

Causal Federated Learning For Neuroimaging

Alvaro Vargas Guerrero



ARTIFICIAL
INTELLIGENCE
RESEARCH GROUP



Roadmap

- ▶ Current State of Modern AI
- ▶ Why AI lags behind in the medical sector
- ▶ Federated Learning: A New-Age Approach to Privacy
- ▶ Open Challenges of Federated Learning
- ▶ The Achilles heel of Machine Learning
- ▶ Introducing Causality
- ▶ Open Challenges of Causality
- ▶ The Intersection of Federated Learning & Causality

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Current State of Modern AI (for us)



perplexity



Gemini

Large Language Models

Current State of Modern AI (for us)



perplexity



Gemini

Large Language Models

DON'T DO THIS!

Ready when you are.

+ Generate me a master thesis on Reinforcement Learning, make no mistakes



DON'T DO THIS!



Reddit · r/selfimprovement

40+ comments · 7 months ago

Anyone else use ChatGPT like a psychologist?

Chatgpt is like a mirror rather than an actual therapist. Most of the time it tells you what you WANT to hear rather than what you NEED to hear ...

40 answers · Top answer: I honestly wouldn't use chat gpt as a therapist for very many reasons. First ...



Reddit · r/adhdwomen

280+ comments · 1 year ago

So has anyone else started using ChatGPT as their ...

I am still in actual therapy and have a human psychologist. ChatGPT is good for when you're panicking and need an immediate answer to something ... [Read more](#)



Reddit · r/changemyview

90+ comments · 7 months ago

Using ChatGPT as a friend/therapist is incredibly dangerous

Using ChatGPT for therapy can help people with no other support system and in my opinion that is a very dangerous route to go down. [Read more](#)



Reddit · r/Healthygamergg

100+ comments · 1 year ago

Unpopular Opinion: ChatGPT is a good "therapist"

ChatGPT helps me organize my thoughts, take different perspectives on ideas and is even able to role play interpersonal conflicts with you.



Reddit · r/Slovakia

70+ comments · 9 months ago

Using the chat gpt as a psychologist/therapist : r/Slovakia

I think that constantly chatting with gpt who agrees with your opinions and attitudes can be quite dangerous. There's no counterpoint, challenge ... [Read more](#)

Current State of Modern AI (for us)



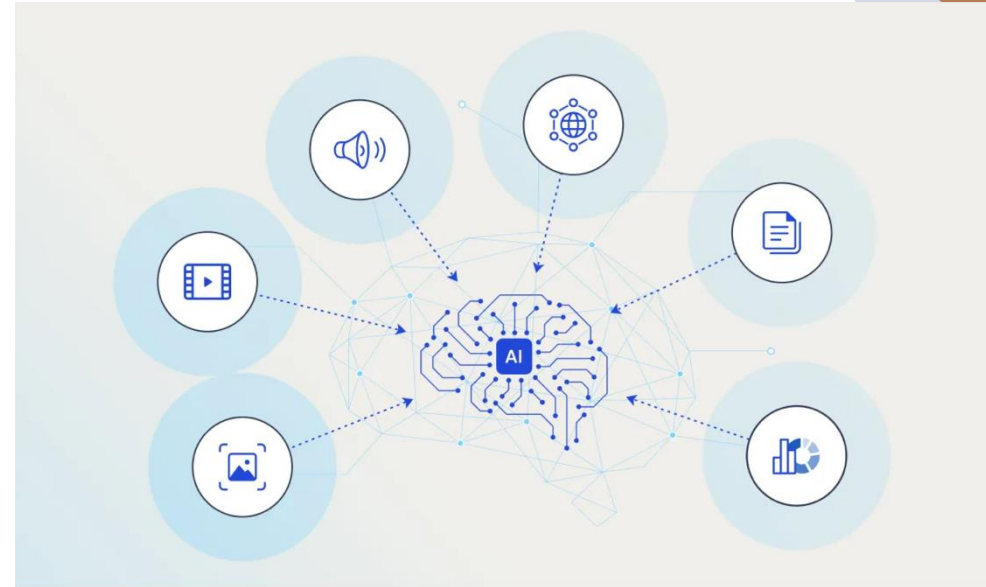
perplexity



Gemini



Multimodal AI



Current State of Modern AI (for us)



Image Generation



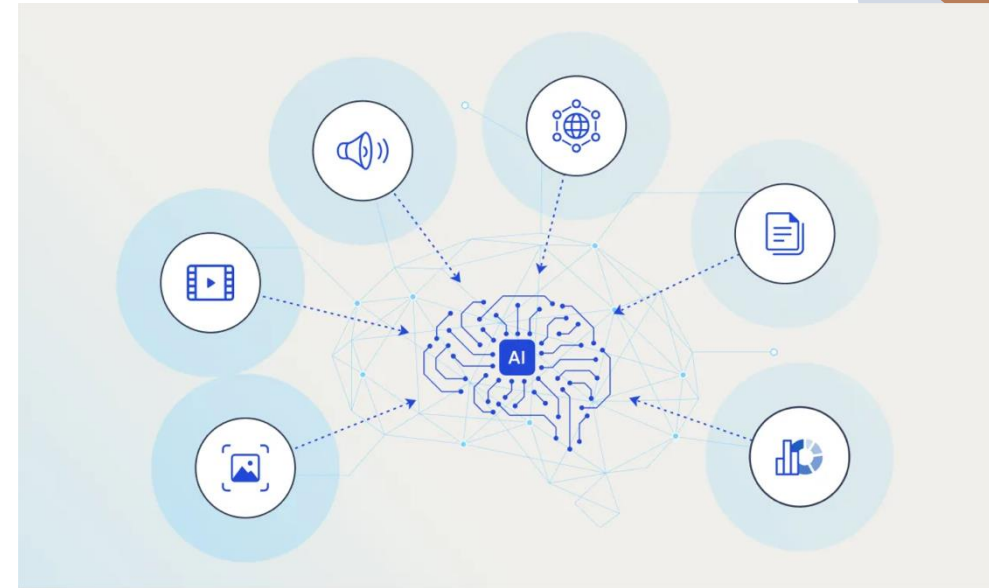
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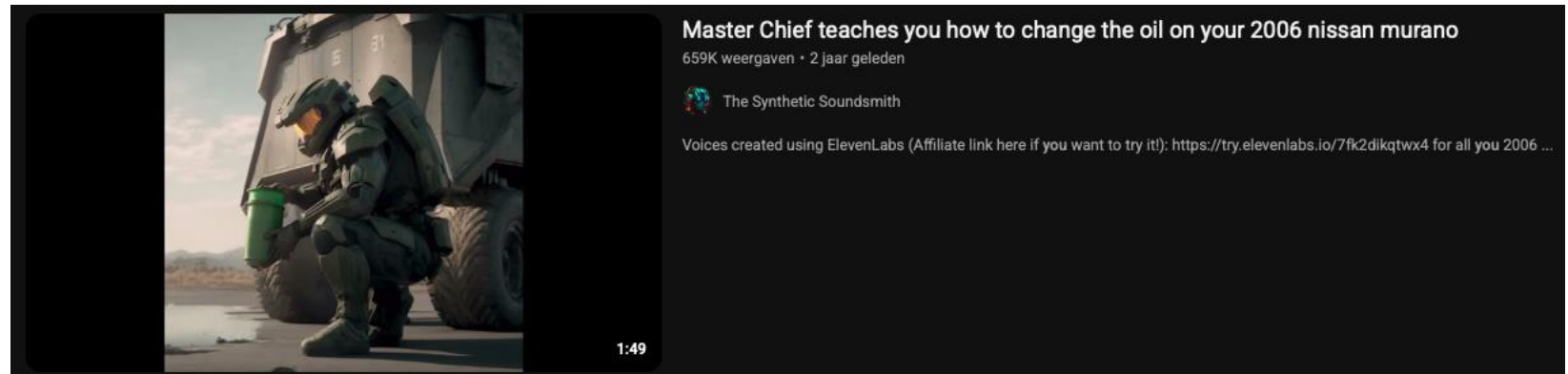
Gemini



Multimodal AI



Audio Generation



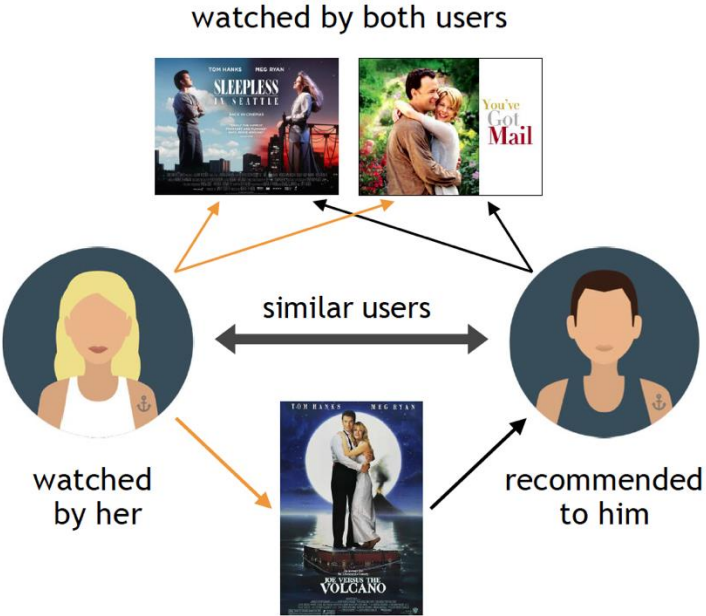
Current State of Modern AI (for us)

Video Generation

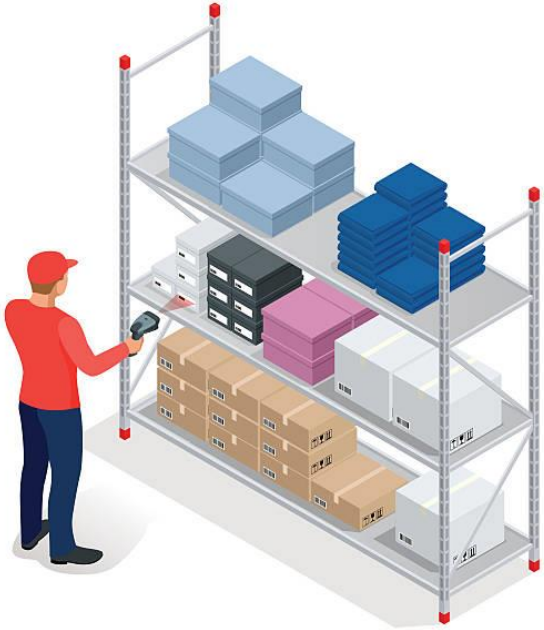


Current State of Modern AI (for the industry)

Collaborative Filtering



Recommendation Systems



Predictive Analysis & Forecasting



Route Optimization

Current State of Modern AI (in healthcare)

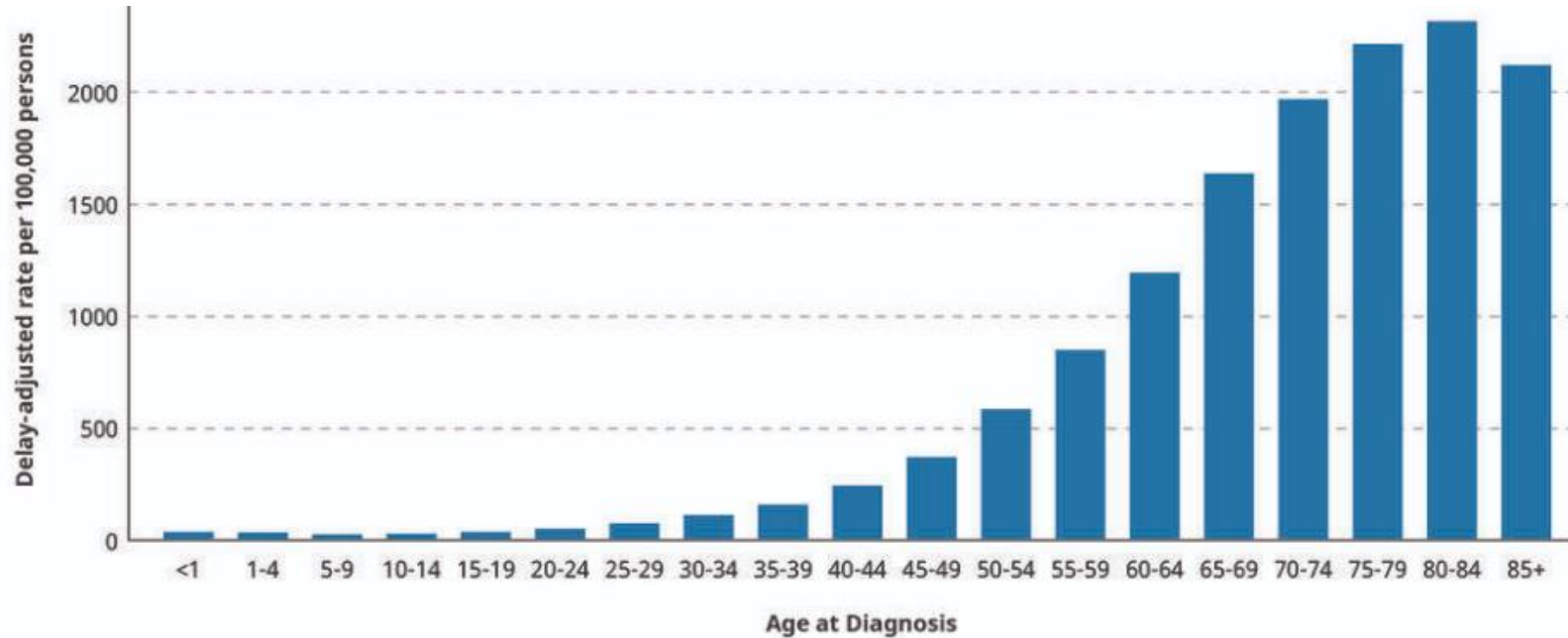


Mostly Theoretical

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Why AI lags behind in the medical sector



Incidence rates by age at diagnosis, all cancer types. Source: SEER 21 2013–2017, all races, both sexes.
Credit: National Cancer Institute

Data Imbalance (non-IID condition)

Why AI lags behind in the medical sector

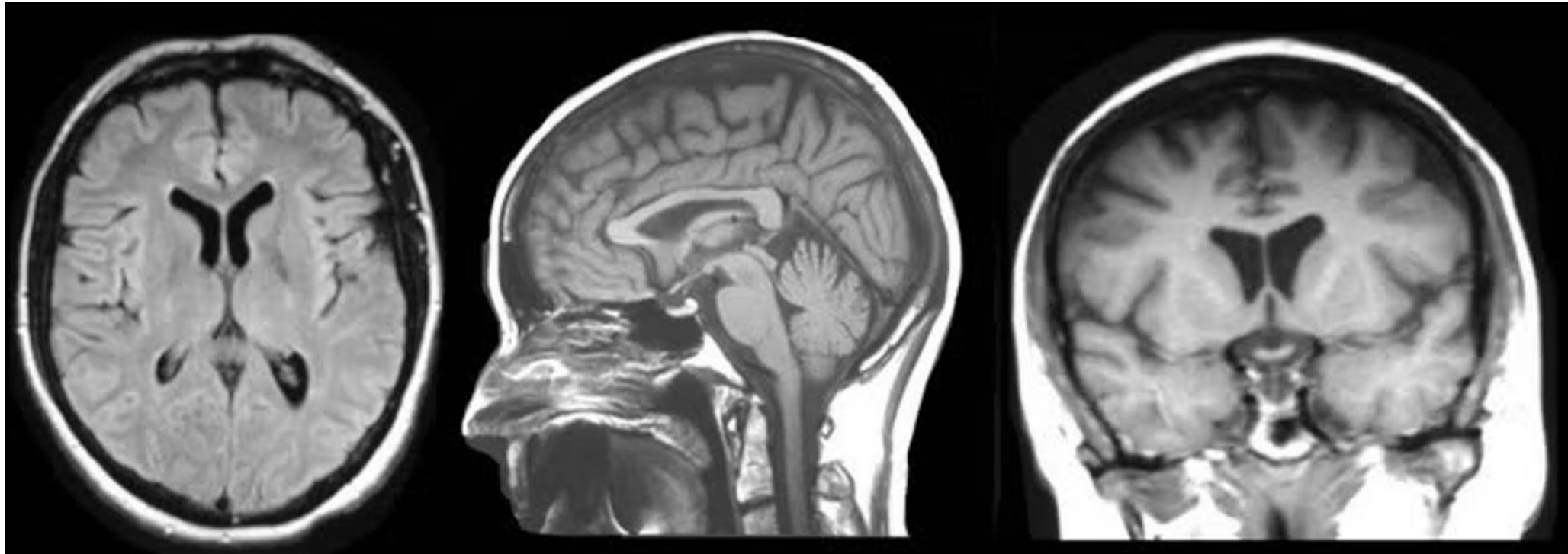


Why AI lags behind in the medical sector



Lack of Data + Biased Data

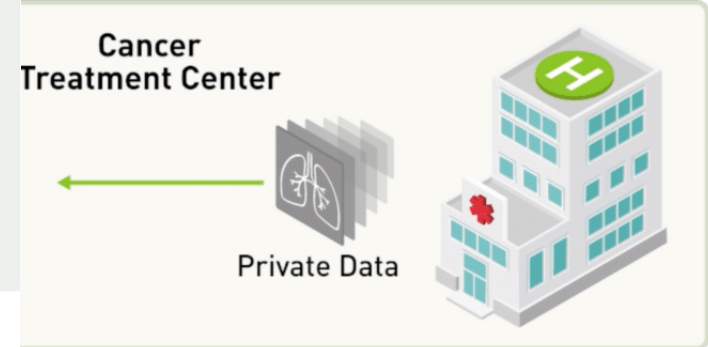
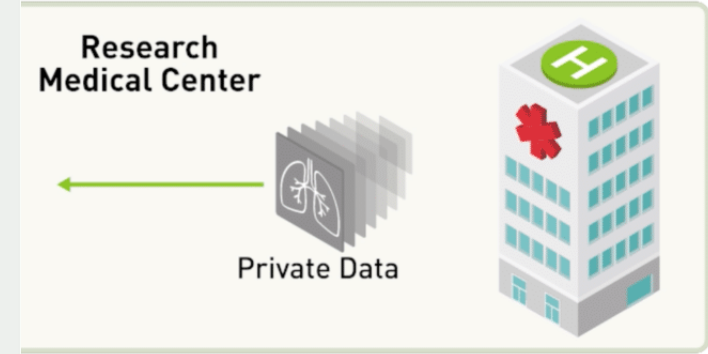
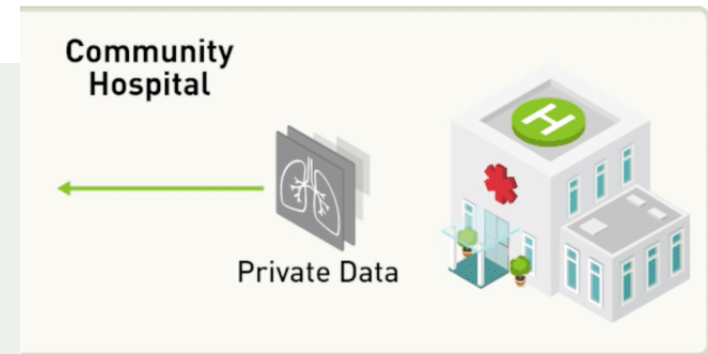
Why AI lags behind in the medical sector



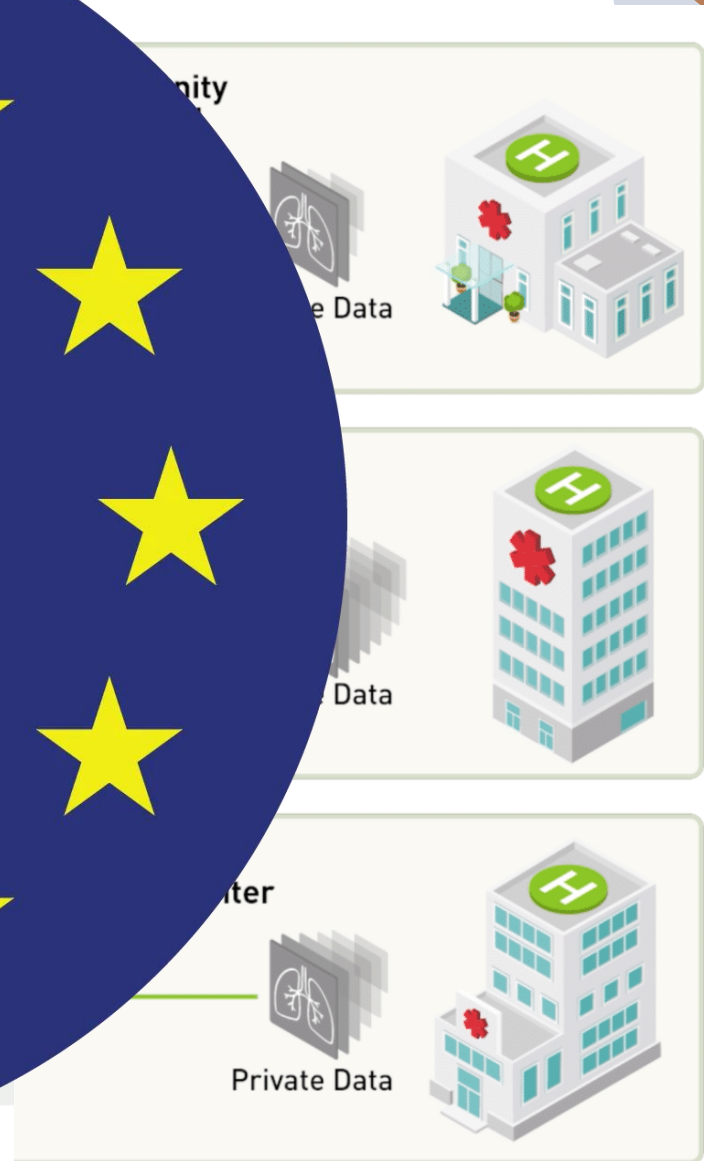
Complexity of Data

**Okay, it's tricky but surely given
enough data, we'll get there, right?**

We propose a solution!



Whoops!



GDPR



**Data Protection
Officer (DPO)**



Compliance



25 May 2018

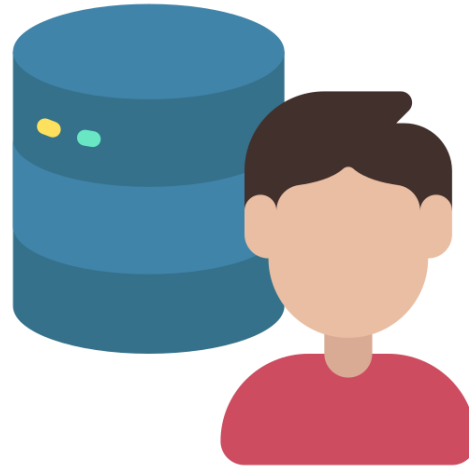


Data Breaches



Personal Data

Can't we just make exceptions to the rule?



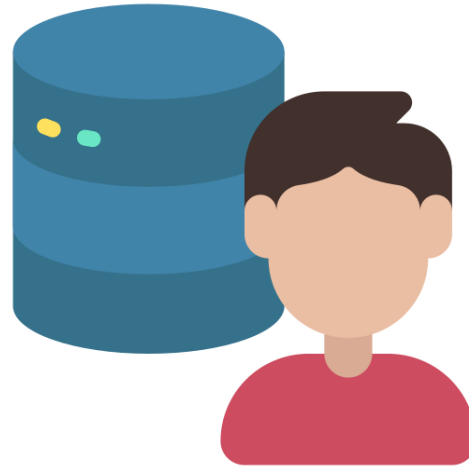
Who should access my private data?

Everyone

Nobody



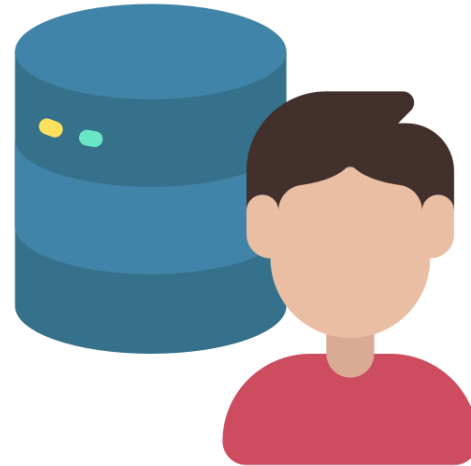
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Who should access my private data?



Can't we just make exceptions to the rule?



Who should access my private data?



BIONTECH



moderna

Johnson & Johnson

Valneva

NOVAVAX

SANOFI



What about them?

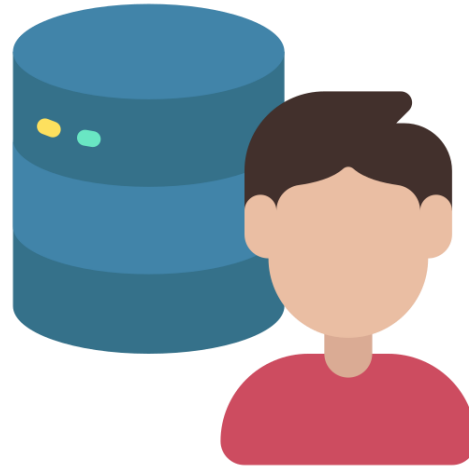
Everyone

Healthcare

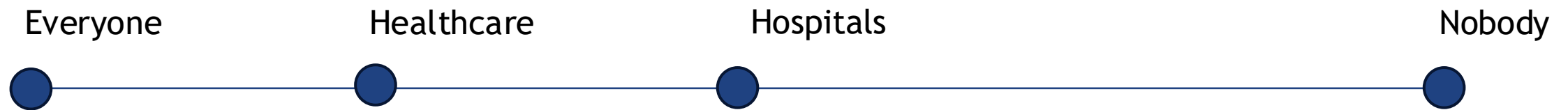
Nobody



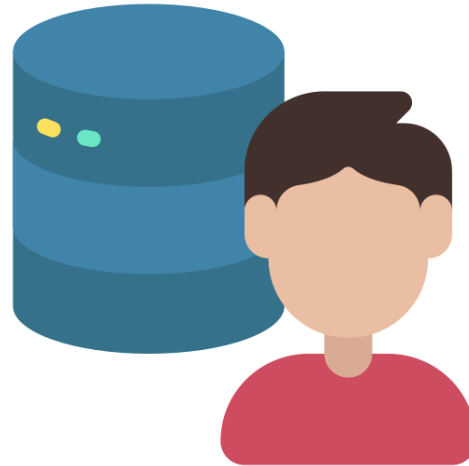
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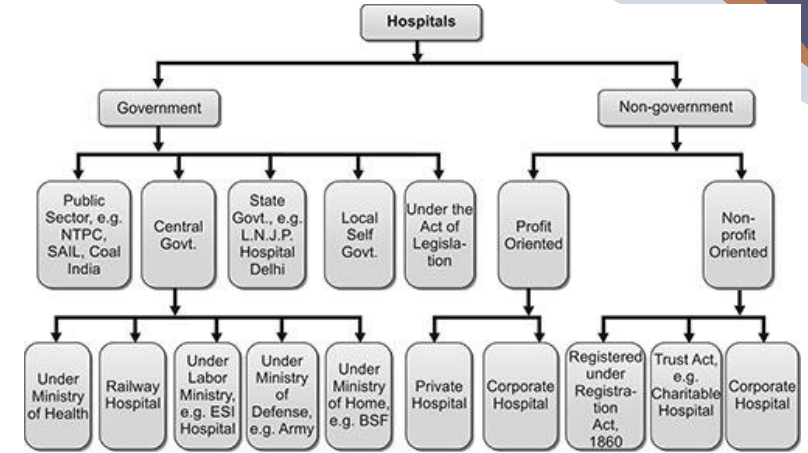
They have no agenda, right?



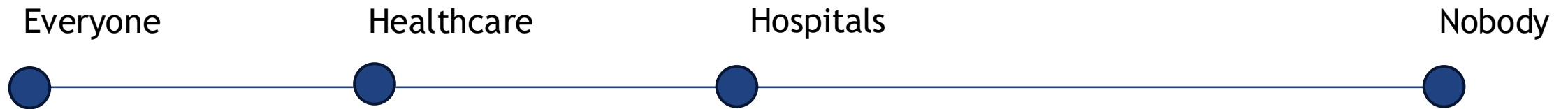
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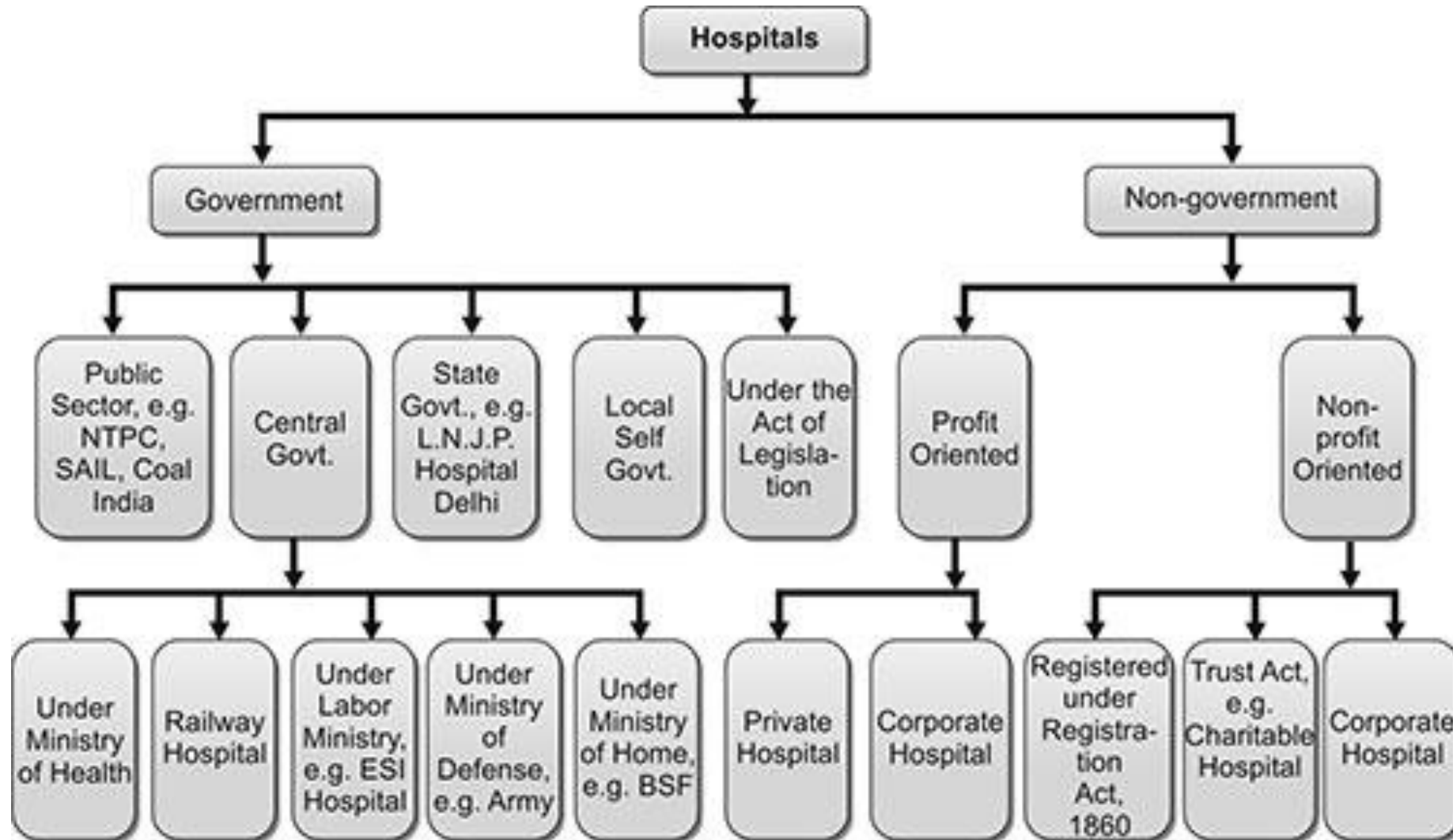
They have no agenda, right?



Wrong!

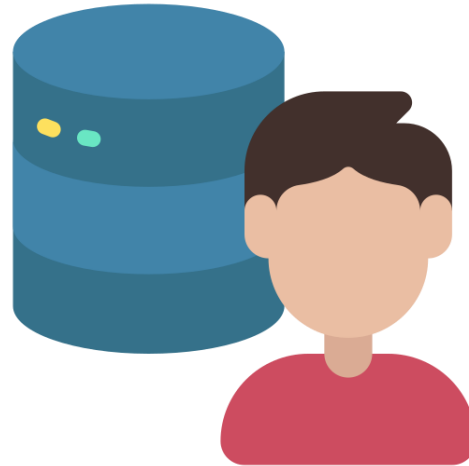


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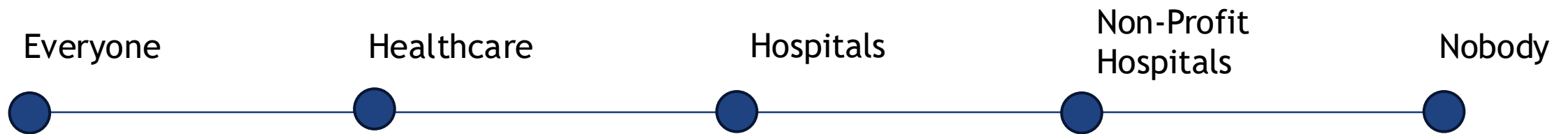


Can't we just make exceptions to the rule?

That seems reasonable, no?

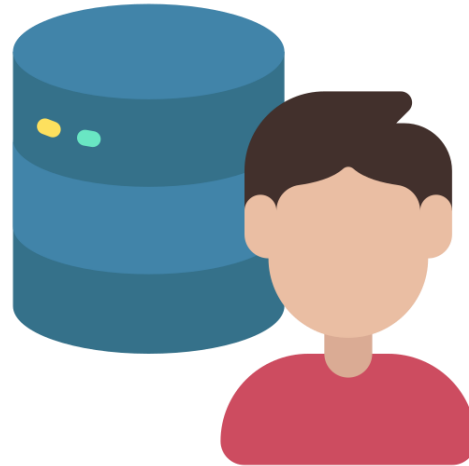


Who should access my private data?



Can't we just make exceptions to the rule?

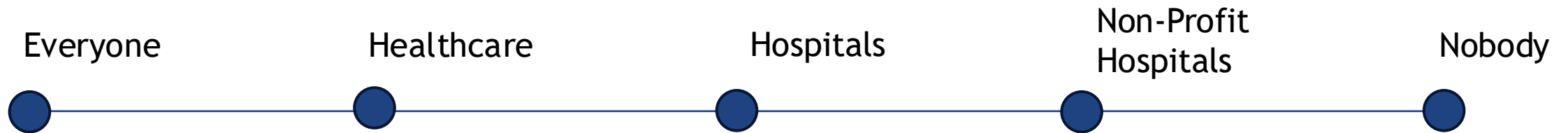
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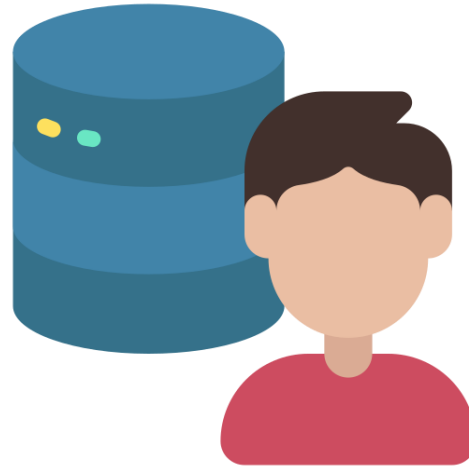
What is the legal definition of Non-Profit Hospitals?



Who should access my private data?



Can't we just make exceptions to the rule?

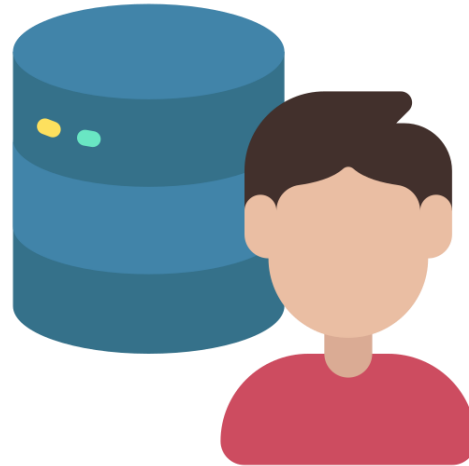


Better safe than sorry!



*: exceptions can be made upon request

Can't we just make exceptions to the rule?



Better safe than sorry!

Jaquar Group Public

DATA SUBJECT CONSENT FORM

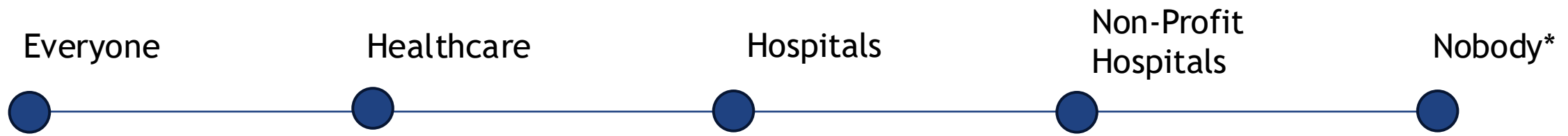
I, [data subject name] am hereby consenting that [Company Name] can process my personal data for the purpose of [specify the processing activity for which consent is being given – example (Personal Data Sharing with third party, direct marketing, image processing etc].

I am aware and I was informed that I may withdraw my consent at any time by using the "DATA SUBJECT CONSENT WITHDRAWAL FORM," either by sending it via email at dpo@jaquar.com or by post at following Jaquar Offices marked to DPO

Company Name	Address
JACUAR UK LIMITED	Surrey House, 36-44 High Street Redhill, Surrey, RH1 1RH United Kingdom
JACUAR EUROPE S.R.L.	VIA E.DE AMICIS NO. 53 Milan Italy
JACUAR EUROPE S.R.L. (BRANCH OF ITALY OFFICE)	Ul Sienna 82, 00-815 Warsaw, Poland
Jaquar Group, Headquarters	Plot No.3, Sector – 11,IMT Manesar, Gurgaon,National Capital Region – 122050,India

Signed by [data subject name]:

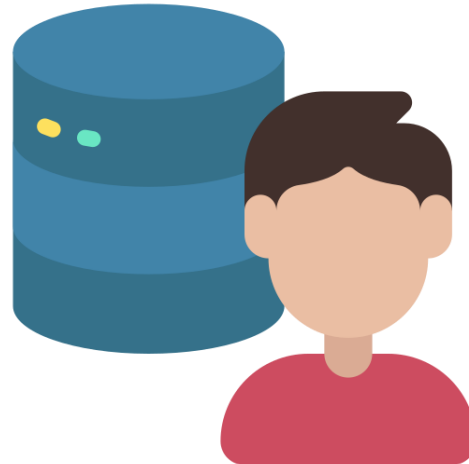
Signature: _____ Date: _____



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Can't we just make exceptions to the rule?

I'm not reading all that!



Better safe than sorry!

Jaquar Group Public

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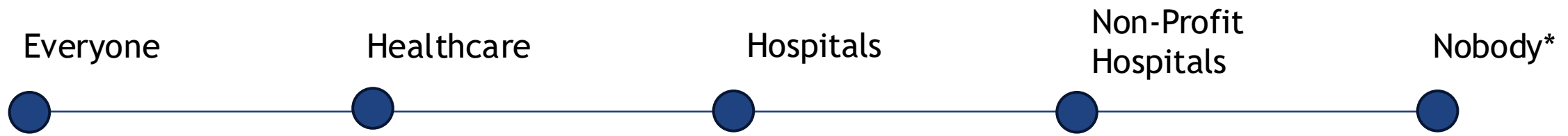
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Signed by [data subject name]:

Signature: _____ Date: _____



*: exceptions can be made upon request

**We still have a lack of data, and no
easy way to obtain more.**

Back to the drawing board

PID	Name	Surname	Gender	DoB	Country	StreetAddress	City	Postal
10000	Adena	Reeves	F	1962-08-28	Montenegro	P.O. Box 936, 9290 Aptent Ave	Morkhoven	71344
10001	Buffy	Warner	M	2009-05-25	Guinea-Bissau	P.O. Box 624, 5536 Nunc St.	Graz	68114-188
10002	Kaye	Green	F	1994-07-23	Norway	P.O. Box 650, 1264 Tellus. St.	Bojano	T04 3WO
10003	Keiko	Gonzalez	M	1973-12-27	Iraq	1889 Magna. Street	Chelsea	8064
10004	Kylynn	Carver	F	1974-01-22	Tanzania	Ap #357-247 Per Rd.	Oberhausen	53534
10005	Daquan	Sosa	F	1961-12-28	Holy See (Vatican City State)	Ap #727-5534 Mauris, Avenue	Eberswalde-Finow	5690ER
10006	Rebekah	Navarro	F	1974-02-01	Saudi Arabia	P.O. Box 698, 3686 Dui. Avenue	Wolvertem	2976
10007	Zane	Benson	M	2002-10-19	Mauritania	Ap #852-3480 Ornare Ave	Dufftown	1137
10008	Jennifer	Pattv	F	1985-08-31	Isle of Man	598-2436 Sit Rd	Rathurst	71612

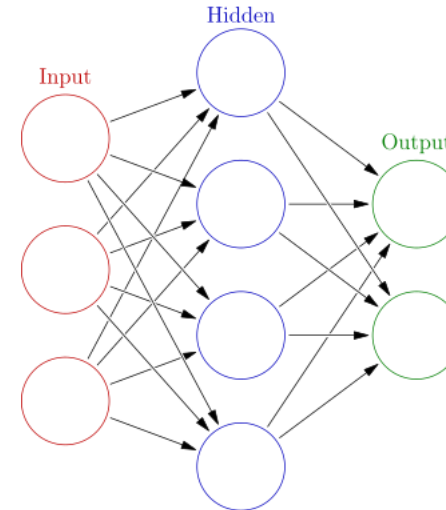
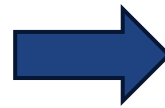
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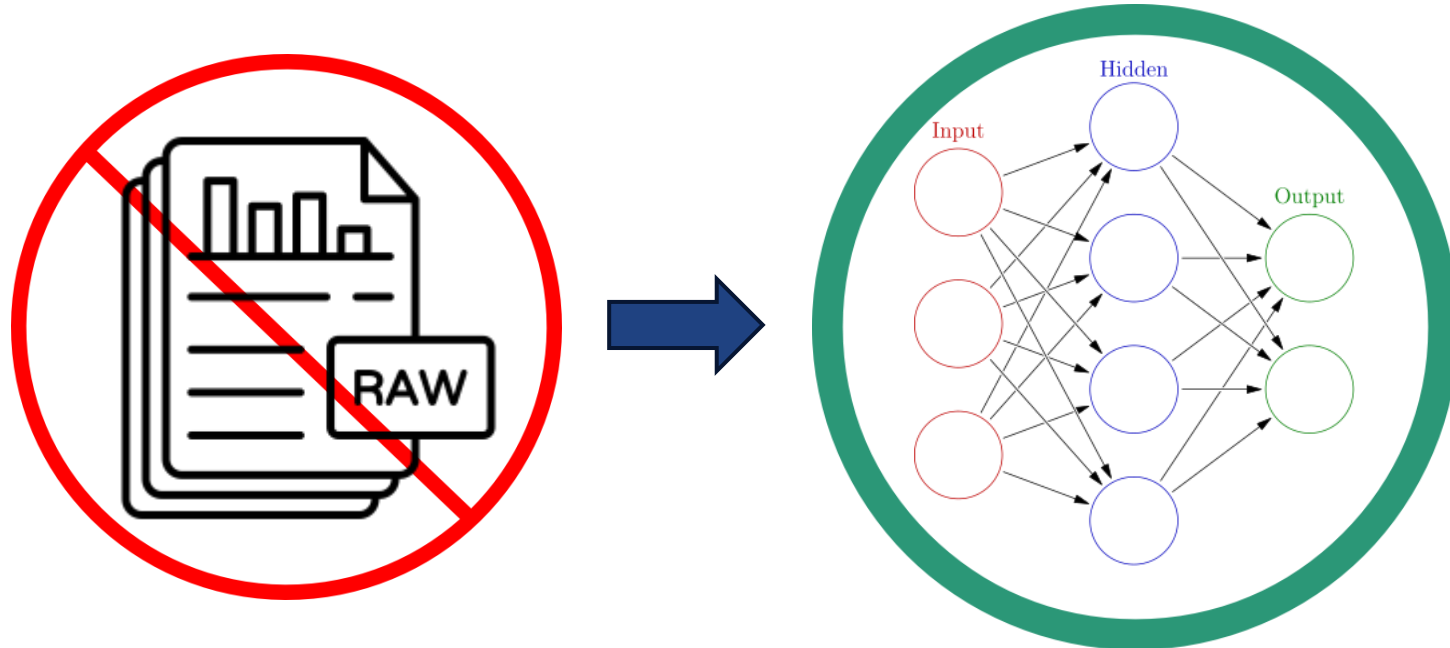
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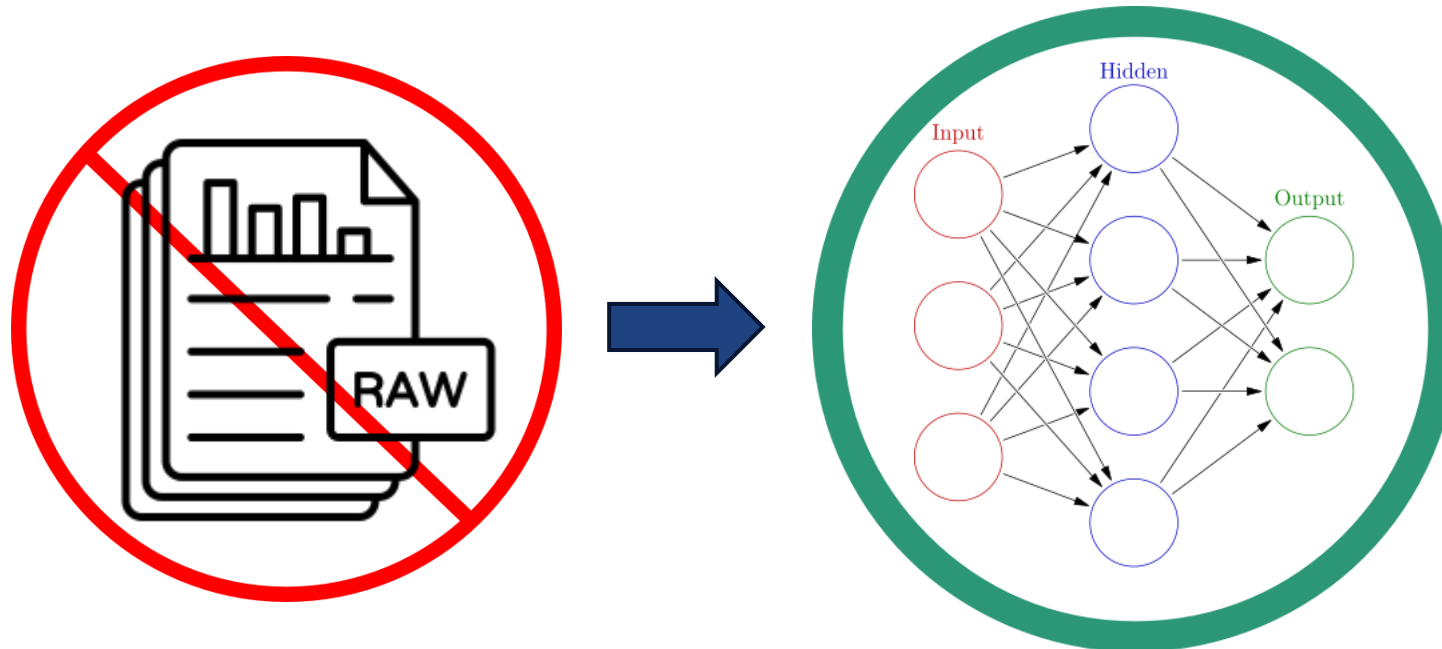
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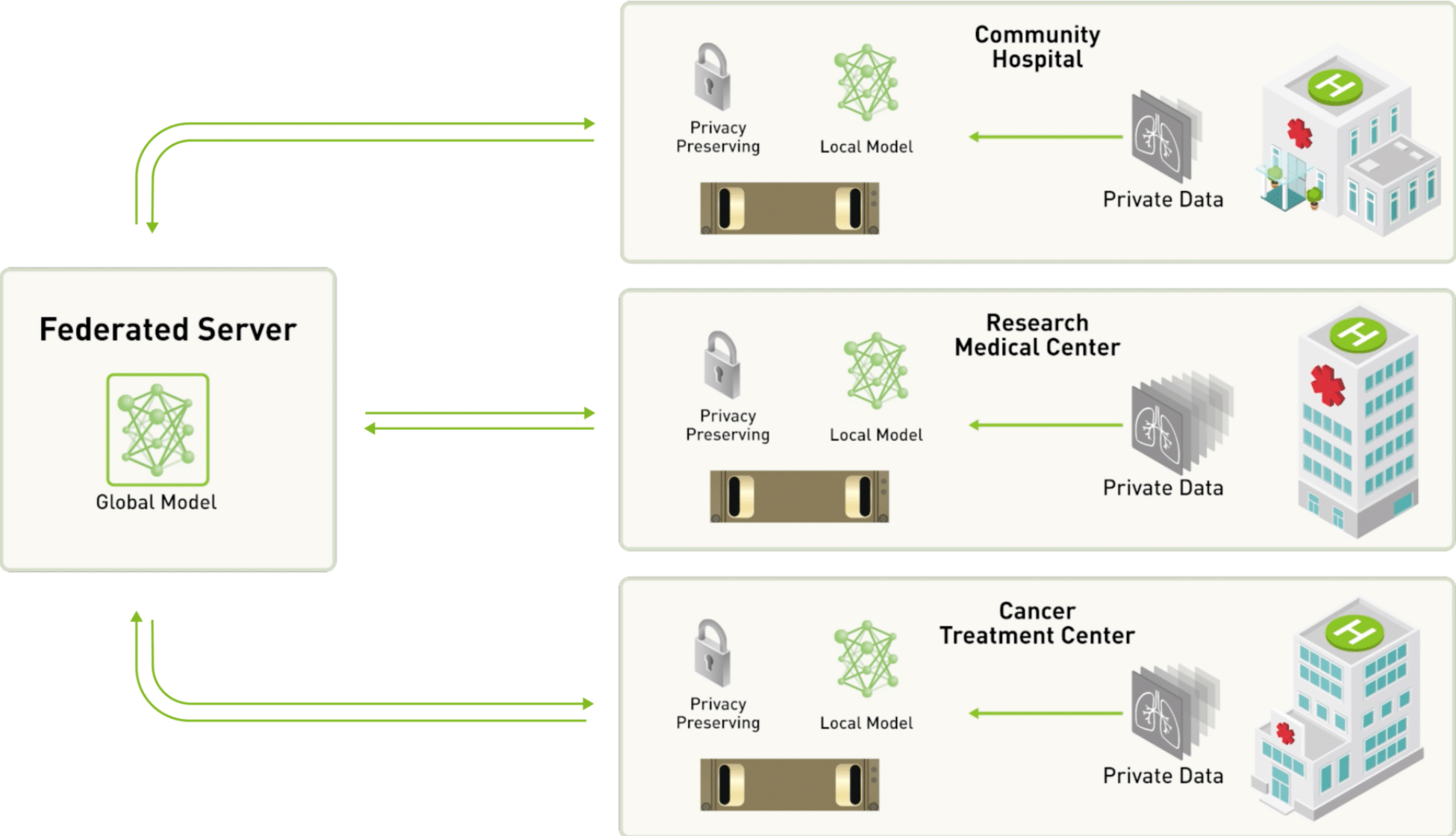
We're not exchanging data,
your Honor



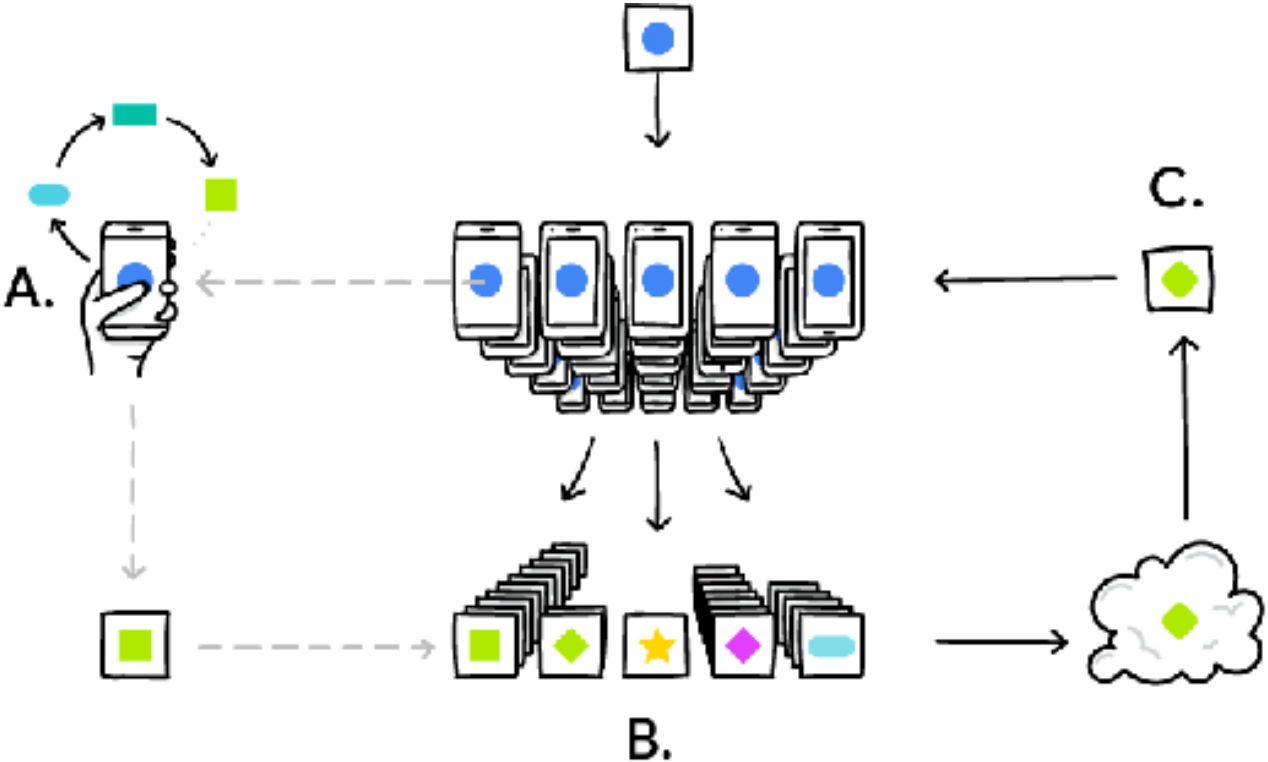
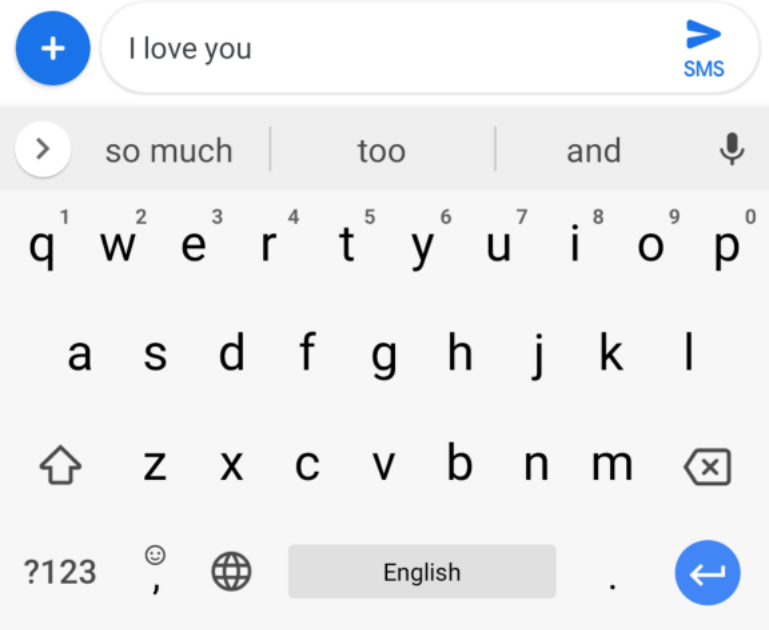
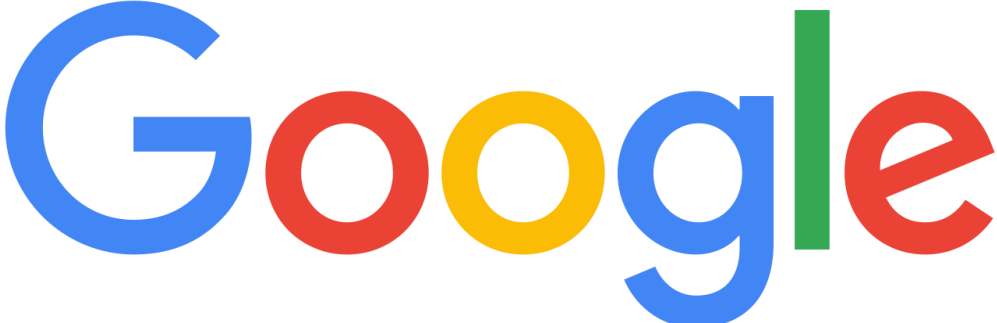
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Federated Learning



Federated Learning: Origins

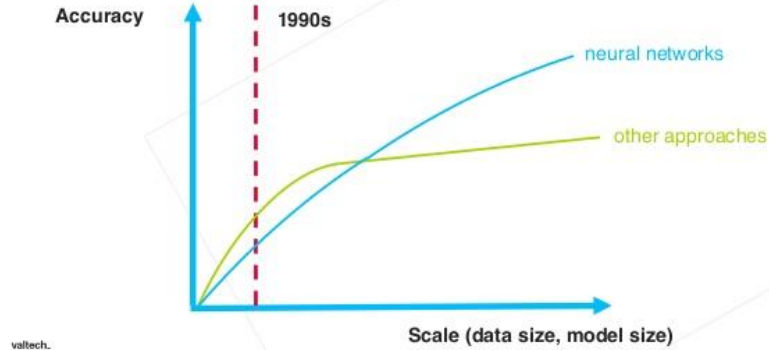


Upsides

- ▶ Increase available data for model training
- ▶ Privacy preservation of original data
- ▶ Data diversity & representation
- ▶ Allows collaboration between institutions
- ▶ Scalability
- ▶ Regulatory & ethical alignment

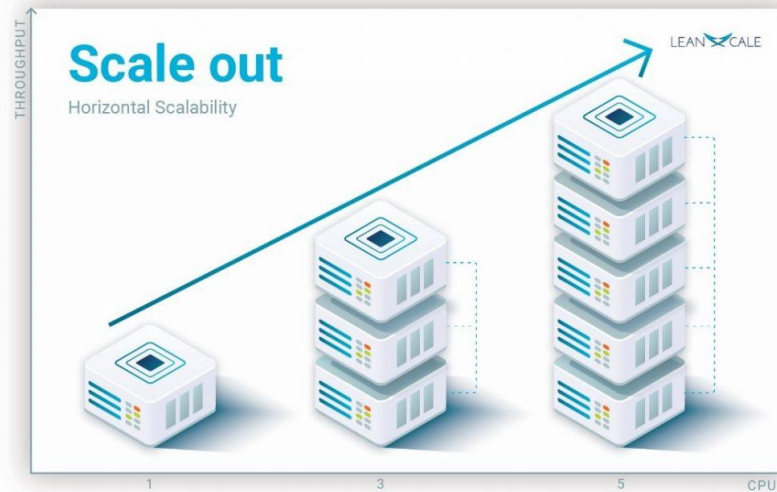


More Data + Bigger Models



valtech.

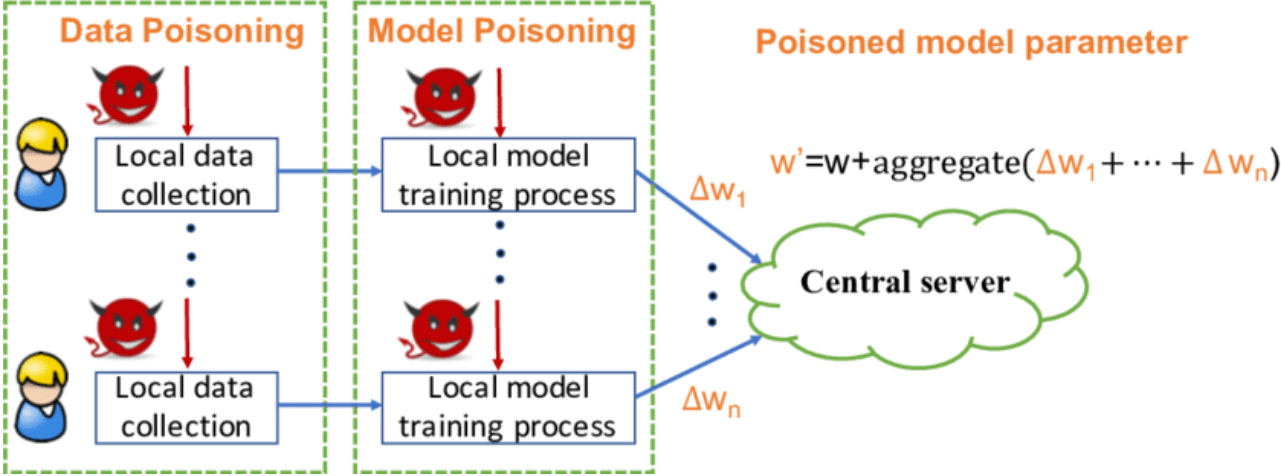
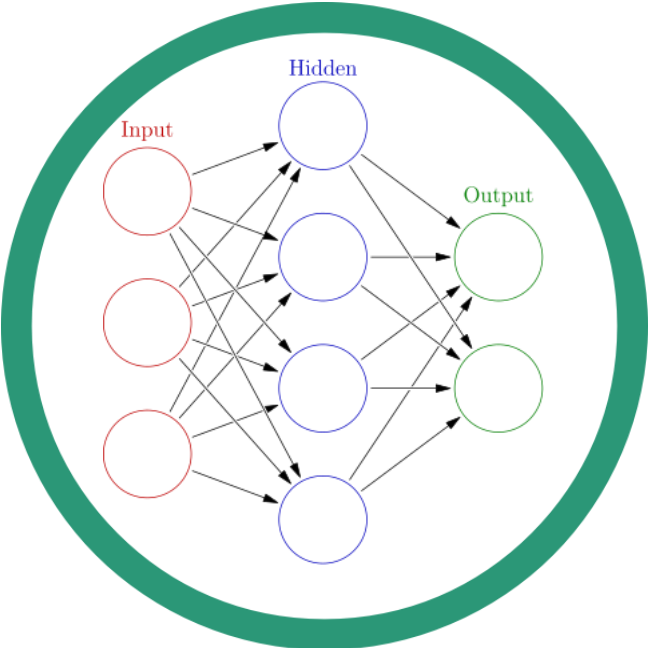
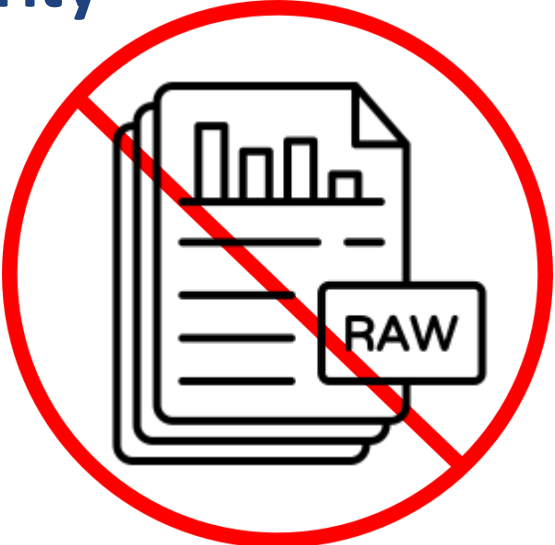
<https://www.scribd.com/document/355752799/Jeff-Dean-s-Lecture-for-YC-AI>



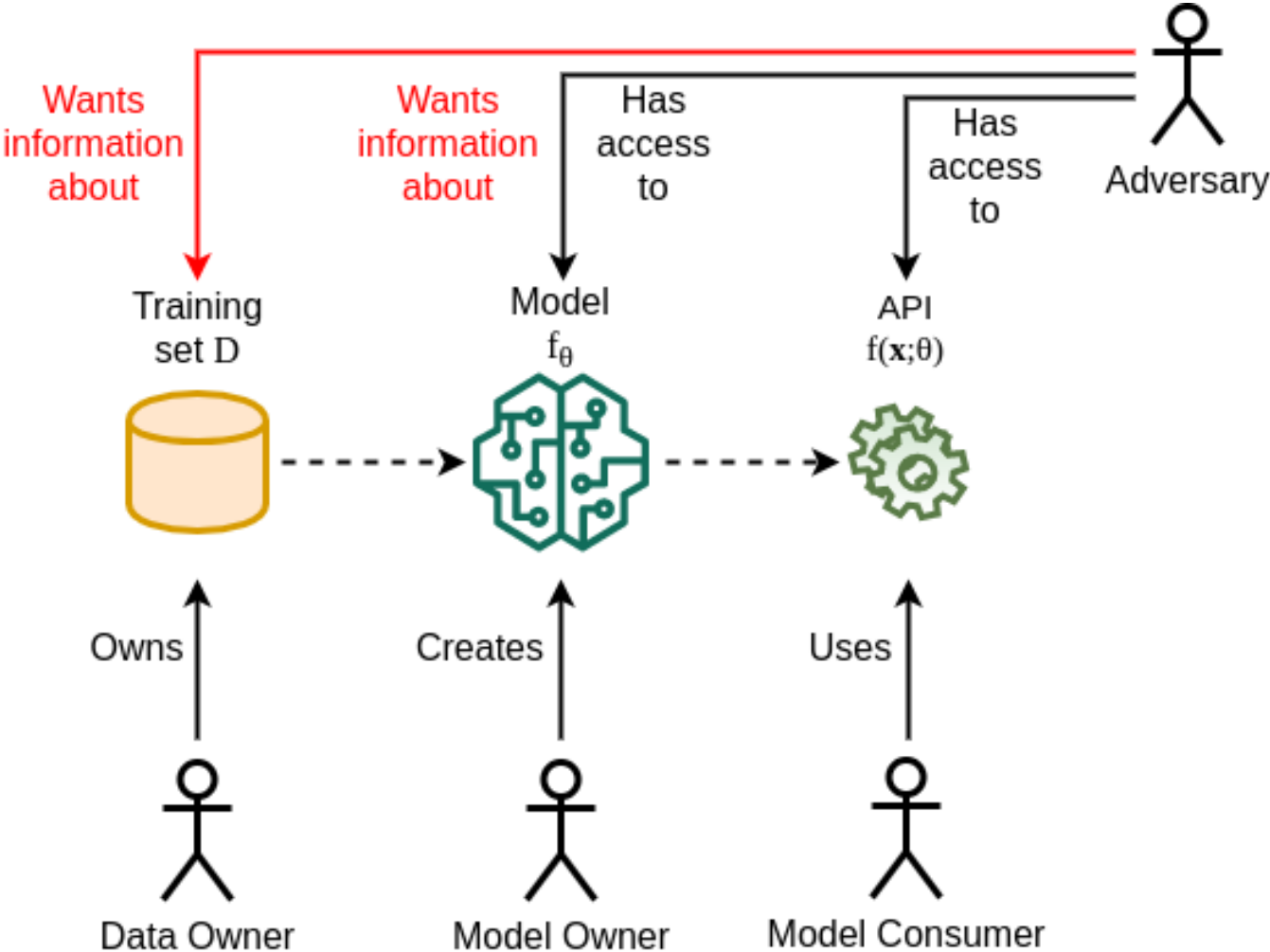
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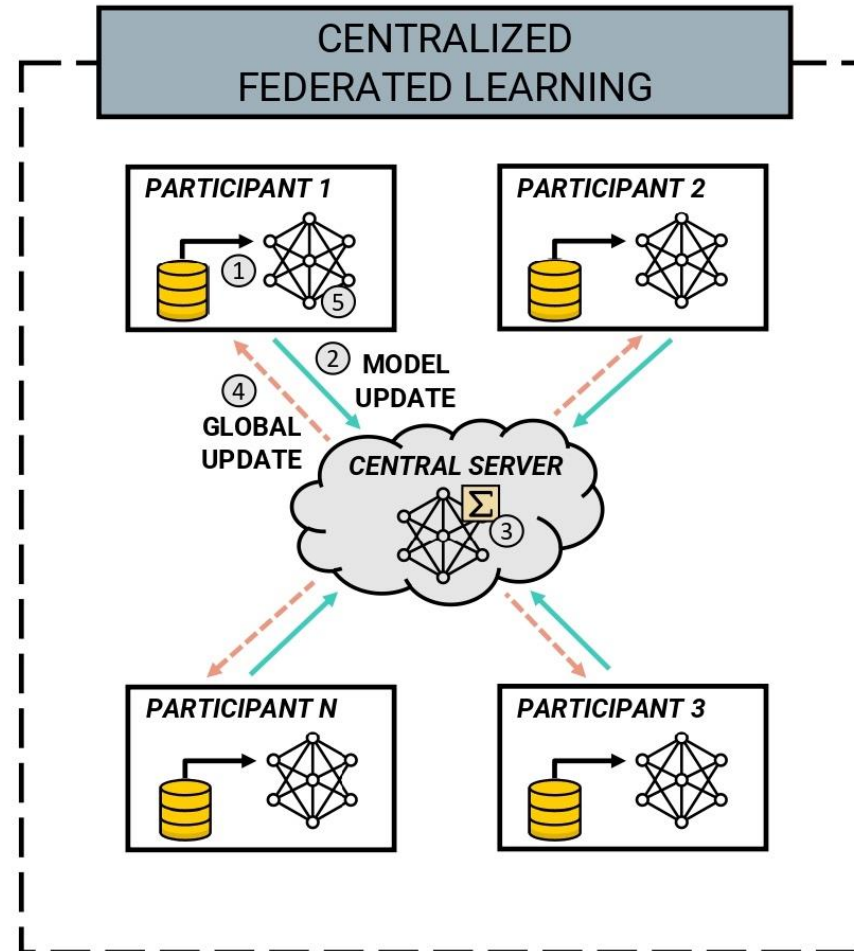
Model Security



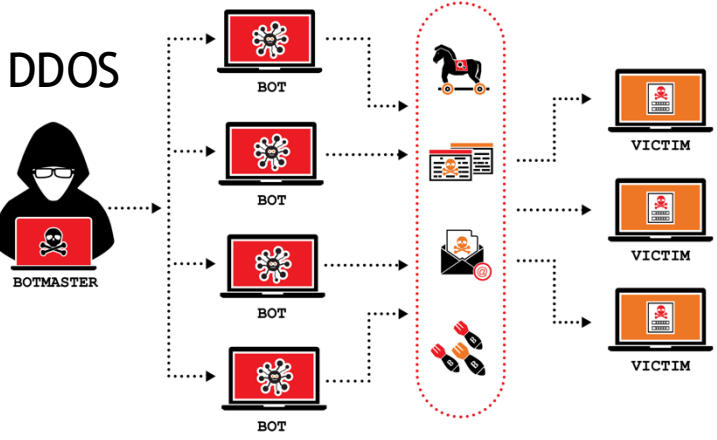
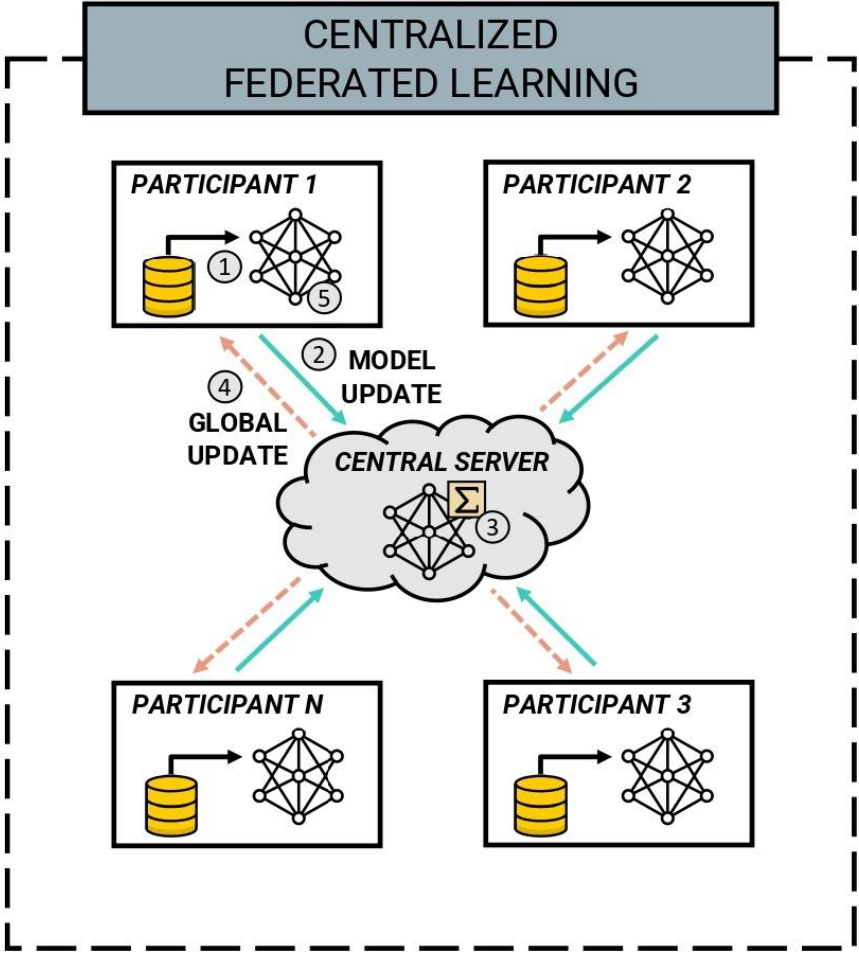
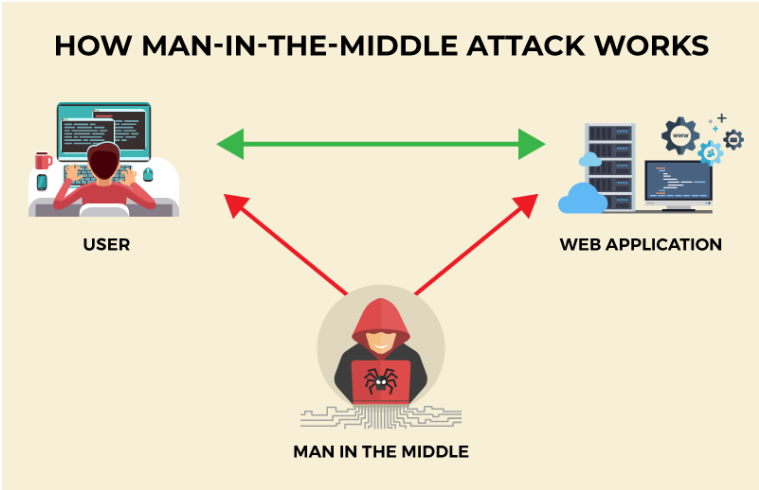
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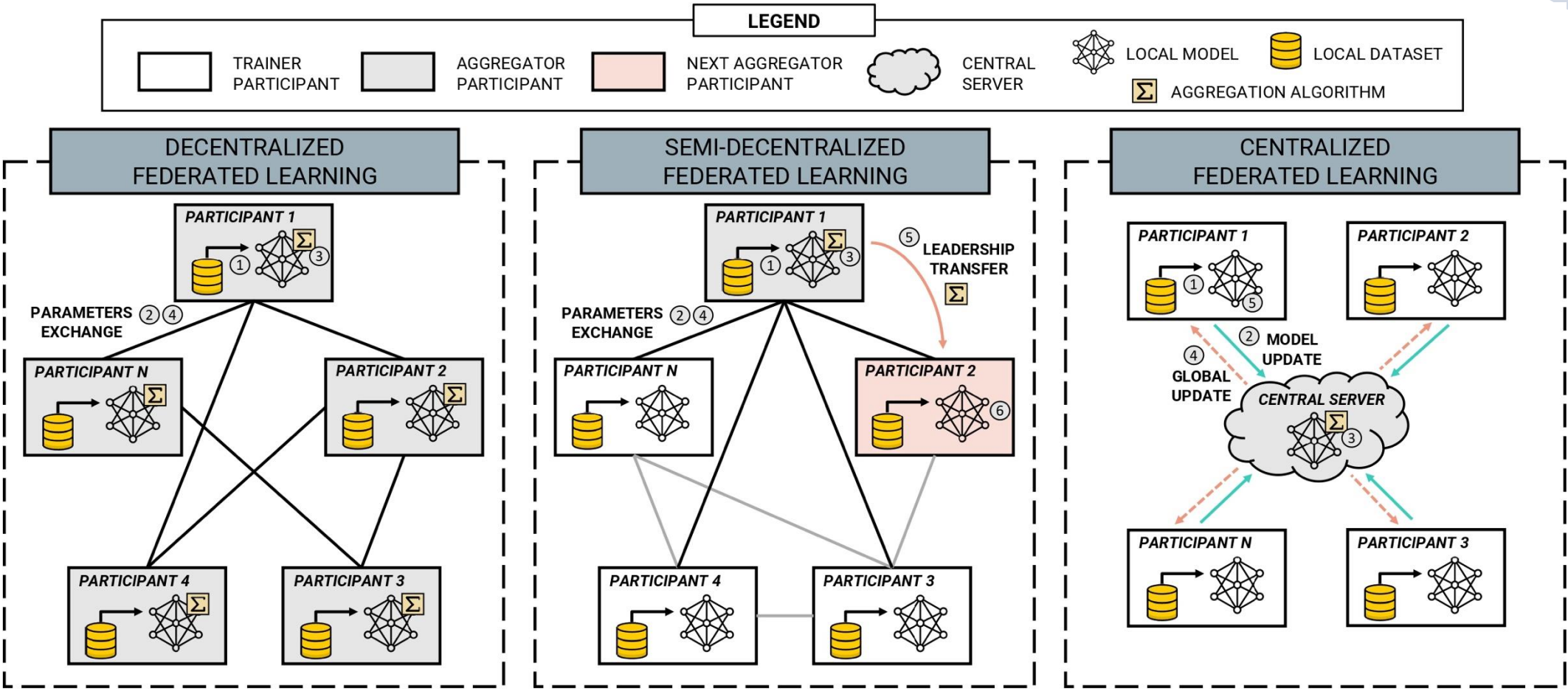
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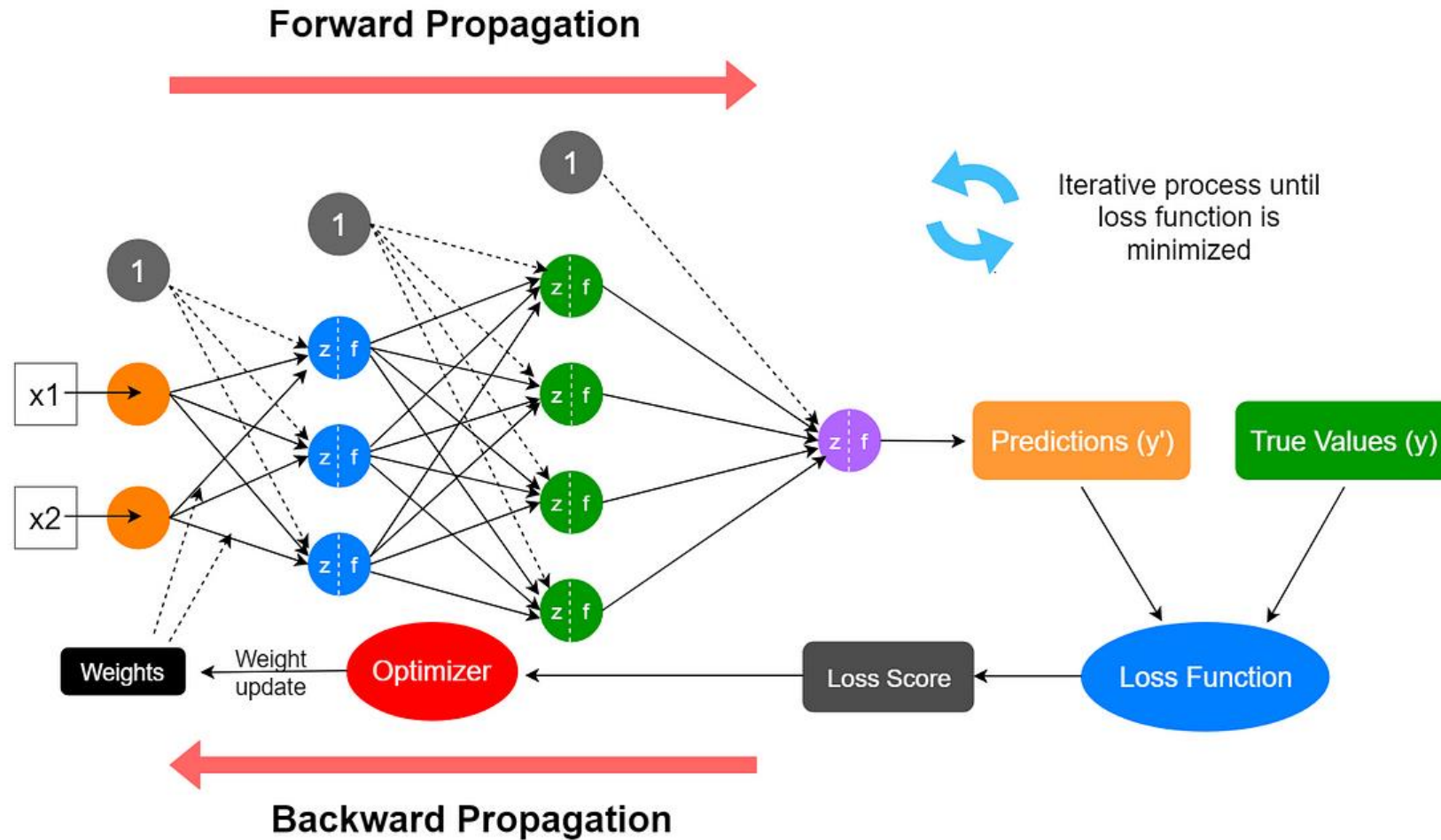
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Model Security



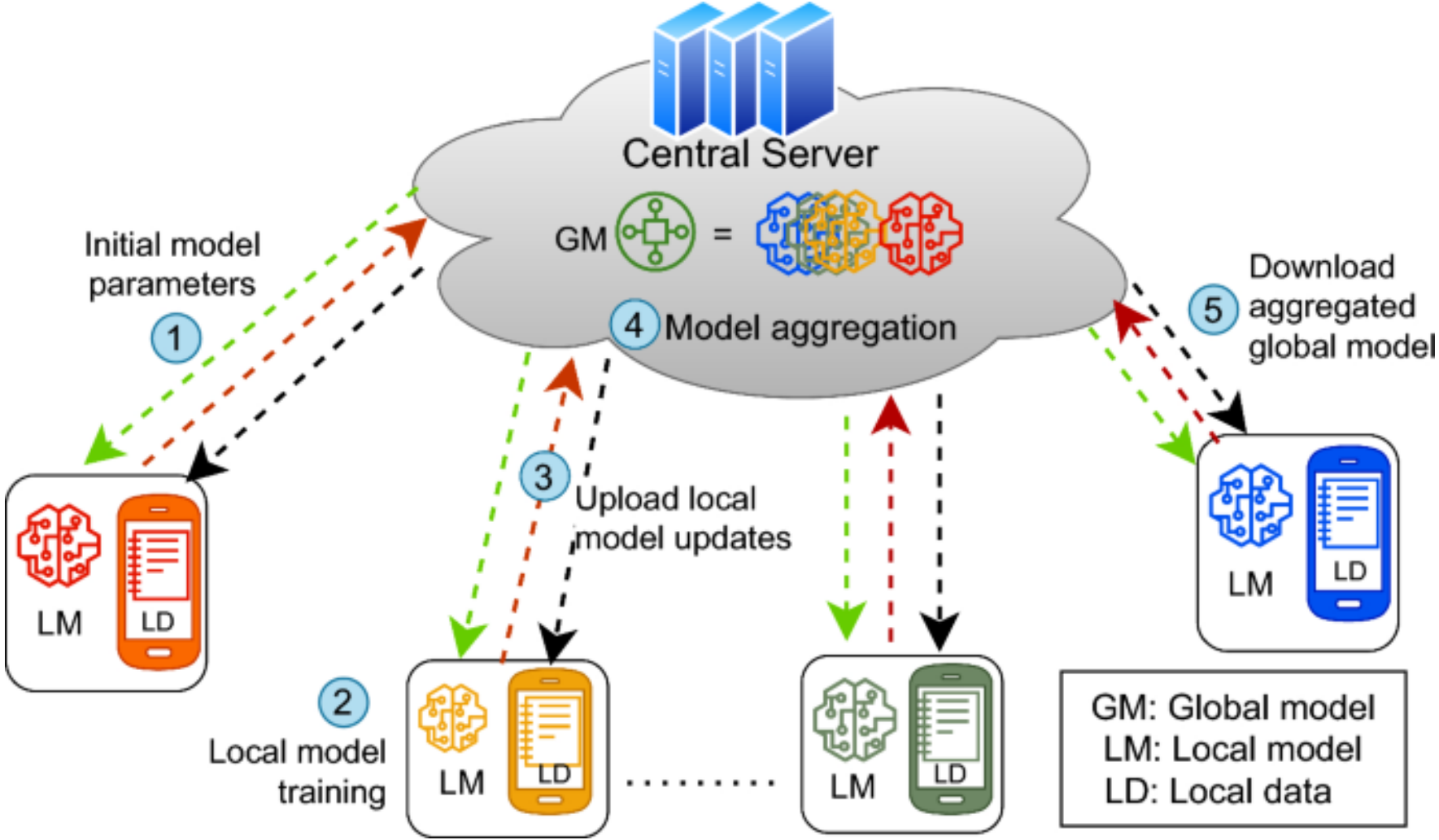
Computation Overhead



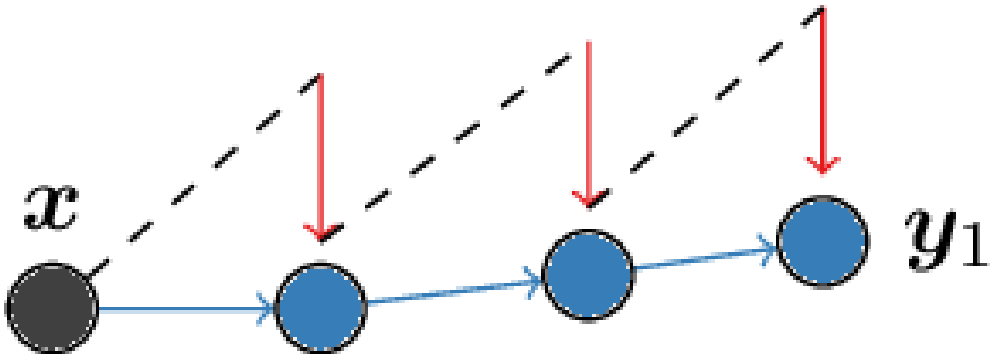
Communication Overhead



Computation Overhead



Heterogeneity



■ x_1^*

⋮ local gradient

↑ correction

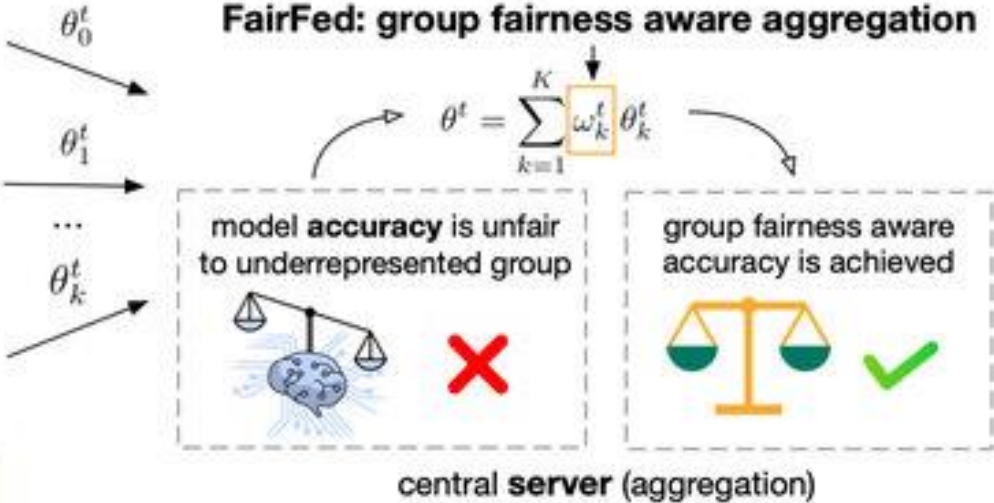
■ x^*

↑ client update

Fairness



clients in federated learning have private data from *diverse groups (race, sex, etc.)*



Fairness



BIONTECH



moderna

Johnson & Johnson

valneva

NOVAVAXAB

SANOFI



Millions of datapoints

hikma.

Hundred thousands of datapoints

Fairness



You're not invited to the Federation



BIONTECH



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valneva

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Incentive Mechanisms



Model Ownership

✓ **GPT-3.5**
\$0.002
(prompt tokens)
\$0.012
(completion tokens)

✓ **Monthly Cost Example**
Small app: \$150–\$500
Mid-sized app: \$3,000–\$7,000
Enterprise: \$50,000+

Lower Price of Use

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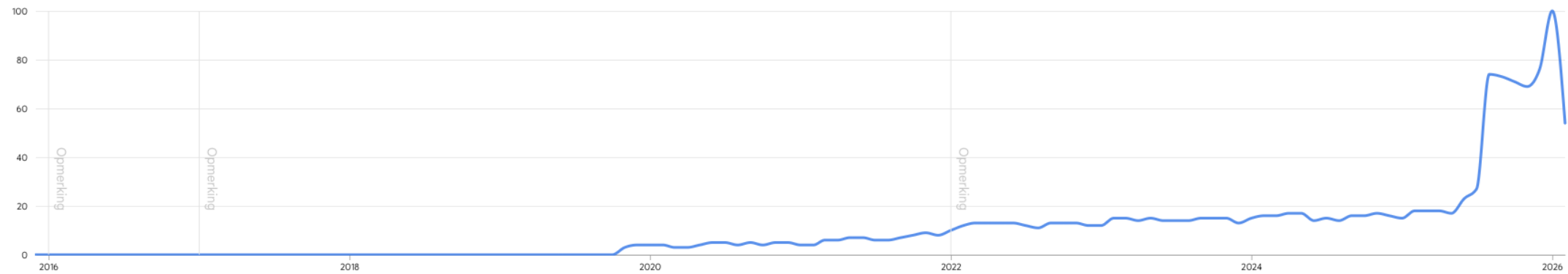
Lower Price of Use

Is more data always good?

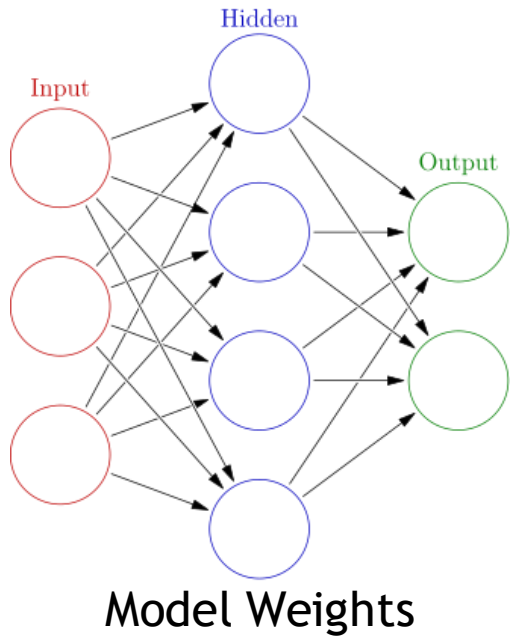
Federation is just getting started!

Interesse in de loop van de tijd ⓘ

Wereldwijd · 1 jan 2016 - 12 feb 2026

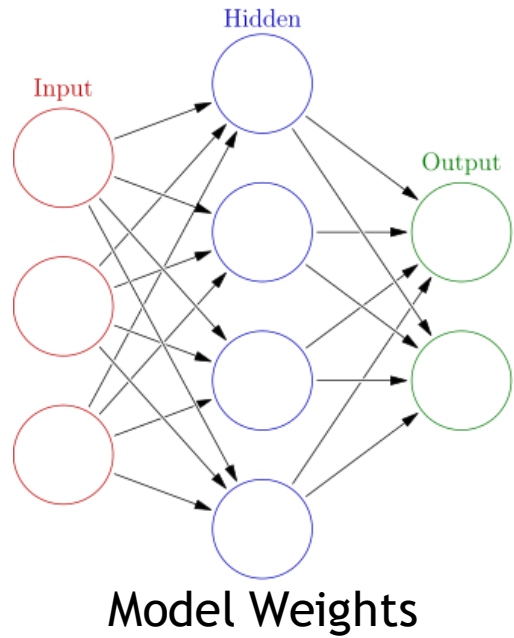


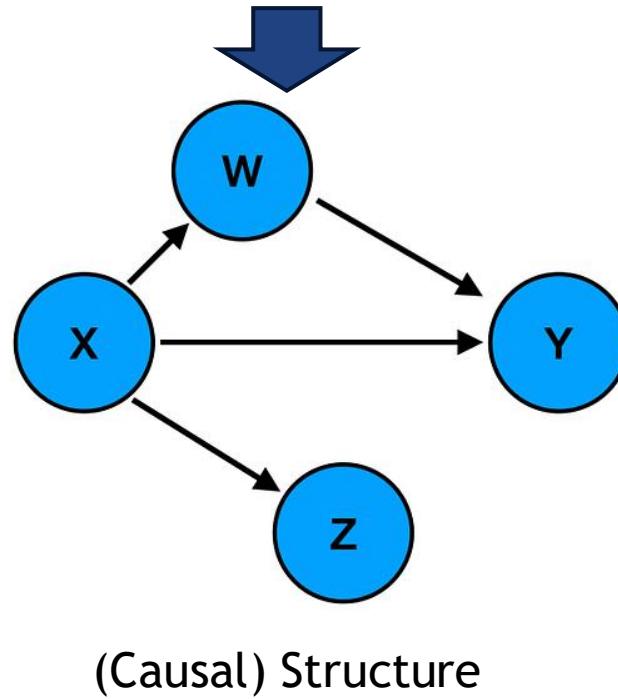
Federation is just getting started!



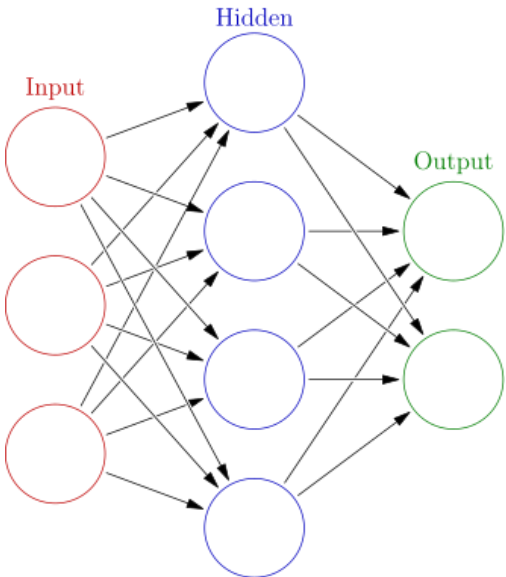


Federation is just getting started!

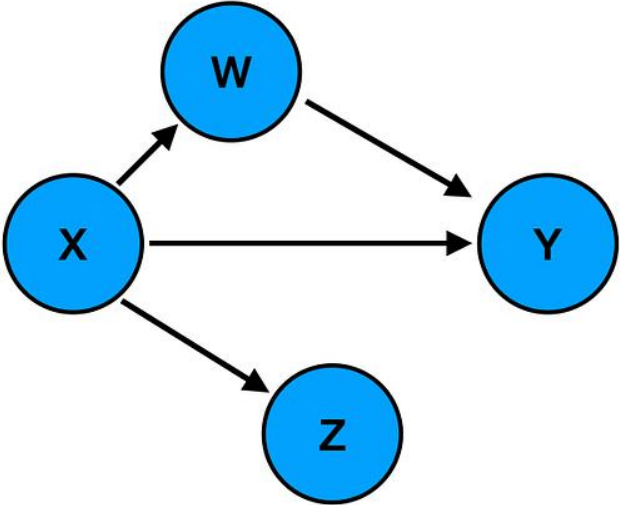




Federation is just getting started!



Model Weights



(Causal) Structure

Synthetic Data (GAN)

The Federation



ARTIFICIAL
INTELLIGENCE
RESEARCH GROUP

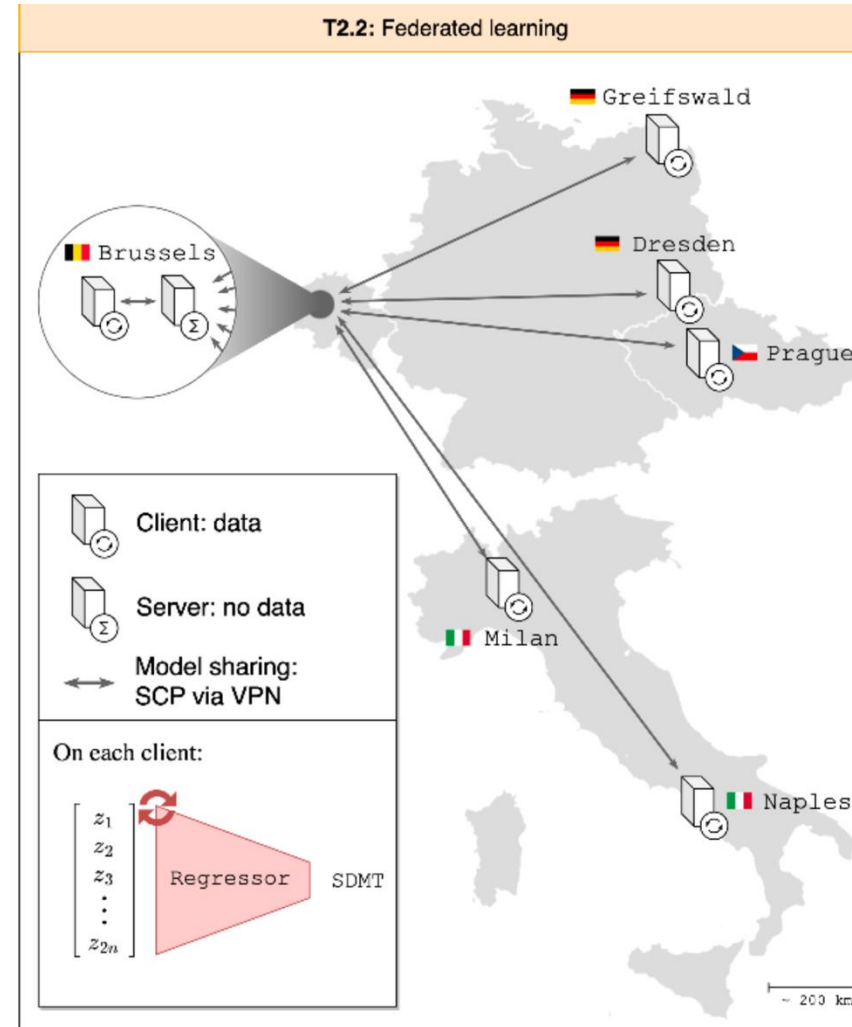
- ▶ Expertise in general AI and computer science.



AIMS

AI-SUPPORTED MODELLING
IN CLINICAL SCIENCES

- ▶ Expertise in cognitive deterioration
- ▶ International MS network with many cases.



The Federation



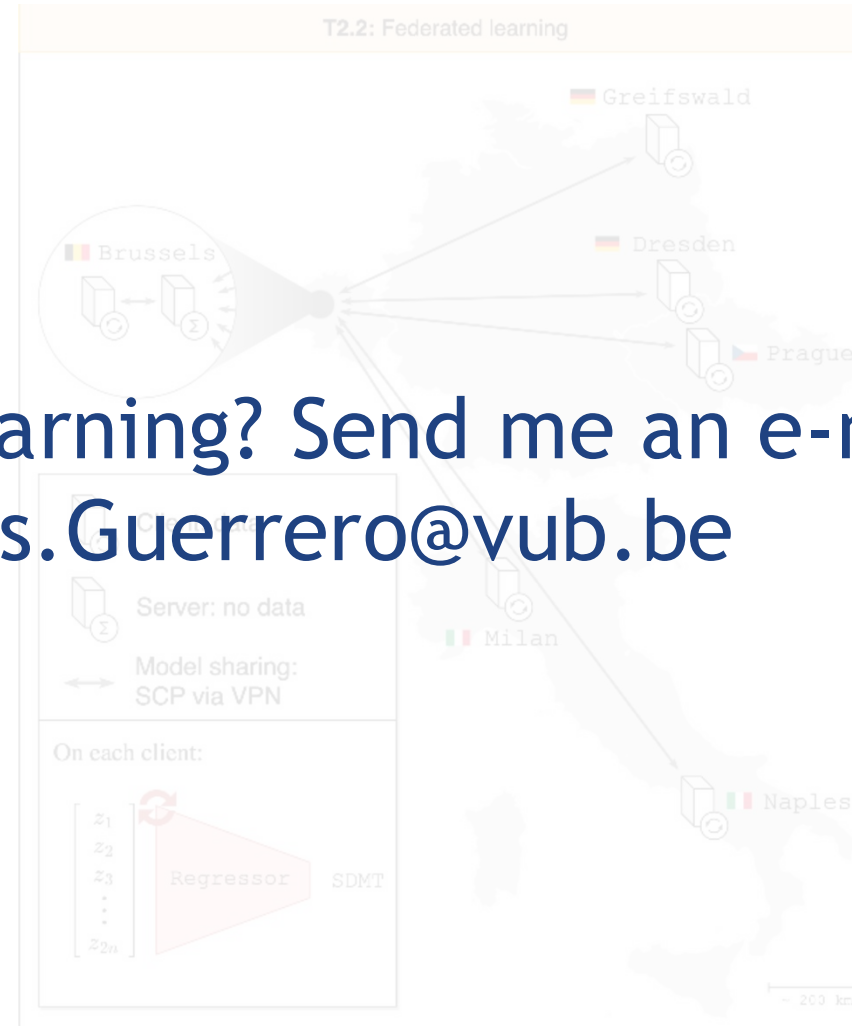
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INTELLIGENCE
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**Interested in Federated Learning? Send me an e-mail!
Alvaro.Javier.Vargas.Guerrero@vub.be**

AI-SUPPORTED MODELLING
IN CLINICAL SCIENCES

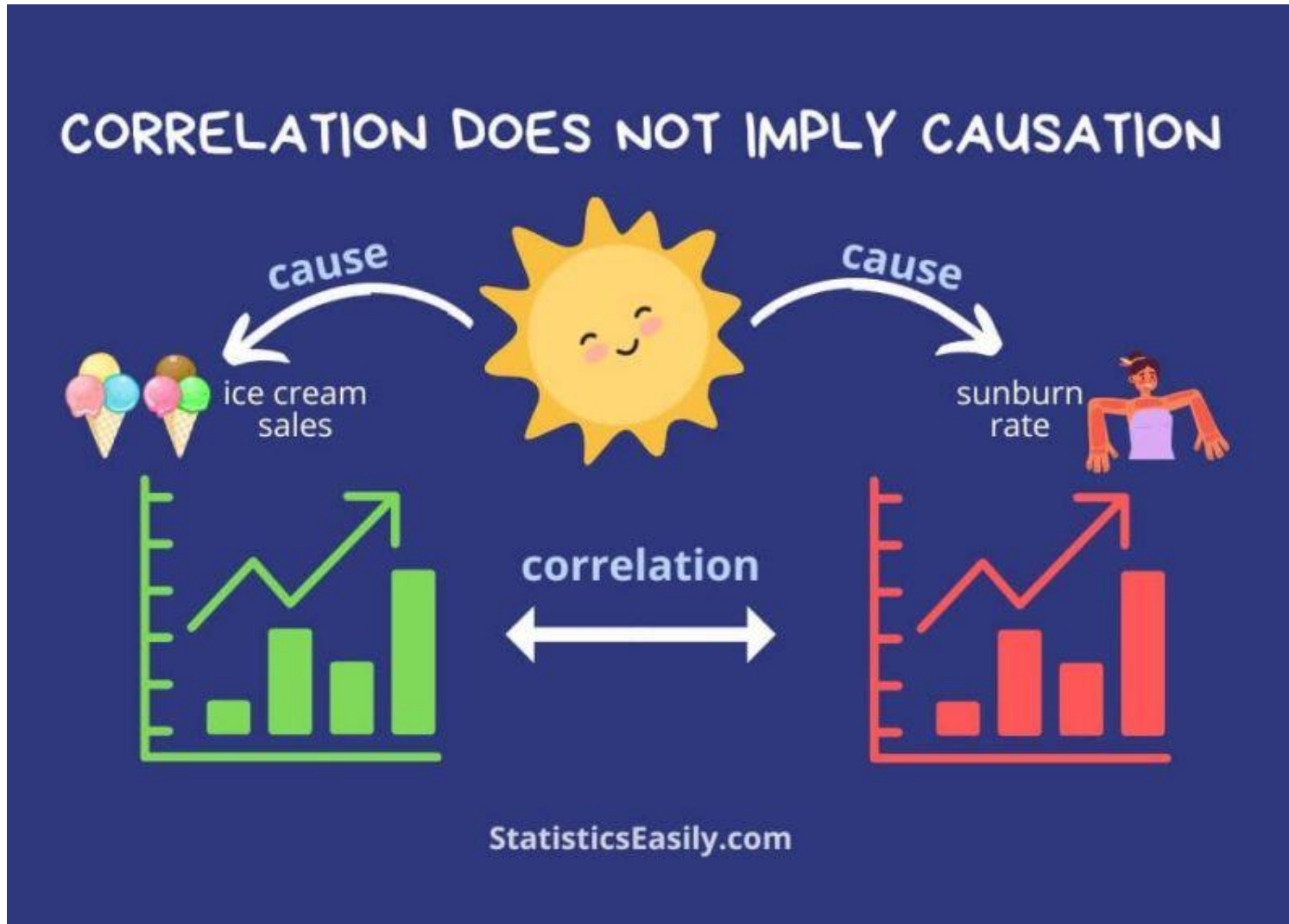
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Roadmap

- ▶ Current State of Modern AI
- ▶ Why AI lags behind in the medical sector
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- ▶ Open Challenges of Federated Learning
- ▶ **The Achilles heel of Machine Learning**
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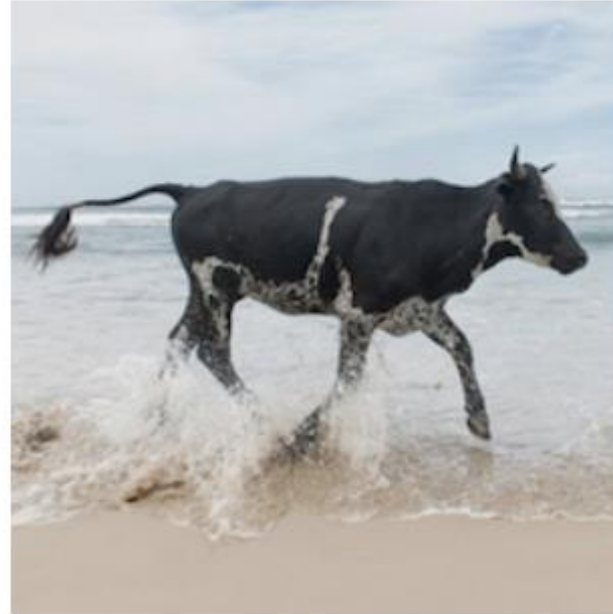
To State The Obvious



The Achilles heel of Machine Learning



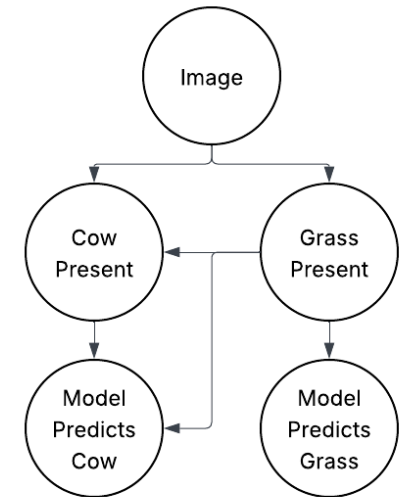
(A) **Cow: 0.99**, Pasture: 0.99, Grass: 0.99, No Person: 0.98, Mammal: 0.98



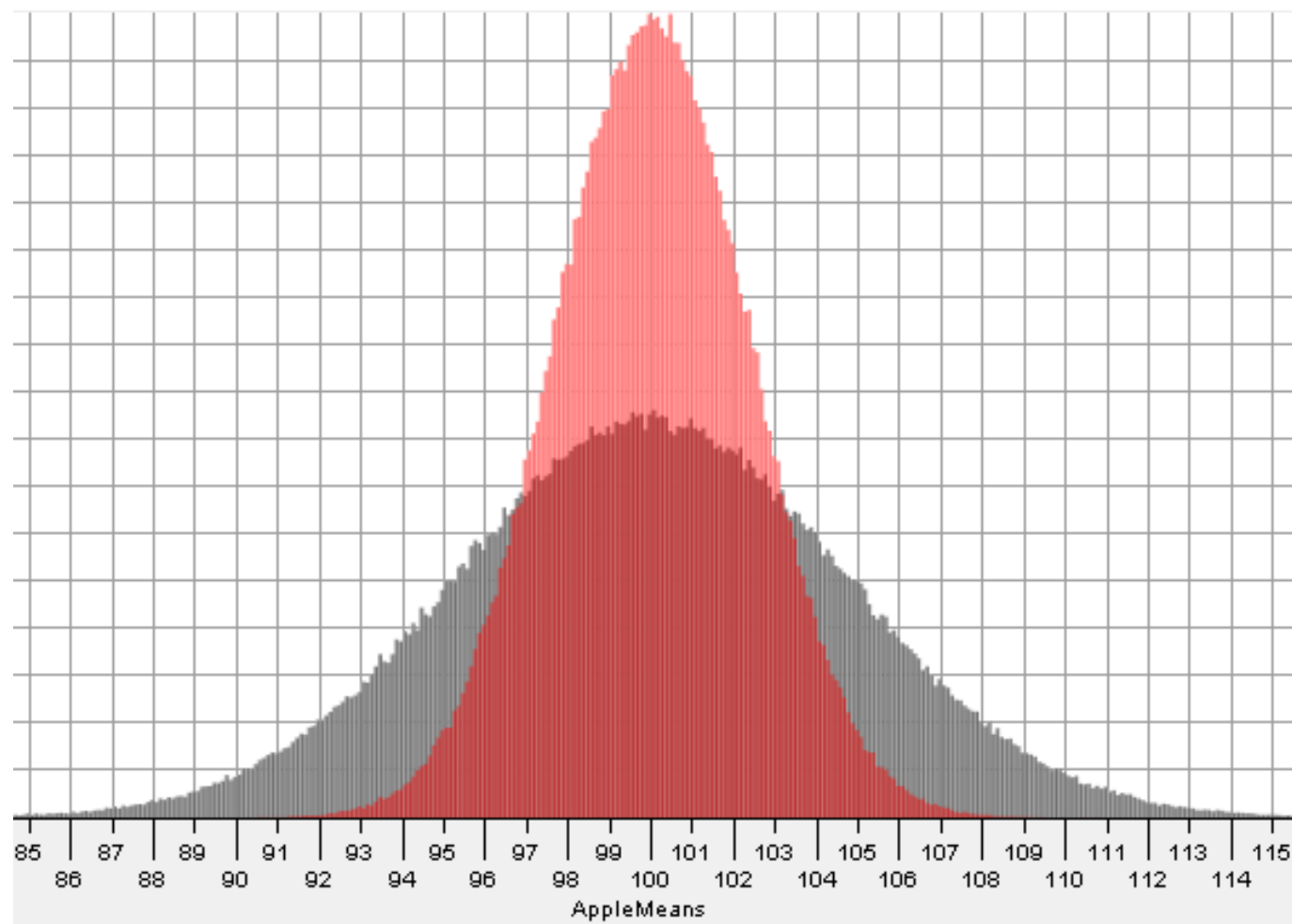
(B) No Person: 0.99, Water: 0.98, Beach: 0.97, Outdoors: 0.97, Seashore: 0.97



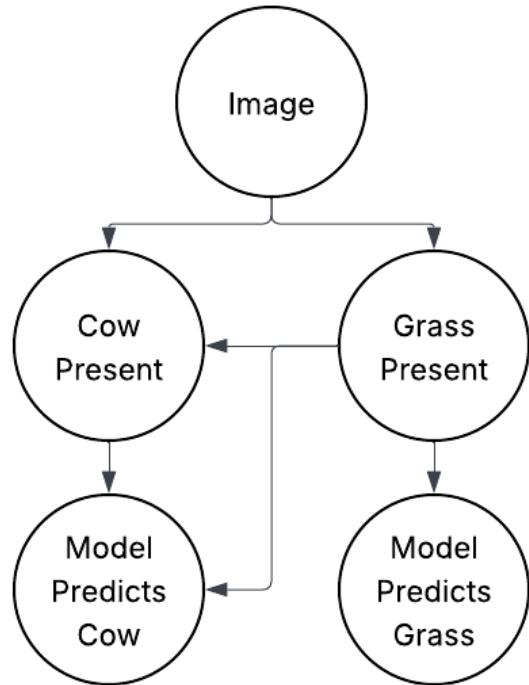
(C) No Person: 0.97, **Mammal: 0.96**, Water: 0.94, Beach: 0.94, Two: 0.94



How to solve bias?



How to solve bias?



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Introducing Causality



- ▶ "Patients who take Drug A tend to recover faster"
 - ▶ **Observation/Correlation** -> $P(R | A)$

Introducing Causality



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- ▶ Which one is it?



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Introducing Causality

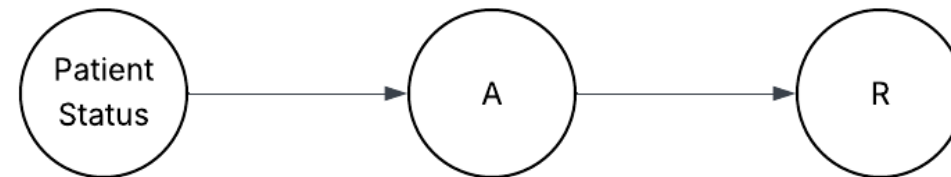


- ▶ “Patients who take Drug A tend to recover faster”
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 - ▶ **Intervention/Causality** -> $P(R | do(A))$
- ▶ **Randomized Control Trials** enforce intervention!

Introducing Causality



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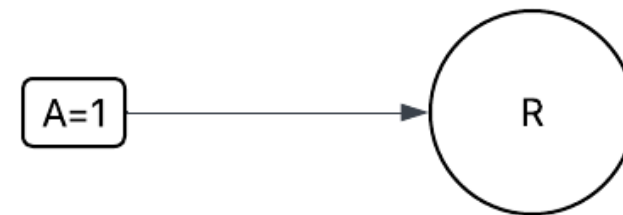


Full Model

Introducing Causality



- ▶ “Patients who take Drug A tend to recover faster”
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Model with intervention $A=1$

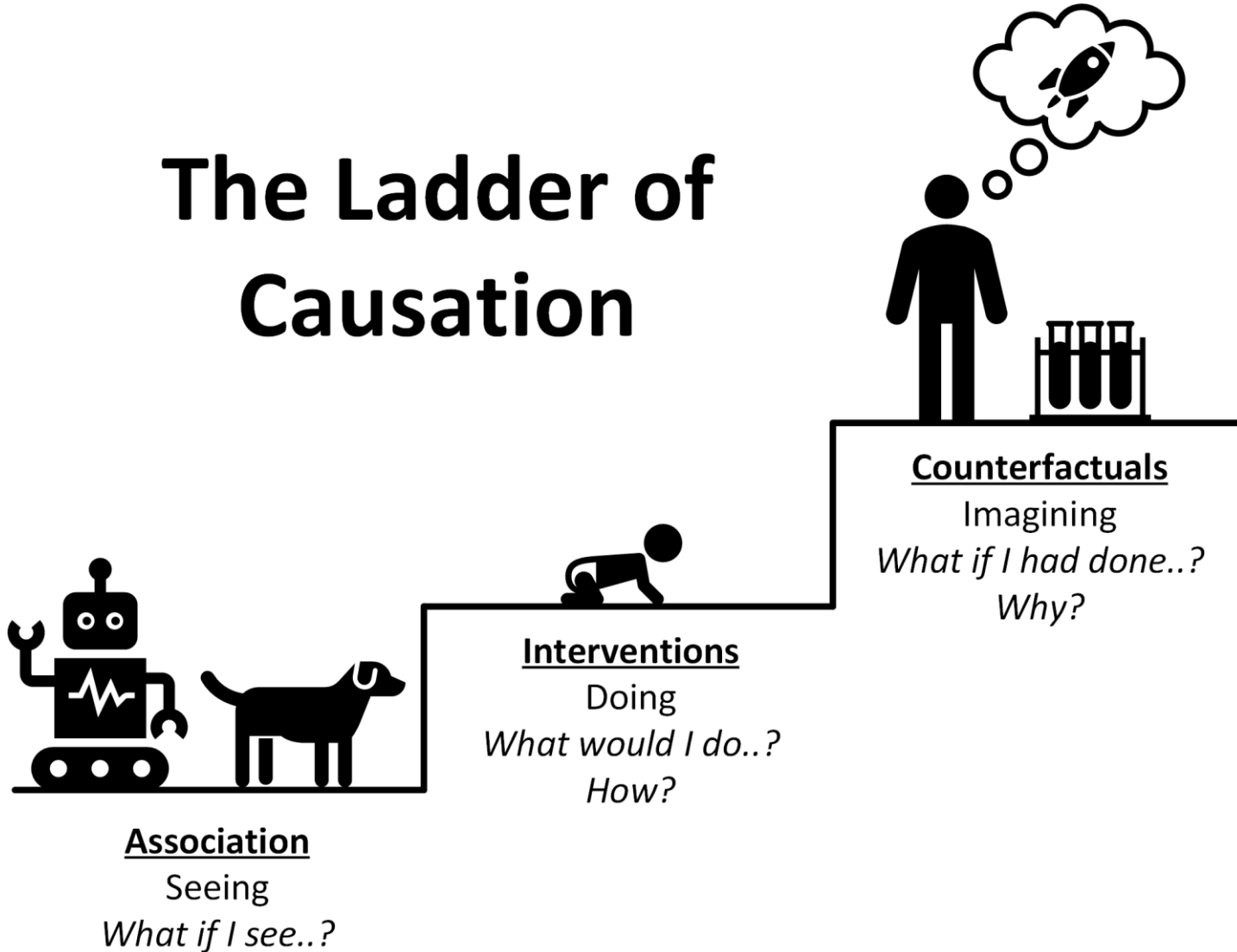
Judea Pearl



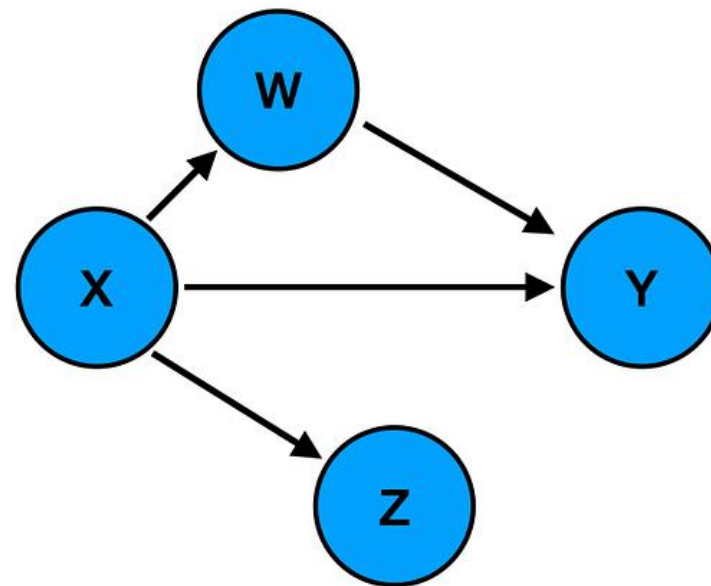
- ▶ “The father of modern Probabilistic AI”: invented Bayesian Networks in the 1980s
- ▶ Leader of the Causal Revolution
- ▶ Turing Award winner
- ▶ Wrote “The Book of Why” for non-mathematicians to understand causality

Ladder of Causation

The Ladder of Causation



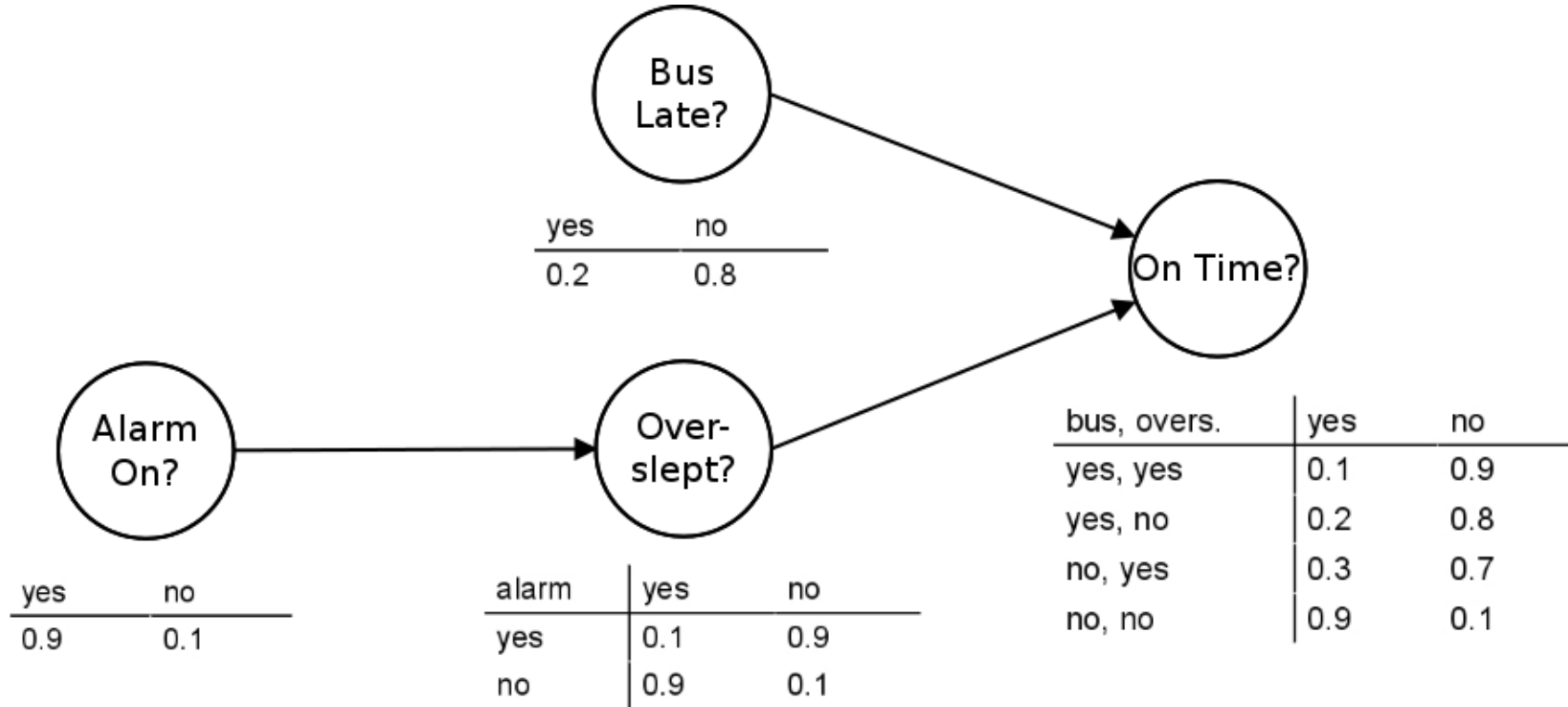
(Causal) Structure Discovery



Rung 1: Bayesian Networks

$$P(A|B) = \frac{P(B|A) P(A)}{P(B)}$$

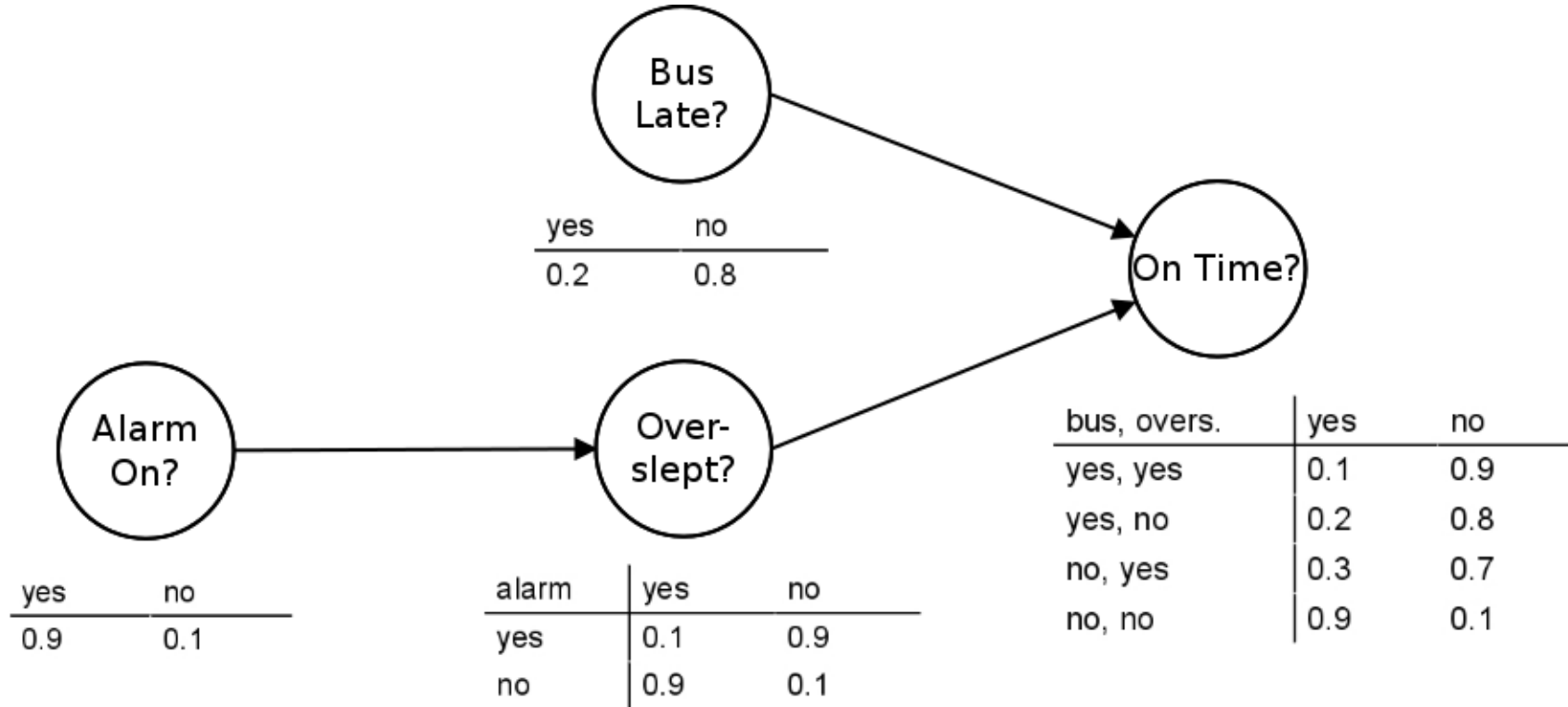
Based on Bayes' Theorem



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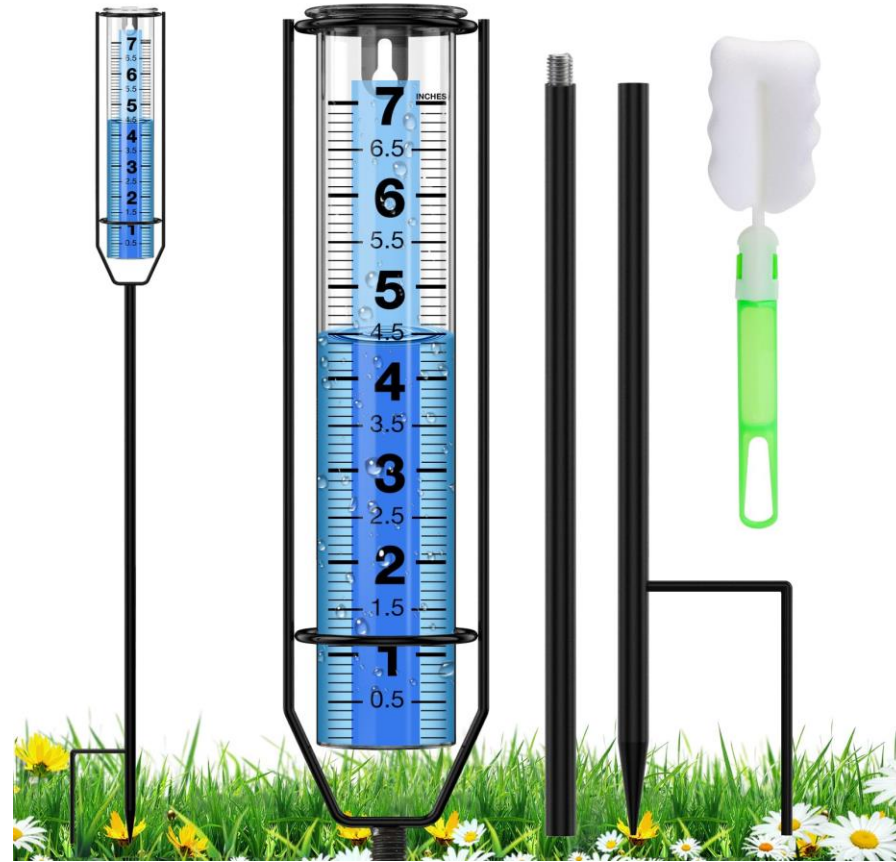
Can only look at associations by design!

The Issues with Rung 1



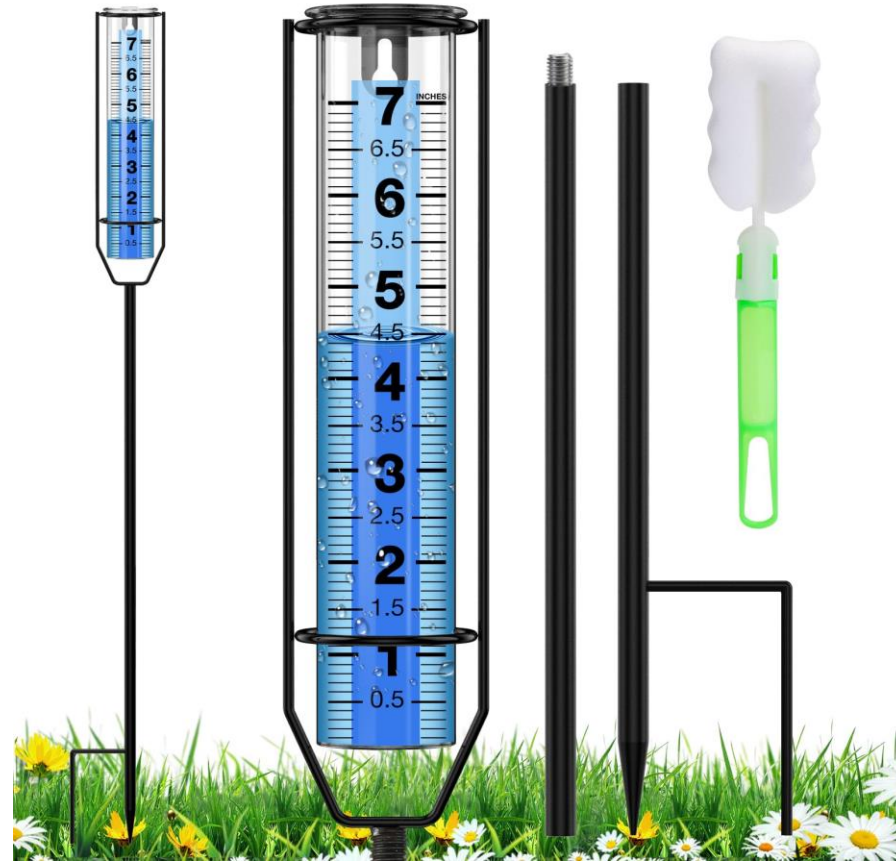
Hidden/Latent Confounder!

The Issues with Rung 1



No Interventions!

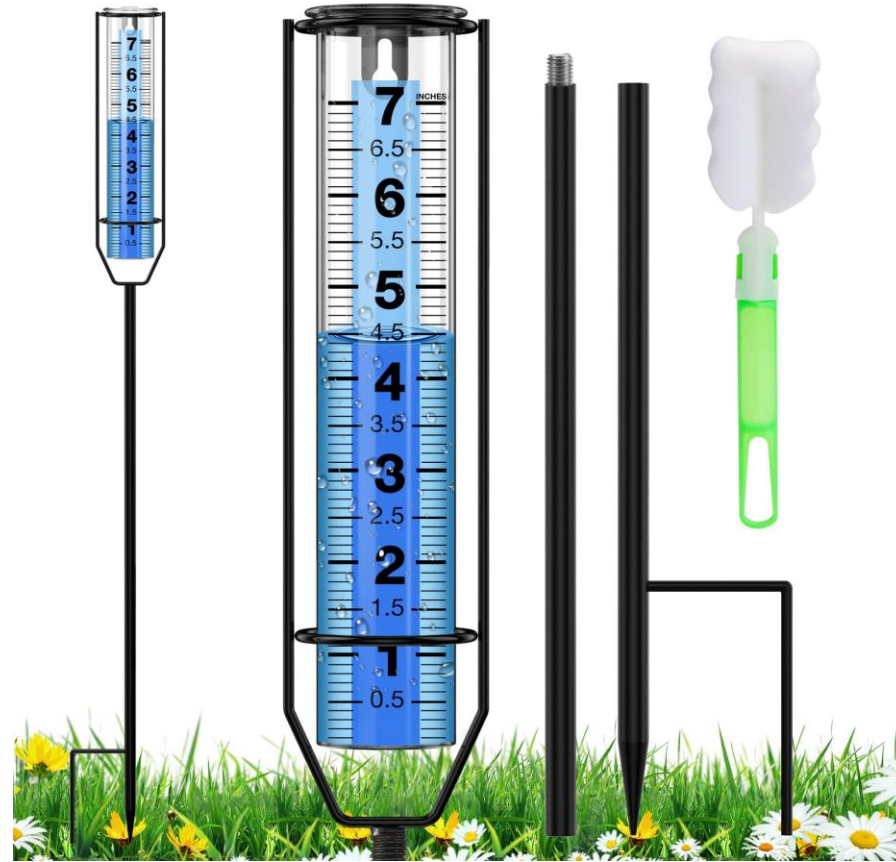
The Issues with Rung 1



Check whether temperature humidity influences the rain gauge.

No Interventions!

The Issues with Rung 1

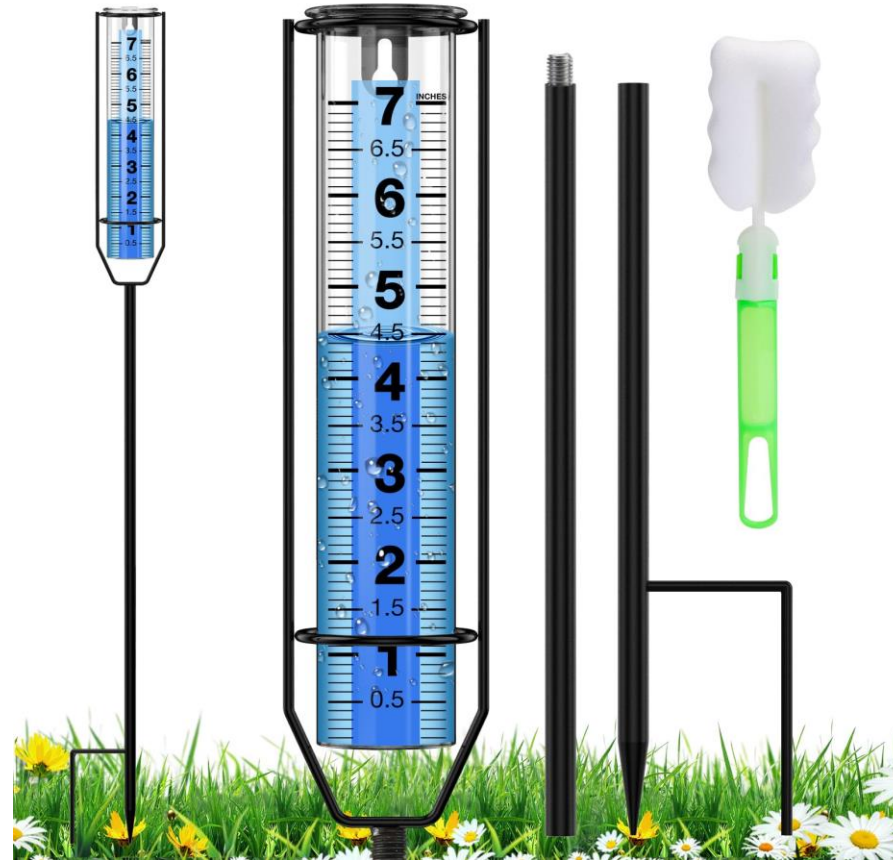


Check whether temperature humidity influences the rain gauge.

Regular Conditions: $P(F | H)$
F = Full
H = Humidity Level

No Interventions!

The Issues with Rung 1



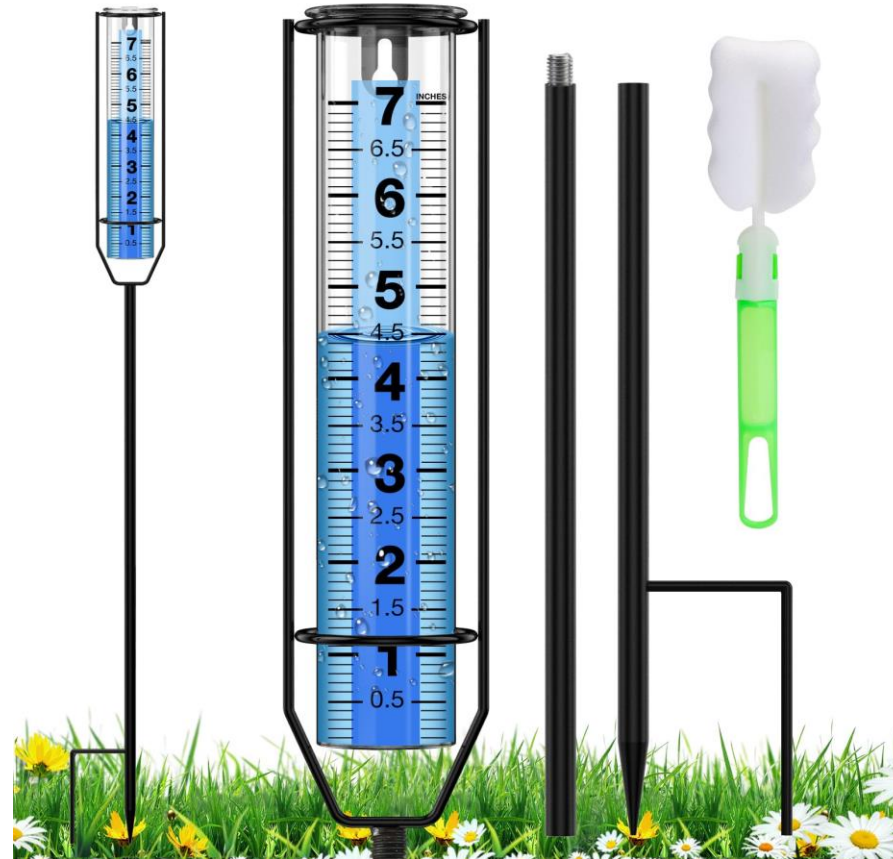
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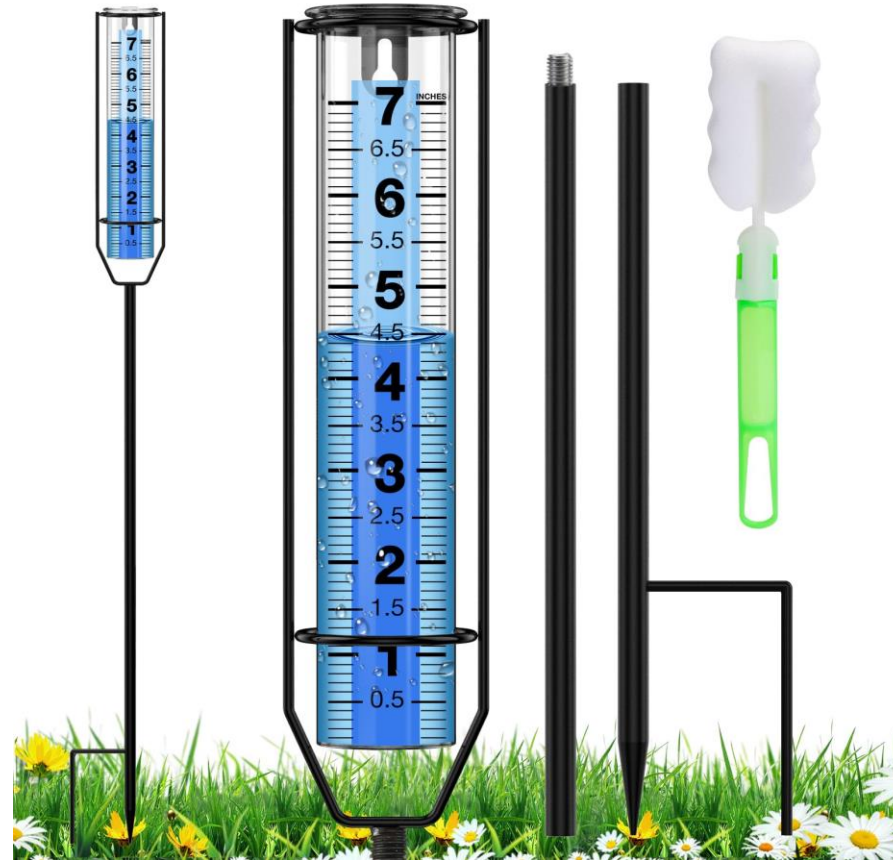
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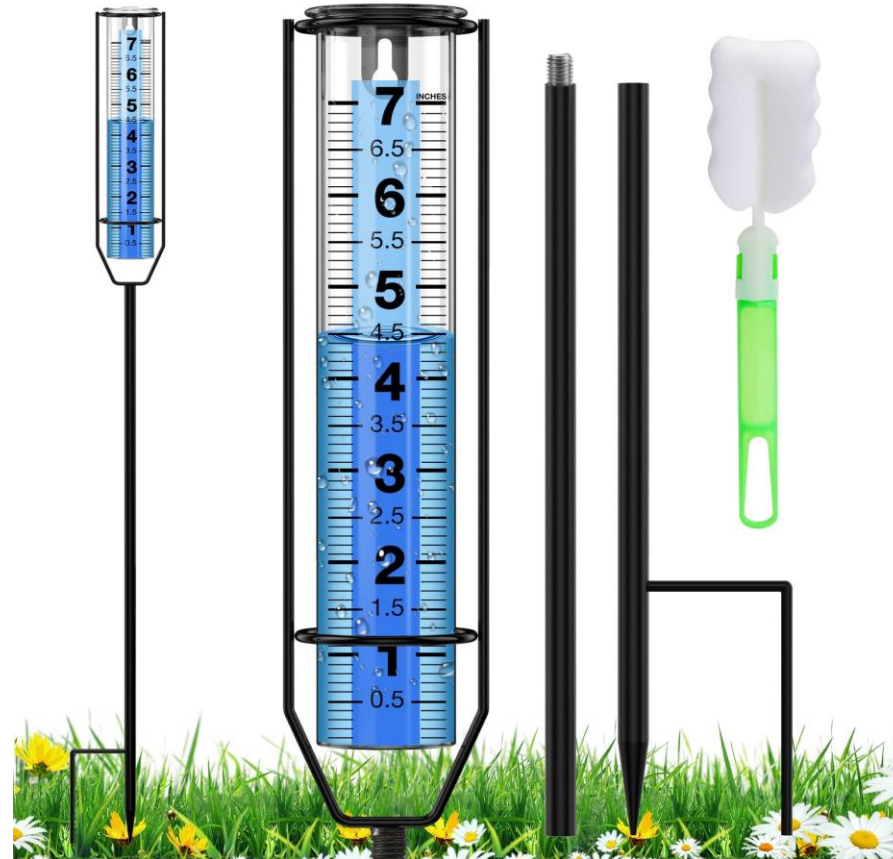
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Unless we model the toddler in the BN, no way to express intervention.

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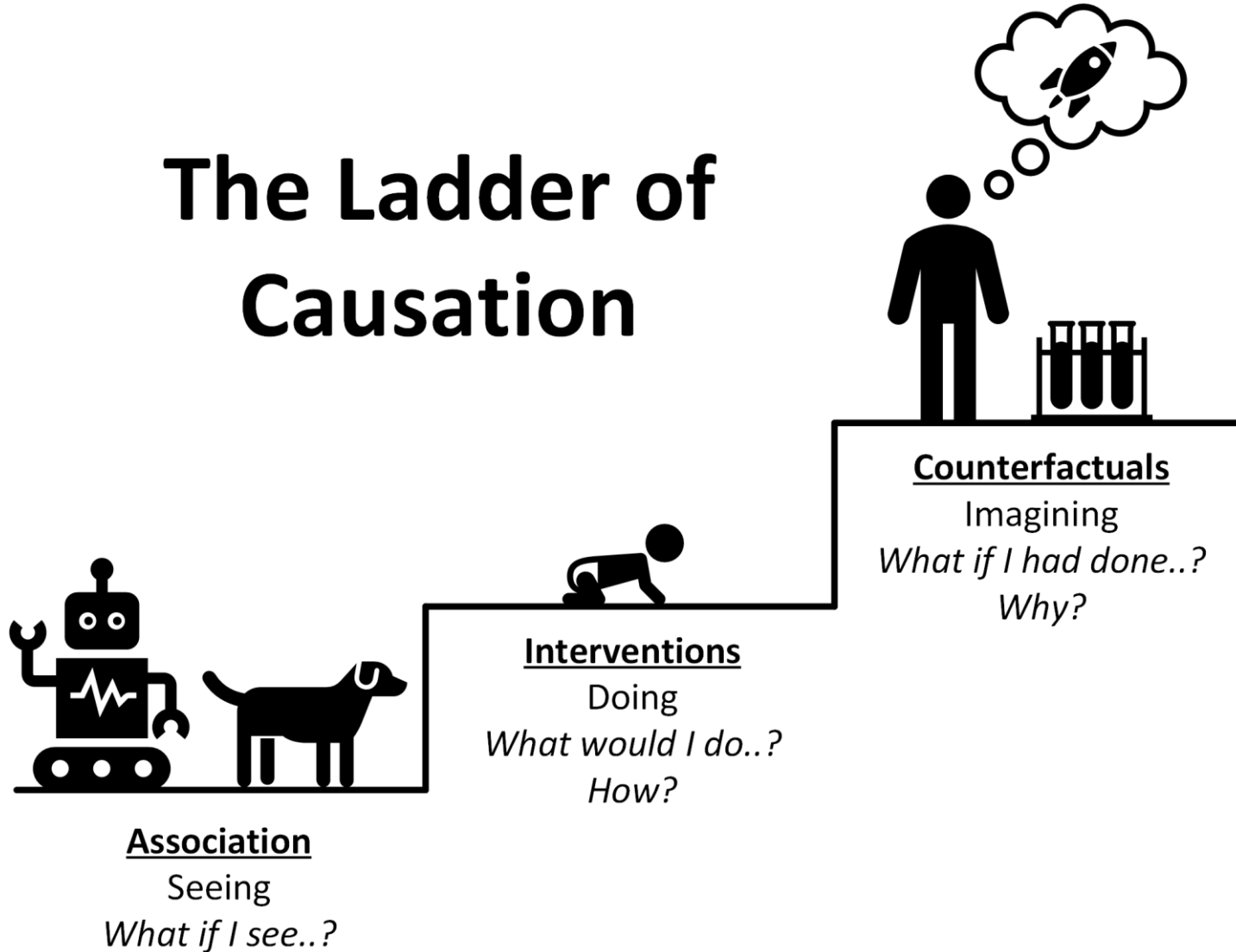
The Issues with Rung 1



No Counterfactuals!

Ladder of Causation

The Ladder of Causation

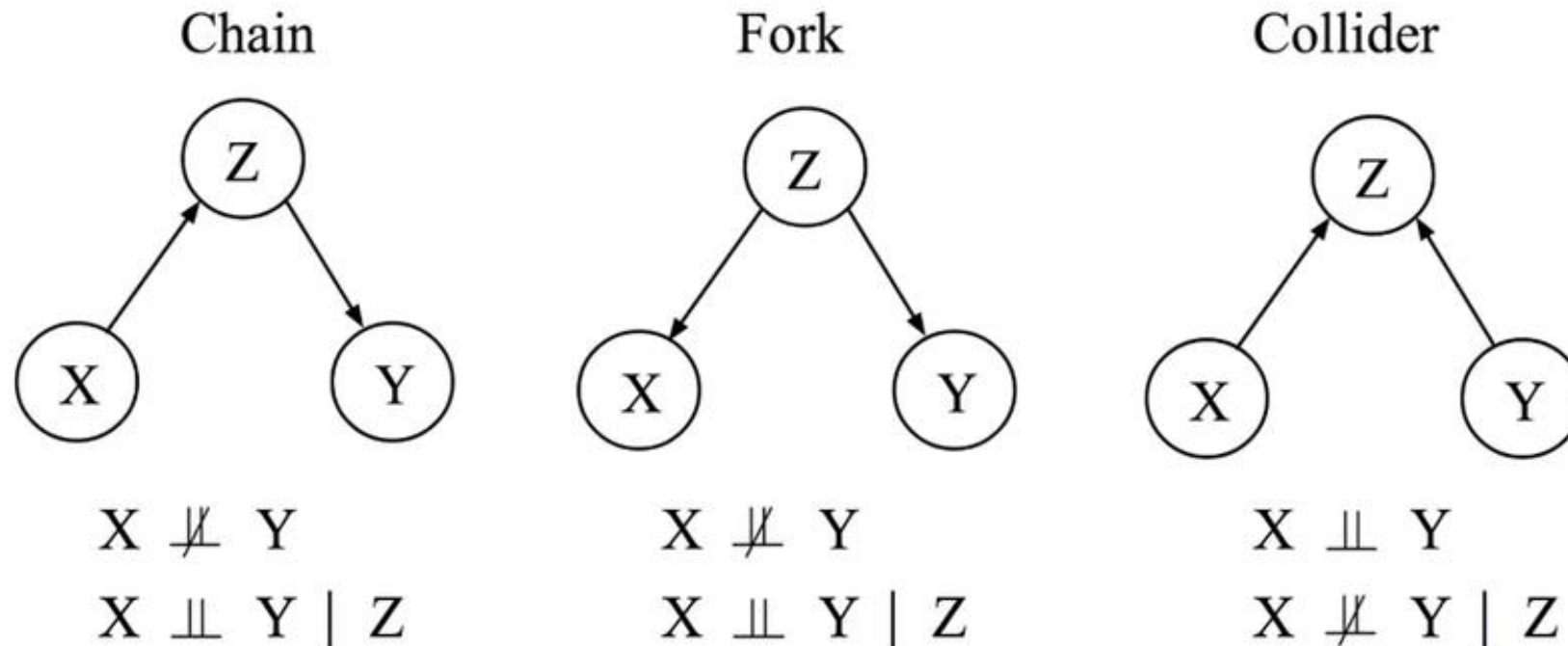


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- ▶ Scales horribly with high dimensional data

$$a_k = \sum_{j=1}^k (-1)^{j-1} \binom{k}{j} 2^{j(k-j)} a_{k-j}$$

Nodes (k)	Number of DAGs (a_k)
1	1
2	3
3	25
4	543
5	29,281
6	3,781,503
7	1,138,779,265

Open Challenges of Causality

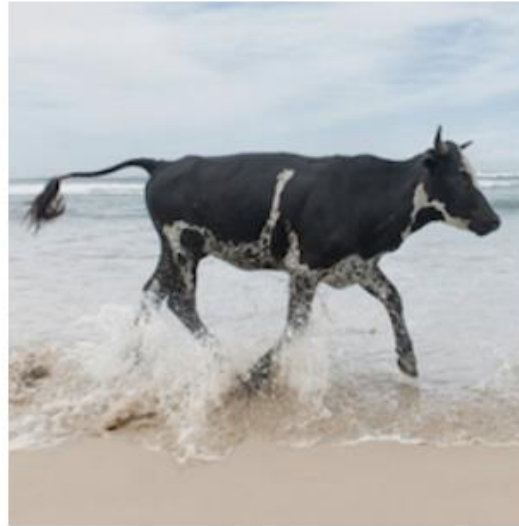
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- ▶ Current Causal algorithms require functional assumptions (linearity) or fail to converge to a single DAG
- ▶ Scales horribly with high dimensional data
- ▶ Most theoretical assumptions are only for discrete data

Potential for Causality in ML Models

- ▶ Causally-guided ML models
 - ▶ Feature Selection
 - ▶ Counterfactual Data Generation



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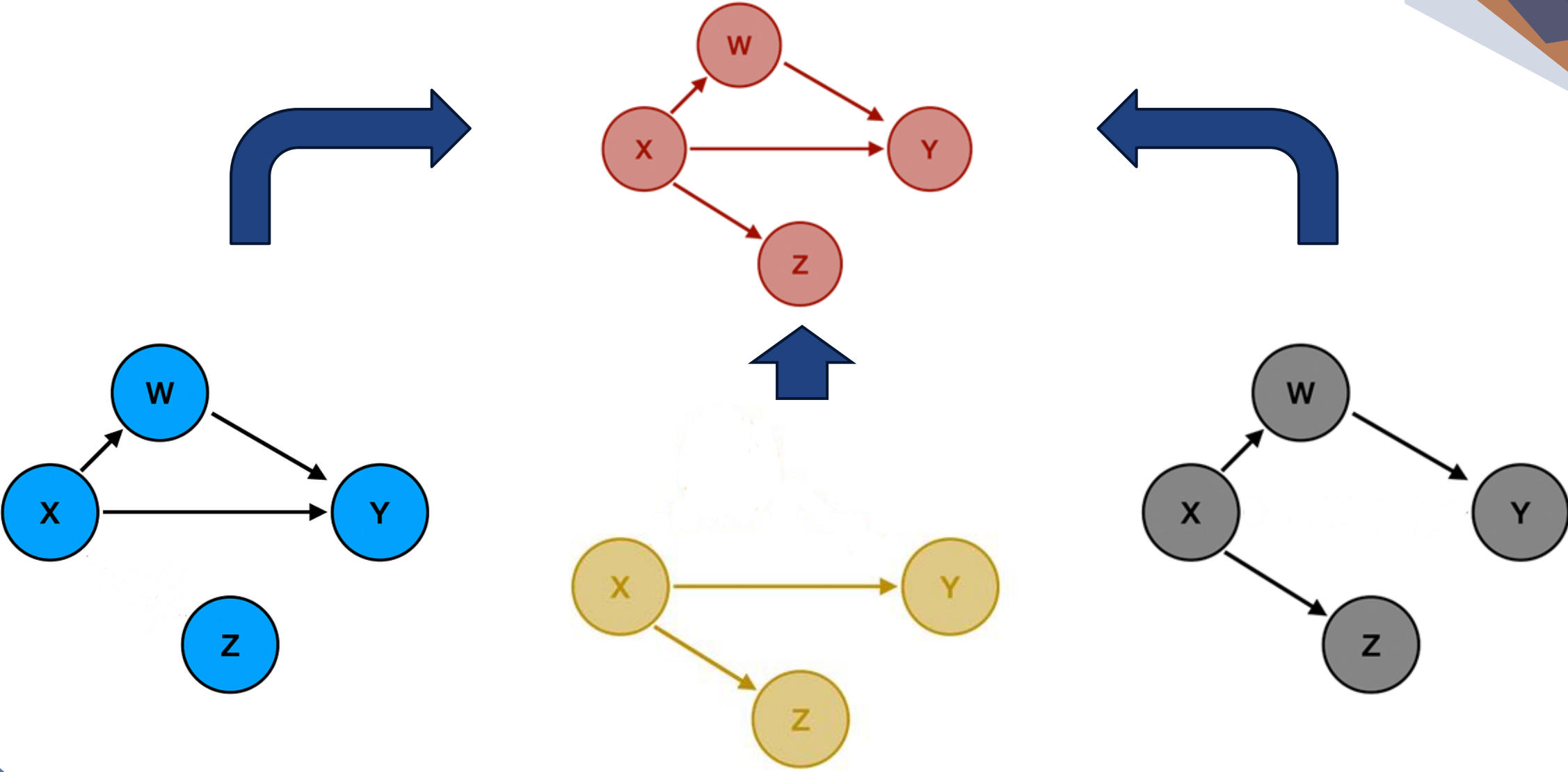
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Federated Causal Discovery



The Federation



ARTIFICIAL
INTELLIGENCE
RESEARCH GROUP

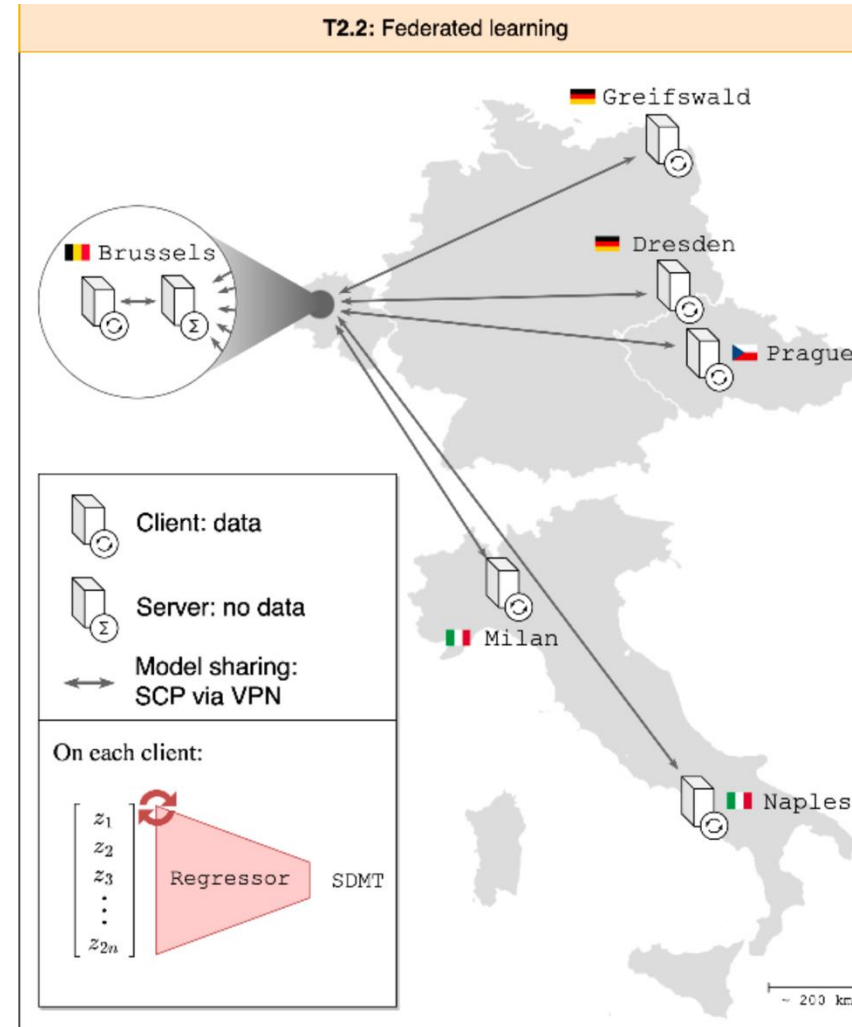
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