and the heuristically determined behavior.

[Oxford Handbooks Online 2017]

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- ~ When talking about bias,
- (a) distinguish between the **procedure or algorithm** and its **effect or impact**,
 - (b) think twice before implying a negative, neutral, or positive assessment.

Meanings of Bias

Bias: A Neutral Interpretation

Heuristic:¹

A procedure, algorithm, calculus, which is not complete or not sound.

Systematic error, Bias:

The incurred consequences for not being complete or sound.

¹Various authors use the term “cognitive bias” for a heuristic that is applied by humans to judge.

HINDSIGHT BIAS



"ALTHOUGH WE GAVE HIM ALL OF THAT MONEY AND SUPPORT, I ALWAYS HAD MY DOUBTS THAT JIM COULD BUILD HIS OWN HELICOPTER."

Meanings of Bias

Bias in algorithms

Cognitive bias

Inductive bias

Statistical bias

Bias in data

Meanings of Bias

Bias in algorithms

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Bias in data



Deviation of a random variable / statistic from its true value.

Meanings of Bias

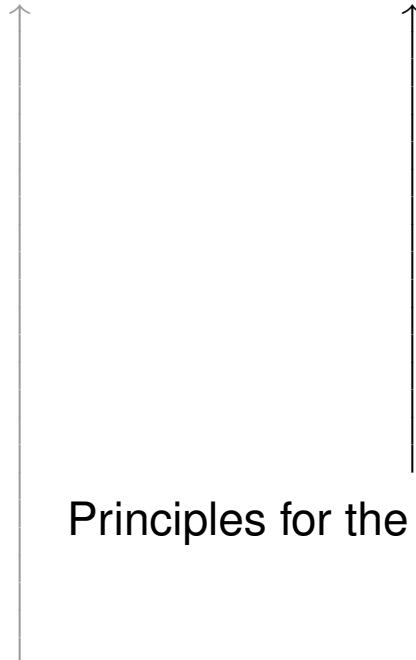
Bias in algorithms

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Principles for the search in the hypothesis space (machine learning).

Deviation of a random variable / statistic from its true value.

Meanings of Bias

Bias in algorithms

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Statistical bias

Rational deviations from logical thought.

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Meanings of Bias

Statistical View

Bias in algorithms

Cognitive bias

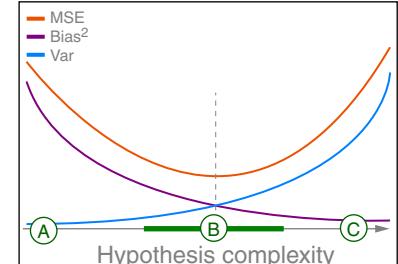
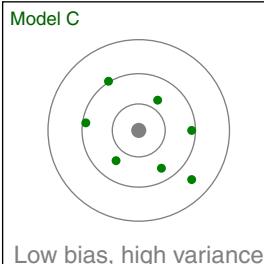
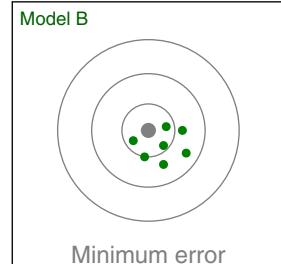
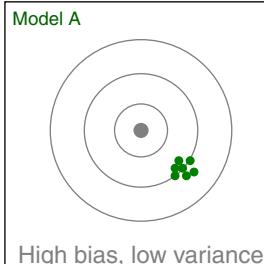
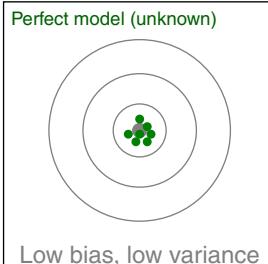
Statistical bias

Inductive bias

Bias in data

Trade unbiasedness for error reduction when learning from samples.

E.g., bias-variance decomposition for squared error: $MSE = \text{Bias}(\hat{f})^2 + \text{Var}(\hat{f}) + \sigma^2$



Meanings of Bias

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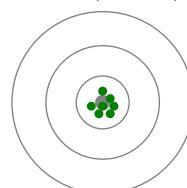
E.g., bias-variance decomposition for squared error: $MSE = \text{Bias}(\hat{f})^2 + \text{Var}(\hat{f}) + \sigma^2$

Compare to bias definition of C. Gonzales (2017):

- Reduce task complexity by analyzing small samples.
- Applying heuristics entail bias but reduce risk of poorly representing unseen data.

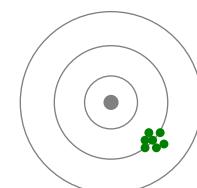
Gigerenzer et al. (2009). Homo heuristicus: Why biased minds make better inferences.

Perfect model (unknown)



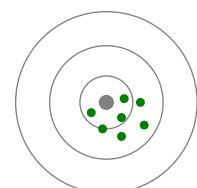
Low bias, low variance

Model A



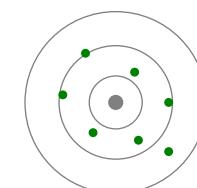
High bias, low variance

Model B



Minimum error

Model C

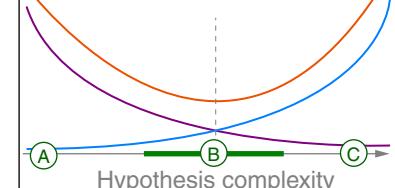


Low bias, high variance

MSE

Bias²

Var



Meanings of Bias

Machine Learning View

Bias in algorithms

Cognitive bias

Statistical bias

Inductive bias

Bias in data

Set of assumptions used to perform induction (= predict outputs for unseen inputs).
E.g., preference rules for hypotheses spaces, model parameters, data exploitation.

Meanings of Bias

Machine Learning View

Bias in algorithms

Cognitive bias

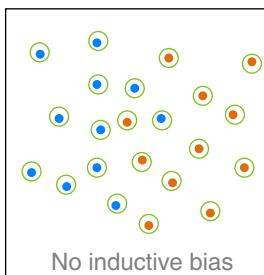
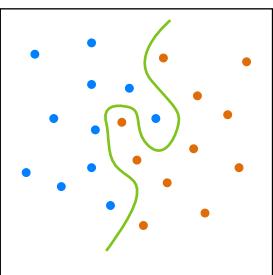
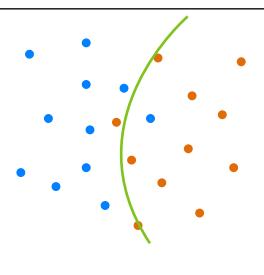
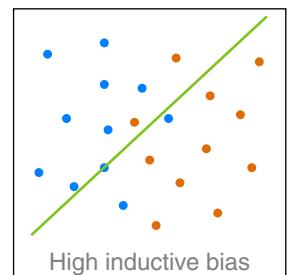
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“Learning without bias is futile.”

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Meanings of Bias

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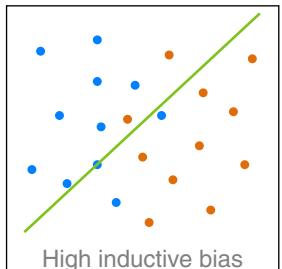
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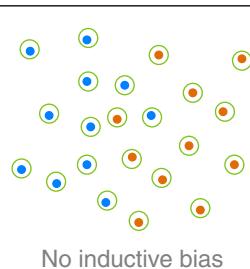
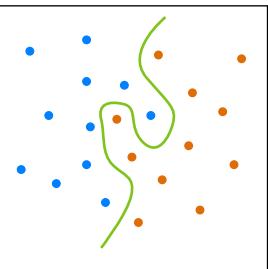
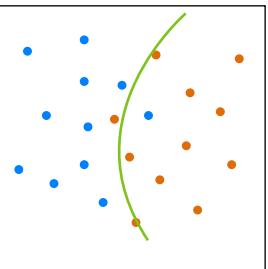
E.g., preference rules for hypotheses spaces, model parameters, data exploitation.

Examples of inductive biases:

- principle of parsimony, small is quick (search), nearest neighbors, maximum margin
- group equivariance, structured perception, drop out (deep learning)
- data augmentation, priors in Bayesian models (learning setup)



High inductive bias



No inductive bias

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Meanings of Bias

Behavioral Economics View

Bias in algorithms

Cognitive bias

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Statistical bias

Bias in data

Systematic patterns of deviation from norm and/or rationality in judgment.

Mental shortcuts (heuristics) that the brain uses to produce decisions or judgments.

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A classification scheme oriented at the addressed problems [B. Benson, 2016-2022] :

Problem 1: Too much information.

Problem 2: Not enough meaning.

Problem 3: Need to act fast.

Problem 4: What should we remember?

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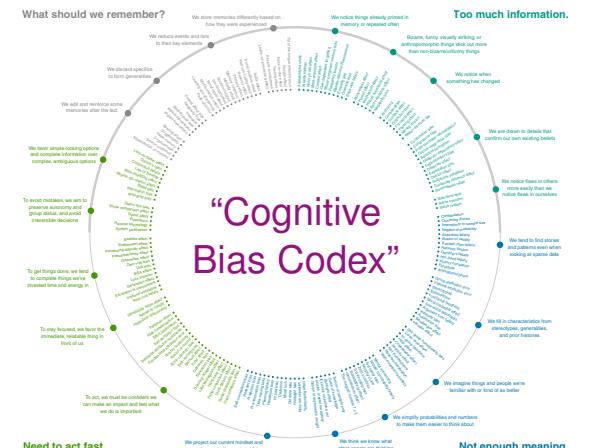
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Connections between the Meanings of Bias (a)

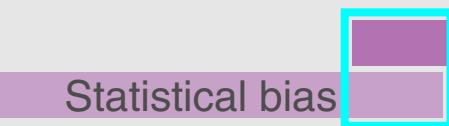
Bias in algorithms

Cognitive bias

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Inductive bias

Statistical bias



(a) Inductive and statistical bias can entail each other.

- Introducing statistical bias may be explained in terms of inductive bias.
↑
- Operationalization of inductive bias may entail statistical bias.
- Keyword: *regularization*

Meanings of Bias

Connections between the Meanings of Bias (a)

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↑
 Operationalization of inductive bias may entail statistical bias.

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Example: LASSO (least absolute shrinkage and selection operator)

- Inductive bias: minimize feature number
↑
 Statistical bias: constrain absolute value of model parameters

Meanings of Bias

Connections between the Meanings of Bias (b)

Bias in algorithms

Inductive bias

Statistical bias

Cognitive bias

Bias in data

(b) Cognitive and inductive bias can entail each other.

- Ensuring inductive bias will become manifest as a cognitive bias.
↑
 Certain cognitive biases inspired inductive biases in machine learning.

- Keyword: *concept learning*

Meanings of Bias

Connections between the Meanings of Bias (b)

Bias in algorithms

Inductive bias

Statistical bias

Cognitive bias

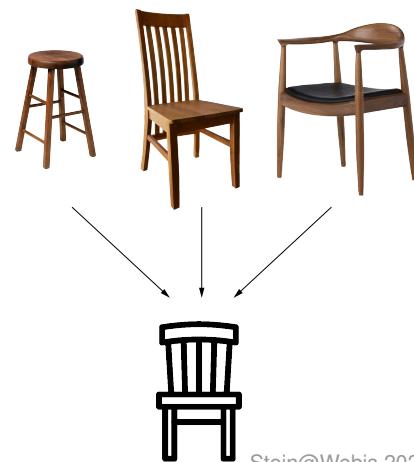
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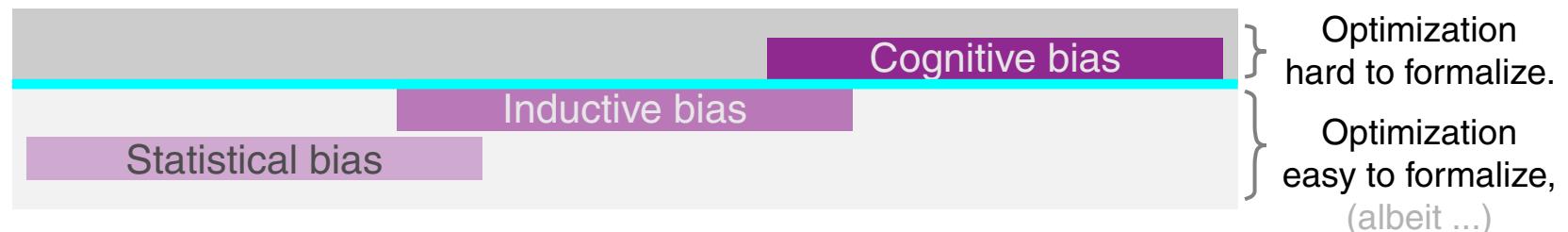
Example: CART (classification and regression tree)

- Cognitive bias: representativeness heuristic, stereotyping
↔
- Inductive bias: minimize description length



Meanings of Bias

Connections between the Meanings of Bias



Meanings of Bias

Connections between the Meanings of Bias



(a) Inductive and statistical biases . . .

- are optimized against a (mathematical) loss function—but,
- trading bias against variance is an alchemical discipline.

(b) Cognitive biases depend on . . .

- cultural backgrounds,
- the zeitgeist,
- they are individually experienced, and, in particular,
- there is no unified value system for their mathematical quantification.

Meanings of Bias

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Source of misunderstandings

Meanings of Bias

Connections to Information Retrieval

Bias in algorithms

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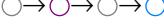
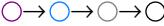
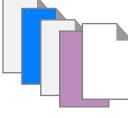
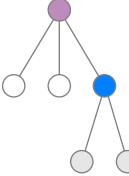
Bias in data

Extent to which IR is challenged.



Addressing Cognitive Biases with IR

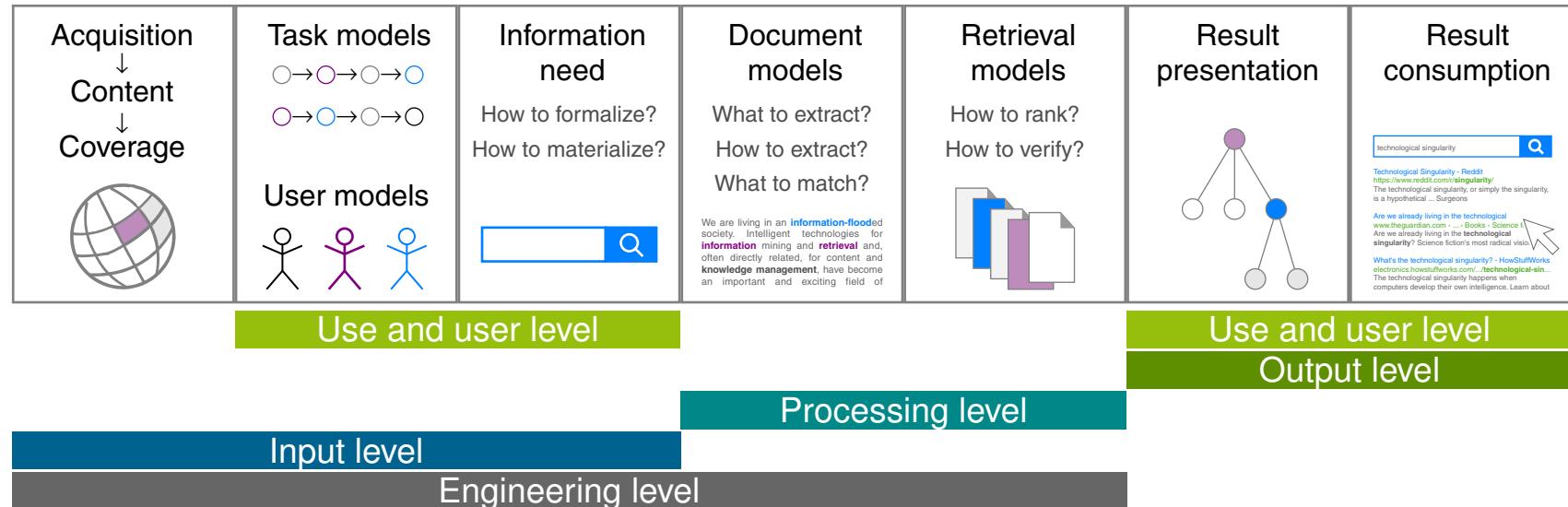
Addressing Cognitive Biases with IR

<p>Acquisition ↓ Content ↓ Coverage</p> 	<p>Task models</p> <p> </p> <p>User models</p> 	<p>Information need</p> <p>How to formalize? How to materialize?</p> 	<p>Document models</p> <p>What to extract? How to extract? What to match?</p> <p>We are living in an information-flooded society. Intelligent technologies for information mining and retrieval and, often directly related, for content and knowledge management, have become an important and exciting field of</p>	<p>Retrieval models</p> <p>How to rank? How to verify?</p> 	<p>Result presentation</p> 	<p>Result consumption</p> <p></p> <p>Technological Singularity - Reddit https://www.reddit.com/r/singularity/ The technological singularity, or simply the singularity, is a hypothetical ... Surgeon</p> <p>Are we already living in the technological singularity? www.theguardian.com... Books : Science electronics.howstuffworks.com... technological-sin... The technological singularity happens when computers develop their own intelligence. Learn about</p>
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Addressing Cognitive Biases with IR

The Heart of IR is Evaluation

- Brenda Dervin, Michael Nilan (1986). Information needs and uses.
- * Tefko Saracevic (1995). Evaluation of evaluation in information retrieval.
- Ellen Voorhees (2001). The philosophy of information retrieval evaluation.
- William Webber (2009). When did the Cranfield tests become the “Cranfield paradigm”?



Addressing Cognitive Biases with IR

IR Technology can Amplify Cognitive Biases

Examples from search behavior* :

- Rely on retrieving information via search engines, rather than remembering (Google effect).
- Initial result presented may color the person's opinion on the topic (anchoring bias).
- Taking a query suggestion (bandwagon effect).
- Selection of result items from known sources (ambiguity effect).
- Overestimate the ability to find relevant items (Dunning-Kruger effect).
- Results returned in response to a query may prime the search (priming effect).
- Given more weight to information presented earlier in a list (order effect).

Prominently affected domains:

- health, medicine
- politics, society

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Addressing Cognitive Biases with IR

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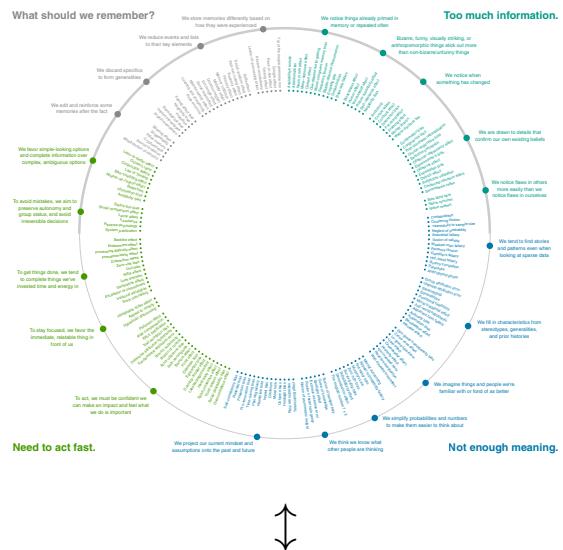
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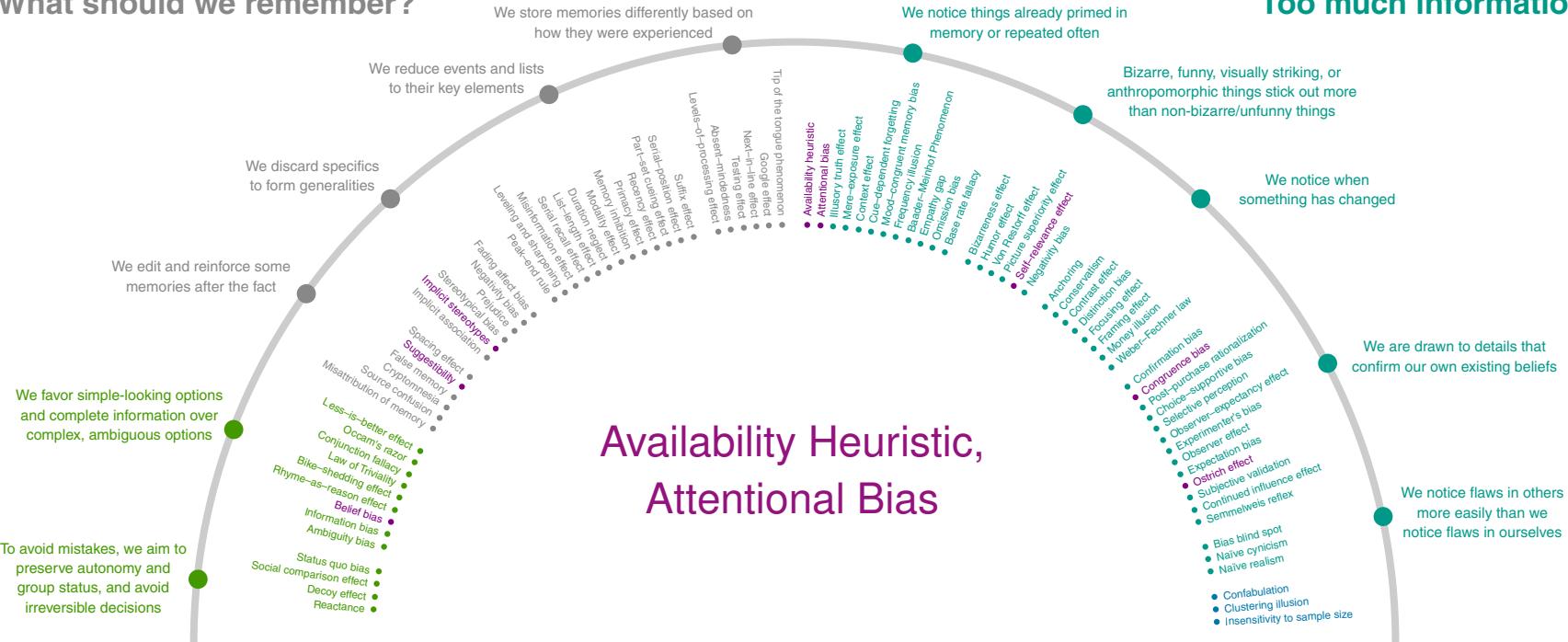


Acquisition ↓ Content ↓ Coverage	Task models ○→○→○→○ ○→○→○→○	Information need How to formalize? How to materialize?	Document models What to extract? How to extract? What to match?	Retrieval models How to rank? How to verify?	Result presentation	Result consumption
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1. We mapped around 100 cognitive biases on the seven phases in the IR pipeline.
2. We analyzed publications from relevant IR venues on technologies to address cognitive biases.

What should we remember?

Too much information.



Availability Heuristic, Attentional Bias

Acquisition
↓
Content
↓
Coverage



Task models
→○→ →○
○→○→ →○

User models
○○○

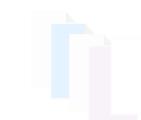
Information need
How to formalize?
How to materialize?



Document models
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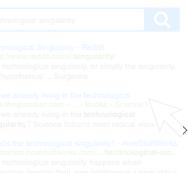
Retrieval models
How to rank?
How to verify?



Result presentation



Result consumption

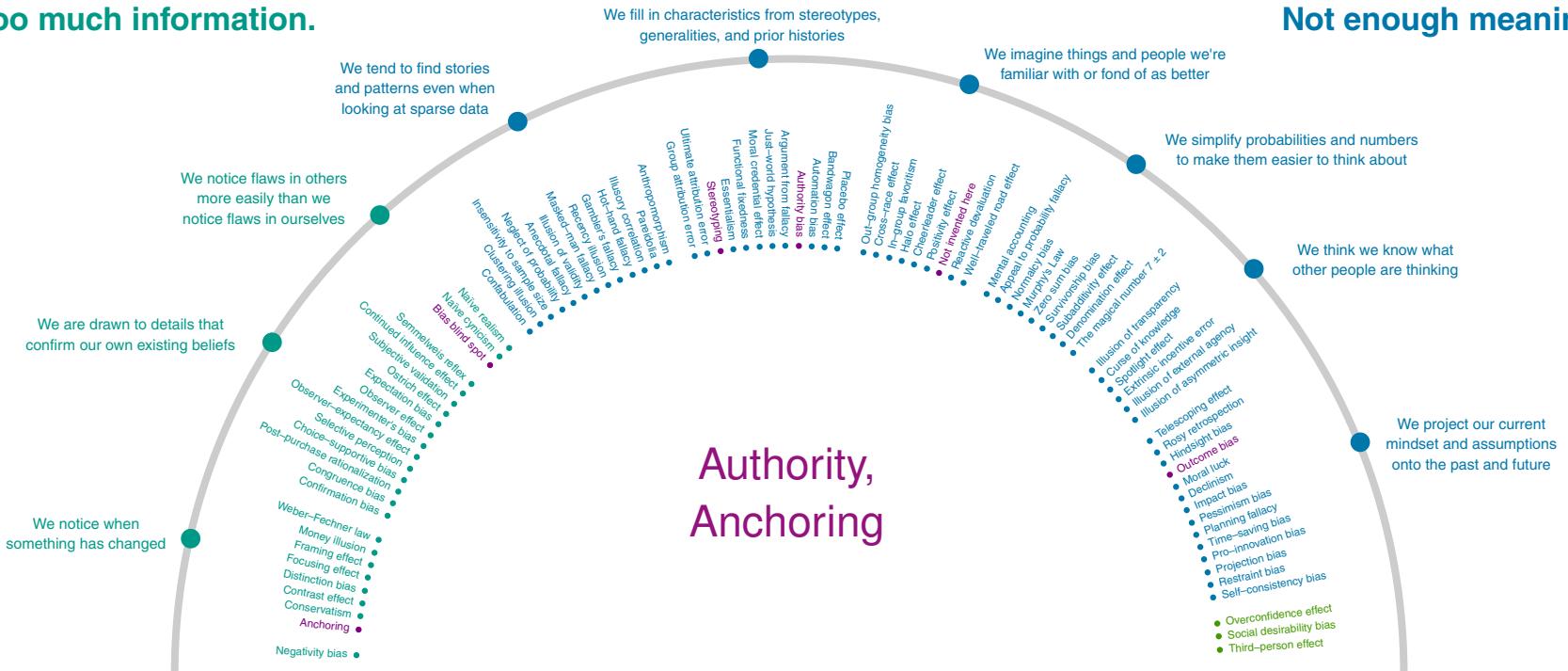


IR systems can assist in systematic and fair review.

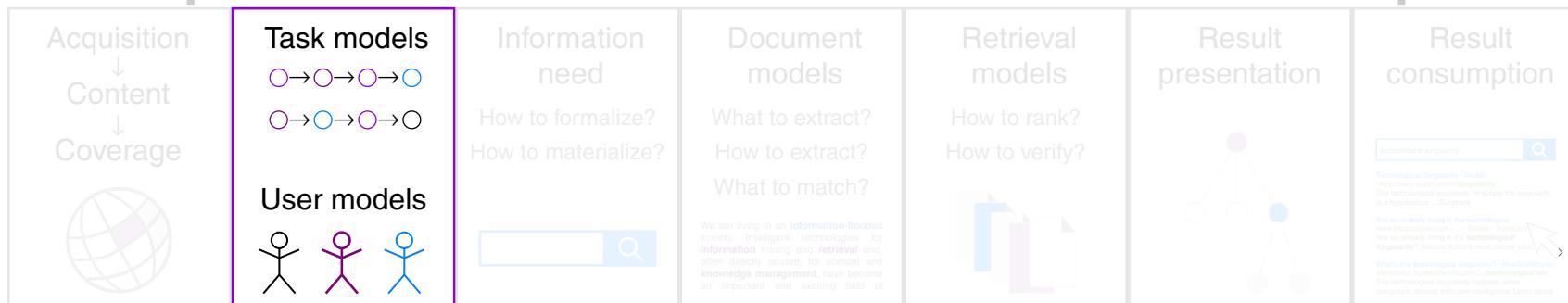
- M. Grossman, G. Cormack, A. Roegiest (2016). TREC 2016 total recall track overview.
- A. Olteanu et al. (2021). FACTS-IR: Fairness, accountability, confidentiality, transparency, and safety in IR.

Too much information.

Not enough meaning.



Authority, Anchoring

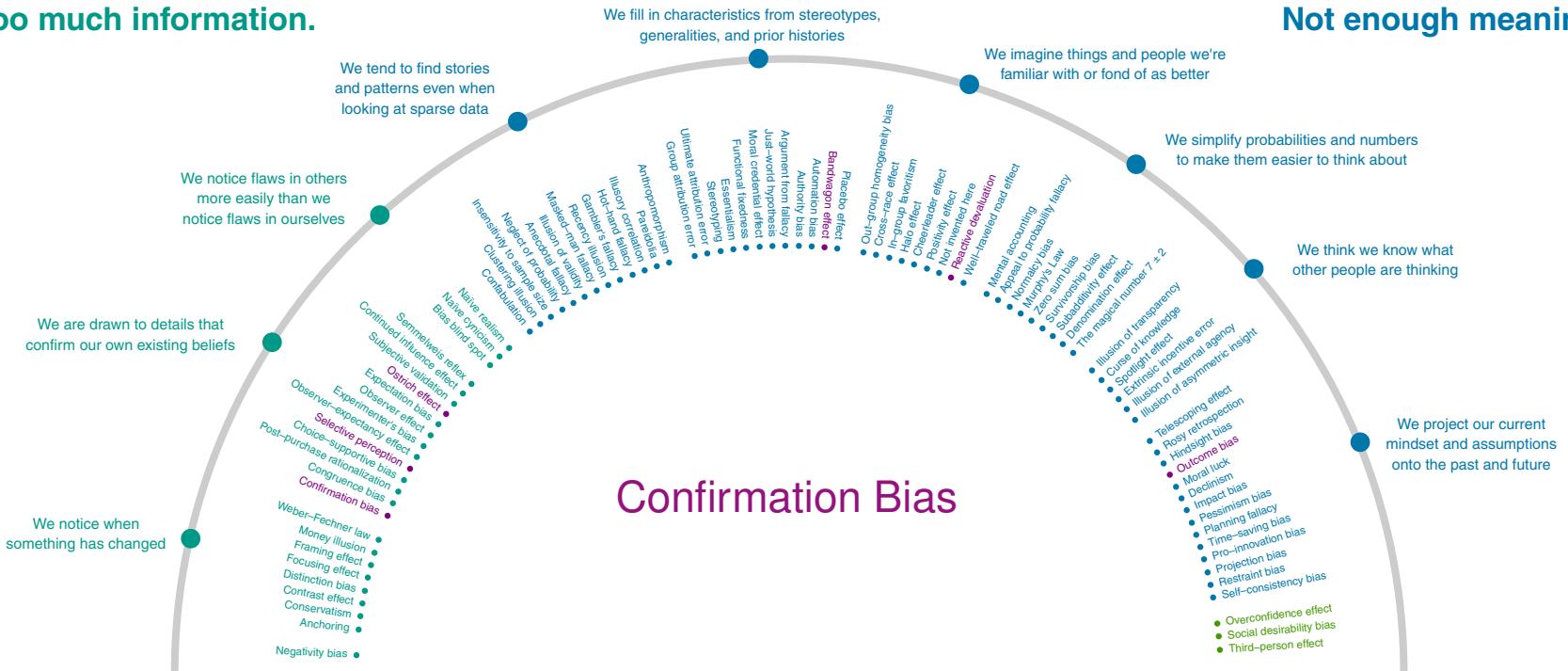


User models can incorporate biases.

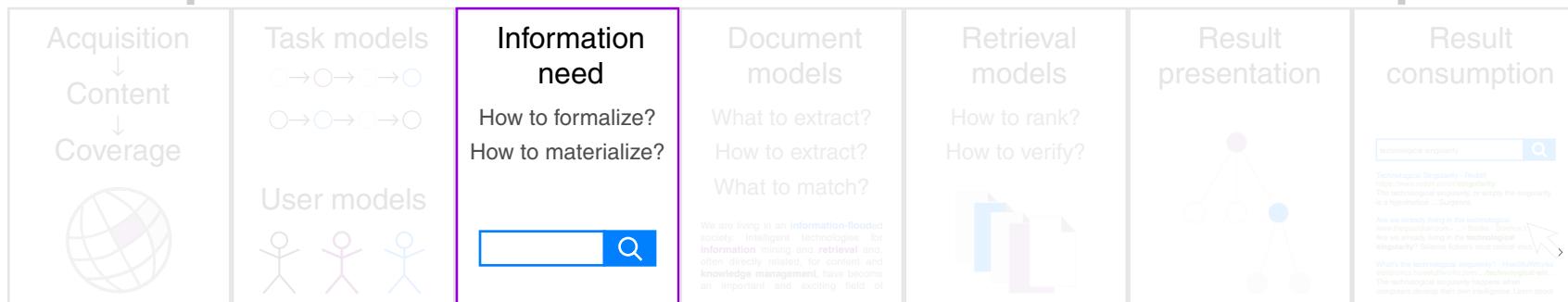
- T. Joachims et al. (2005). Accurately interpreting clickthrough data as implicit feedback.
 - N. Chen et al. (2022). Constructing better evaluation metrics by incorporating the anchoring effect into the user model.

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Not enough meaning.



Confirmation Bias



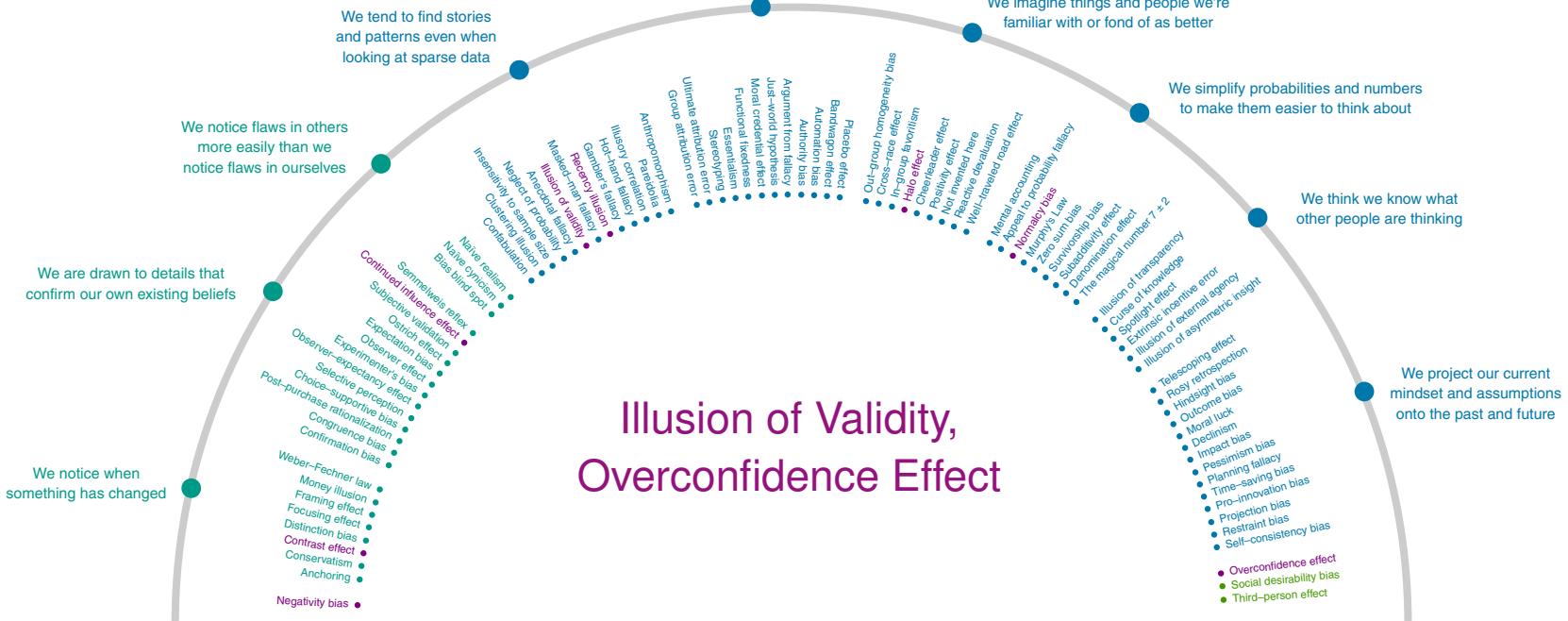
Query assistance (auto-completion, suggestion) can nudge searchers towards critical queries.

- Y. Yamamoto, T. Yamamoto (2018). Query priming for promoting critical thinking in web search.
 - S. Pothirattanachaikul et al. (2020). Analyzing the effects of “People also ask” on search behaviors and beliefs.

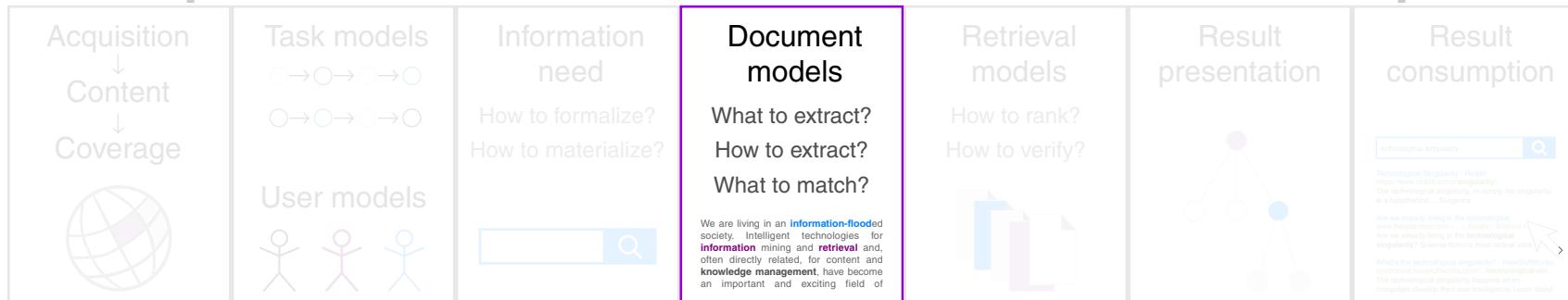
Too much information.

We fill in characteristics from stereotypes, generalities, and prior histories

Not enough meaning.



Illusion of Validity, Overconfidence Effect



IR systems can assist in checking claim veracity.

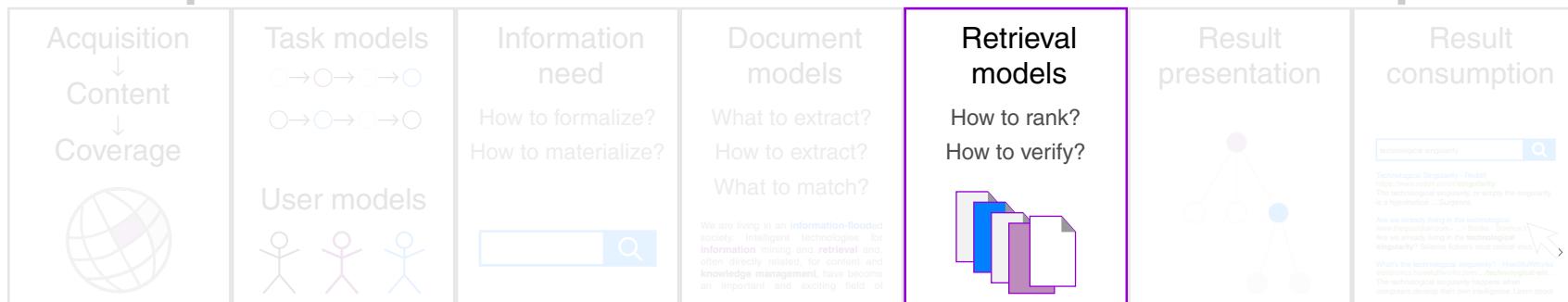
- P. Nakov et al. (2022). Overview of the CLEF'22 CheckThat! lab task on detecting previously fact-checked claims.
 - Y. Qu et al. (2021). Human-in-the-loop systems for truthfulness: A study of human and machine confidence.

Too much information.

Not enough meaning.



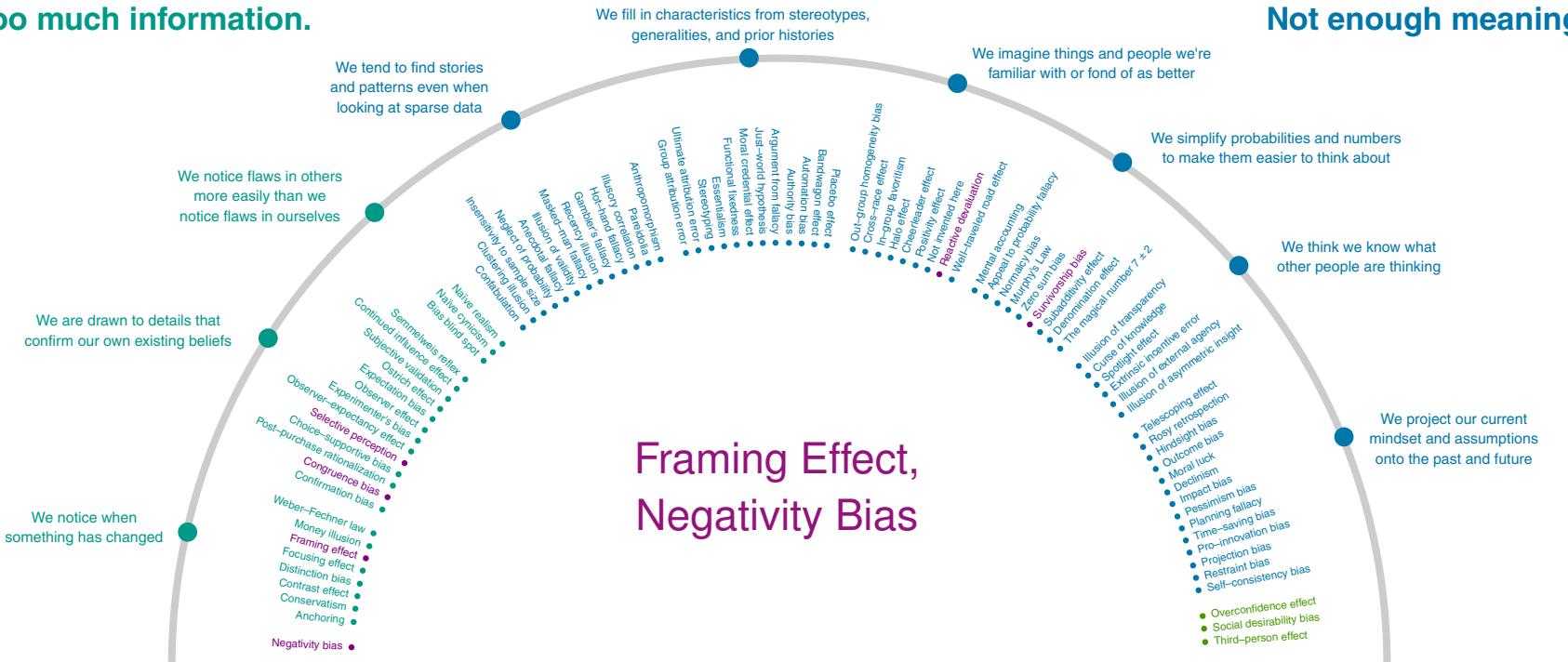
Naïve Realism, In-group favoritism



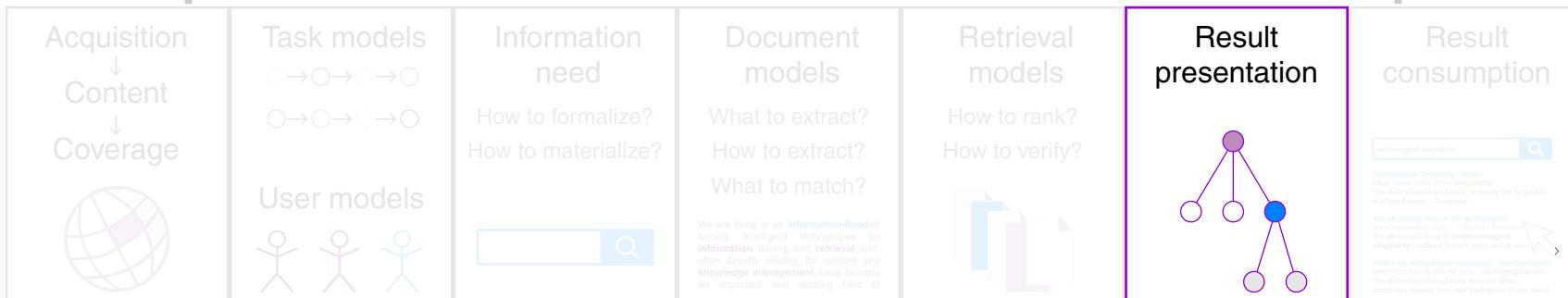
Result lists can be tweaked to reflect normative distributions.

- M. Ekstrand et al. (2022). Overview of the TREC'21 fair ranking track.
 - P. Sapiezynski et al. (2019). Quantifying the impact of user attention on fair group representation in ranked lists.

Too much information.



Framing Effect, Negativity Bias

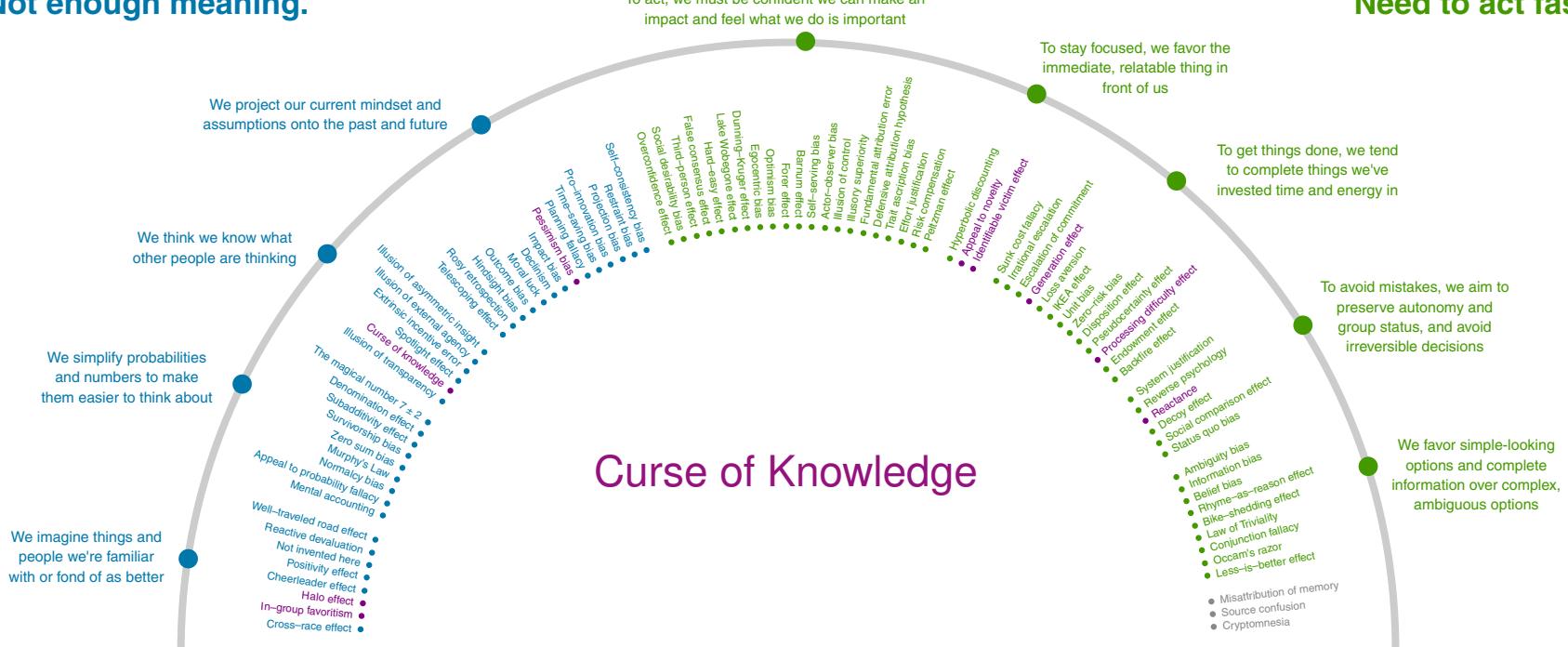


Result captions (title + snippet + URL in a SERP) can be changed to influence user behavior.

- C. Clarke et al. (2007). The influence of caption features on clickthrough patterns in web search.
- R. W. White (2013). Beliefs and biases in web search.

Not enough meaning.

Need to act fast.



Acquisition
↓
Content
↓
Coverage



Task models
→○→ →○
○→○→ →○



Information need
How to formalize?
How to materialize?



Document models
What to extract?
How to extract?
What to match?



Retrieval models
How to rank?
How to verify?



Result presentation

Result consumption

Technological singularity
Technological Singularity - Reddit
<https://www.reddit.com/singularity/>
The technological singularity, or simply the singularity, is a hypothetical ... Surgeon
Are we already living in the technological singularity? Science fiction's most radical vision
Are we already living in the technological singularity? Books & Science
Are we already living in the technological singularity? Science fiction's most radical vision
What's the technological singularity? - HowStuffWorks
electronics.howstuffworks.com/.../technological-sin...
The technological singularity happens when computers develop their own intelligence. Learn about

Complex documents can be simplified to make them more accessible.

- L. Ermakova et al. (2022). Overview of the CLEF'22 SimpleText task on query biased simplification of scientific texts.
- M. Maddela et al. (2021). Controllable text simplification with explicit paraphrasing.



Related Research @ Webis

Cat / Lifespan

15 years

Domesticated

*Feedback*[How Long Do Cats Live? | petMD](#)www.petmd.com/blogs/thedailyvet/.../how_long_do_cats_live-11496 ▾

Aug 8, 2011 - This question, typically rephrased as, "How long will my cat (or dog, horse, etc.) live," is something veterinarians hear on a daily basis.

[Aging Cats: Changes, Health Problems, Food, and More](#)pets.webmd.com/cats/guide/aging-cats-qa ▾

WebMD veterinarian experts answer common questions cat owners have ... What else can you expect as your cat ages? ... Q: How long do cats usually live?

[What Is the Life Span of the Common Cat? - Cats - About.com](#)cats.about.com/About_Home/Cats ▾

How long is the common cat supposed to live? Questions and answers from the About Guide to Cats.

[Ageing - How long do cats live | Adelaide Animal Hospital](#)adelaidevet.com.au/pet/.../how-long-do-cats-live-ageing-and-your-feline ▾

Life expectancy depends on many things, including one important factor - whether your cat is an indoor-only cat or an outdoor cat. Indoor cats generally live from 12-18 years of age. Many may live to be in their early 20s. The oldest reported cat lived to be an

Cat

Animal



The domestic cat or the feral cat is a small, typically furry, carnivorous mammal. They are often called house cats when kept as indoor pets or simply cats when there is no need to distinguish them from other felids and felines. [Wikipedia](#)

Scientific name: Felis catus**Lifespan:** 15 years (Domesticated)**Gestation period:** 64 – 67 days**Higher classification:** Felis**Daily sleep:** 12 – 16 hours**Mass:** 3.6 – 4.5 kg (Adult)*Feedback*



Cat / Lifespan

15 years

Domesticated



Feedback

How Long Do Cats Live? | petMD

www.petmd.com/blogs/thedailyvet/.../how_long_do_cats_live-11496 ▾
Aug 8, 2011 - This question, typically rephrased as, "How long will my cat (or d horse, etc.) live," is something veterinarians hear on a daily basis.

Aging Cats: Changes, Health Problems, Food, and More | pets.webmd.com/cats/guide/aging-cats-qa

WebMD veterinarian experts answer common questions cat owners have ... What can you expect as your cat ages? ... Q: How long do cats usually live?

What Is the Life Span of the Common Cat? - Cats - About cats.about.com

About Home ▾ Cats ▾
How long is the common cat supposed to live? Questions and answers from the Guide to Cats.

Ageing - How long do cats live | Adelaide Animal Hospital

adelaidevet.com.au/pet.../how-long-do-cats-live-ageing-and-your-feline ▾
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Cat

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Scientific name: Felis catus

Lifespan: 15 years (Domesticated)

Gestation period: 64 – 67 days



Konrad
Lischka

How does Google know when my cat will die?

23. September 2015 by Konrad Lischka, in [Blog @en](#)



How long do cats live? Exactly 15 years says Google.com. Not "10 to 15", not "about 15 years", but "15 years". That sounds like a definitive answer. It's Google's answer to the search query "[How long do cats live](#)".

Related Research @ Webis

Dilemma of the Direct Answer

“A user’s choice between convenience and diligence when using an information retrieval system.”

Related Research @ Webis

Dilemma of the Direct Answer

“A user’s choice between convenience and diligence when using an information retrieval system.”

What is the speed of light?

the speed of light =

299 792 458 m / s

[More info](#)

Speed of light

Unit of speed



The speed of light in vacuum, commonly denoted c , is a universal physical constant important in many areas of physics. Its exact value is defined as 299792458 metres per second. [Wikipedia](#)

[About Featured Snippets](#) [Feedback](#)

- M. Potthast, M. Hagen, B. Stein (2020). The dilemma of the direct answer.

What can be done about overpopulation?

5 possible solutions to overpopulation

- Empower women. Studies show that women with access to reproductive health services find it easier to break out of poverty, while those who work are more likely to use birth control. ...
- Promote family planning. ...
- Make education entertaining. ...
- Government incentives.

Jul 10, 2017

 <https://www.positive.news> › society

5 possible solutions to overpopulation - Positive News - Positive News

[About Featured Snippets](#) [Feedback](#)

What is the impact of CRISPR/Cas9?

The discovery of **CRISPR/Cas9**, a branch of the bacterial adaptive immune system, as a potential genomic editing tool holds the promise of facile targeted cleavage. Its novelty lies in its RNA-guided endonuclease activity, which enhances its efficiency, scalability, and ease of use.

 <https://www.ncbi.nlm.nih.gov> › pub...

The Impact of CRISPR/Cas9-Based Genomic Engineering on Biomedical ...

[About Featured Snippets](#) [Feedback](#)

Related Research @ Webis

Dilemma of the Direct Answer (continued)

Direct answers amplify various cognitive biases, among others:

1. Authority bias.

Puts forward the single result with the authority of the search engine.

2. Confirmation bias / overconfidence.

Likely the most prominent answer, thus confirming people already believing in it.

3. Naive realism / survivorship bias.

Suggests a “simple” one-answer truth.

4. Mere-exposure effect / illusory truth effect.

Expose users to just one answer (mere exposure increases the liking of ideas).

5. Outgroup homogeneity bias.

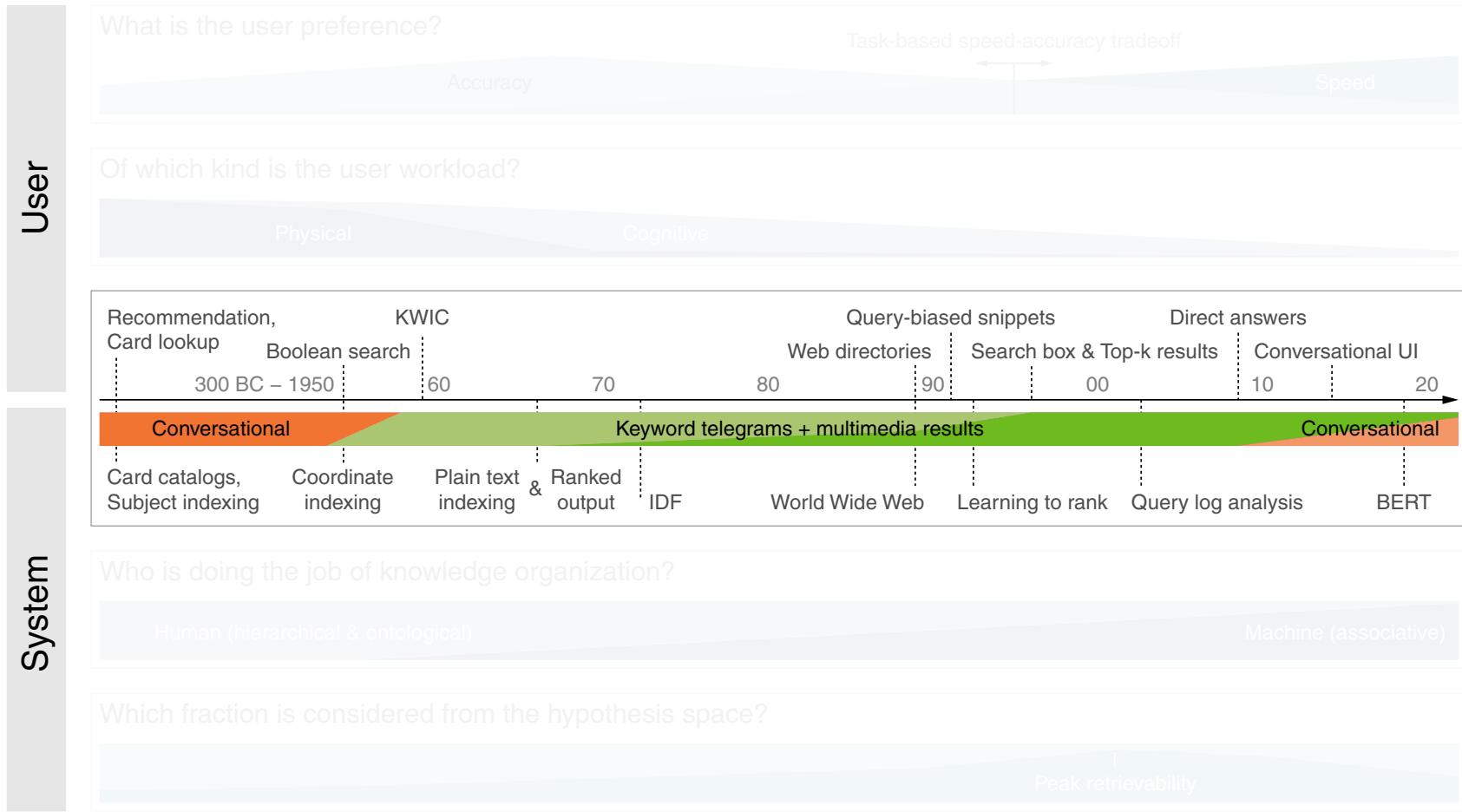
Implies a well-accepted opinion.

6. Reactance.

If the direct answer not the one that one believes in, it can cause reactance in users.

Related Research @ Webis

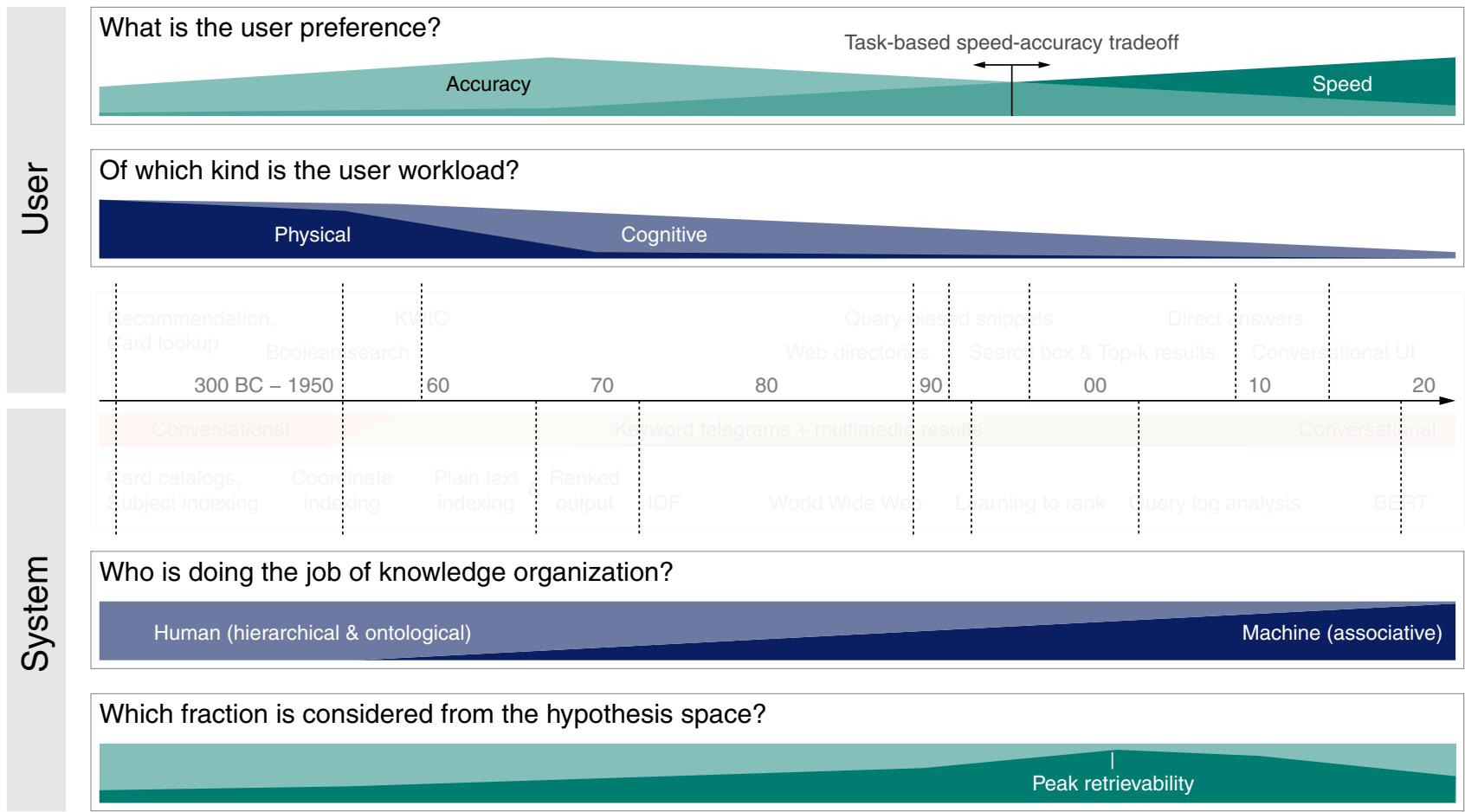
Dilemma of the Direct Answer (continued)



- M. Potthast, M. Hagen, B. Stein (2020). The dilemma of the direct answer.

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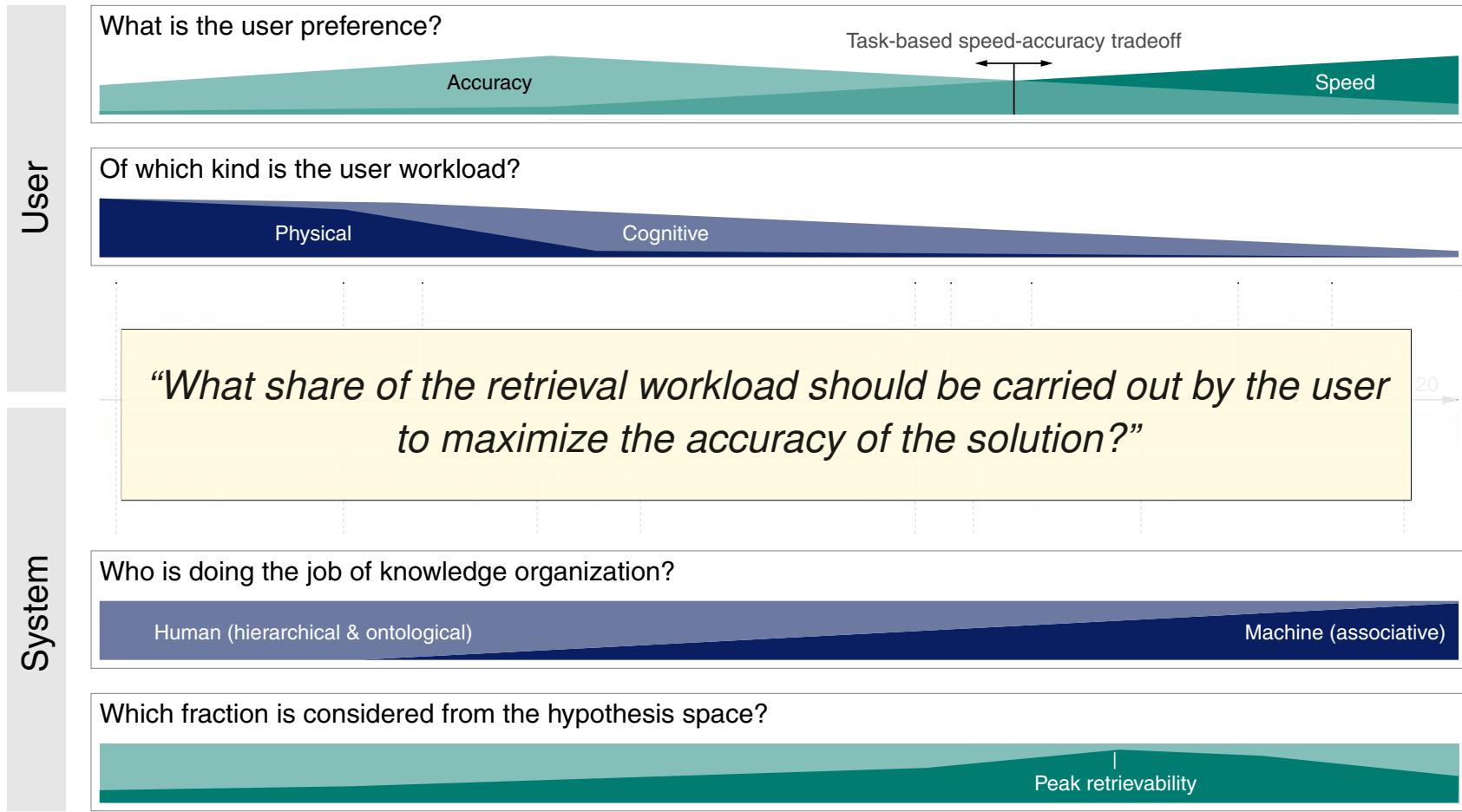
Dilemma of the Direct Answer (continued)



- M. Potthast, M. Hagen, B. Stein (2020). The dilemma of the direct answer.

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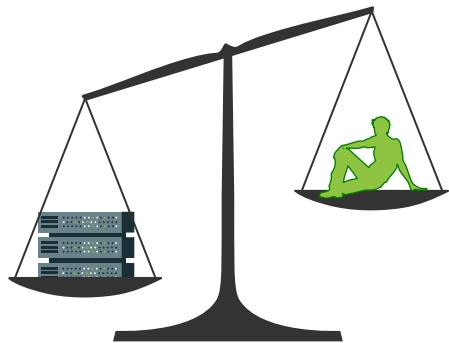
Dilemma of the Direct Answer (continued)



- M. Potthast, M. Hagen, B. Stein (2020). The dilemma of the direct answer.

Related Research @ Webis

Information Retrieval and the Balance of Responsibilities



More power to the machine?



Empower the user?

- support deliberation
- raise awareness
- demonstrate mechanisms
- provide meta information
- ...

Related Research @ Webis

- (1) Rationalization
- (2) Bias Annotation
- (3) Reframing
- (4) Information Labeling**
- (5) SERP Axiomatization
- (6) Conversation Control
- (7) Medical Retrieval

Related Research @ Webis

(1) Rationalize Answers → Information Seeker Deliberation

- An argument search engine for the web. [args.me]

Released: 2017.

About 350,000 arguments over 1,200 topics.

Evidence types: discussions, news, people.

- (1) Rationalization
- (2) Bias Annotation
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- Making arguments “digestible” with images. [\[images.args.me\]](http://images.args.me)

CLEF'22 & CLEF'23: Touché shared task on image retrieval for arguments.

About 70,000 images over 100 topics.

- (1) Rationalization
- (2) Bias Annotation
- (3) Reframing
- (4) Information Labeling
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□ Making arguments “digestible” with images. [images.args.me]

CLEF'22 & CLEF'23: Touché shared task on image retrieval for arguments.

About 70,000 images over 100 topics.

□ What are the values behind arguments? [values.args.me]

Basis: Schwartz et al. value continuum (2012).

SemEval'23: Shared task on human value detection.

About 10,000 arguments reflecting 20 values.

Forthcoming: ValueEval'24 with EU Commission's JRC.

- (1) Rationalization
- (2) Bias Annotation
- (3) Reframing
- (4) Information Labeling
- (5) SERP Axiomatization
- (6) Conversation Control
- (7) Medical Retrieval

-
- H. Wachsmuth et al. (2017). Building an argument search engine for the web.
 - J. Kiesel et al. (2021). Image retrieval for arguments using stance-aware query expansion.
 - J. Kiesel et al. (2022). Identifying the human values behind arguments.

Related Research @ Webis

(4) An Information Nutrition Label → Provide Meta Information

TRUMP'S ATTACK ON SESSIONS OVER CLINTON PROSECUTION HIGHLIGHTS HIS OWN 'WEAK' STANCE



by ADAM SHAW | 25 Jul 2017 | 5,500

President Trump's decision Tuesday to attack Attorney General Jeff Sessions over Sessions' "position" on Hillary Clinton's various scandals only serves to highlight Trump's own hypocrisy on the issue — and is likely to fuel concerns from his base who see

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INFORMATION NUTRITION LABEL		
Best before: Jan 1, 2018		
Per 1,000 words		Recommended daily allowance
Fact	30%	60%
Opinion	40%	20%
Controversy	9.0	—
Emotion	6.7	1.3
Topicality	8.7	5.0
Reading level	4.0	8.0
Technicality	2.0	—
Authority	4.3	9.0
Viralness	—	1.0
Additional substances: advertising, subscription, invective, images (2), tweets, video clips		
Traces: product placement		

- (1) Rationalization
- (2) Bias Annotation
- (3) Reframing
- (4) Information Labeling**
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- (6) Conversation Control
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- T. Gollub, M. Potthast, B. Stein (2018). Shaping the information nutrition label.
- N. Fuhr et al. (2017). An information nutritional label for online documents.

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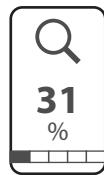
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Additional substances: advertising, subscription, invective, images (2), tweets, video clips		
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verbosity



virality



verifiability



emotionality



reliability

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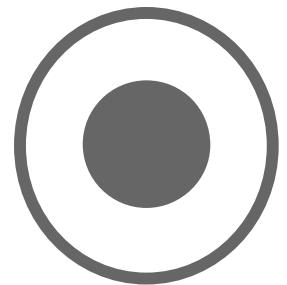
(4) An Information Nutrition Label

- (1) Rationalization
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- (3) Reframing
- (4) Information Labeling**
- (5) SERP Axiomatization
- (6) Conversation Control
- (7) Medical Retrieval

“It is not our intention to say what is true or what is false, right or wrong, and in particular not what is good or bad.*

*That is, an Information Nutrition Label is
not a substitute for a moral compass.”*

* Norbert Fuhr, Anastasia Giachanou, Gregory Grefenstette, Iryna Gurevych, Andreas Hanselowski, Kalervo Jarvelin, Rosie Jones, Yiqun Liu, Josiane Mothe, Wolfgang Nejdl, Isabella Peters, Benno Stein @ Schloss Dagstuhl (2017)



Summary

Bias in algorithms

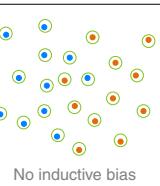
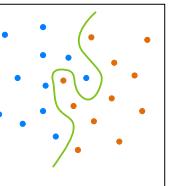
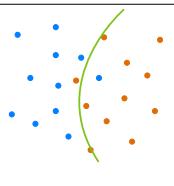
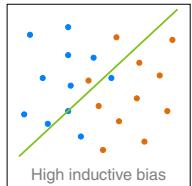
Cognitive bias

Inductive bias

Statistical bias

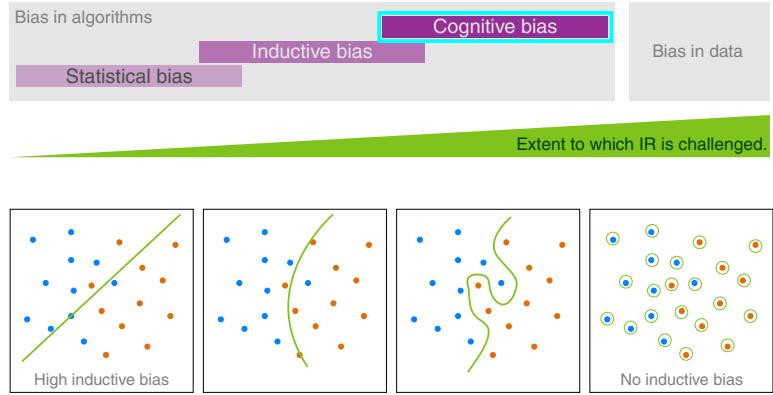
Bias in data

Extent to which IR is challenged.

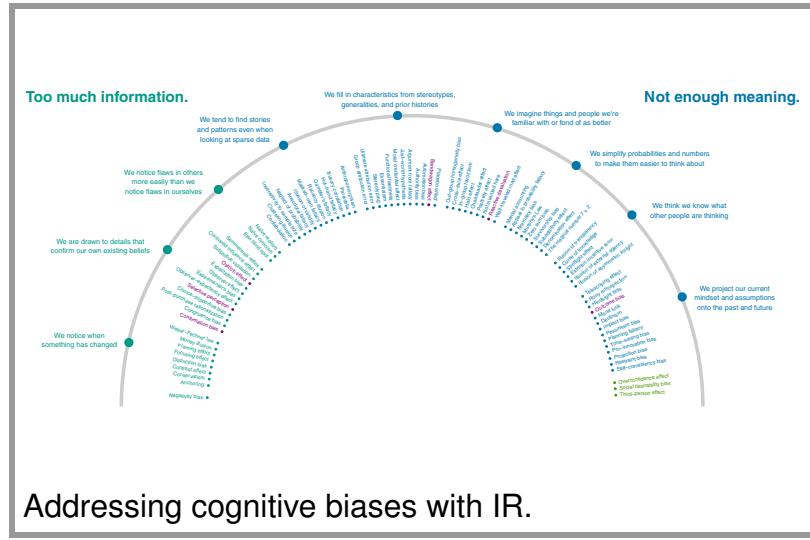


The meanings of bias, and their connections.

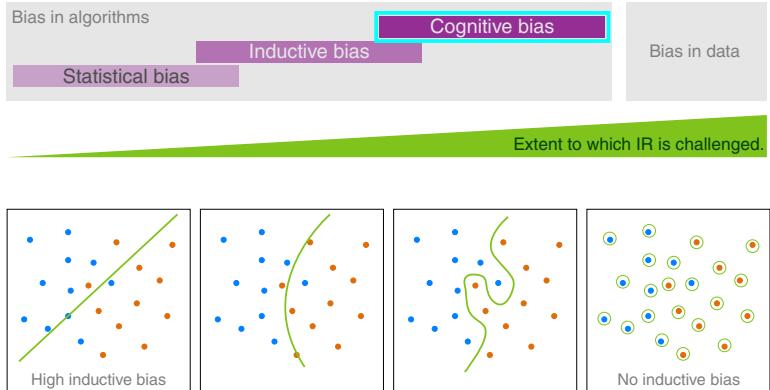
Summary



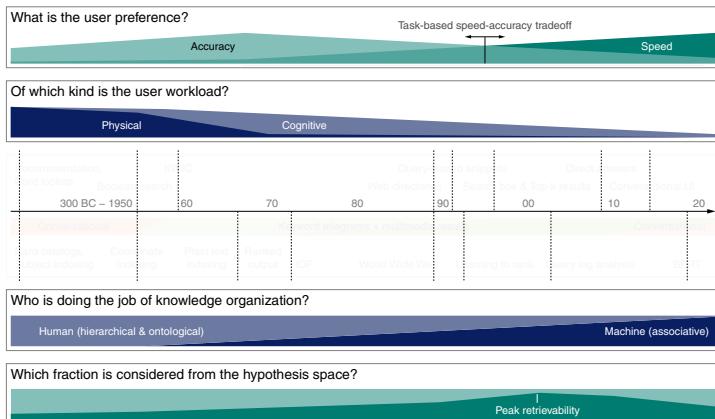
The meanings of bias, and their connections.



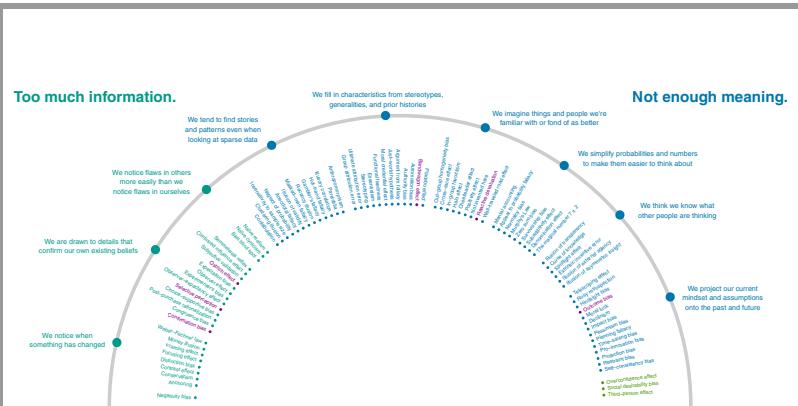
Summary



The meanings of bias, and their connections.



Direct answers—the pride of IR?



Addressing cognitive biases with IR.

Summary

Bias in algorithms

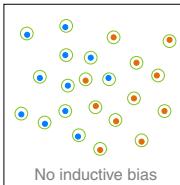
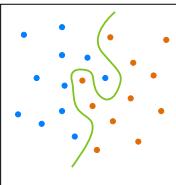
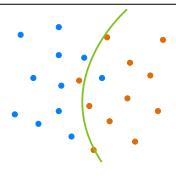
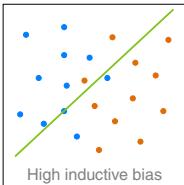
Cognitive bias

Inductive bias

Statistical bias

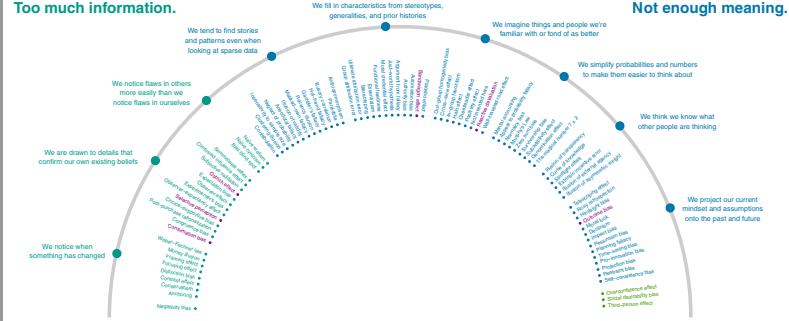
Bias in data

Extent to which IR is challenged.



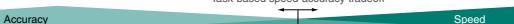
The meanings of bias, and their connections.

Too much information.



Addressing cognitive biases with IR.

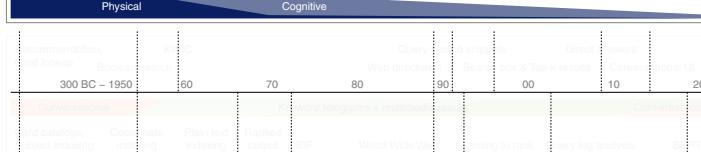
What is the user preference?



Accuracy

Speed

Of which kind is the user workload?



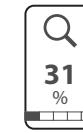
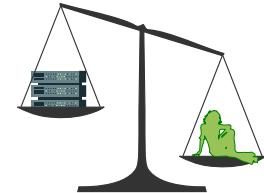
Who is doing the job of knowledge organization?



Which fraction is considered from the hypothesis space?



Direct answers—the pride of IR?



More power to machines—or, empower the user?



J. Ajjour



J. Bevendorff



A. Bondarenko



W. Chen



M. Fröbe



M. Ghosen



T. Gollub



M. Heinrich



J. Kiesel



N. Kolyada



N. Mirzakhmedova



M. Völkske



M. Wiegmann



M. Wolska



K. Al-Khatib



M. Hagen



M. Potthast



B. Stein



H. Wachsmuth

Thank You!

AVAILABILITY HEURISTIC



"THEY MUST HAVE A DEATH WISH TO SWIM IN THAT WATER."

ANCHORING EFFECT



"BREATH-TAKING ISN'T IT? THE SELLER WANTED 5,000 BUT I GOT IT FOR JUST 4,500!"

CONFIRMATION BIAS



"AHA! I KNEW IT!"

FRAMING EFFECT

THANKS TO OUR AGGRESSIVE
STANCE ON CLIMATE CHANGE,
THIS GOVERNMENT HAS
REDUCED CARBON EMISSIONS
BY ALMOST 5%!



WE ❤ YOU!

CARBON EMISSIONS REDUCED BY
JUST 4.6% IN LAST 5 YEARS



CURSE OF KNOWLEDGE

An introduction into Goncharov polylogarithms

$$\begin{aligned} \text{Li}_1(z_1 - z_0) &= \text{Alt}_0 \left\{ \frac{\omega(z_1 - z_2, z_3)}{\omega(z_1 - z_2, z_3 - z_4)} \omega(z_2 - z_3, z_4) \omega(z_3 - z_4) \right\} \in \mathbb{C} \\ \text{Li}_2(z) &= \text{Re} \left(\text{Li}_{2,0}(z) - \text{Li}_{2,0}(z) \omega(z) \text{Li}_{2,0}(z) \omega(z)^2 \text{Li}_{2,0}(z) \right) \\ \text{Li}_2(z) &= \text{Li}_{2,0}(z) + \frac{1}{2} \log^2(z) \\ \sum_{k=0}^{n-1} (-1)^k \text{Li}_{2,k}(z) &= \text{Li}_{2,n}(z) \\ \text{Li}_{2,n}(z) &= \int_0^z \frac{dt}{t} \text{Li}_{2,n-1}(t) \end{aligned}$$

$$\begin{aligned} \text{Li}_{2,0}(z) &= \ln z \text{Li}_2(z) + \ln z (1-z) \log z \\ \text{Li}_{2,0}(F) &\stackrel{\text{def}}{=} \lambda^2 F^n \quad \{z\} = (1-z) \wedge z \\ \rightarrow \sum_{k=0}^{n-1} (-1)^k \text{Li}_{2,k}(z) &= \int_0^z \frac{dt}{t} \text{Li}_{2,n-1}(t) \\ \text{Li}_{2,n}(z) &= \sum_{k=0}^{n-1} (-1)^k \text{Li}_{2,k}(z) \end{aligned}$$

$$\text{Li}_{2,n}(z) = \sum_{k=0}^{n-1} (-1)^k \text{Li}_{2,k}(z)$$



"WELL I DON'T KNOW HOW YOUR LECTURES WENT, BUT I CAN'T SEEM TO GET THROUGH TO THESE PEOPLE!"

Homo Heuristicus: Why Biased Minds Make Better Inferences

Gerd Gigerenzer, Henry Brighton

Max Planck Institute for Human Development

Abstract

Heuristics are efficient cognitive procedures that humans use to make decisions under uncertainty. They are often based on simple rules of thumb that reduce cognitive effort. (a) This article reviews research that shows how heuristics can be adaptive. It discusses the discovery of less-is-more effects; (b) the article examines in which environments a give from vague labels to computational models of heuristics that identifies their building blocks. The cognitive system as relying on an “adaptive methodology” that accounts for individual differences in people’s adaptive use of heuristics. Evidence for people’s adaptive use of heuristics comes from studies of the available information, yet a biased mind is better than an unbiased mind relying on more relevant information.

Keywords: Heuristics; Decision-making;

As far as we can know, animals have no concept of probability, and so have humans. To measure the size of a rock, an ant has no yardstick but a fixed period while laying down a path. To estimate the length of a trail, an ant follows a different irregular path, and estimate the length of the old trail. This heuristic is remarkable: it is based on counter frequencies. A peacock similarly uses a heuristic: it displays in a lek eager to get females, calculates the one with the highest ex-

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are computationally intractable, and this is why engineers and artificial intelligence (AI) researchers often rely on heuristics to make computers smart.

In the 1970s, the term *heuristic* acquired a different connotation, undergoing a shift from being regarded as a method that makes computers smart to one that explains why people are not smart. Daniel Kahneman, Amos Tversky, and their collaborators published a series of experiments in which people’s reasoning was interpreted as exhibiting fallacies. “Heuristics and biases” became one phrase. It was repeatedly emphasized that heuristics are sometimes good and sometimes bad, but virtually every experiment was designed to show that people violate a law of logic, probability, or some other standard of rationality. On the positive side, this influential research drew psychologists’ attention to cognitive heuristics and helped to create two new fields: behavioral economics, and behavioral law and economics. On the negative side, heuristics became seen as something best to avoid, and consequently, this research was disconnected from the study of heuristics in AI and behavioral biology. Another negative and substantial consequence was that computational models of heuristics, such as lexicographic rules (Fishburn, 1974) and elimination-by-aspects (Tversky, 1972), became replaced by one-word labels: availability, representativeness, and anchoring. These

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