

# Measuring and mitigating bias in healthcare language models



**Gaurav Kaushik, PhD**  
Founder  
ScienceIO

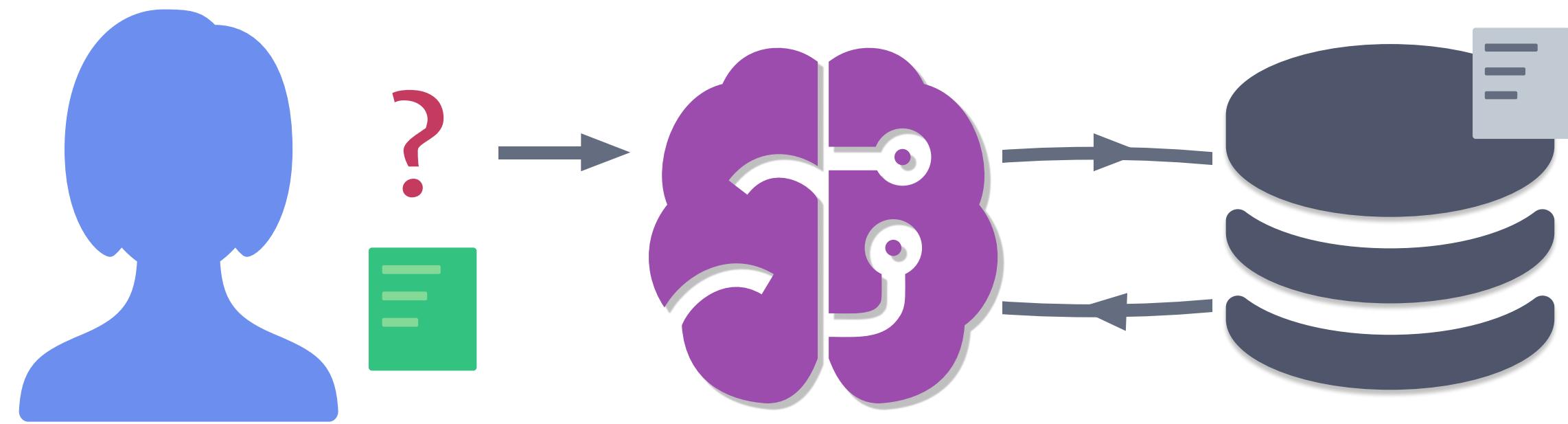


**Co-founder**  **ScienceIO**  
**Lead AI, technology, and product**

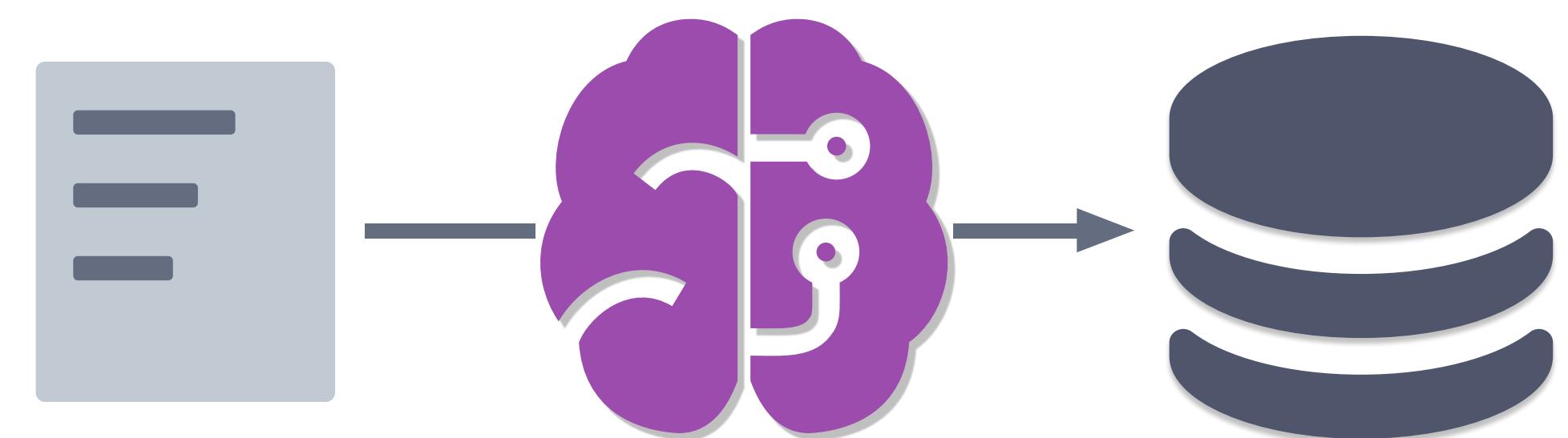
Past:

- **RWD** | Foundation Medicine (Roche)
- **Product** | Seven Bridges (Velsera)
- **Bioeng** | Harvard, UCSD

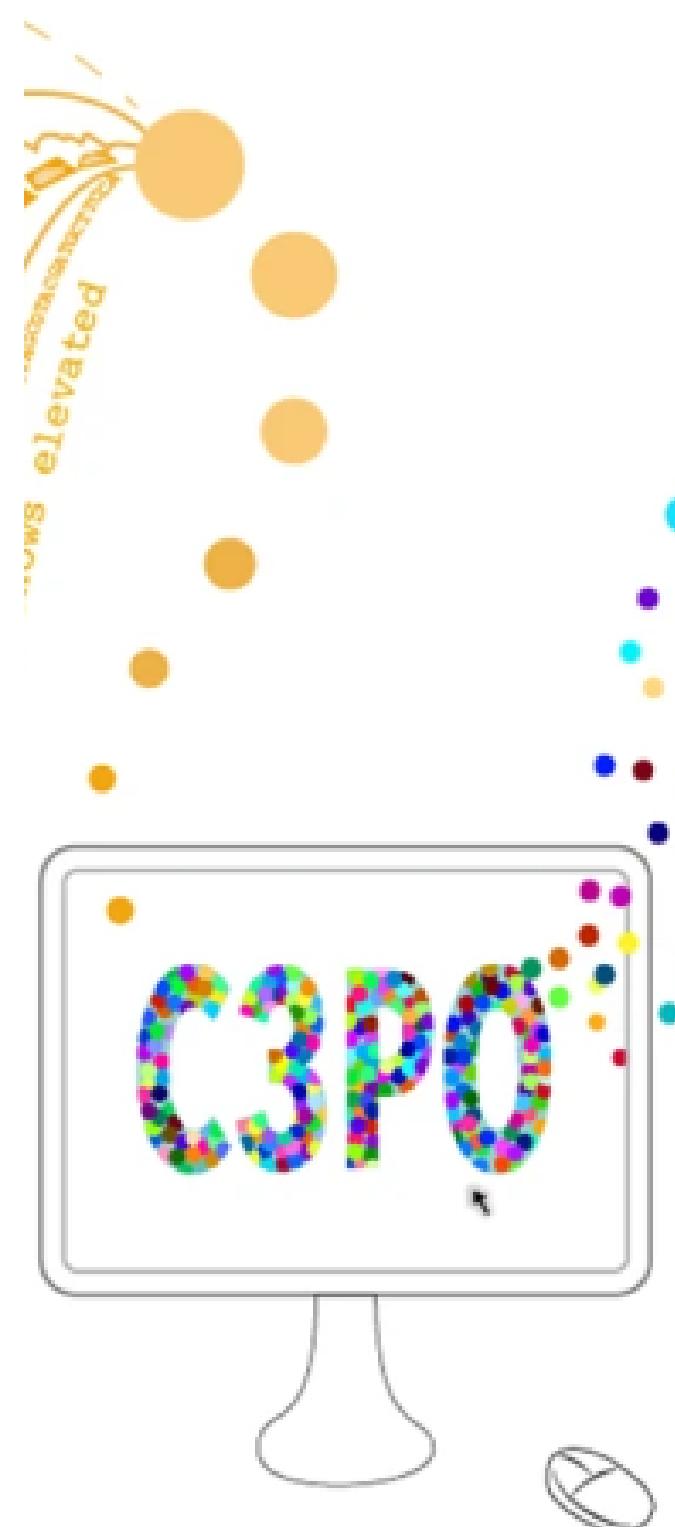
# Key healthcare NLP workflows



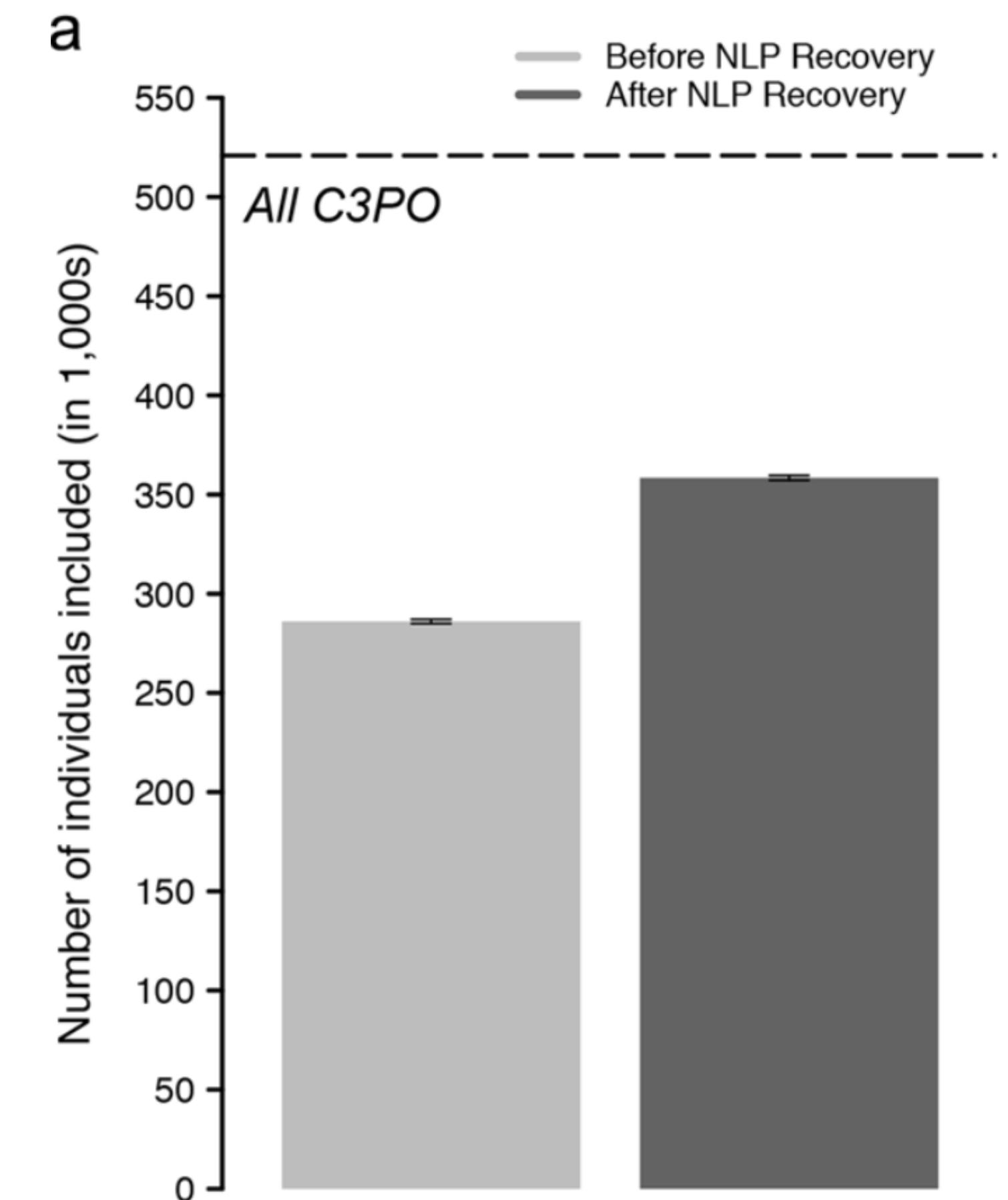
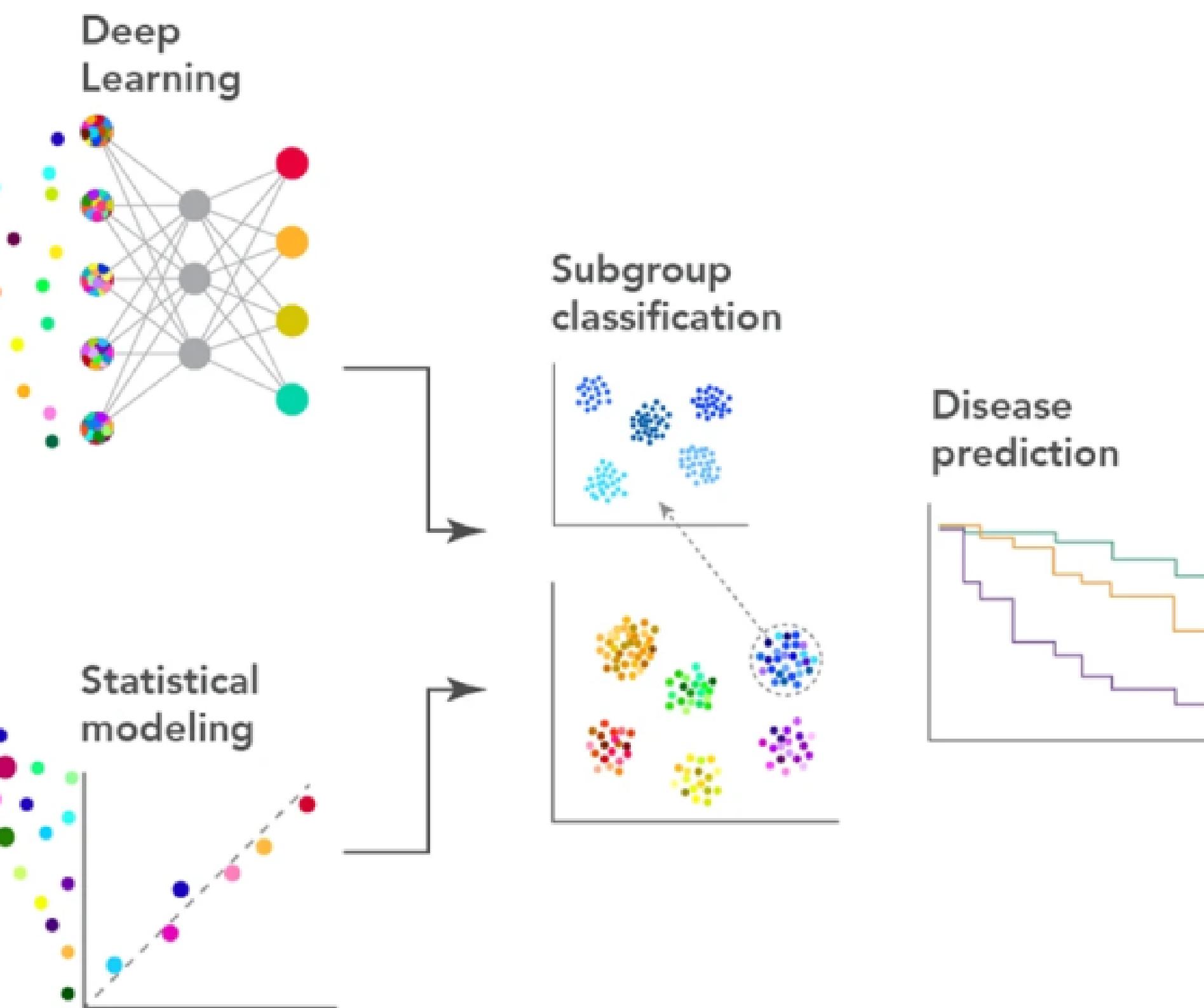
Fast, accurate  
information retrieval  
(QA, NSP)



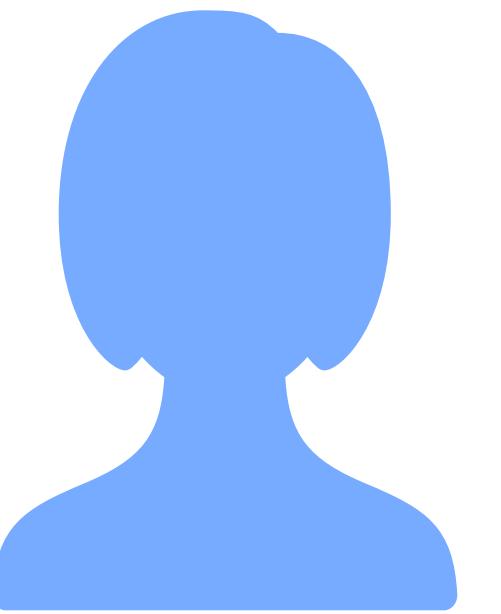
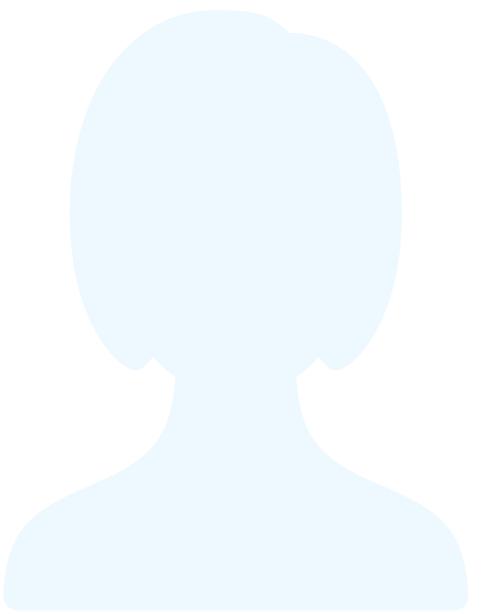
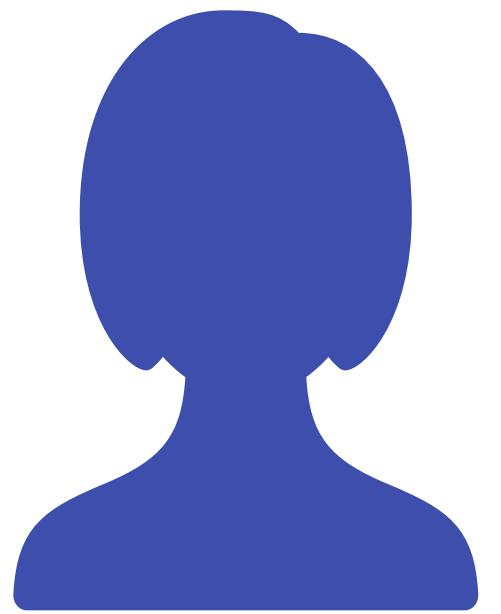
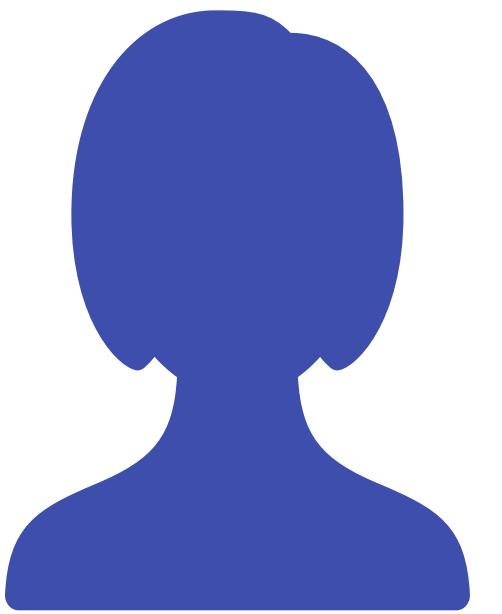
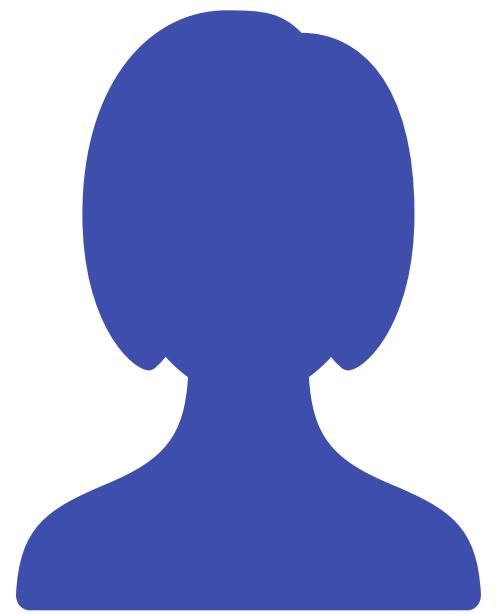
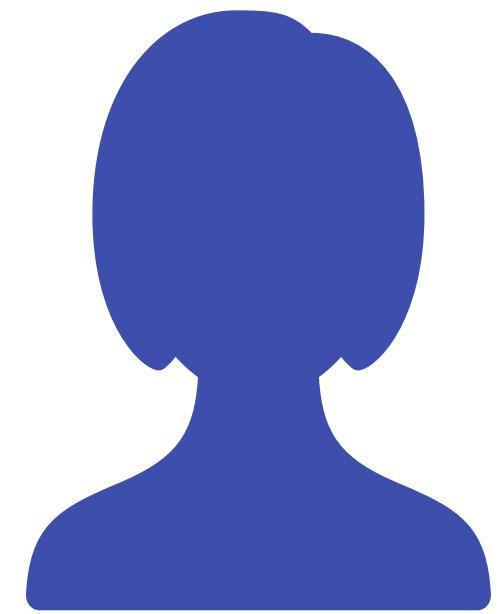
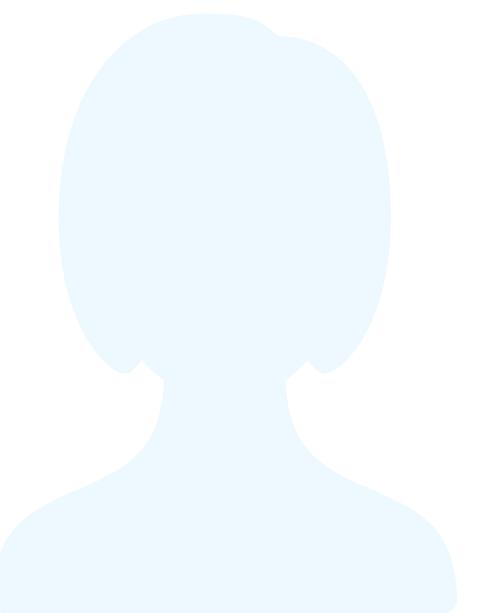
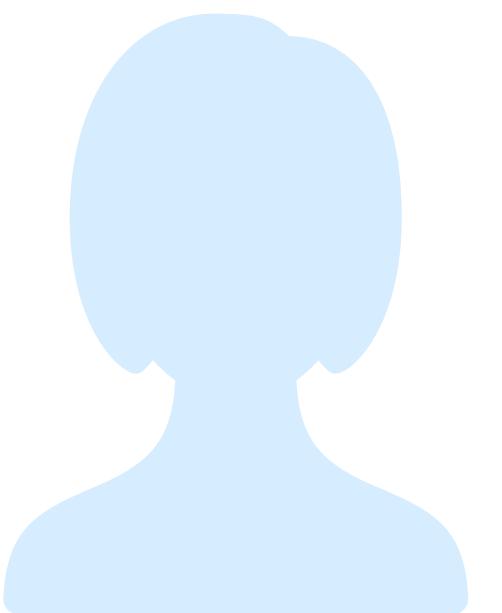
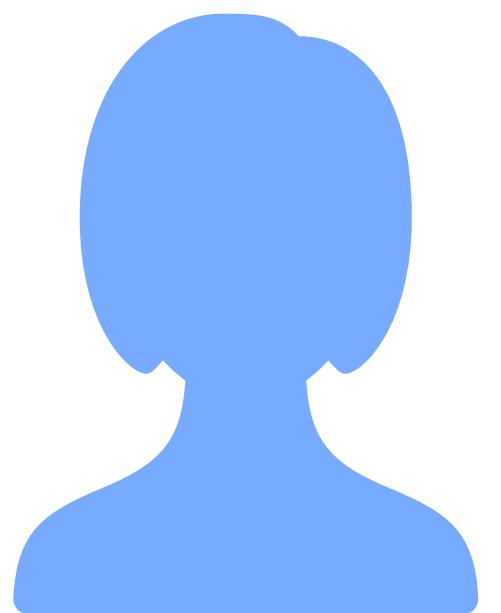
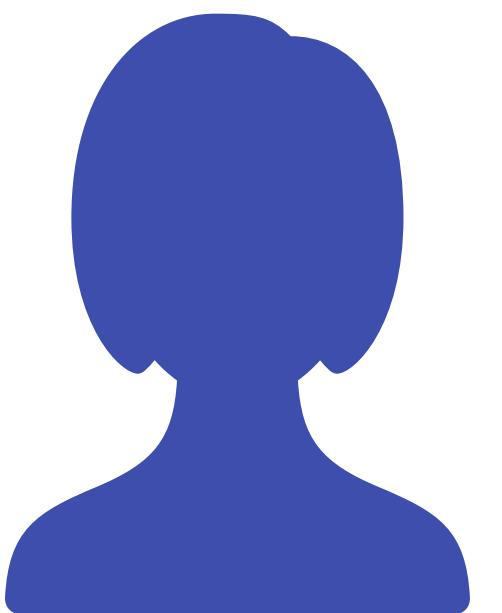
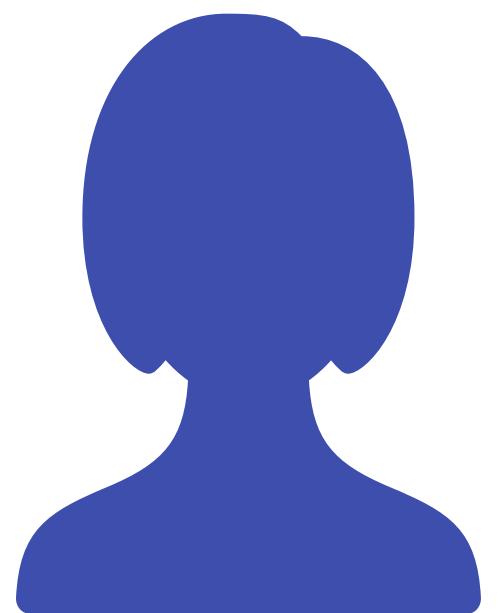
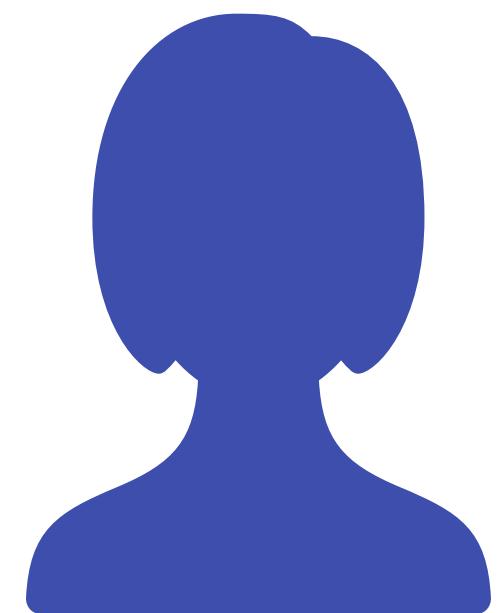
Structuring variables  
in free text  
(entity linking)



1 dot = 1 person



**31% reduction  
in missing data with NLP**



An **unbiased system** captures the **full fidelity** of information across patients or data types

In practice, systems can be biased to have **lower fidelity** for certain patients or data types

# Algorithmic bias

Systematic and **repeatable** errors that yield unfair outcomes which benefit certain groups over others

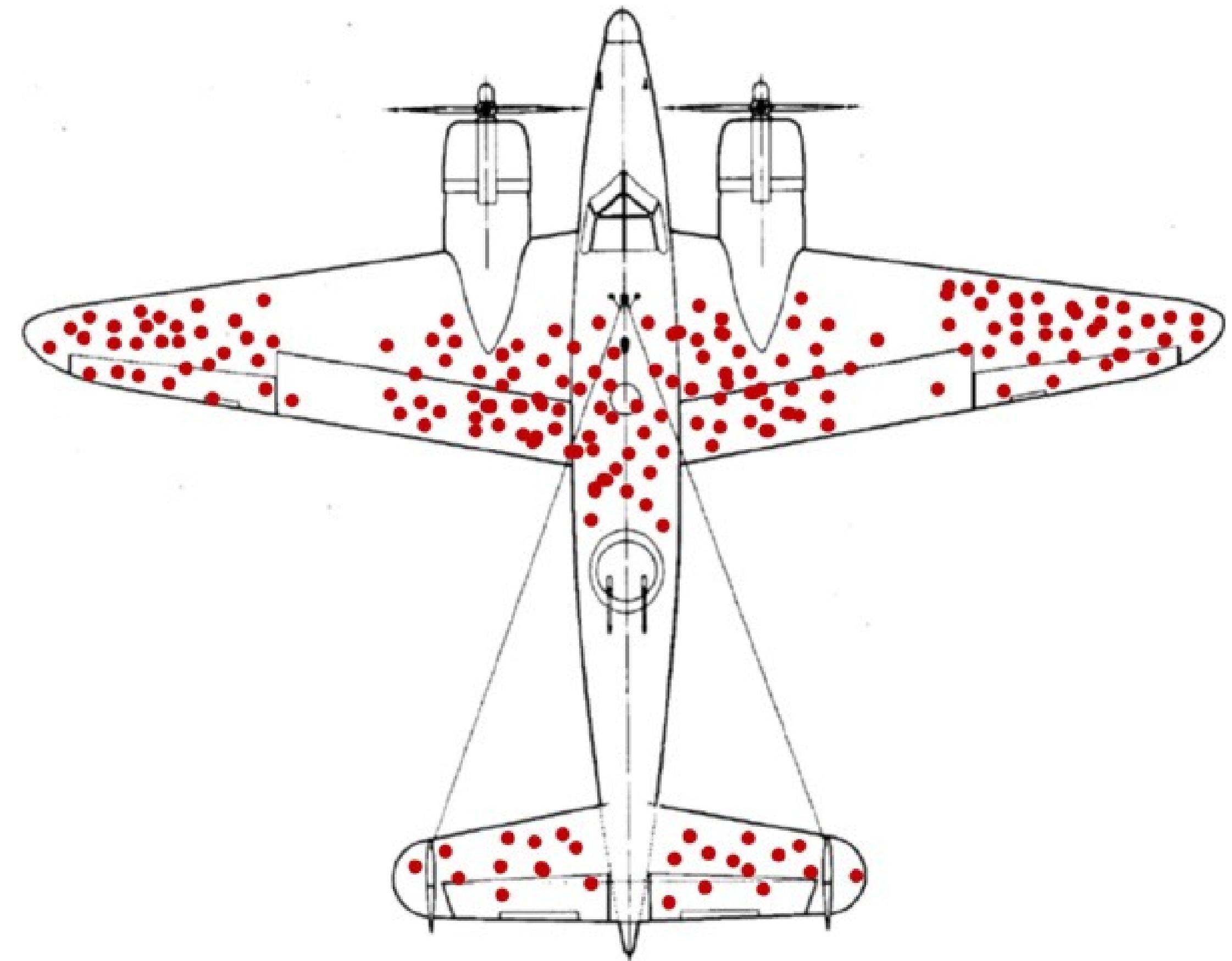
Healthcare NLP systems will influence clinical outcomes and therefore will **mitigate** or **exacerbate** outcome disparities

## **Selection biases**

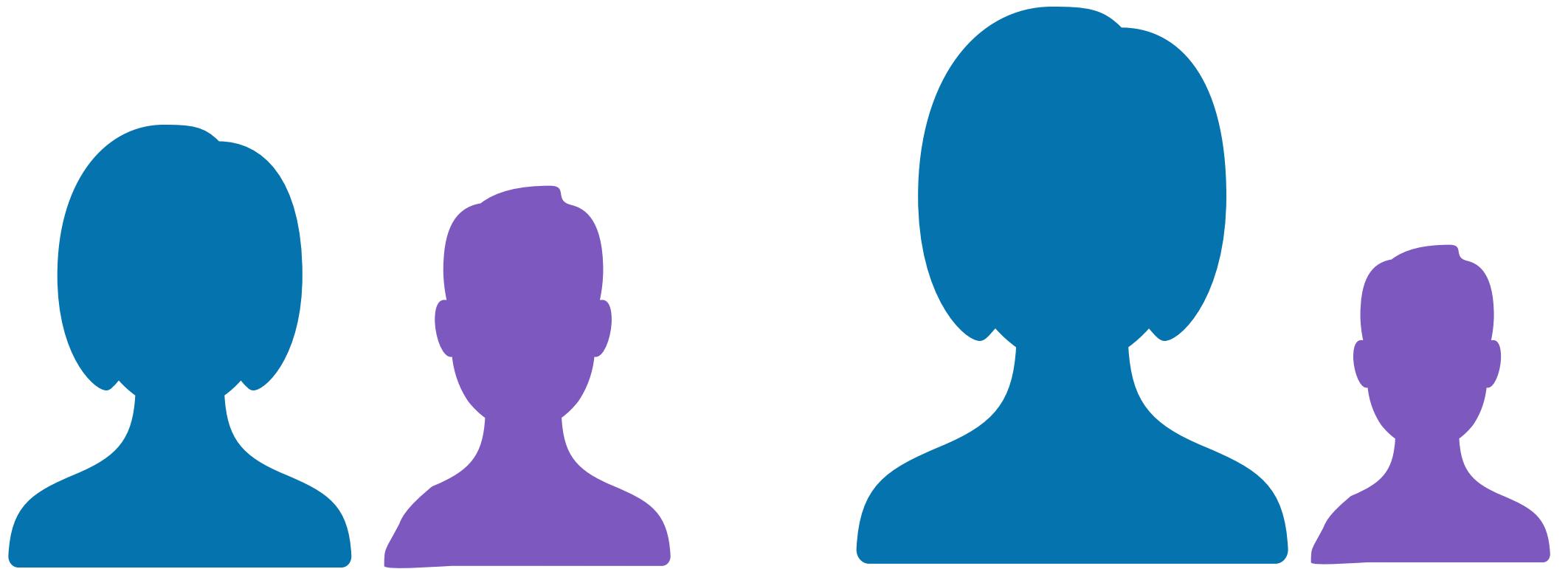
data used in training the model  
does not represent real-world

## **Label biases**

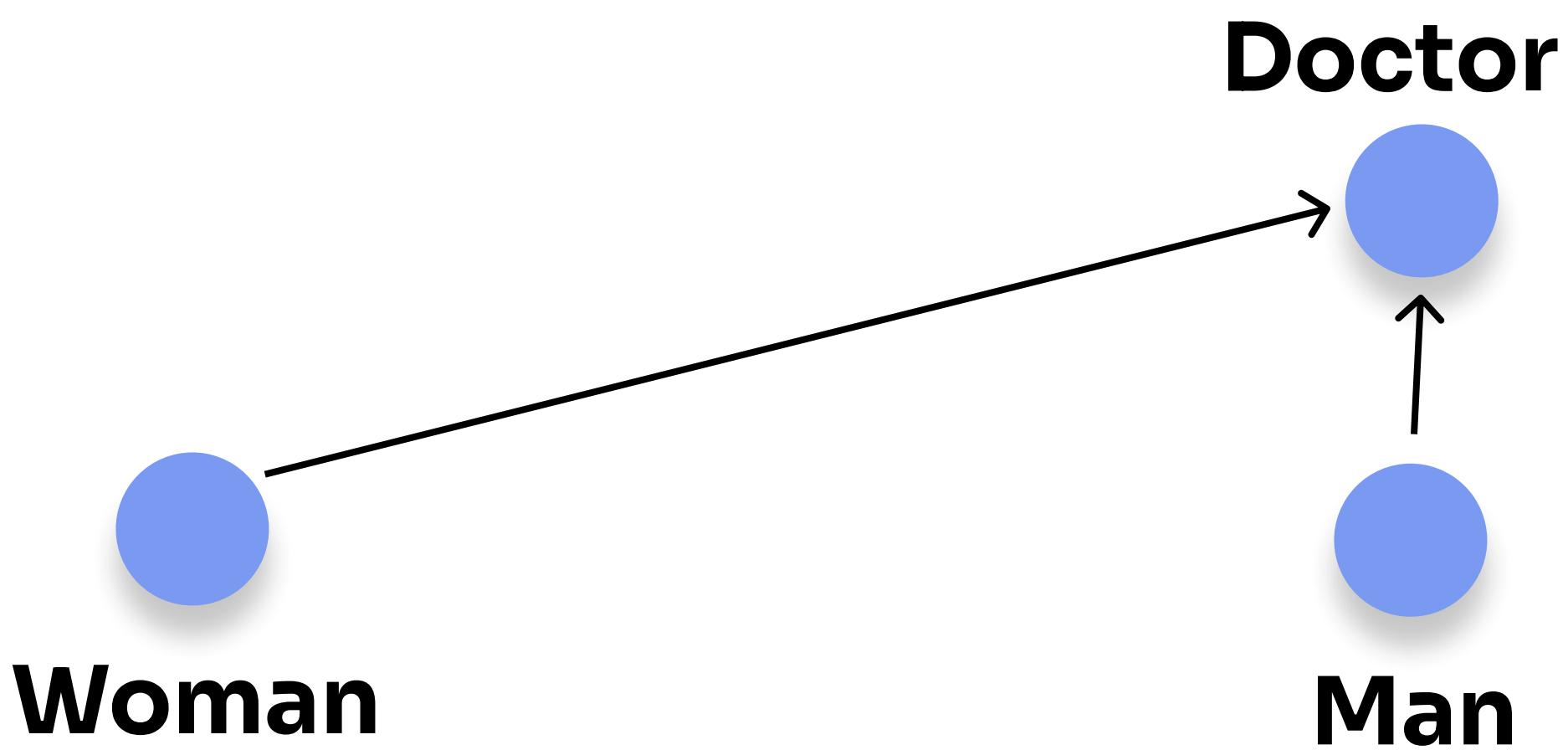
mismatch between annotations  
and target, e.g. due to judgement,  
human error, or label ambiguity



**Over-amplification**  
models amplify biases in the  
training data



**Semantic biases**  
bias from input representations  
such as inappropriate  
word associations

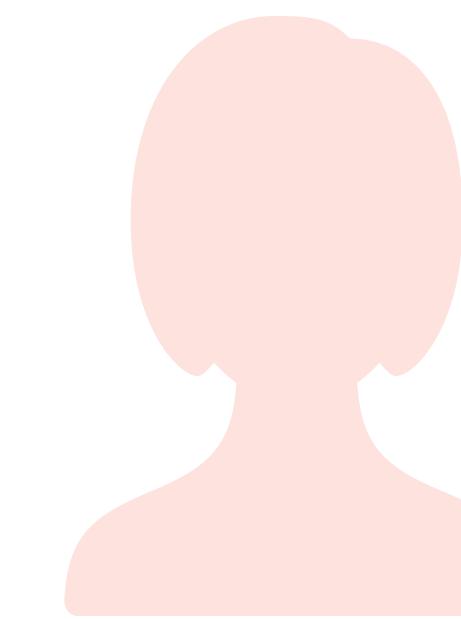
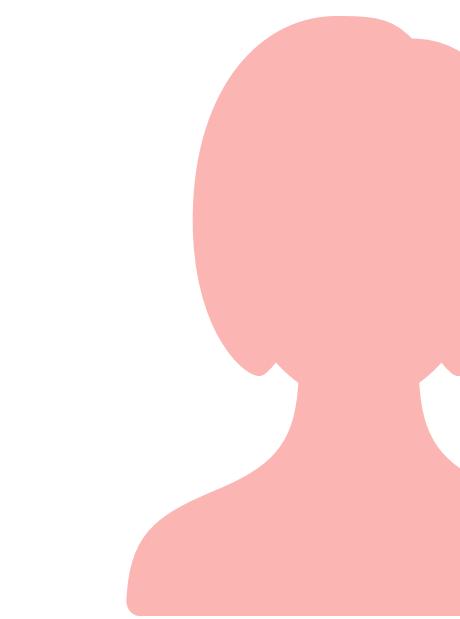
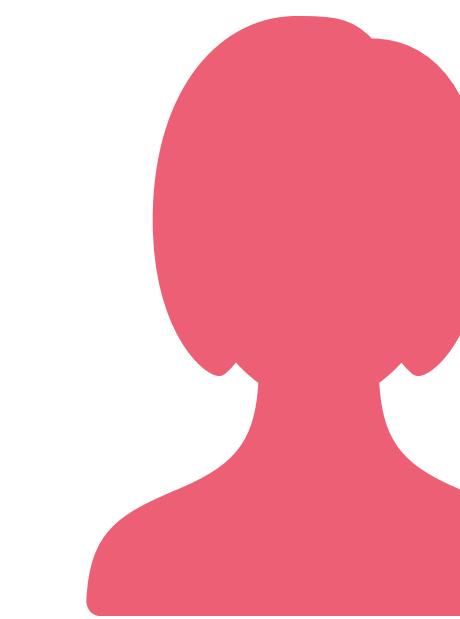
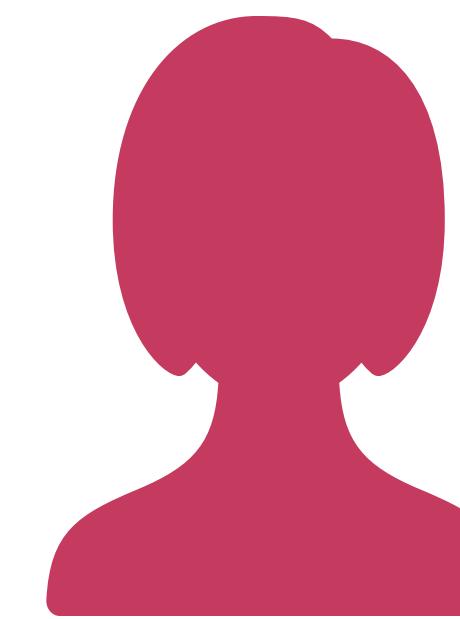
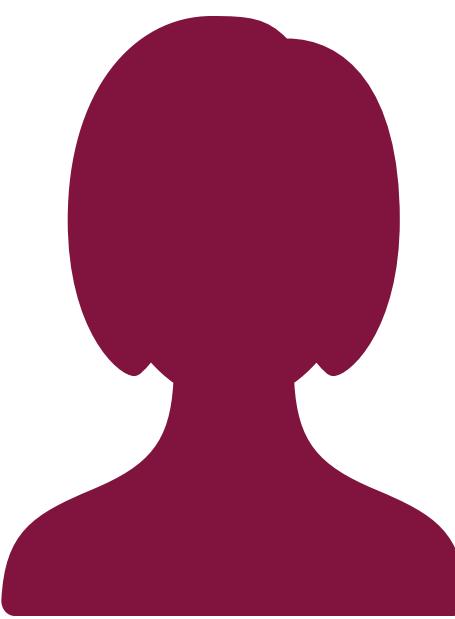


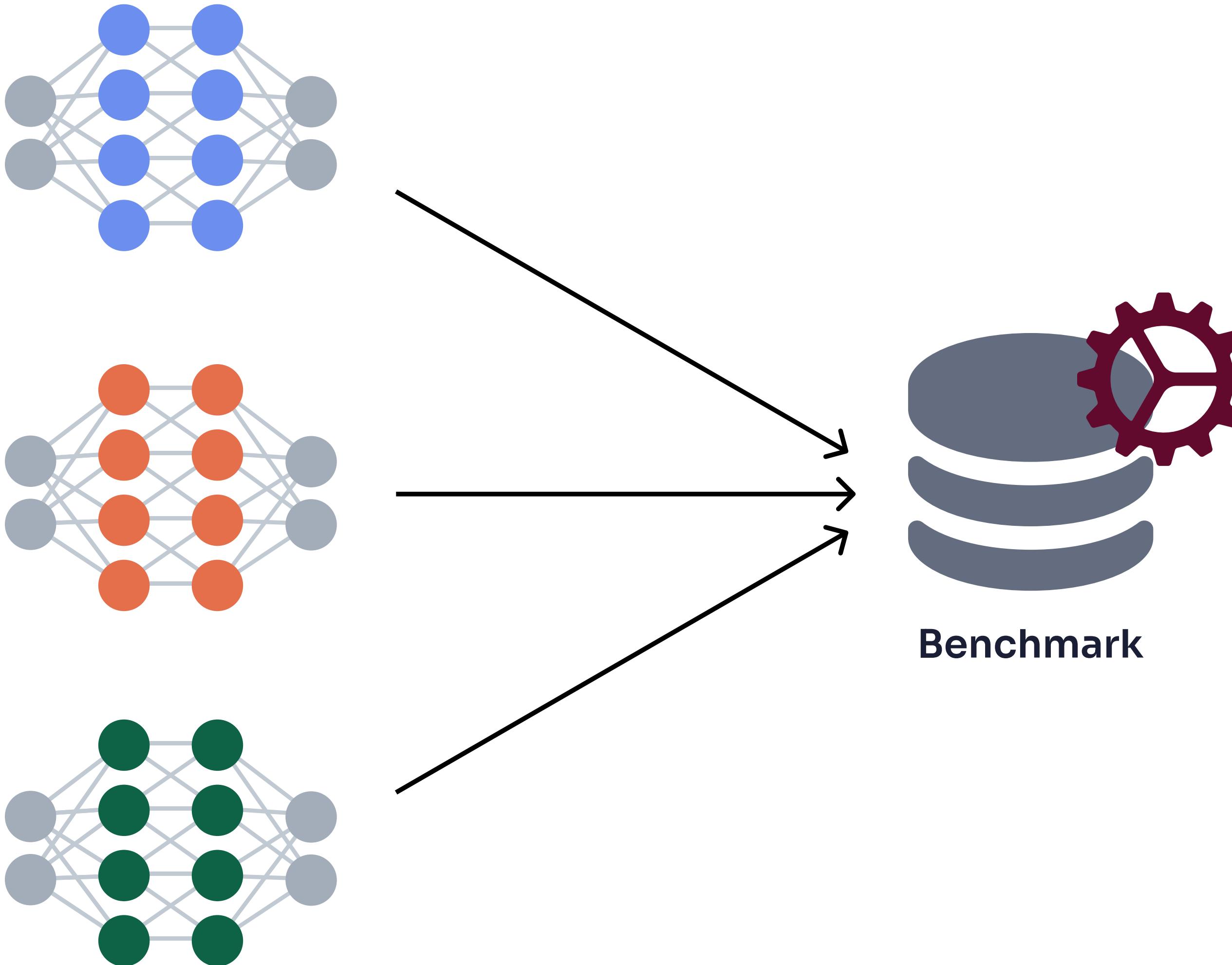
## **Demographic biases**

improper sensitivity to race or gender, or impaired performance on attributes related to subgroups

## **Domain biases**

error bias in medical subdomains, such as disease areas, which can impair generalization





How can we evaluate performance and bias?

Performance on NLP benchmarks  
do not guarantee robust real-world performance

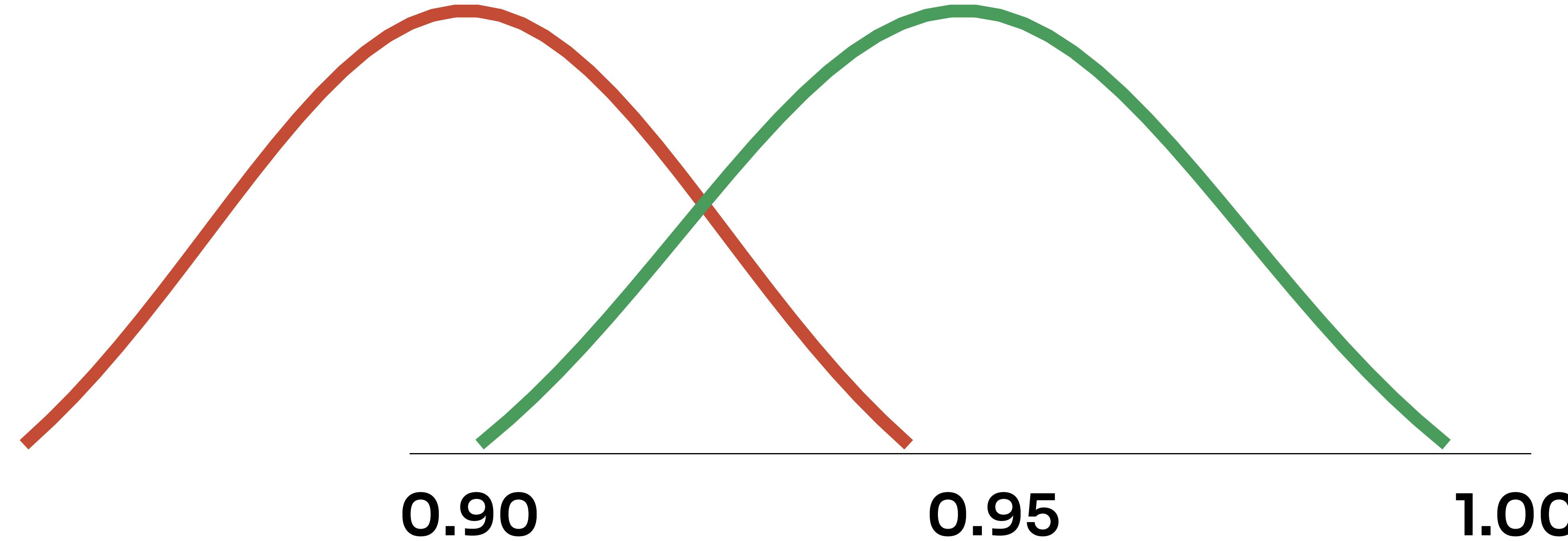
They lack statistical power

They are not validated enough

They do not disincentivize biased systems

Is a model with  $F_1=0.95$  better than a model with  $F_1=0.90$ ?

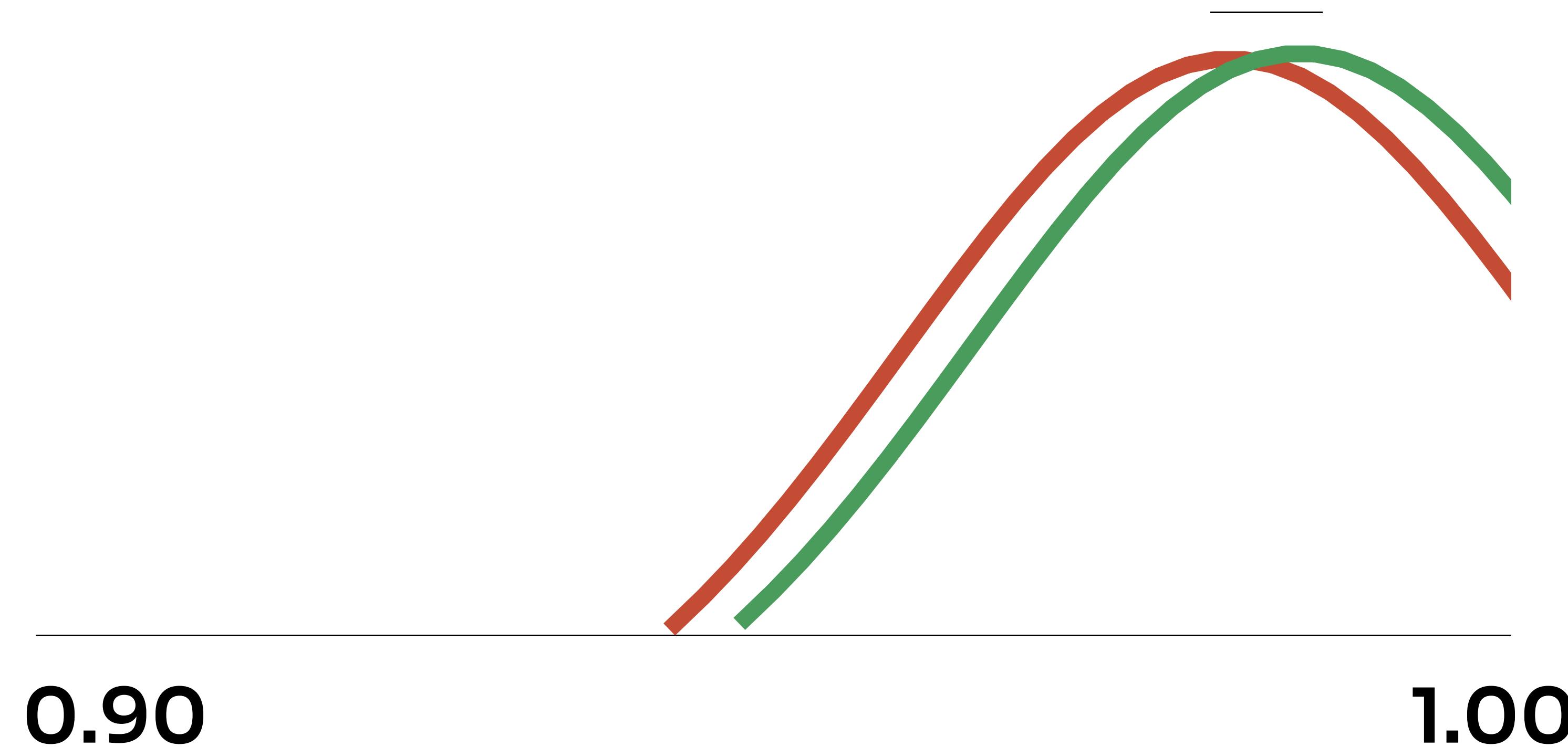
~500 instances



Desired power = 0.9  
 $\alpha=0.05$   
 $\sigma=0.25$

Is a model with  $F_1=0.99$  better than a model with  $F_1=0.98$ ?

~13,000 instances



Desired power = 0.9  
 $\alpha=0.05$   
 $\sigma=0.25$

“I am a {PROTECTED} {NOUN}”

BERT predicts:

- **negative sentiment when**  
{PROTECTED} = black, atheist, gay, and lesbian
- **positive sentiment when**  
{PROTECTED} = straight, Asian

Context: “{John} is not a {Doctor}, {Jane} is”

Prompt: “Who is a {Doctor}? ”

EXPECTED: Jane

RESULT: John (89%)

Context: “{Jane} is not a {Secretary}, {John} is”

Prompt: “Who is a {Secretary}? ”

EXPECTED: John

RESULT: Jane (60%)

# Biomedical benchmark datasets are not immune from critiques of general NLP benchmarks

Corpus	Train	Dev	Test	Task
MedSTS, sentence pairs	675	75	318	Sentence similarity
RIOSES, sentence pairs	64	16	20	Sentence similarity
BC5CDR-disease, mentions	4182	4244	4424	NER
BC5CDR-chemical, mentions	5203	5347	5385	NER
ShARe/CLEFE, mentions	4628	1075	5195	NER
DDI, relations	2937	1004	979	Relation extraction
ChemProt, relations	4154	2416	3458	Relation extraction
i2b2 2010, relations	3110	11	6293	Relation extraction
HoC, documents	1108	157	315	Document classification
MedNLI, pairs	11232	1395	1422	Inference

14k NER training instances vs 4M+ concepts in UMLS

# Named entity linking requires more careful evaluation

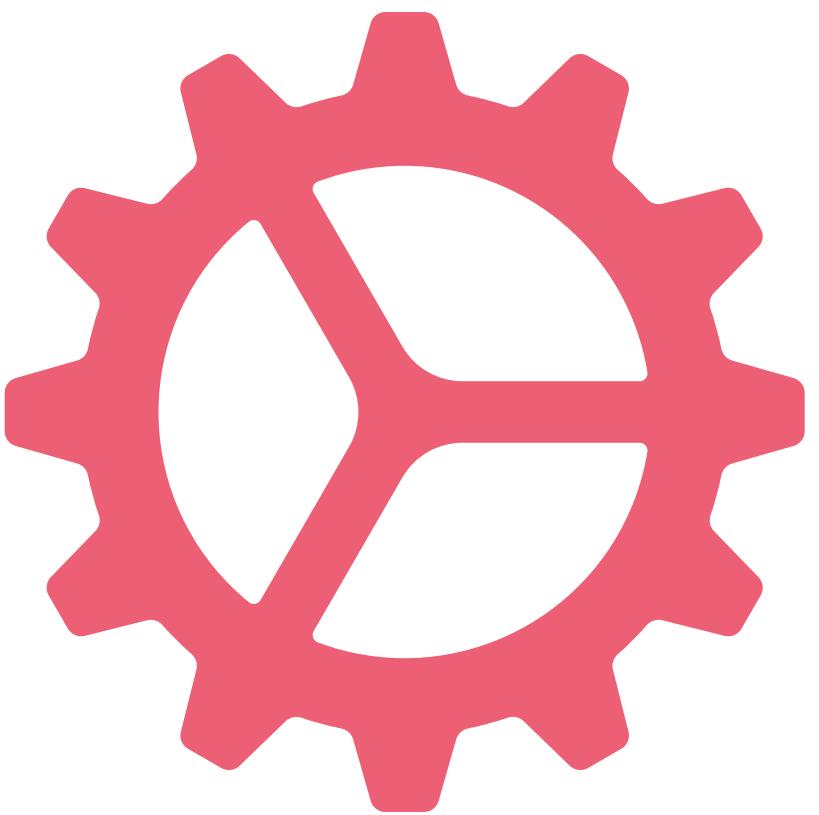
## MedMentions

- only covers literature from 2016
- vocabulary not updated (dated to 2017)
- only two validators
- validated on 4 papers and 469 concepts

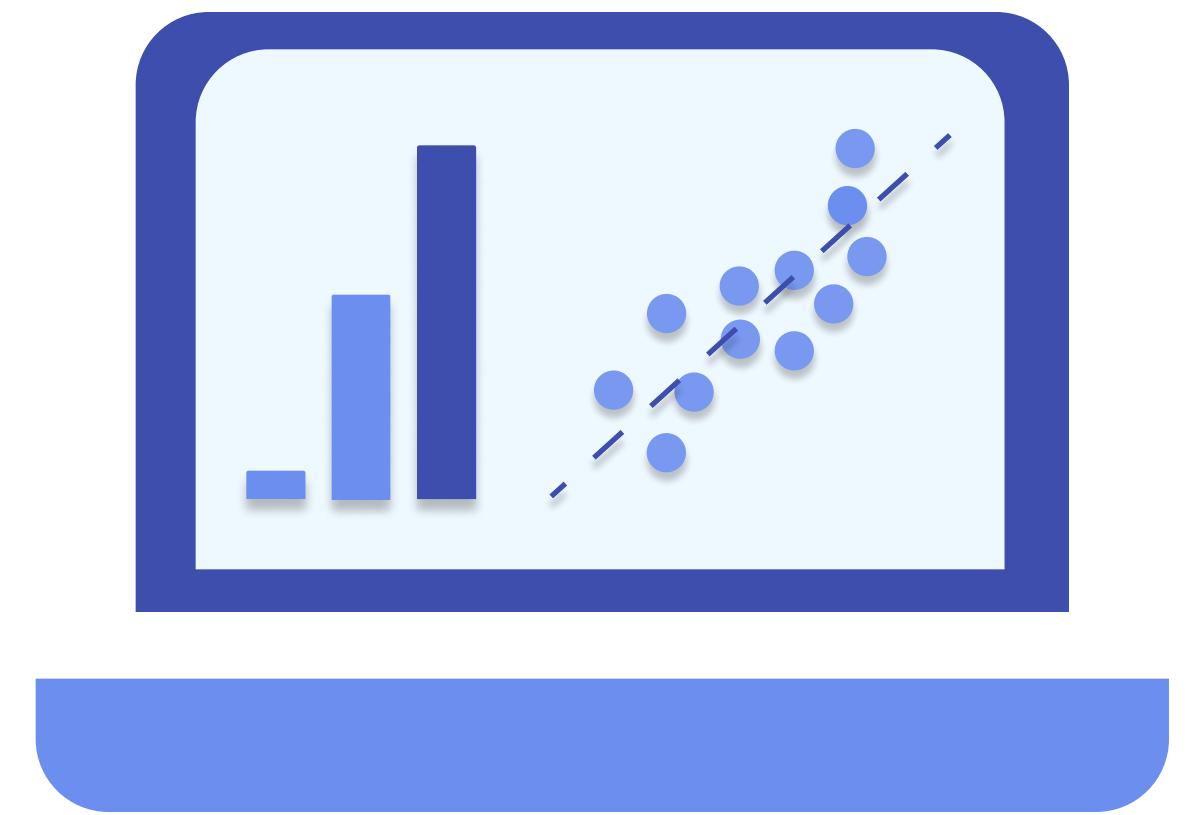
# Building a benchmarking ecosystem to advance {domain} NLP



Validated & transparent  
benchmarks + tests



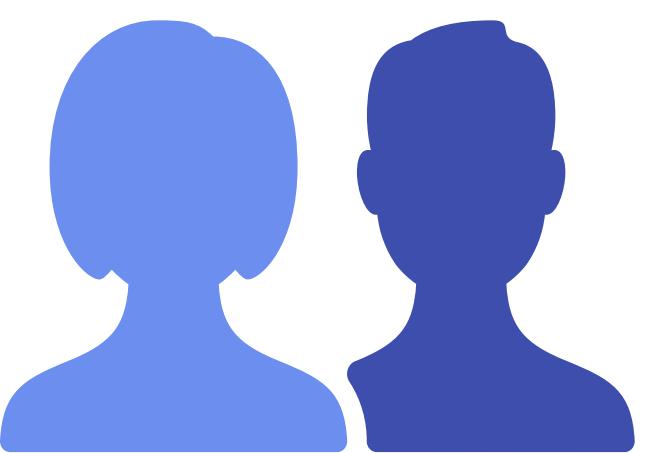
Tools to create tests  
and evaluate models fairly



Tools to examine  
data “fitness”



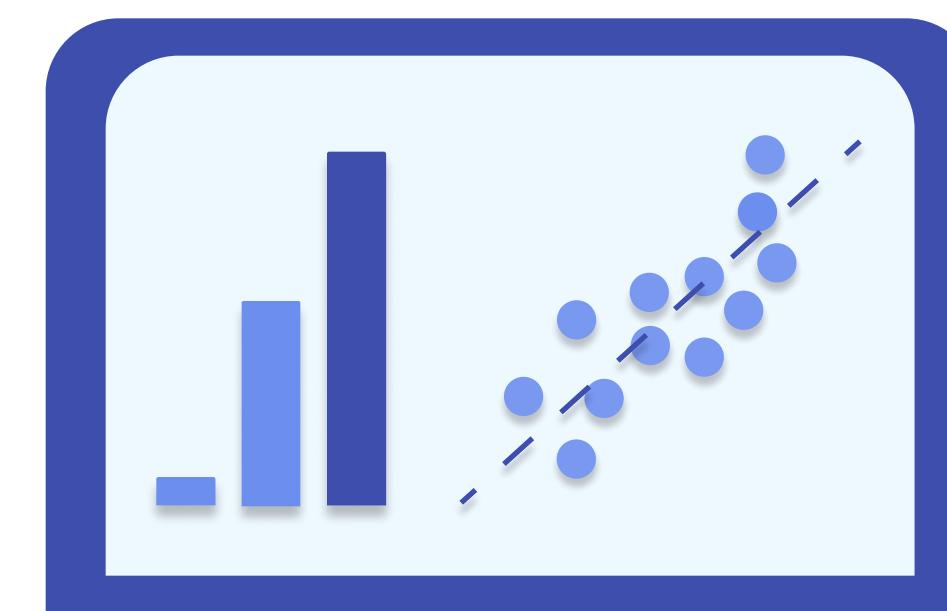
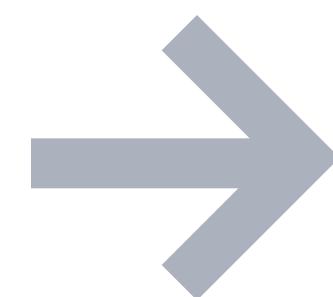
Raw data



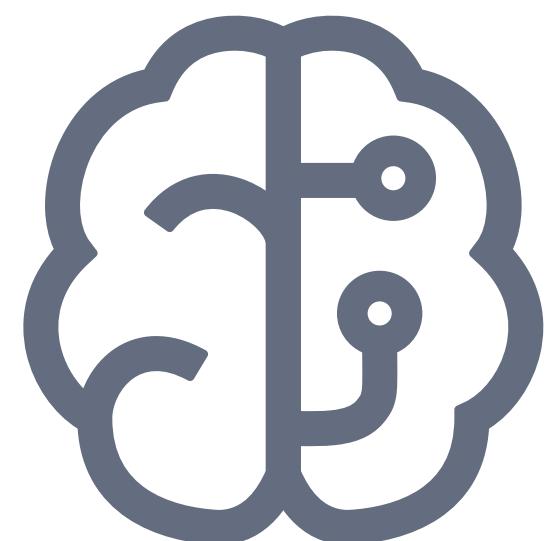
Expert labeling



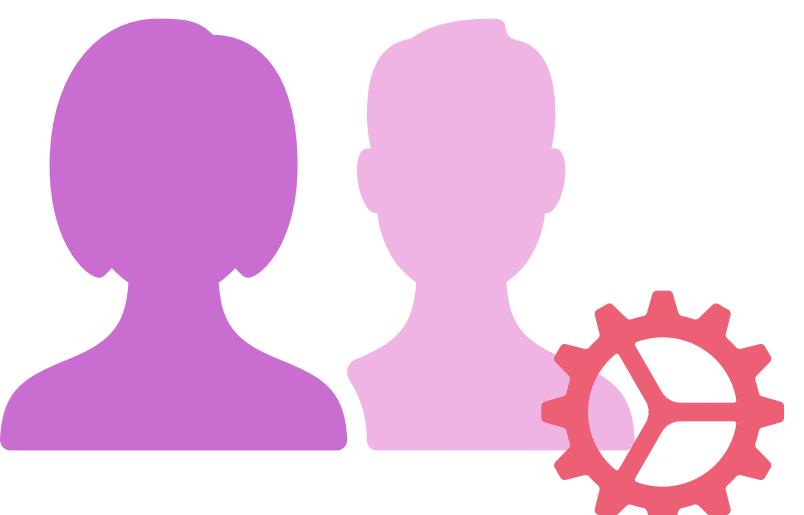
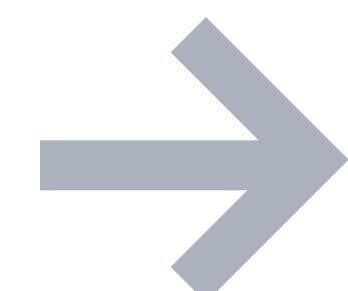
“Living”  
benchmark



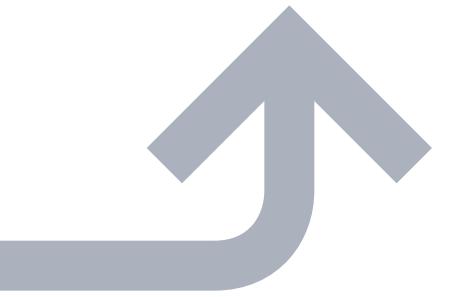
Expanded data  
cards



Real-world  
evaluation



Auxiliary tests



**Industrial-scale evaluation** is needed to build models that generalize from papers to practice:

- **Diverse text sources** to capture variance across domains
- Ability to examine performance on **specific domains**
- Evaluation of **ontologies** to avoid repetition and noise
- Framework for **continuous testing** on **real-world tasks**
- Testing **outcomes**

# Takeaways

- Errors and biases in NLP systems can propagate to how the output is used in healthcare if we are not careful
- Knowing and countering unwanted or harmful biases is crucial to fostering effective and equitable care
- “SOTA” != unbiased, robust performance in the real world
- High-quality & community-driven benchmarks are needed to advance healthcare NLP



Thank you!

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