# The Evolution of Web Search

Martin Potthast University of Kassel, hessian.AI, and ScaDS.AI

November 19th, 2024

#### Web Search



#### Language Models



### **Retrieval-Augmented Generation**



#### The Infinite Index



#### Biases







#### Native Advertising





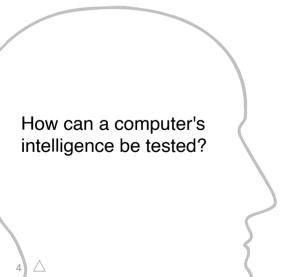
# Information Retrieval in a Nutshell

### □ A vague request.

Expression of a complex information need: a question

### Billions of documents.

Text, images, audio files, videos, ...





## Information Retrieval in a Nutshell

### □ A vague request.

Expression of a complex information need: a question, or just a few keywords.

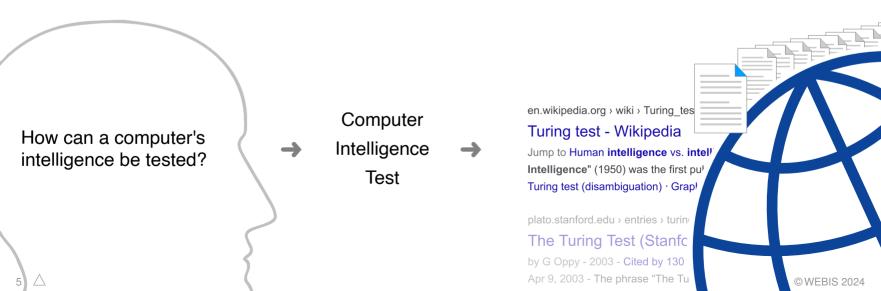
### Billions of documents.

Text, images, audio files, videos, ...

### □ High class imbalance.

Only a tiny fraction of all documents are relevant to the request.

Retrieve relevant documents in milliseconds.



User

		Ranked output			Snippets			Direct answers		
Card lookup	Boolean search	outpu	IL	Web dire	ectories	Search	ר box	Co	nversati	ional UI
300 BC	- 1950	60	70	80	90		2000	10		20
Pre-digital		i	Digitization	& indexing		F	Relevance			Answering
Card catalogs		Plain te indexir	•	World Wid	le Web	Learning	to rank	Query log analys	sis	LLM

System

<sup>•</sup> M. Potthast, M. Hagen, B. Stein (2020). The dilemma of the direct answer.









<sup>•</sup> M. Potthast, M. Hagen, B. Stein (2020). The dilemma of the direct answer.

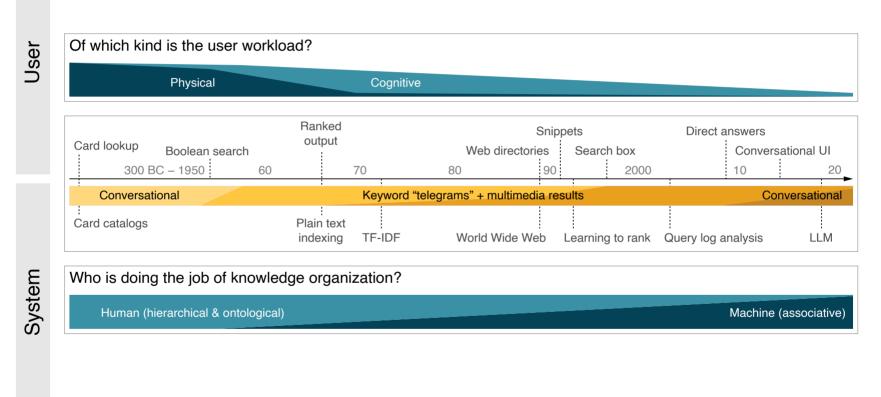


	Ranked output	S	nippets	Direct answers	
Card lookup Boolean search	output	Web directorie	s Search box	Conversational UI	
300 BC – 1950 60	70	80	90 2000	10 20	
Conversational	K	eyword "telegrams" + multimedia	results	Conversational	
Card catalogs	Plain text indexing TI	-IDF World Wide Web	<ul> <li>Learning to rank</li> </ul>	Query log analysis LLM	

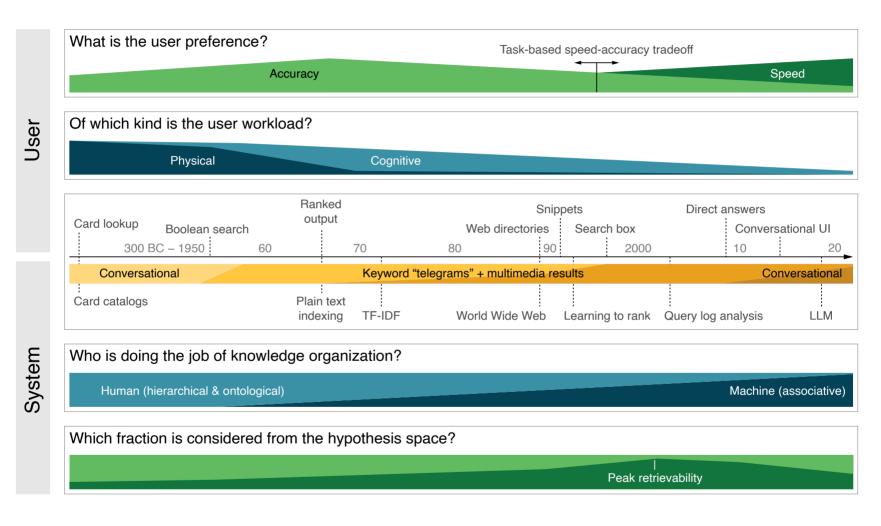




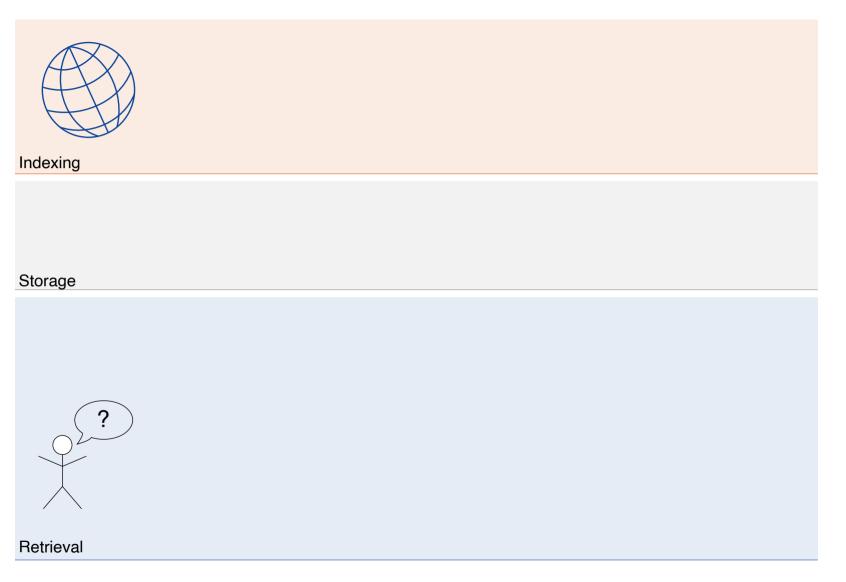
• M. Potthast, M. Hagen, B. Stein (2020). The dilemma of the direct answer.

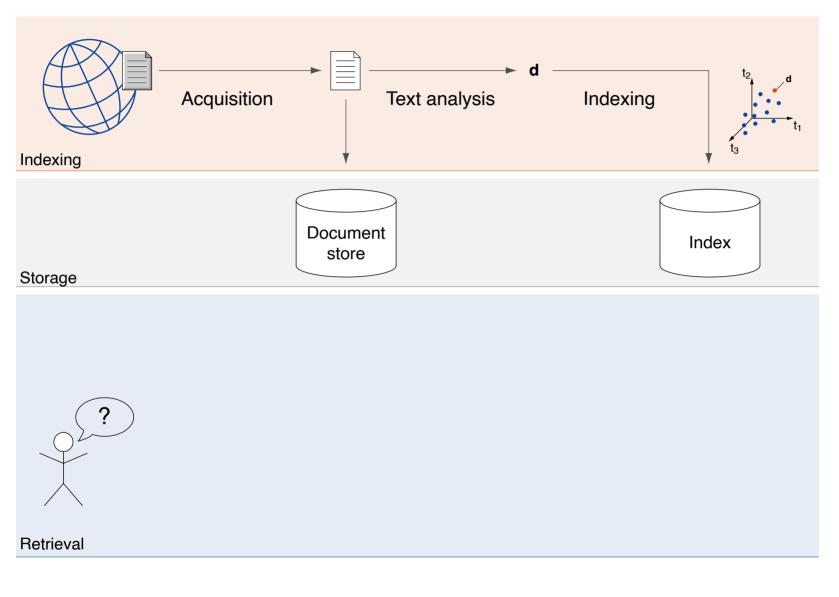


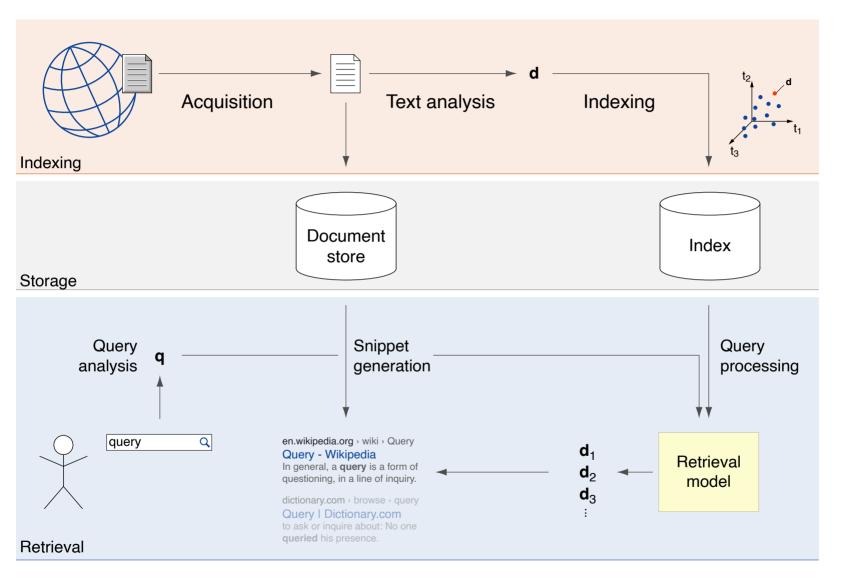
<sup>•</sup> M. Potthast, M. Hagen, B. Stein (2020). The dilemma of the direct answer.

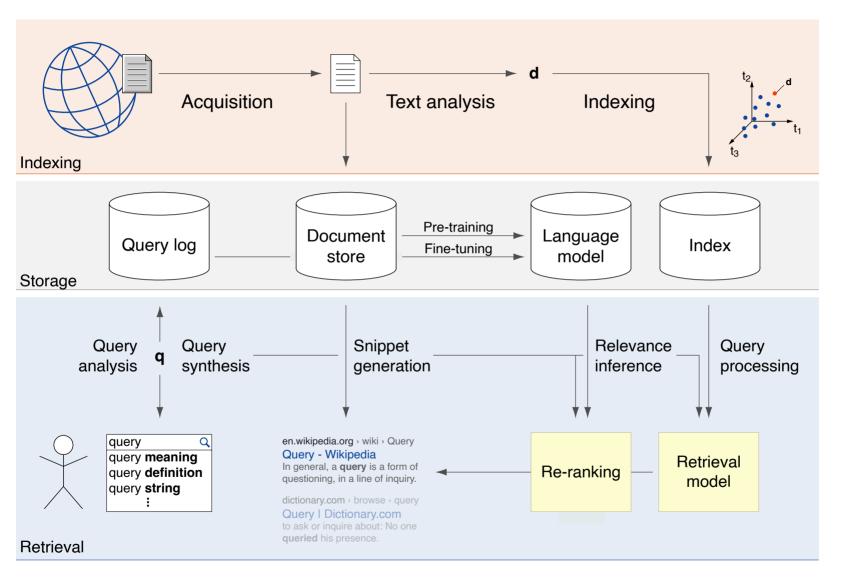


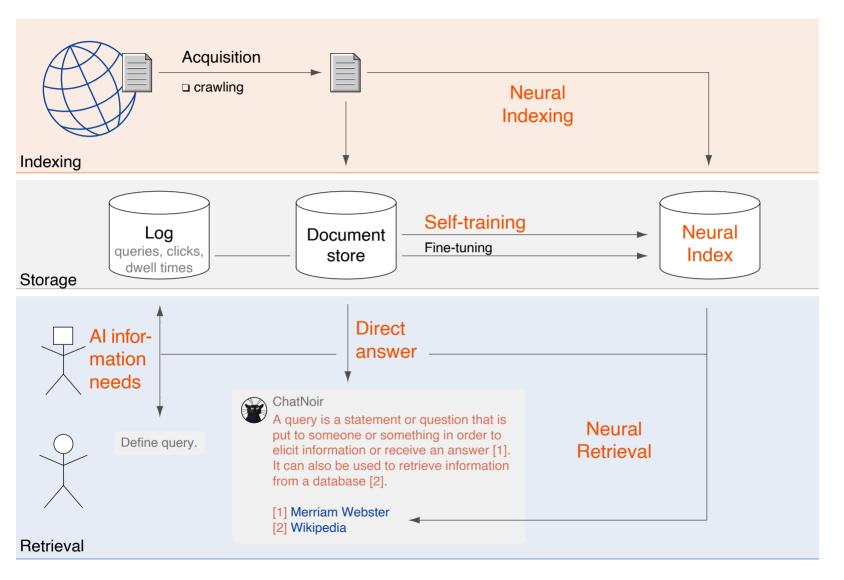
<sup>•</sup> M. Potthast, M. Hagen, B. Stein (2020). The dilemma of the direct answer.



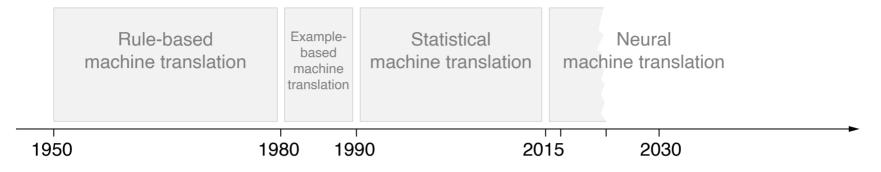


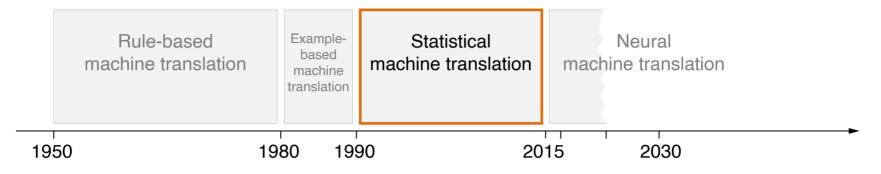






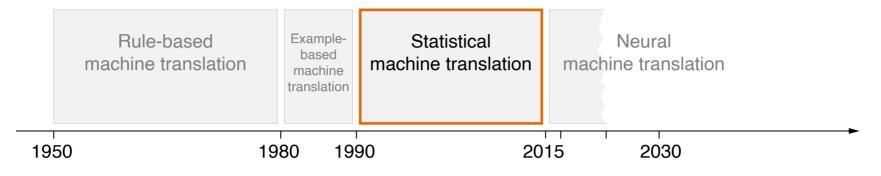






A statistical language model

is a probability distribution over all possible texts.

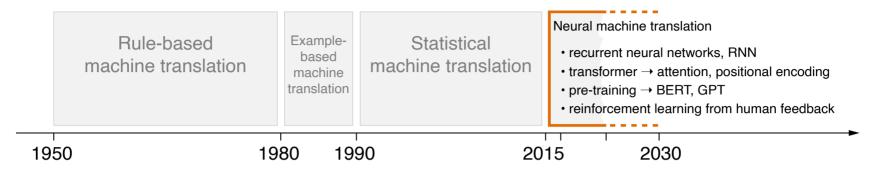


A statistical language model

is a probability distribution over all possible texts.

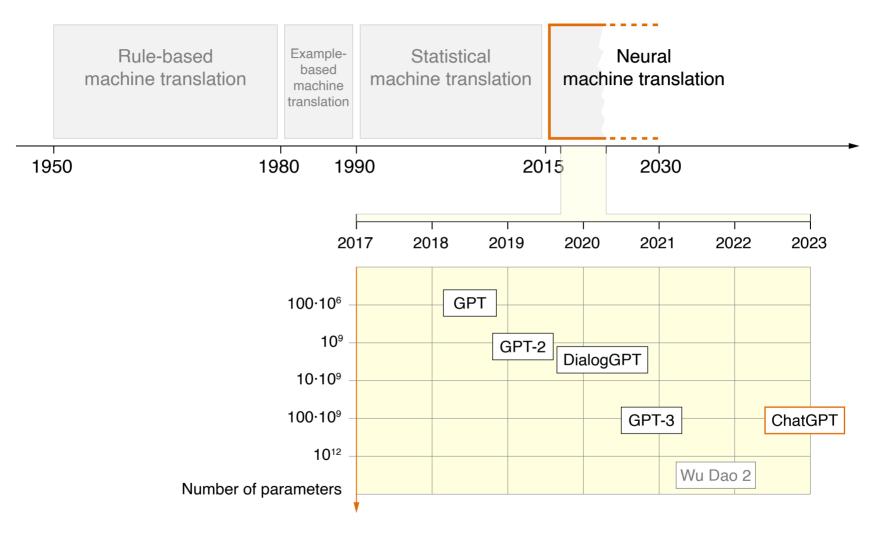
### Illustration:

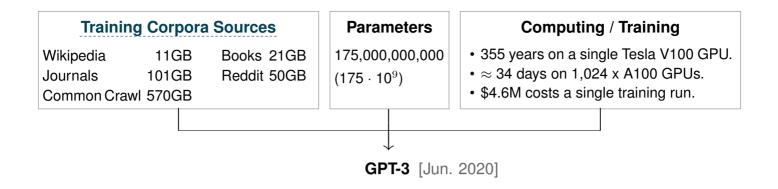
(1) i love my ?
N №
(2) see ... works. № №

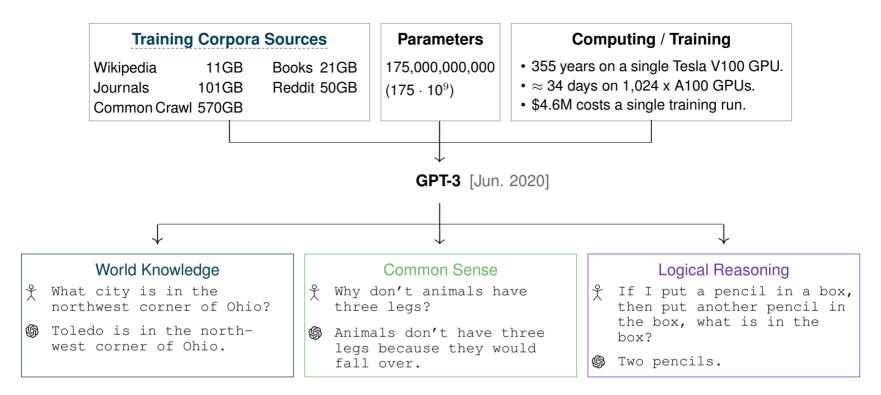


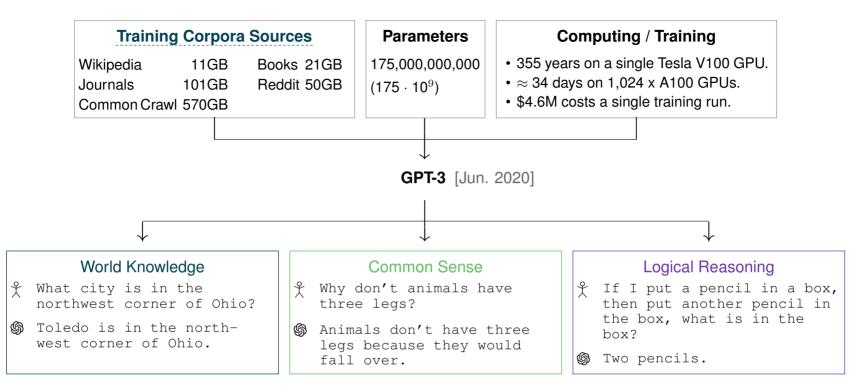
A neural language model

approximates a statistical language model.





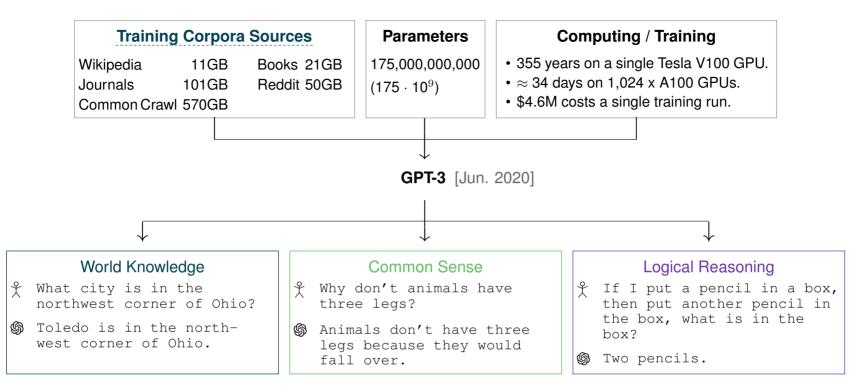




#### + Learn to follow instructions and to comply with answer policies.

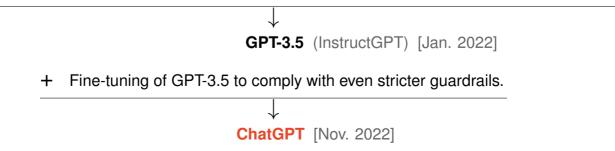
- (1) Fine-tuning of GPT-3 to follow instructions: 13,000 popular prompts with hand-written answers.
- (2) Training of a reward model: 33,000 prompts with 4-9 answers, ranked from best to worse.
- (3) Training of the fine-tuned GPT-3 model from Step (1) to follow the reward policy.

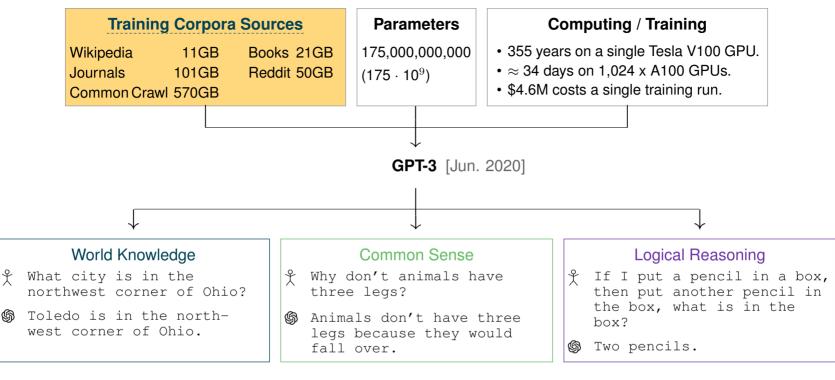




#### + Learn to follow instructions and to comply with answer policies.

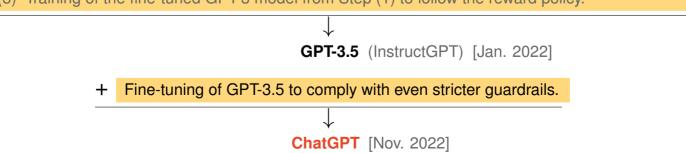
- (1) Fine-tuning of GPT-3 to follow instructions: 13,000 popular prompts with hand-written answers.
- (2) Training of a reward model: 33,000 prompts with 4-9 answers, ranked from best to worse.
- (3) Training of the fine-tuned GPT-3 model from Step (1) to follow the reward policy.





+ Learn to follow instructions and to comply with answer policies.

- (1) Fine-tuning of GPT-3 to follow instructions: 13,000 popular prompts with hand-written answers.
- (2) Training of a reward model: 33,000 prompts with 4-9 answers, ranked from best to worse.
- (3) Training of the fine-tuned GPT-3 model from Step (1) to follow the reward policy.



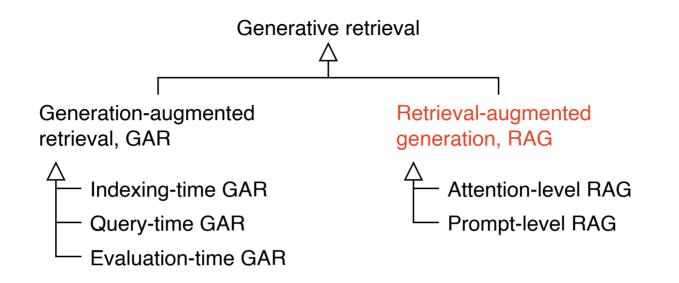


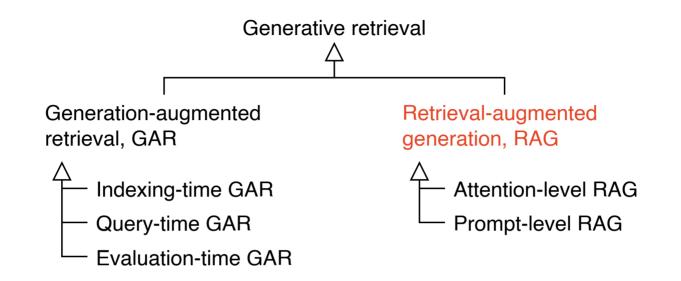
Query	Query
	Convenient, but uncertain veracity
	<ul> <li>Authoritative, but tedious to analyze</li> </ul>

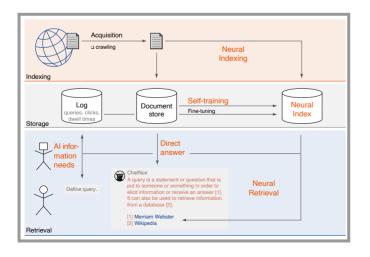
Query	Query
The dilemma of the direc	t answer: [Potthast et al., 2020]
A user's choice between o when using an informa	0
	<ul> <li>Convenient, but uncertain veracity</li> <li>Authoritative, but tedious to analyze</li> </ul>

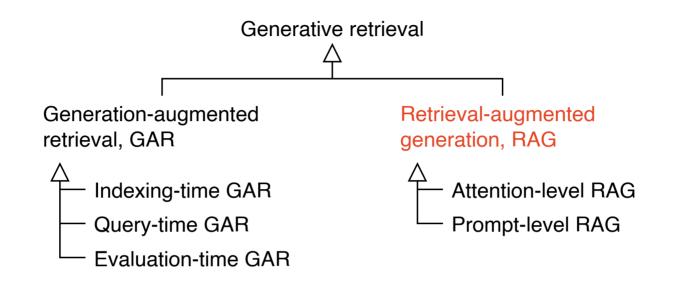
Query	Query
	Convenient, but uncertain veracity
	<ul> <li>Authoritative, but tedious to analyze</li> </ul>

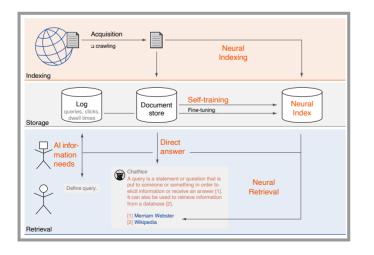
Query	Query
	[1]
	[4]
	[1] [2] [3] [4]











Attention-level RAG: [Lewis et al., 2020]

- Neural retrieval of document embeddings at query time
- Attention to retrieved document embeddings during text generation
- End-ot-end tuning of generator and retriever at training time

Prompt-level RAG combines existing systems:

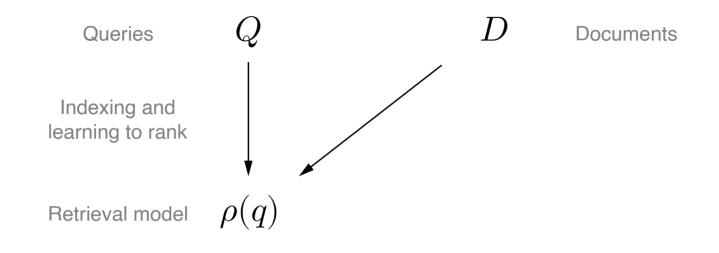
Queries

Q

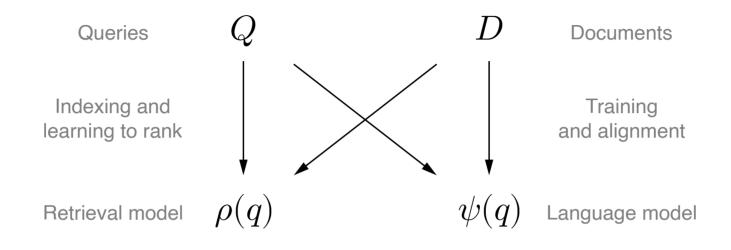
D

Documents

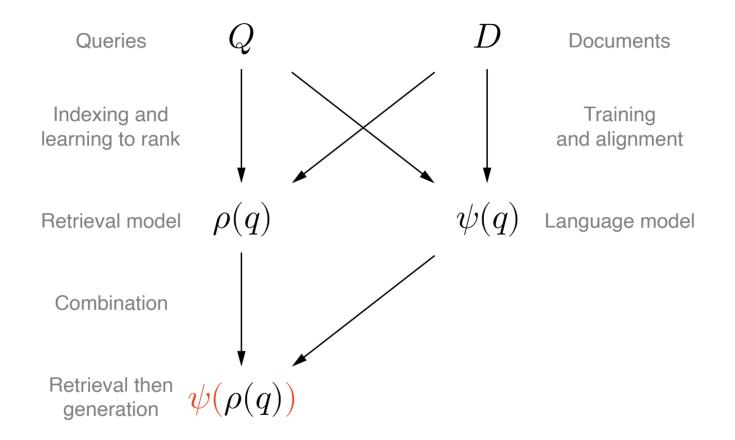
Prompt-level RAG combines existing systems:



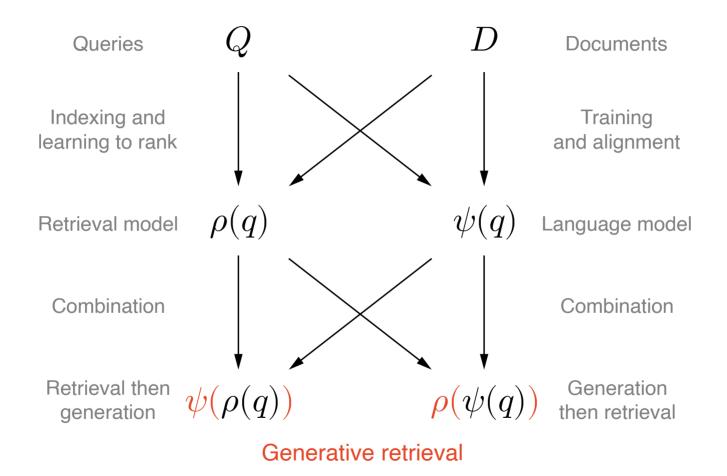
Prompt-level RAG combines existing systems:



Prompt-level RAG combines existing systems:

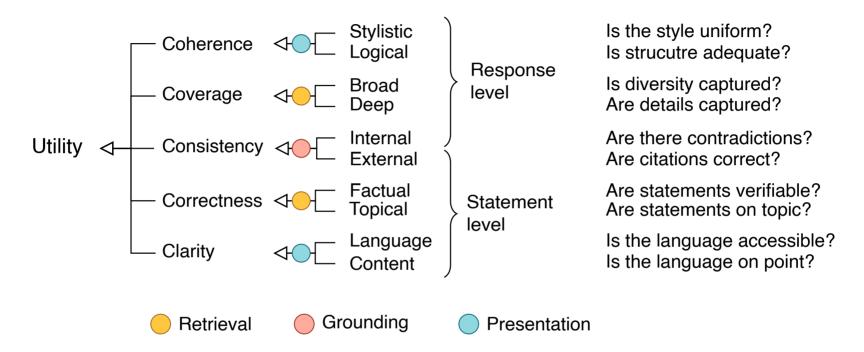


Prompt-level RAG combines existing systems:



39 🛆

#### What are quality criteria?



- □ A manual judgment of generated answers is necessary.
- □ Manual assessments may be streamlined using LLMs. [Faggioli et al., 2023]
- □ Judgments from past evaluations can be reused as points of comparison.
- □ For systems in use, A/B tests are a viable alternative.



# The Library of Babel

[Jorge Luis Borges, 1941]

# The Library of Babe

[Jorge Luis Borges, 1941]

Infinite library with all possible texts from all letter combinations

The people in it spend their lives searching for meaningful text fragments

## The Library of Babel

[Jorge Luis Borges, 1941]

Infinite library with all possible texts from all letter combinations

- The people in it spend their lives searching for meaningful text fragments
- □ When prompted, a language model "retrieves" a relevant text [Deckers et al., 2023]:

A language model is an infinite index

Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.



Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.



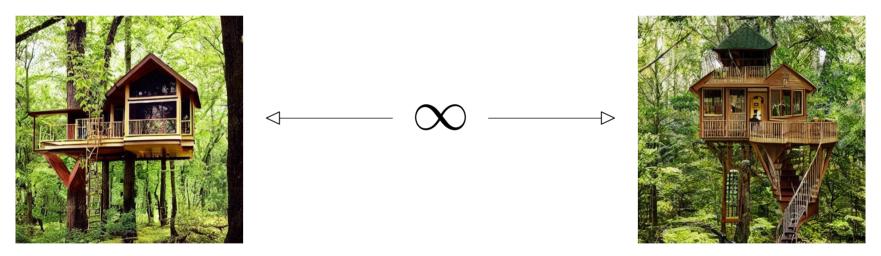
Query 2:



Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:



Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:

Big treehouse in rain forest with two floors, green roof, and spiral staircase.





 $\triangleleft 0$ 



Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:

Big treehouse in rain forest with two floors, green roof, and spiral staircase.





<0-





Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:







Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:





Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:

Big treehouse in rain forest with two floors, green roof, and spiral staircase.





< -0





Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:







Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:







Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:







Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:







Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:







Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:







Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:









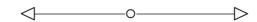
Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

#### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:







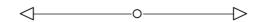
Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:







Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:









Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:

0-1>







Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:

-0-D







Query 1:

Golden treehouse in lush forest with big glass window and intricate woodwork.

### Query 2:





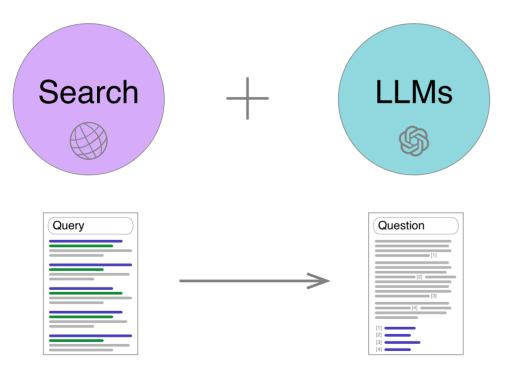


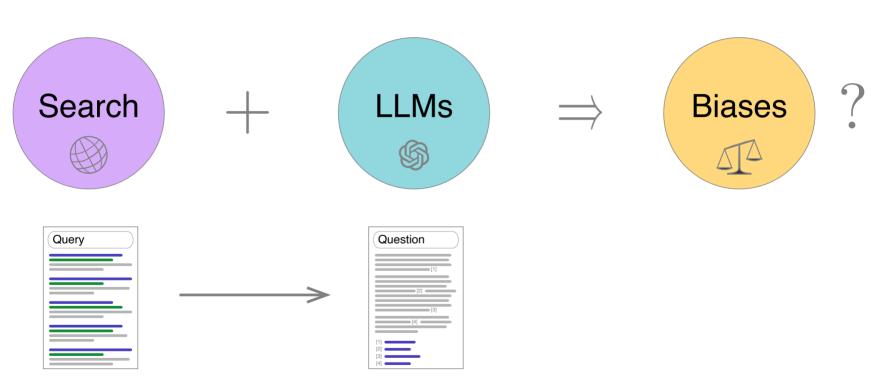




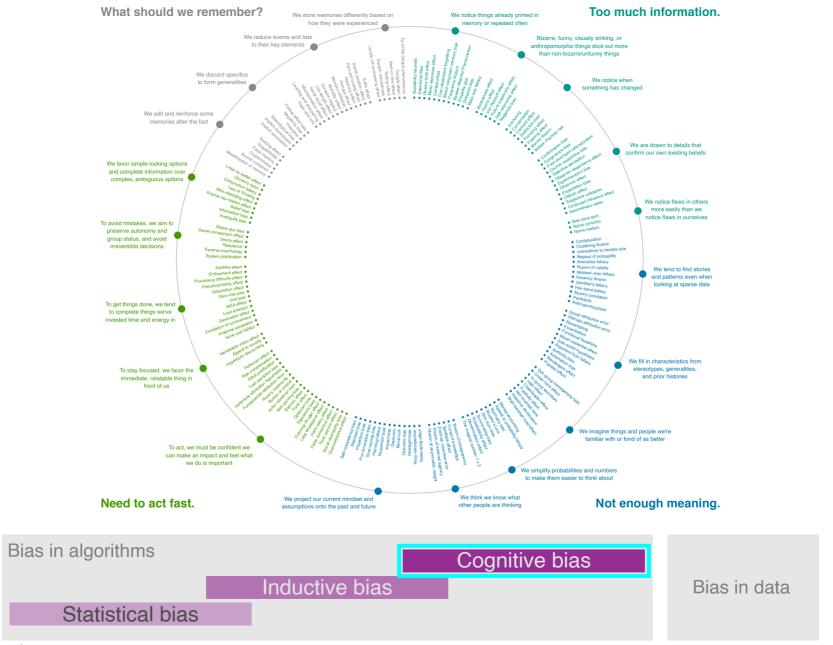
### **On Biases**

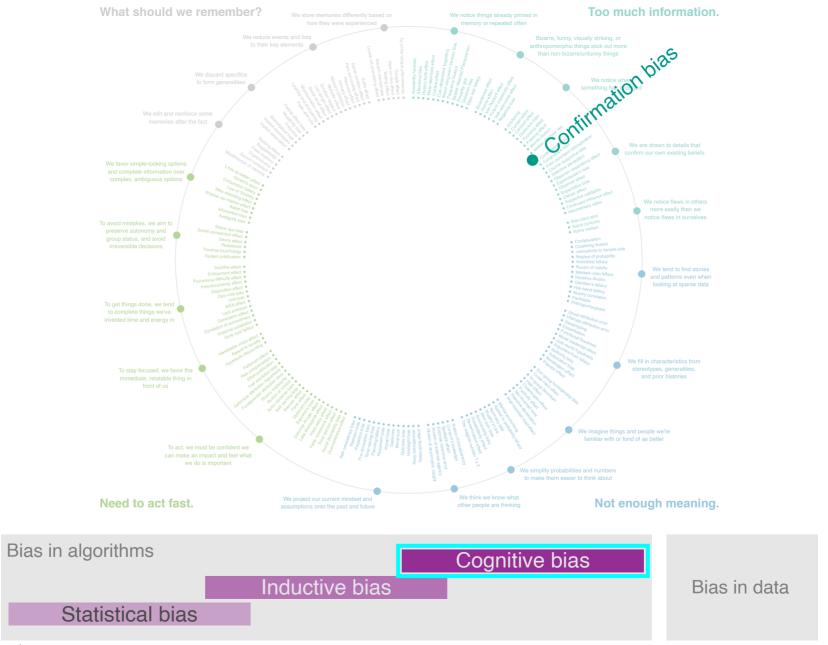


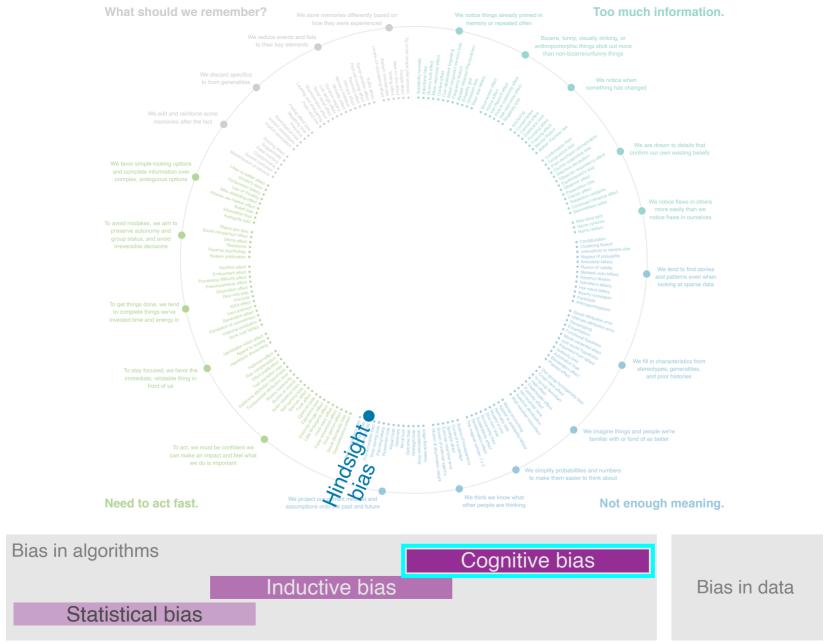


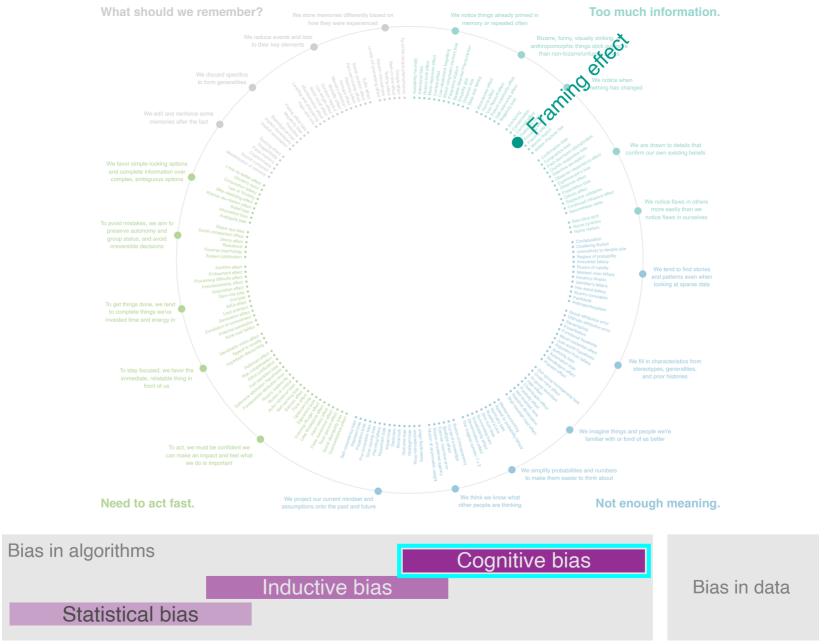


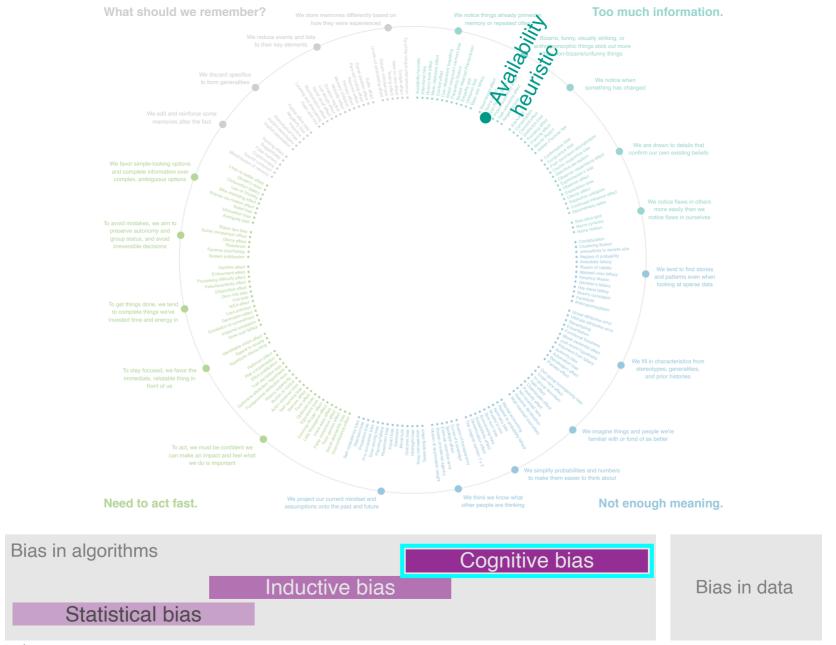


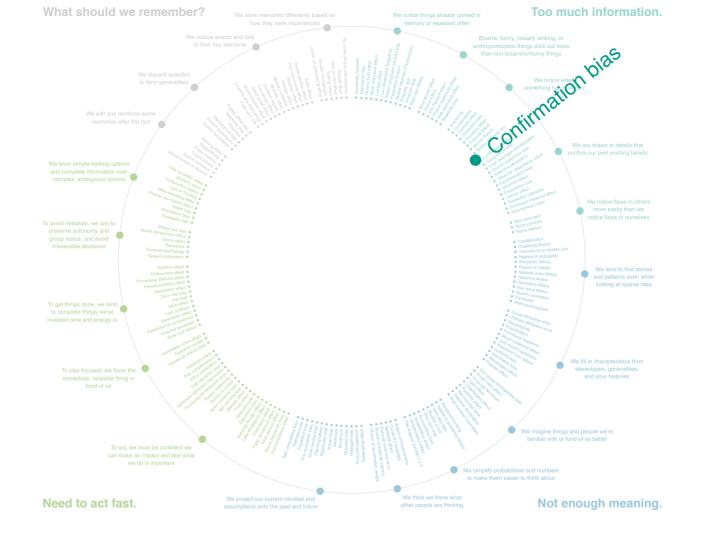












## Query: "Why is a high protein diet the best for losing weight quickly?"

#### **High Protein Diet Benefits**

November 19, 2023

#### ຊ Anonymous

Why is a high protein diet the best for losing weight quickly?

#### OhatGPT

A high protein diet is often considered effective for losing weight quickly for several reasons:

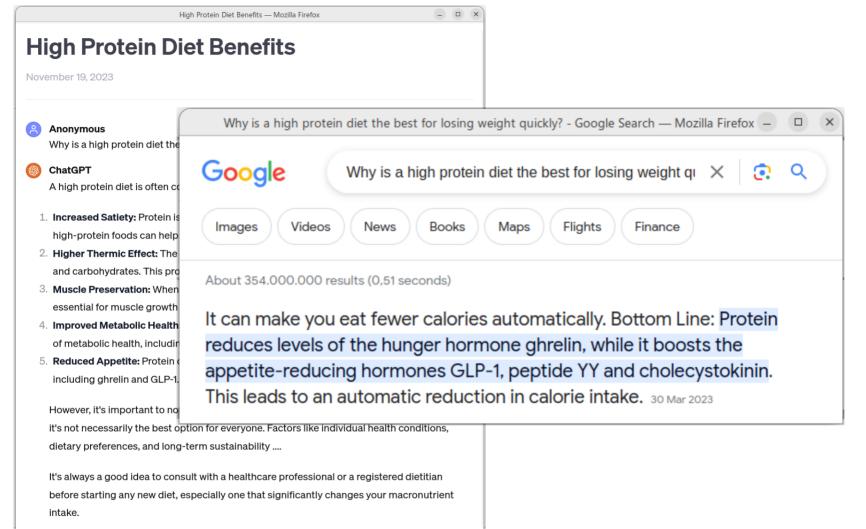
- 1. **Increased Satiety:** Protein is more satiating than carbohydrates or fats. This means that high-protein foods can help you feel full longer, reducing overall calorie intake.
- Higher Thermic Effect: The body uses more energy to metabolize protein compared to fats and carbohydrates. This process, known as the thermic effect ...
- Muscle Preservation: When losing weight, it's important to maintain muscle mass. Protein is
  essential for muscle growth and repair. A high protein intake can help ...
- Improved Metabolic Health: High-protein diets have been shown to improve several markers of metabolic health, including blood sugar levels, ...
- 5. Reduced Appetite: Protein can influence hormones that play a role in hunger and fullness, including ghrelin and GLP-1. By helping to balance these hormones, ...

However, it's important to note that while a high protein diet can be effective for weight loss, it's not necessarily the best option for everyone. Factors like individual health conditions, dietary preferences, and long-term sustainability ....

It's always a good idea to consult with a healthcare professional or a registered dietitian before starting any new diet, especially one that significantly changes your macronutrient intake.

Report content | Terms of use | Privacy policy

### Query: "Why is a high protein diet the best for losing weight quickly?"



Report content | Terms of use | Privacy policy

Query: "Why is a high protein diet the best for losing weight quickly?"

## Balance of Responsibilities in Information Retrieval





#### More power to the machine?

- □ effectively installed
- standardized guardrailing
- protection of vulnerable groups

**D** ...

#### Empower the user?

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

• • • • •













🚺 Netspeak	×	+												
	🕽 🔒 https://netsp	eak.org/#q=	see++works				1	33%		☆	G	⊻	lii\	•
	Notonoo	1												
	Netspea	K On	e word lea	ids to	another									
						Engl	lich	Ge	erma	n				
						Lig	1511							
	see works							i	X	Э				
	how to ? this			The	? finds or	ne word.								
	see works			The	finds n	nany wo	rds.							
	it's [ great we	-			[] compa									
	and knows #n				# finds si									
	{ more show r md ? g?p	ne }			<pre>{ } check space is i</pre>									
	see how it work	(5		The	Space is i		50,00	0	20	0/0				
	see if it works						00,00		14					
	see works						57,00		7.5					
	see how this w	orke					55,00		7.3					
	see what works						51,00		6.7					
	see the works	,							6.7					
	see if that work	(C					51,00		3.7					
	see your good						28,00		3.7					
	see your good						28,00	_	3.3					
	see how techno						25,00							
			(5				23,00		3.0					
	see if this work	-					17,00		2.3					
	see more works						17,00		2.2					
	see if it really v	vorks					15,00		2.1					
	see his works						12,00		1.7					
	see how well it						11,00	0	1.5	0/-				

Image: Section 1         Image: Section 1       Image: Secti	peak × +		
EnglishGermani love my ? i × Ohow to ? thisThe ? finds one word.see worksThe finds many words.it's [ great well ]The [ ] compare options.and knows #muchThe # finds similar words.{ more show me }The { } check the order.md ? g?pThe space is important.i love my job72,00010%i love my gamily41,0005.9%i love my mew34,0004.9%i love my friends33,0004.7%i love my pet27,0003.8%i love my dog26,0003.7%i love my life24,0003.4%i love my baby24,0003.4%i love my soldier22,0003.1%i love my cat21,0002.9%i love my computer18,0002.6%	🛛 🚺 🔒 https://netspeak.org/#q=i+lo	ve+my+? 133% ···· ☆ C	<u>↓</u>  II/
EnglishGermani love my ? i × Ohow to ? thisThe ? finds one word.see worksThe finds many words.it's [ great well ]The [ ] compare options.and knows #muchThe # finds similar words.{ more show me }The { } check the order.md ? g?pThe space is important.i love my job72,00010%i love my gamily41,0005.9%i love my mew34,0004.9%i love my friends33,0004.7%i love my pet27,0003.8%i love my dog26,0003.7%i love my life24,0003.4%i love my baby24,0003.4%i love my soldier22,0003.1%i love my cat21,0002.9%i love my computer18,0002.6%			
i love my ?i × 9how to ? thisThe ? finds one word.see worksThe finds many words.it's [ great well ]The [] compare options.and knows #muchThe # finds similar words.{ more show me }The { } check the order.md ? g?pThe space is important.i love my job72,000i love my country44,0006.2%i love my family41,000i love my wife38,000i love my wife33,000i love my new34,000i love my pet27,000i love my dog26,000i love my life24,000i love my soldier22,000i love my soldier22,000i love my cat21,000i love my cat21,000i love my computer18,000	Netspeak One w	ord leads to another.	
i love my ?i × 9how to ? thisThe ? finds one word.see worksThe finds many words.it's [ great well ]The [] compare options.and knows #muchThe # finds similar words.{ more show me }The { } check the order.md ? g?pThe space is important.i love my job72,000i love my country44,0006.2%i love my family41,000i love my wife38,000i love my wife33,000i love my new34,000i love my pet27,000i love my dog26,000i love my life24,000i love my soldier22,000i love my soldier22,000i love my cat21,000i love my cat21,000i love my computer18,000			
i love my ?i × 9how to ? thisThe ? finds one word.see worksThe finds many words.it's [ great well ]The [] compare options.and knows #muchThe # finds similar words.{ more show me }The { } check the order.md ? g?pThe space is important.i love my job72,000i love my country44,0006.2%i love my family41,000i love my wife38,000i love my wife33,000i love my new34,000i love my pet27,000i love my dog26,000i love my life24,000i love my soldier22,000i love my soldier22,000i love my cat21,000i love my cat21,000i love my computer18,000			
how to ? thisThe ? finds one word. see workssee worksThe finds many words. it's [ great well ]it's [ great well ]The [ ] compare options. and knows #muchand knows #muchThe # finds similar words. { more show me } md ? g?pi love my job72,000i love my job72,000i love my family41,000i love my family41,000i love my family38,000i love my mew34,000i love my friends33,000i love my pet27,000i love my dog26,000i love my life24,000i love my busband26,000i love my soldier22,000i love my cat21,000i love my cat21,000i love my cat22,000i love my soldier22,000i love my computer18,000i love my computer26,000		English German	
how to ? thisThe ? finds one word. see workssee worksThe finds many words. it's [ great well ]it's [ great well ]The [ ] compare options. and knows #muchand knows #muchThe # finds similar words. { more show me } md ? g?pi love my job72,000i love my job72,000i love my family41,000i love my family41,000i love my family38,000i love my mew34,000i love my friends33,000i love my pet27,000i love my dog26,000i love my life24,000i love my busband26,000i love my soldier22,000i love my cat21,000i love my cat21,000i love my cat22,000i love my soldier22,000i love my computer18,000i love my computer26,000			
how to ? thisThe ? finds one word. see workssee worksThe finds many words. it's [ great well ]it's [ great well ]The [ ] compare options. and knows #muchand knows #muchThe # finds similar words. { more show me } md ? g?pi love my job72,000i love my job72,000i love my family41,000i love my family41,000i love my family38,000i love my mew34,000i love my friends33,000i love my pet27,000i love my dog26,000i love my life24,000i love my busband26,000i love my soldier22,000i love my cat21,000i love my cat21,000i love my cat22,000i love my soldier22,000i love my computer18,000i love my computer26,000	i love my ?	i X 🤊	
see worksThe finds many words.it's [ great well ]The [ ] compare options.and knows #muchThe # finds similar words.{ more show me }The { } check the order.md ? g?pThe space is important.i love my country44,000i love my family41,000i love my wife38,000i love my new34,000i love my pet27,000i love my dog26,000i love my husband26,000i love my life24,000i love my soldier22,000i love my cat21,000i love my cat21,000i love my cat22,6%			
it's [ great well ]The [ ] compare options. and knows #much ( more show me } The # finds similar words. ( more show me } The { } check the order. md ? g?pi love my job72,00010%i love my job72,0006.2%i love my country44,0006.2%i love my family41,0005.9%i love my wife38,0005.4%i love my new34,0004.9%i love my friends33,0004.7%i love my pet27,0003.8%i love my dog26,0003.7%i love my life24,0003.4%i love my soldier22,0003.1%i love my cat21,0002.9%i love my computer18,0002.6%			
and knows #much { more show me } md ? g?pThe # finds similar words. The { } check the order. md ? g?pi love my job72,00010%i love my country44,0006.2%i love my country41,0005.9%i love my family41,0005.9%i love my mew34,0004.9%i love my new33,0004.7%i love my pet27,0003.8%i love my dog26,0003.7%i love my life24,0003.4%i love my soldier22,0003.1%i love my cat21,0002.9%i love my computer18,0002.6%			
md?g?p       The space is important.         i love my job       72,000       10%         i love my country       44,000       6.2%         i love my family       41,000       5.9%         i love my wife       38,000       5.4%         i love my new       34,000       4.9%         i love my friends       33,000       4.7%         i love my pet       27,000       3.8%         i love my dog       26,000       3.7%         i love my husband       26,000       3.7%         i love my life       24,000       3.4%         i love my soldier       22,000       3.1%         i love my soldier       22,000       3.1%         i love my cat       21,000       2.9%         i love my computer       18,000       2.6%			
i love my job       72,000       10%         i love my country       44,000       6.2%         i love my family       41,000       5.9%         i love my wife       38,000       5.4%         i love my new       34,000       4.9%         i love my friends       33,000       4.7%         i love my pet       27,000       3.8%         i love my dog       26,000       3.7%         i love my husband       26,000       3.7%         i love my life       24,000       3.4%         i love my soldier       22,000       3.1%         i love my cat       21,000       2.9%         i love my computer       18,000       2.6%	{ more show me }	The { } check the order.	
i love my country44,0006.2%i love my family41,0005.9%i love my wife38,0005.4%i love my new34,0004.9%i love my friends33,0004.7%i love my pet27,0003.8%i love my dog26,0003.7%i love my life24,0003.4%i love my soldier22,0003.1%i love my cat21,0002.9%i love my computer18,0002.6%	md ? g?p	The space is important.	
i love my family41,0005.9%i love my wife38,0005.4%i love my new34,0004.9%i love my friends33,0004.7%i love my pet27,0003.8%i love my dog26,0003.7%i love my husband26,0003.7%i love my life24,0003.4%i love my soldier22,0003.1%i love my cat21,0002.9%i love my computer18,0002.6%	i love my <mark>job</mark>	72,000 10%	
i love my wife38,0005.4%i love my new34,0004.9%i love my friends33,0004.7%i love my pet27,0003.8%i love my dog26,0003.7%i love my husband26,0003.7%i love my life24,0003.4%i love my soldier22,0003.1%i love my cat21,0002.9%i love my computer18,0002.6%	i love my <mark>country</mark>	44,000 6.2%	
i love my new34,0004.9%i love my friends33,0004.7%i love my pet27,0003.8%i love my dog26,0003.7%i love my husband26,0003.7%i love my life24,0003.4%i love my baby24,0003.4%i love my soldier22,0003.1%i love my cat21,0002.9%i love my computer18,0002.6%	i love my <mark>family</mark>	41,000 5.9%	
i love my friends33,0004.7%i love my pet27,0003.8%i love my dog26,0003.7%i love my husband26,0003.7%i love my life24,0003.4%i love my baby24,0003.4%i love my soldier22,0003.1%i love my cat21,0002.9%i love my computer18,0002.6%	i love my wife	38,000 5.4%	
i love my pet27,0003.8%i love my dog26,0003.7%i love my husband26,0003.7%i love my life24,0003.4%i love my baby24,0003.4%i love my soldier22,0003.1%i love my cat21,0002.9%i love my computer18,0002.6%	i love my new	34,000 4.9%	
i love my dog26,0003.7%i love my husband26,0003.7%i love my life24,0003.4%i love my baby24,0003.4%i love my soldier22,0003.1%i love my cat21,0002.9%i love my computer18,0002.6%	i love my friends	33,000 4.7%	
i love my dog26,0003.7%i love my husband26,0003.7%i love my life24,0003.4%i love my baby24,0003.4%i love my soldier22,0003.1%i love my cat21,0002.9%i love my computer18,0002.6%	i love my <mark>pet</mark>	27,000 3.8%	
i love my husband26,0003.7%i love my life24,0003.4%i love my baby24,0003.4%i love my soldier22,0003.1%i love my cat21,0002.9%i love my computer18,0002.6%	i love my <mark>dog</mark>	26,000 3.7%	
i love my life24,0003.4%i love my baby24,0003.4%i love my soldier22,0003.1%i love my cat21,0002.9%i love my computer18,0002.6%			
i love my baby24,0003.4%i love my soldier22,0003.1%i love my cat21,0002.9%i love my computer18,0002.6%			
i love my soldier       22,000       3.1%         i love my cat       21,000       2.9%         i love my computer       18,000       2.6%	i love my baby		
i love my cat       21,000       2.9%         i love my computer       18,000       2.6%			
i love my computer 18,000 2.6%			
i love my work 16,000 2.4%			

## 2022 WHAT'S IN MY AI? - ALT VIEW



Google Patents.         0.48%           The New York Times.         0.06%           Los Angeles Times.         0.06%           The Guardian.         0.06%           Public Library of Science.         0.06%           Forbes.         0.05%           Huffington Post.         0.05%           Patents.com.         0.05%           Scribd.         0.044	
Other	

Google	3.4%
Archive	1.3%
Blogspot	1.0%
GitHub	0.9%
The New York Times	0.7%
Wordpress	0.7%
Washington Post	0.7%
Wikia	0.7%
BBC	0.7%
Other	89.9%

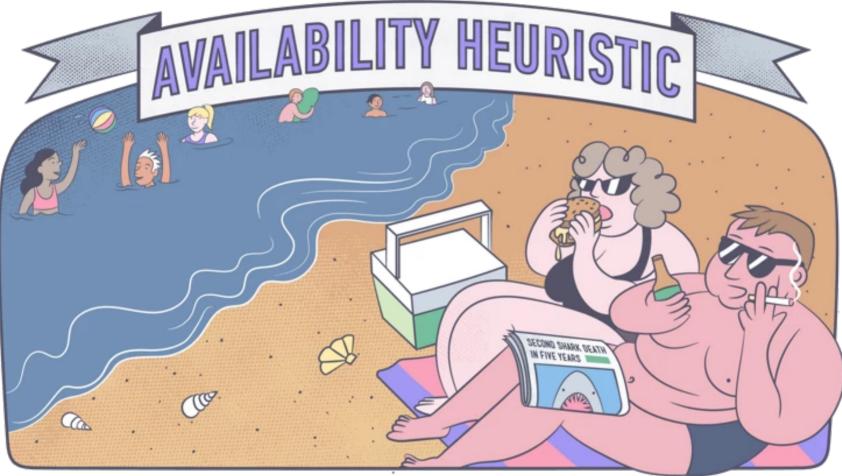
Reddit links

Common Crawl

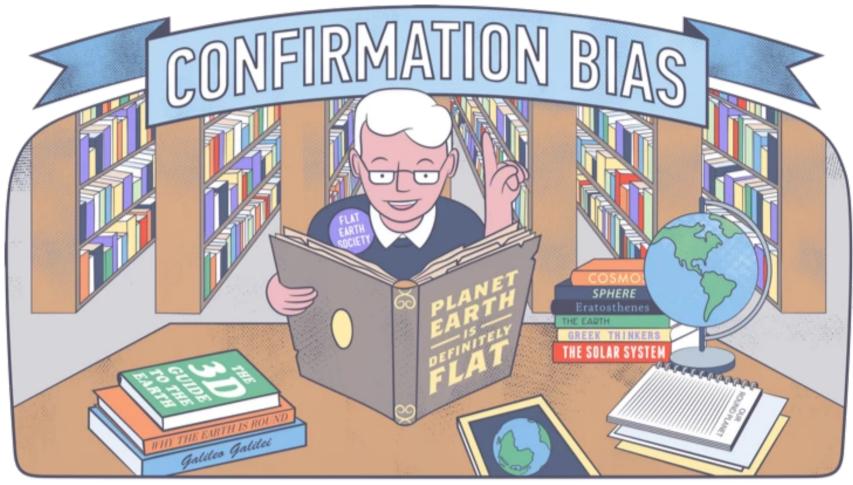
English Wikipedia

Romance	26.1%
Fantasy	13.6%
Science Fiction	7.5%
New Adult	6.9%
Young Adult	6.8%
Thriller	5.9%
Mystery	5.6%
Vampires	5.4%
Horror	4.1%
Other	18.0%
BookCorpus (GPT-1 on)	(v)

Schlief LifeArchitect.ai/whats-in-my-ai

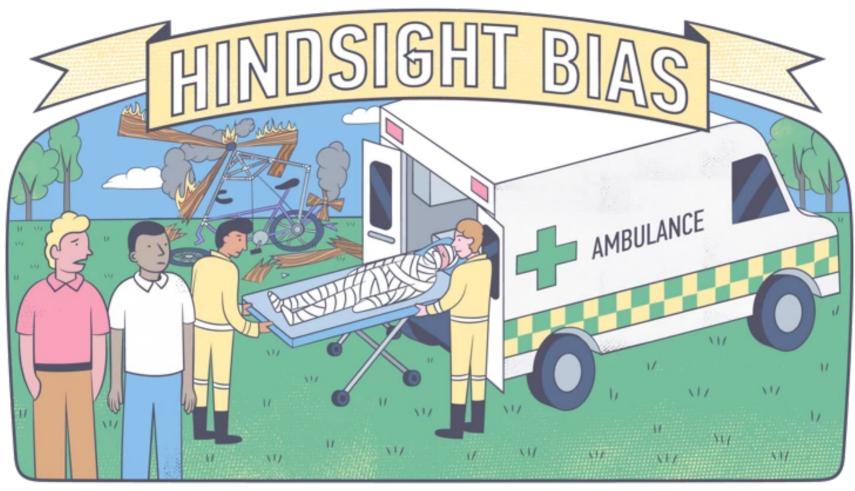


"THEY MUST HAVE A DEATH WISH TO SWIM IN THAT WATER."

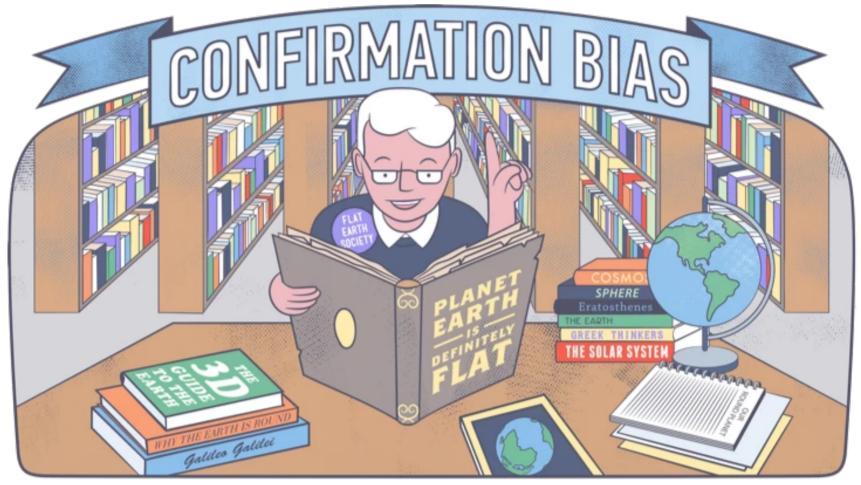


"AHA! I KNEW IT!"





"ALTHOUGH WE GAVE HIM ALL OF THAT MONEY AND SUPPORT, I ALWAYS HAD MY DOUBTS THAT JIM (OULD BUILD HIS OWN HELI(OPTER."



"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]

## 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]

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.
- G. Gigerenzer, P. Todd, ABC Research Group (2000). Simple heuristics that make us smart.
- 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]

### 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.
- G. Gigerenzer, P. Todd, ABC Research Group (2000). Simple heuristics that make us smart.
- 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]

## 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.
- G. Gigerenzer, P. Todd, ABC Research Group (2000). Simple heuristics that make us smart.
- 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

- $\rightsquigarrow$  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

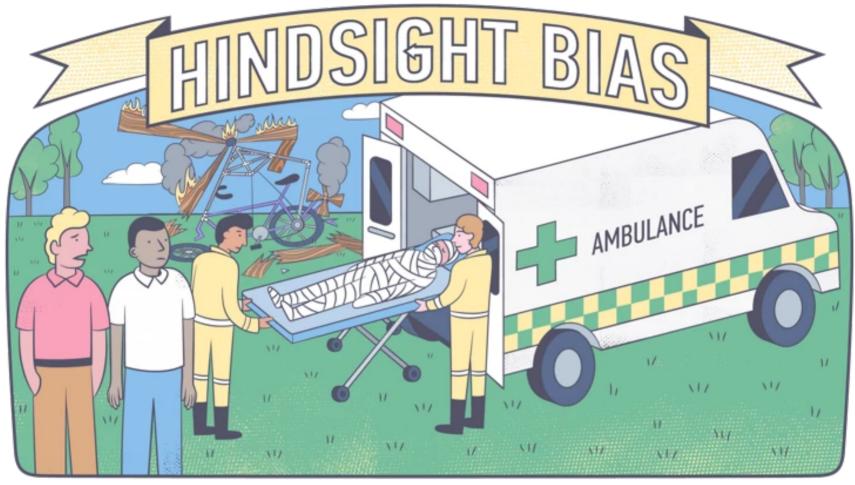
#### Heuristic:

• Various authors use the term "cognitive bias" for a heuristic that is applied by humans to judge.

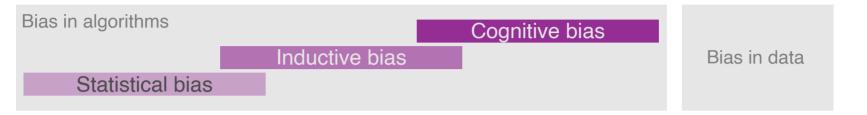
#### A procedure, algorithm, calculus, which is not complete or not sound.

#### Systematic error, Bias:

The incurred consequences for not being complete or sound.



"ALTHOUGH WE GAVE HIM ALL OF THAT MONEY AND SUPPORT, I ALWAYS HAD MY DOUBTS THAT JIM (OULD BUILD HIS OWN HELI(OPTER."



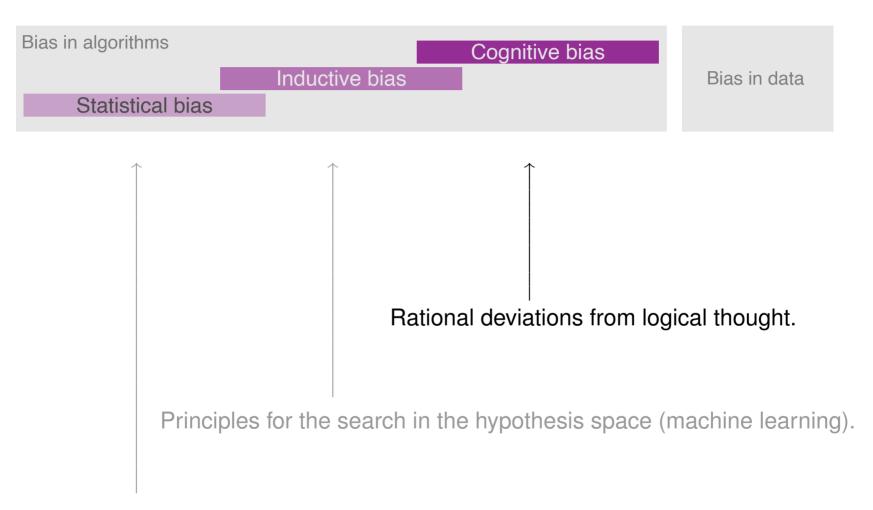


Deviation of a random variable / statistic from its true value.



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

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



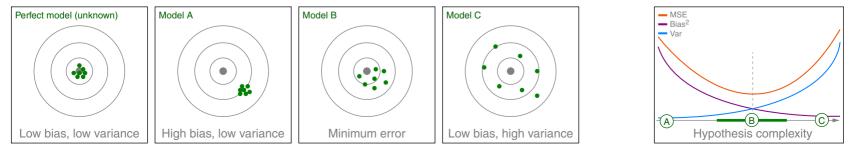
Deviation of a random variable / statistic from its true value.

## Meanings of Bias Statistical View



Trade unbiasedness for error reduction when learning from samples.

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



© https://www.towergateinsurance.co.uk/liability-insurance/hindsight-biases (2016)

## Meanings of Bias Statistical View



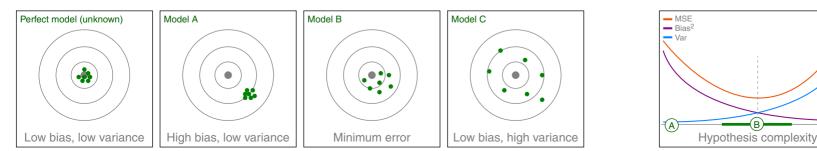
Trade unbiasedness for error reduction when learning from samples.

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

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.



© https://www.towergateinsurance.co.uk/liability-insurance/hindsight-biases (2016)

(C)->

## Meanings of Bias Machine Learning View



Set of assumptions used to perform induction (= predict outputs for unseen inputs).

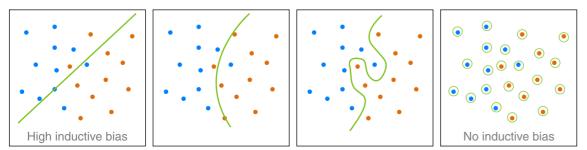
E.g., preference rules for hypotheses spaces, model parameters, data exploitation.

## Meanings of Bias Machine Learning View



Set of assumptions used to perform induction (= predict outputs for unseen inputs).

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



"Learning without bias is futile."

- T. Mitchell (1980)
- C. Schaffer (1997)
- W. Dembski et al. (2009)
- G. Montañet et al. (2019)

© https://www.towergateinsurance.co.uk/liability-insurance/hindsight-biases (2016)

## Meanings of Bias Machine Learning View

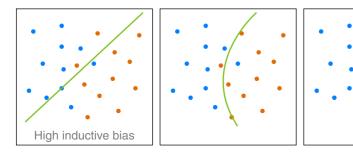


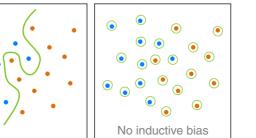
Set of assumptions used to perform induction (= predict outputs for unseen inputs).

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)





"Learning without bias is futile."

- T. Mitchell (1980)
- C. Schaffer (1997)
- W. Dembski et al. (2009)
- G. Montañet et al. (2019)

© https://www.towergateinsurance.co.uk/liability-insurance/hindsight-biases (2016)

## Meanings of Bias Behavioral Economics View



Systematic patterns of deviation from norm and/or rationality in judgment. Mental shortcuts (heuristics) that the brain uses to produce decisions or judgments.

## Meanings of Bias Behavioral Economics View



Systematic patterns of deviation from norm and/or rationality in judgment. Mental shortcuts (heuristics) that the brain uses to produce decisions or judgments.

#### 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?

## Meanings of Bias Behavioral Economics View



Systematic patterns of deviation from norm and/or rationality in judgment. Mental shortcuts (heuristics) that the brain uses to produce decisions or judgments.

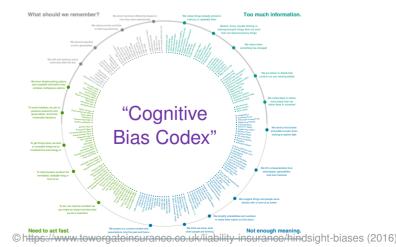
#### A classification scheme oriented at the addressed problems [B. Benson, 2016-2022] :

Problem 1: Too much information.

Problem 2: Not enough meaning.

Problem 3: Need to act fast.

Problem 4: What should we remember?



### Meanings of Bias Connections between the Meanings of Bias (a)



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

- Introducing statistical bias may be explained in terms of inductive bias.
   1
- Operationalization of inductive bias may entail statistical bias.
- □ Keyword: *regularization*

## Meanings of Bias Connections between the Meanings of Bias (a)



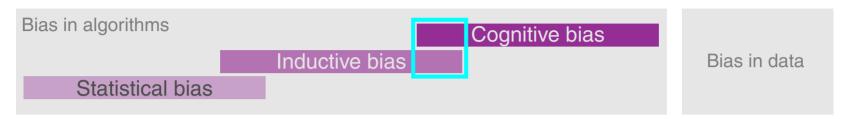
(a) Inductive and statistical bias can entail each other.

- Introducing statistical bias may be explained in terms of inductive bias.
   1
- Operationalization of inductive bias may entail statistical bias.
- □ Keyword: *regularization*

Example: LASSO (least absolute shrinkage and selection operator)

- Inductive bias: minimize feature number
- $\uparrow$
- Statistical bias: constrain absolute value of model parameters

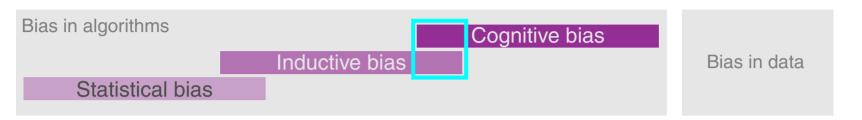
### Meanings of Bias Connections between the Meanings of Bias (b)



(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)



(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

#### Example: CART (classification and regression tree)

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

Connections between the Meanings of Bias



Connections between the Meanings of Bias



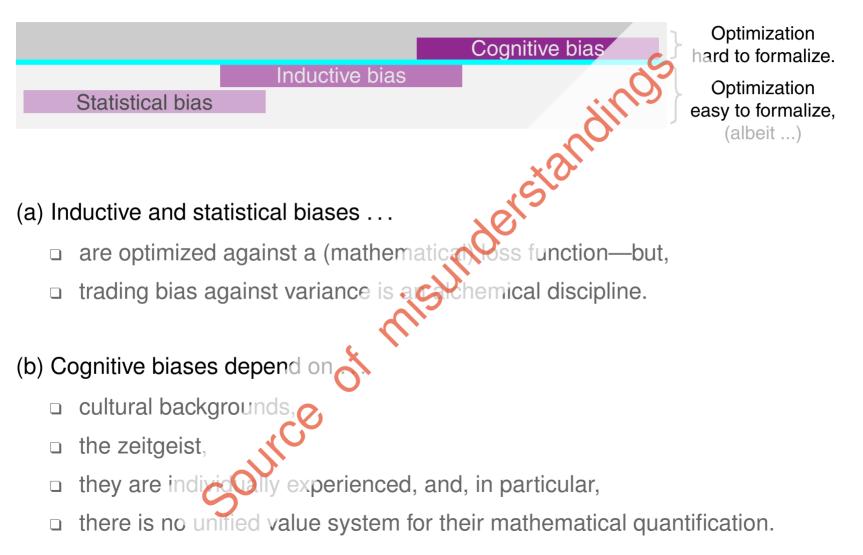
(a) Inductive and statistical biases ...

- □ 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.

Connections between the Meanings of Bias



### Meanings of Bias Connections to Information Retrieval

