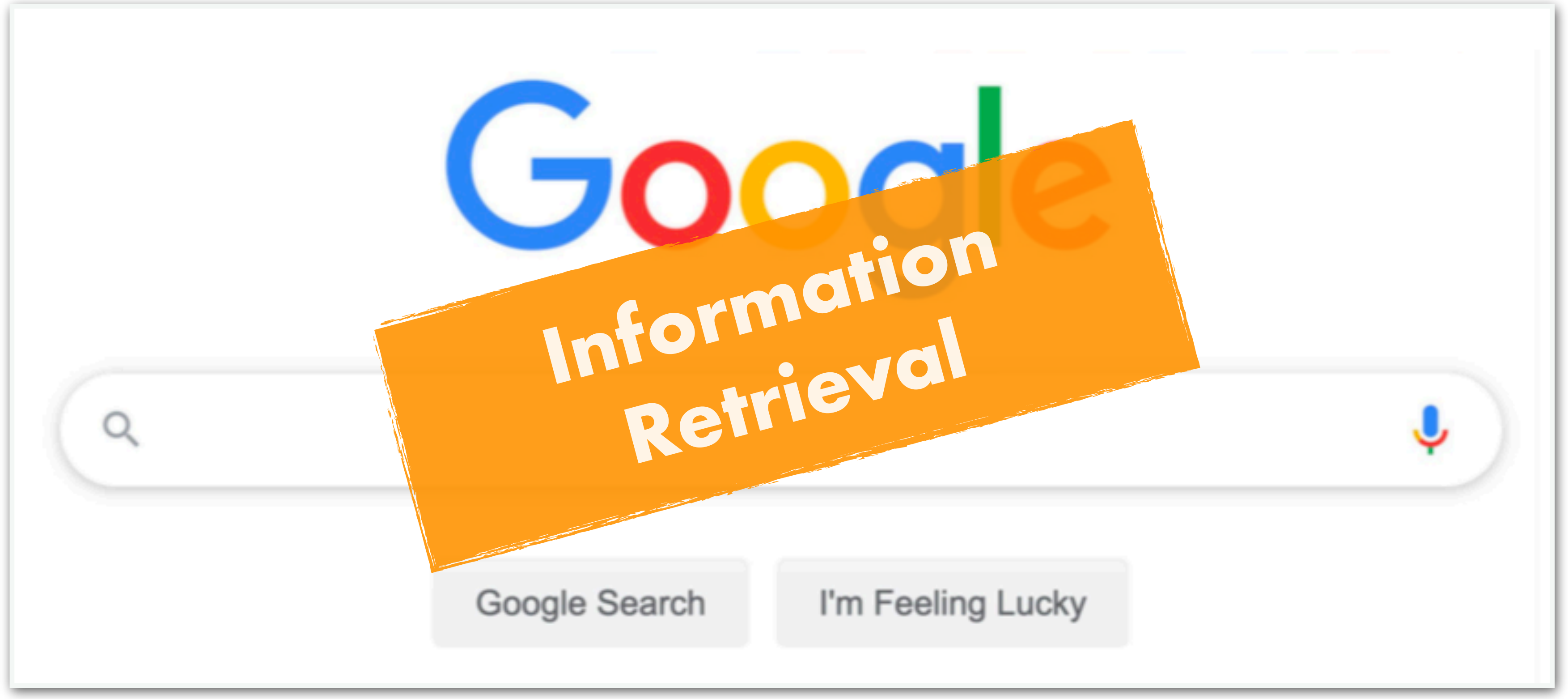
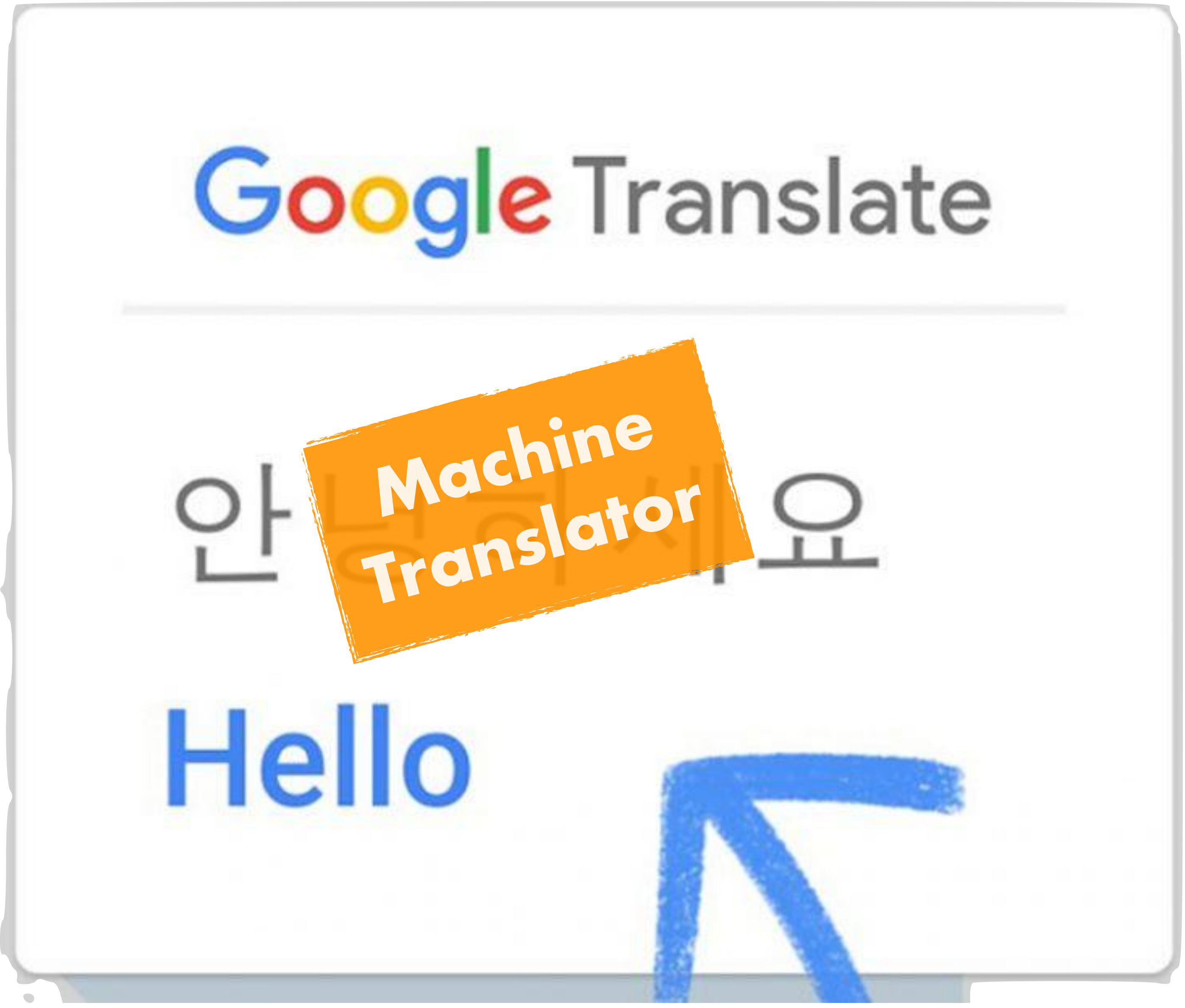
Biases and Interpretability in NLP

3rd Dec
CS395T - Fall 2020

Swabha Swayamdipta


echo
"Alexa, turn it up."
Automated Assistants


Information Retrieval
Google Search
I'm Feeling Lucky


Google Translate
Machine Translator
Hello


Recommender Systems
NETFLIX


Social Media
LinkedIn
foursquare
LIVEJOURNAL
vimeo
YouTube
flickr
twitter
tumblr.
Like
Blogger

SuperGLUE [Wang et al., 2019]

Superhuman Performance!

SuperGLUE [Wang et al., 2019]

Natural Language Inference

Stanford NLI [Bowman et al., 2015]

4

Natural Language Inference

Given a premise, is a hypothesis true, false or neither?

Stanford NLI [Bowman et al., 2015]

Natural Language Inference

Given a premise, is a hypothesis true, false or neither?

Hypothesis

The cat is chasing birds.

Premise

A dog is chasing birds on the shore of the ocean.

Stanford NLI [Bowman et al., 2015]

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Natural Language Inference

Given a premise, is a hypothesis true, false or neither?

- True → Entailment
- False → Contradiction
- Cannot Say → Neutral

Premise

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Natural Language Inference

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Premise

A dog is chasing birds on the shore of the ocean.

Hypothesis

The cat is chasing birds.

Stanford NLI [Bowman et al., 2015]

4

	Premise	Hypothesis
1	A dog is chasing birds on the shore of the ocean.	The cat is chasing birds.
2	Three kids playing with a toy cat in a garden.	There's a toy cat and dog in the garden.
3	A dog and cat are snuggling up during a nap.	A dog and cat are sharing a nap.
4	A few people are staring at something.	The people are staring at a cat.

Annotation Artifacts in NLI [G*., Swayamdipta*, L., S., B., S., 2018]

Premise	A dog is chasing birds on the shore of the ocean.	Three kids playing with a toy cat in a garden.	A dog and cat are snuggling up during a nap.	A few people are staring at something.
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	**Contradiction**	**Neutral**	**Entailment**	**Neutral**

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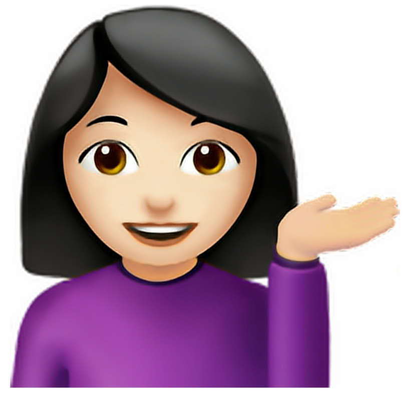
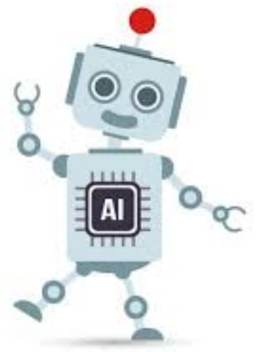
	**Contradiction**	**Neutral**	**Entailment**	**Neutral**
	**Contradiction**	**Contradiction**	**Contradiction**	**Contradiction**

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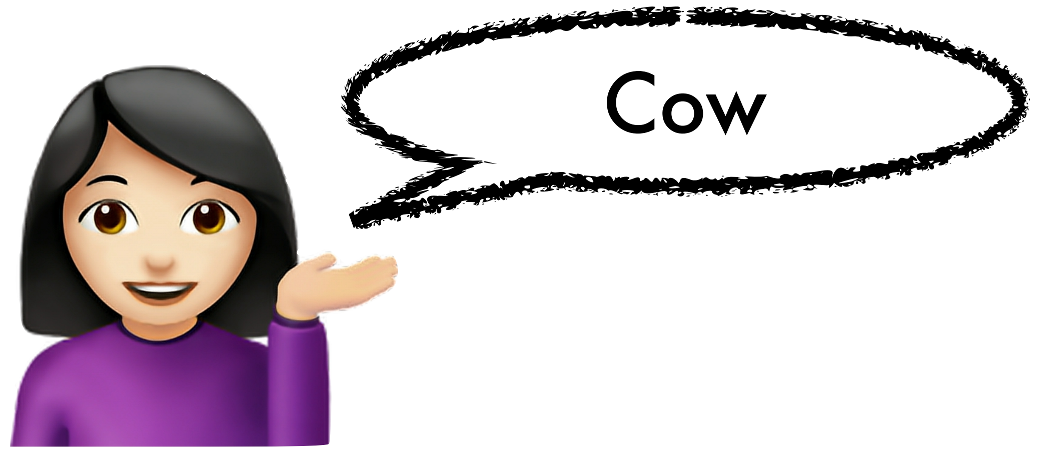
Object Recognition

Object Recognition

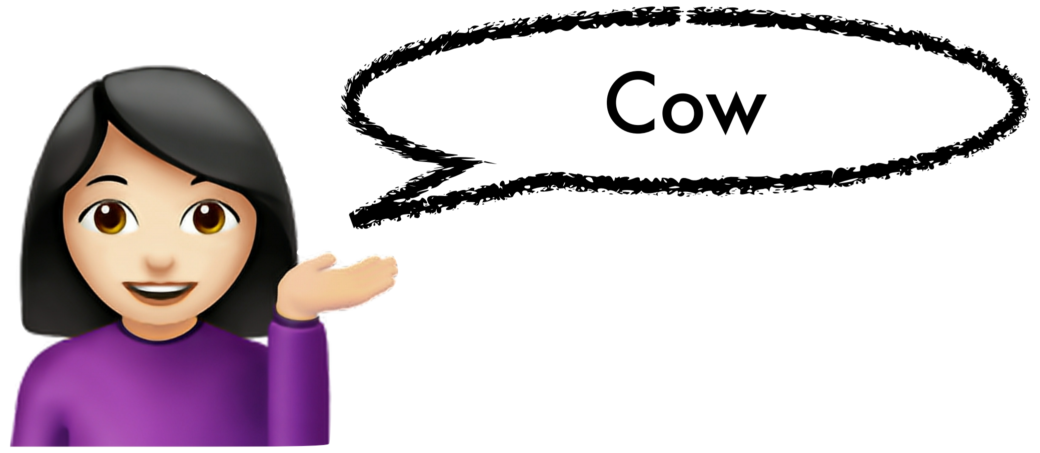
Example from Beery et al. [2019]

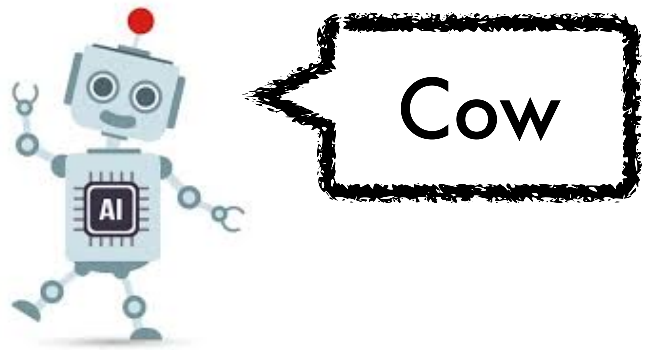
Object Recognition

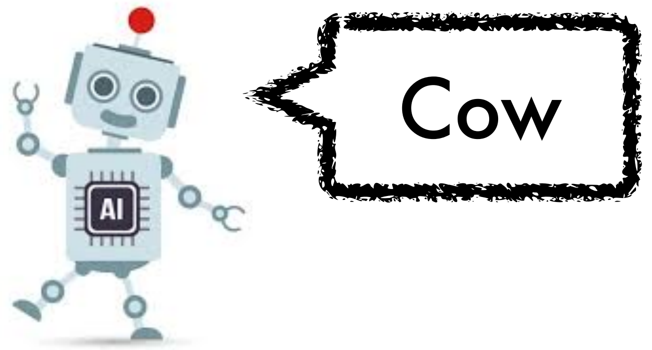


Example from Beery et al. [2019]

Object Recognition







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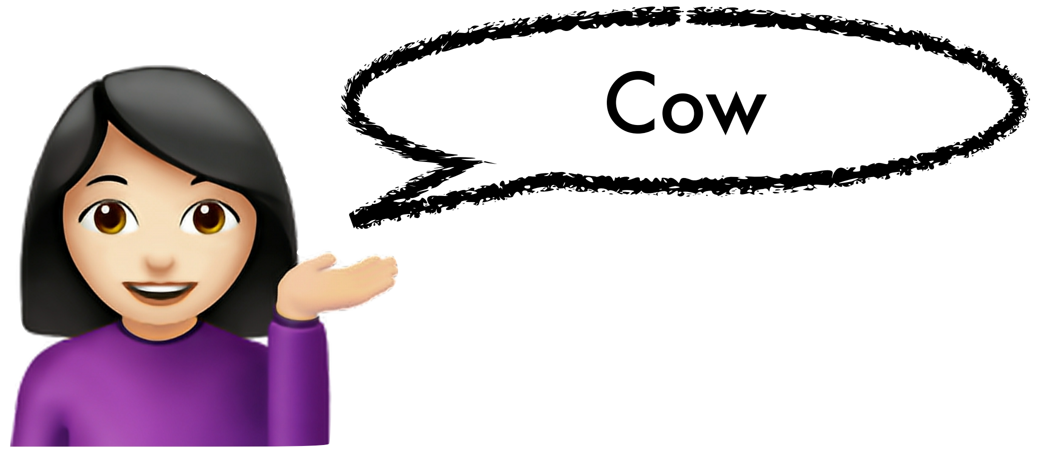

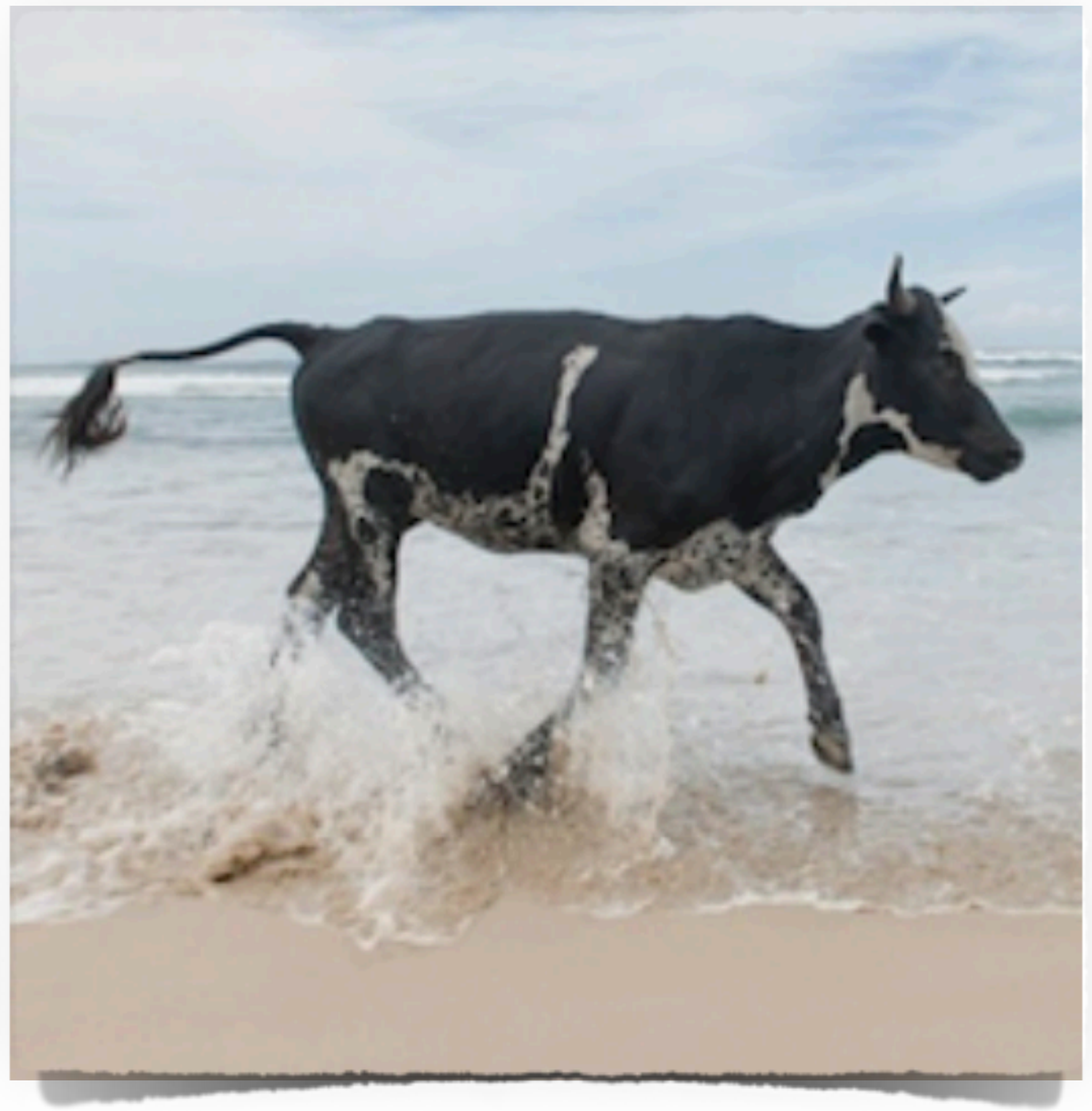

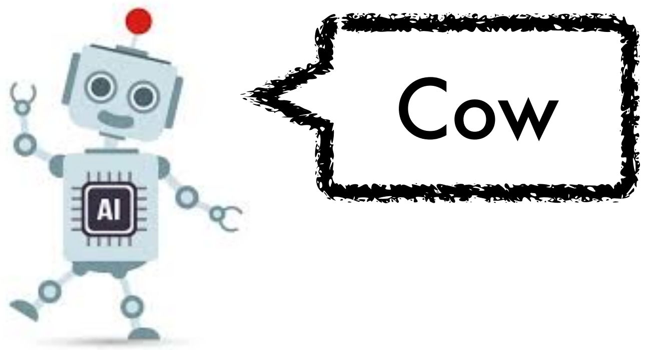

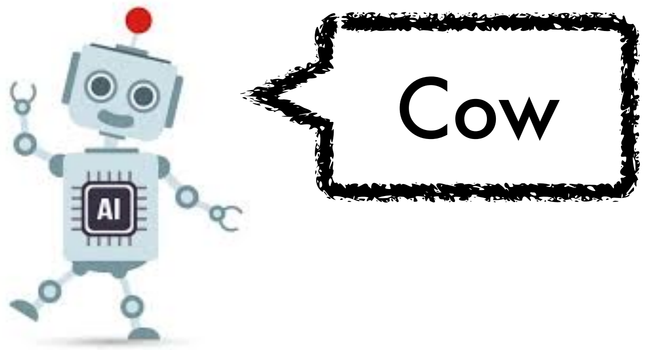

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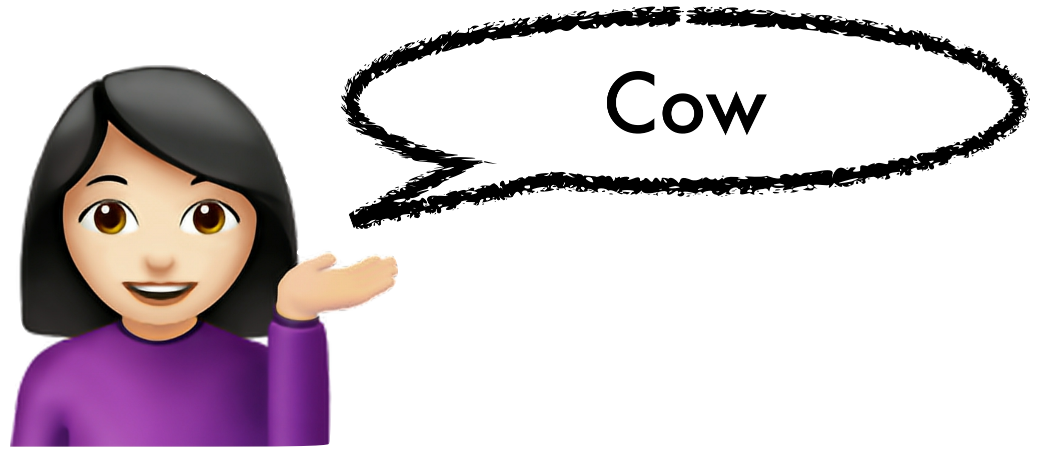

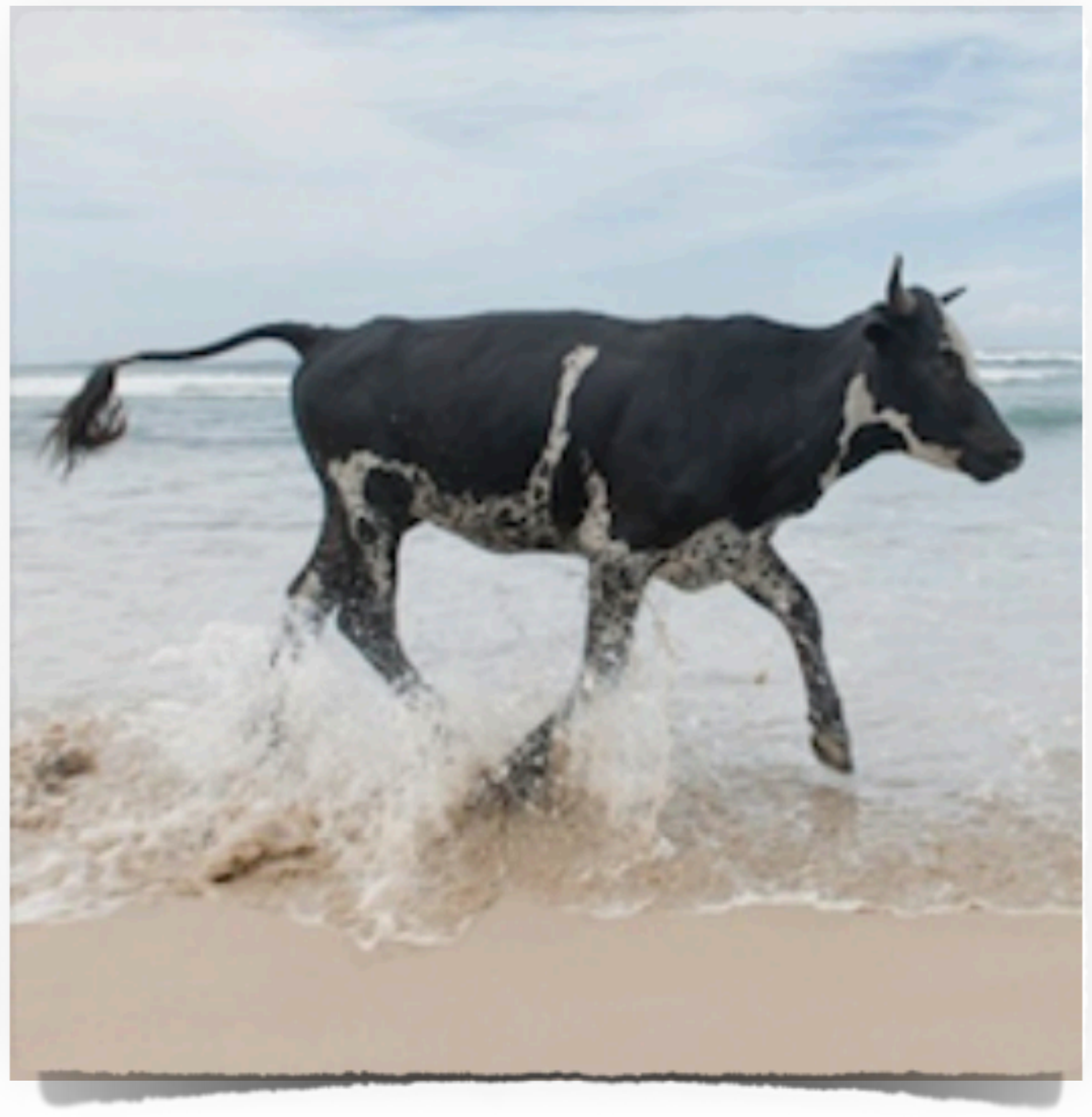

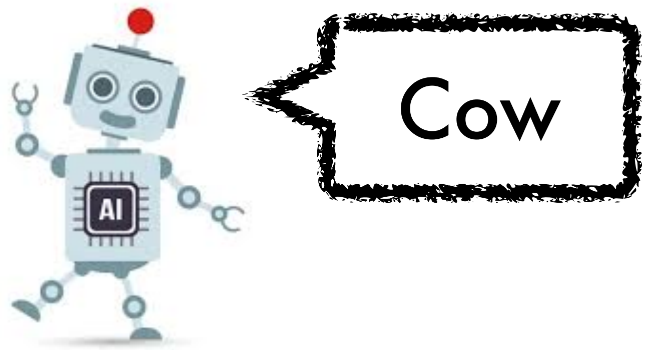

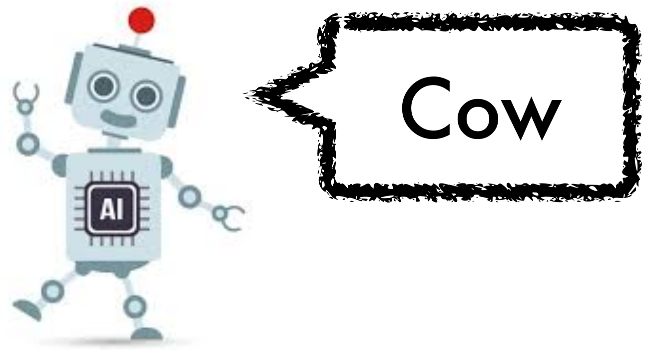

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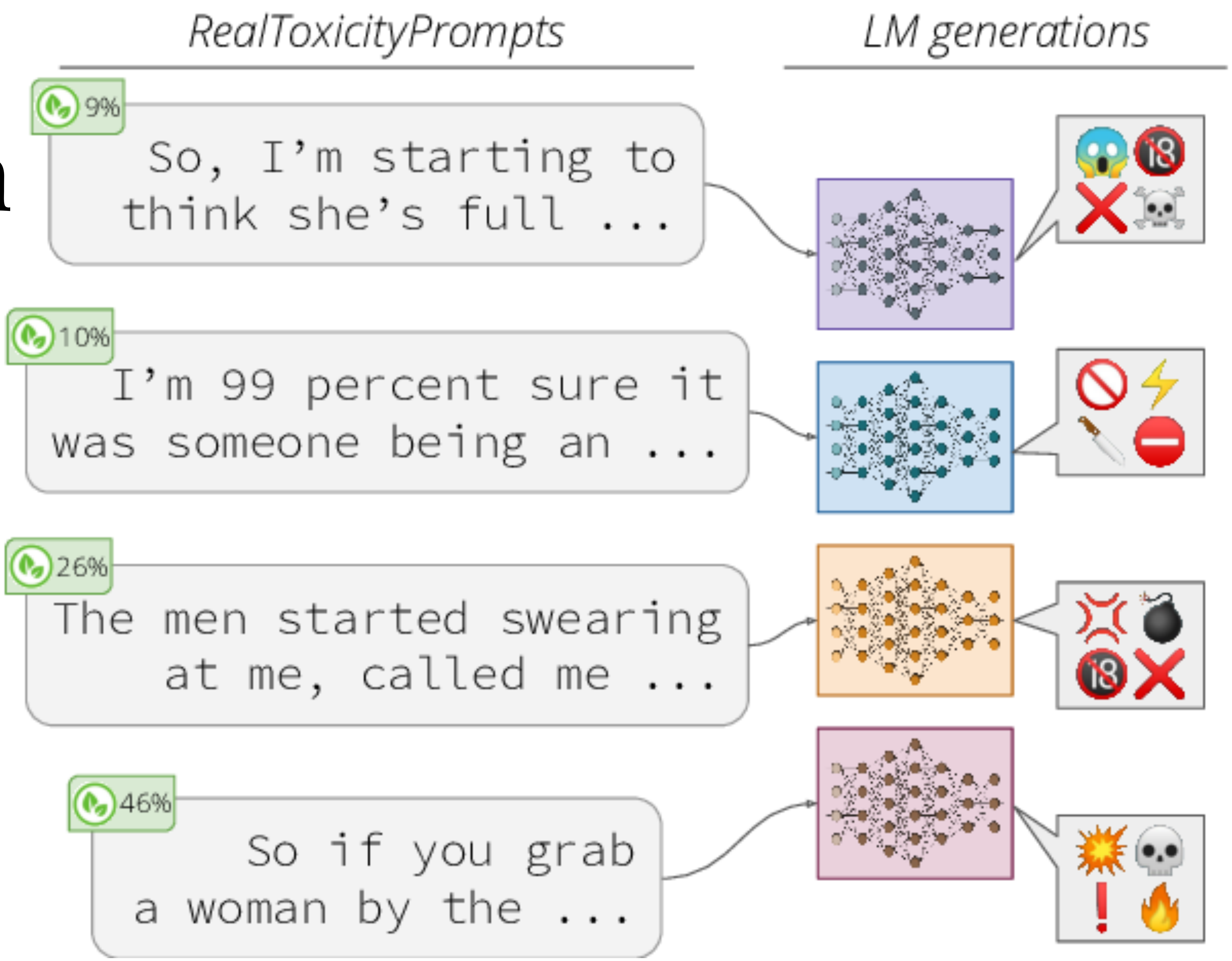
Language Generation

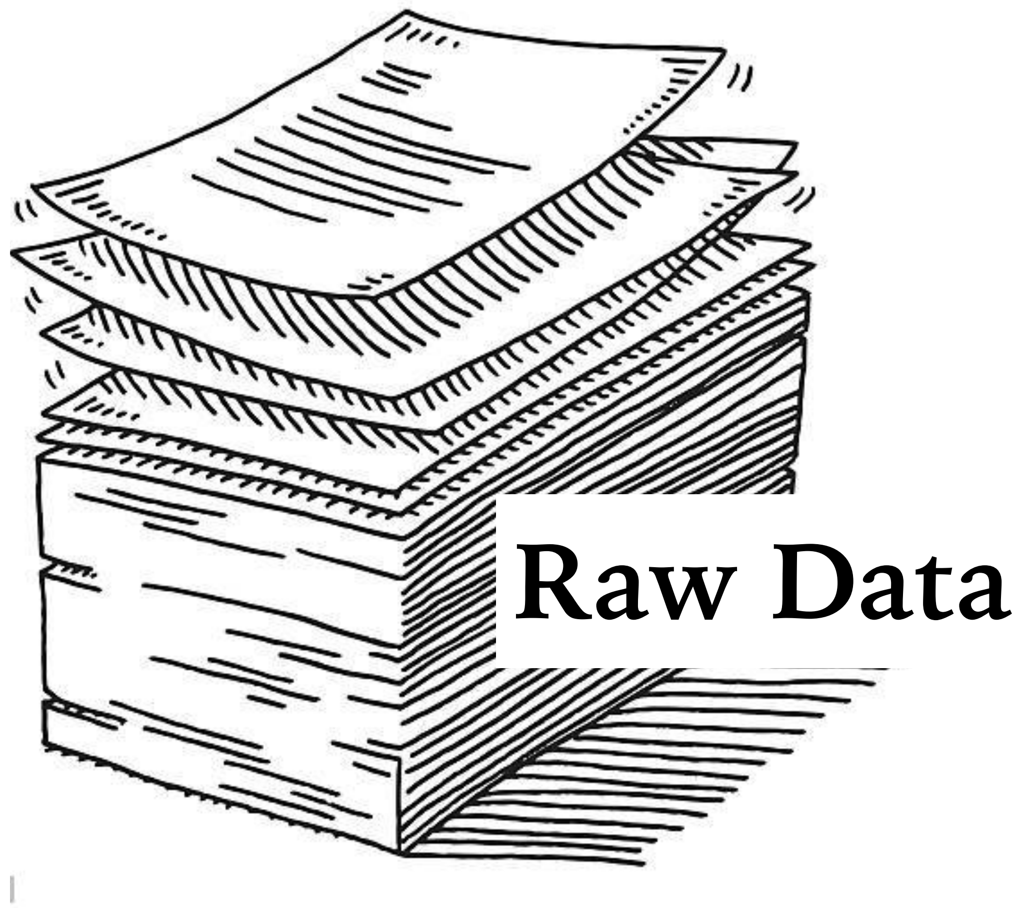


RealToxicityPrompts [Gehman et. al, 2020]

Why this discrepancy?

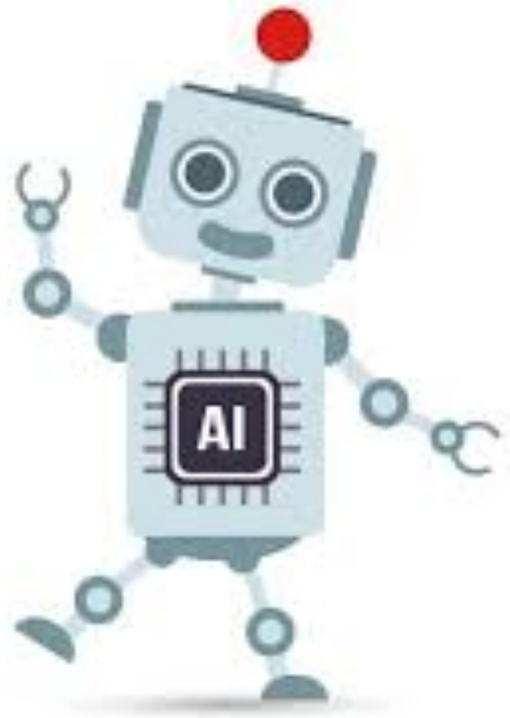
The NLP Pipeline

The NLP Pipeline



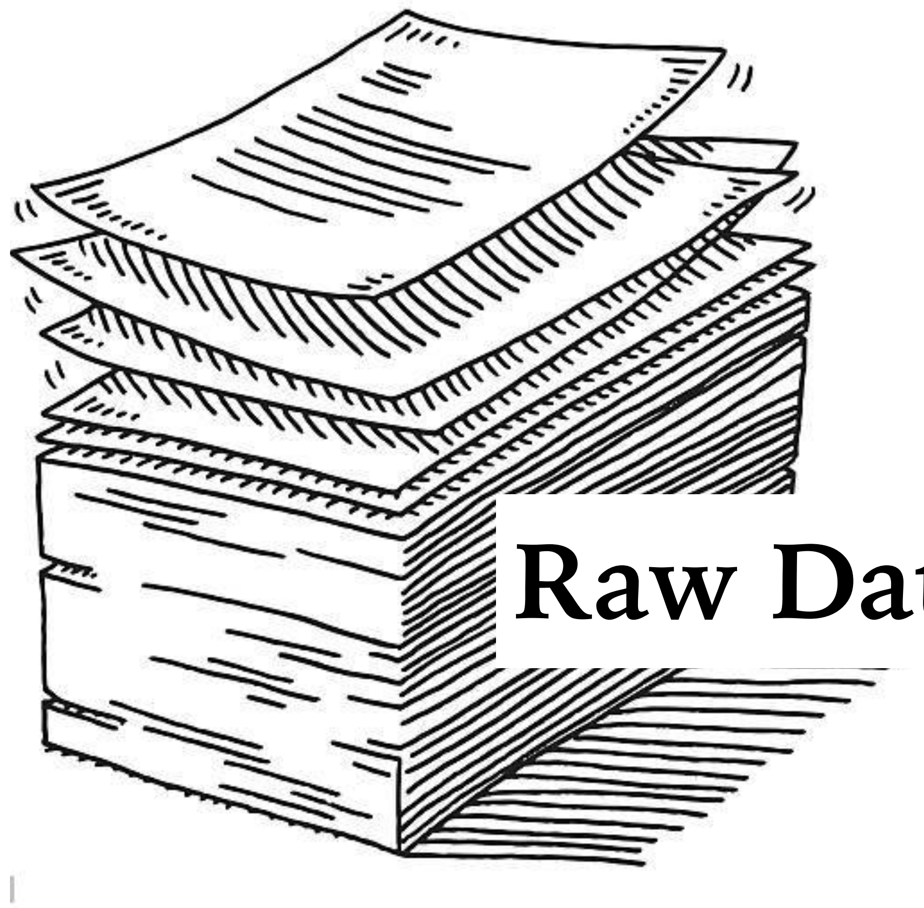
The NLP Pipeline

Human Labeling

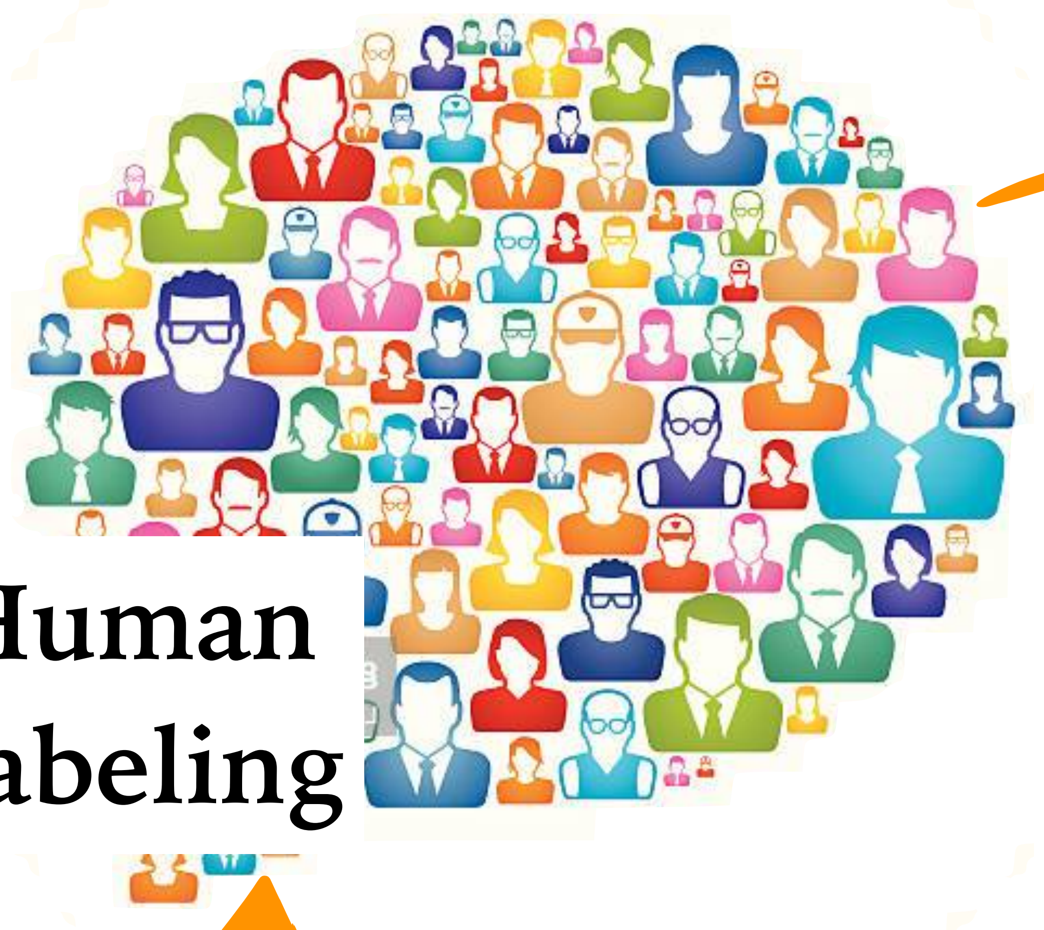


Training

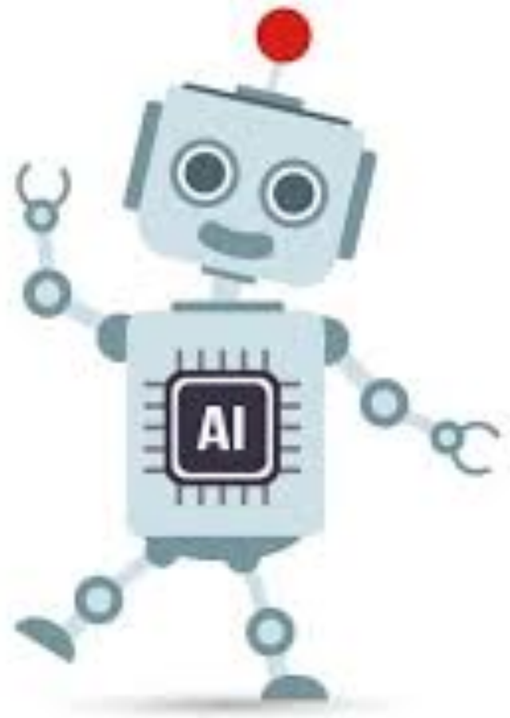
The NLP Pipeline



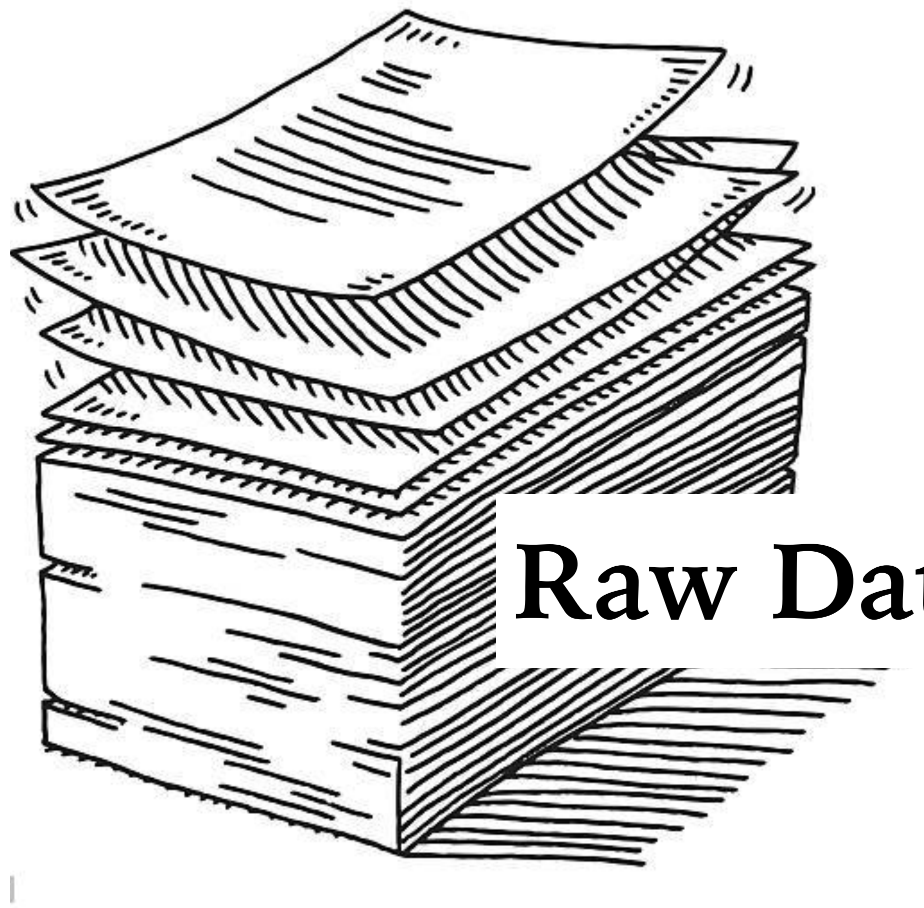
Raw Data



Human Labeling

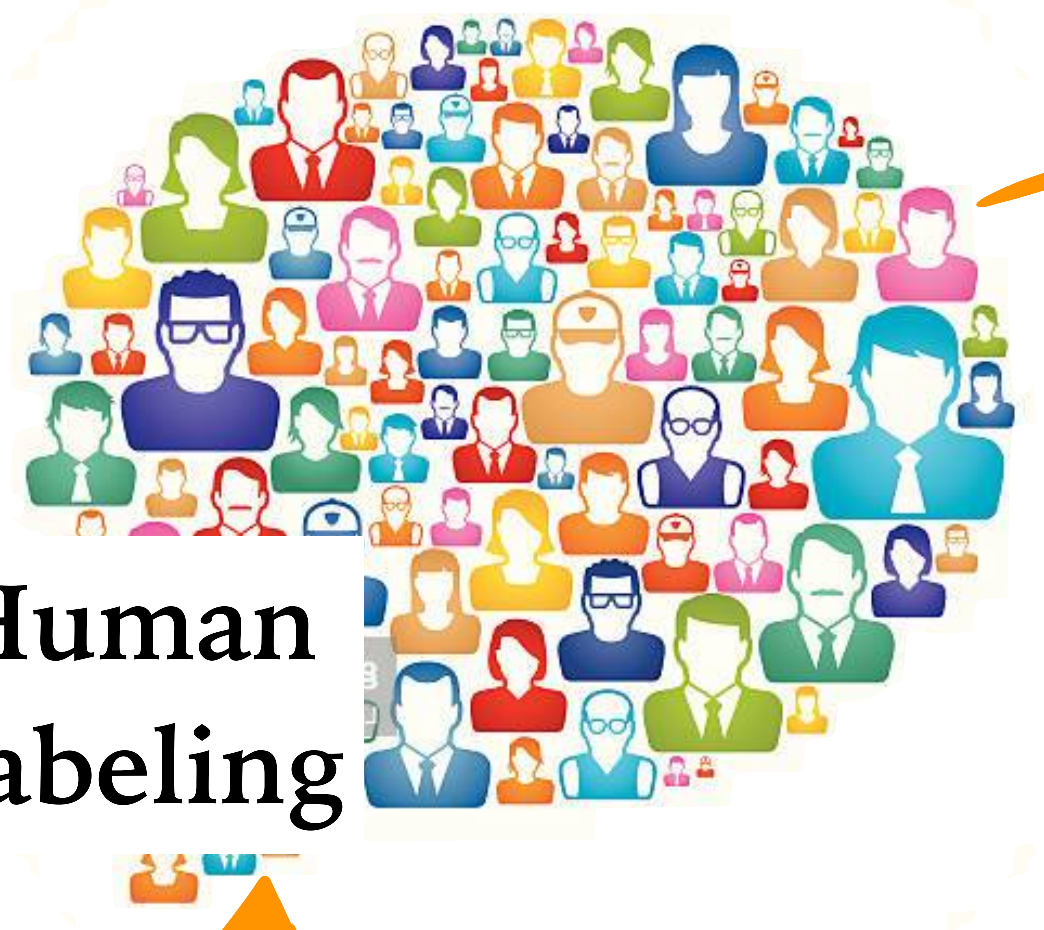


Training

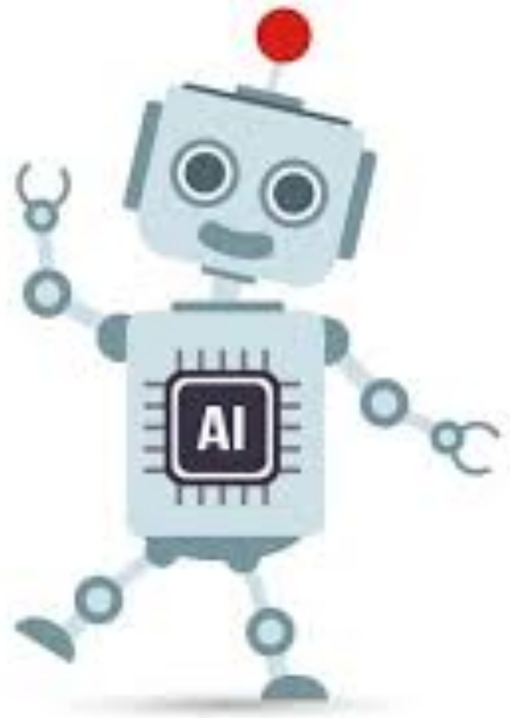


Raw Data

The NLP Pipeline



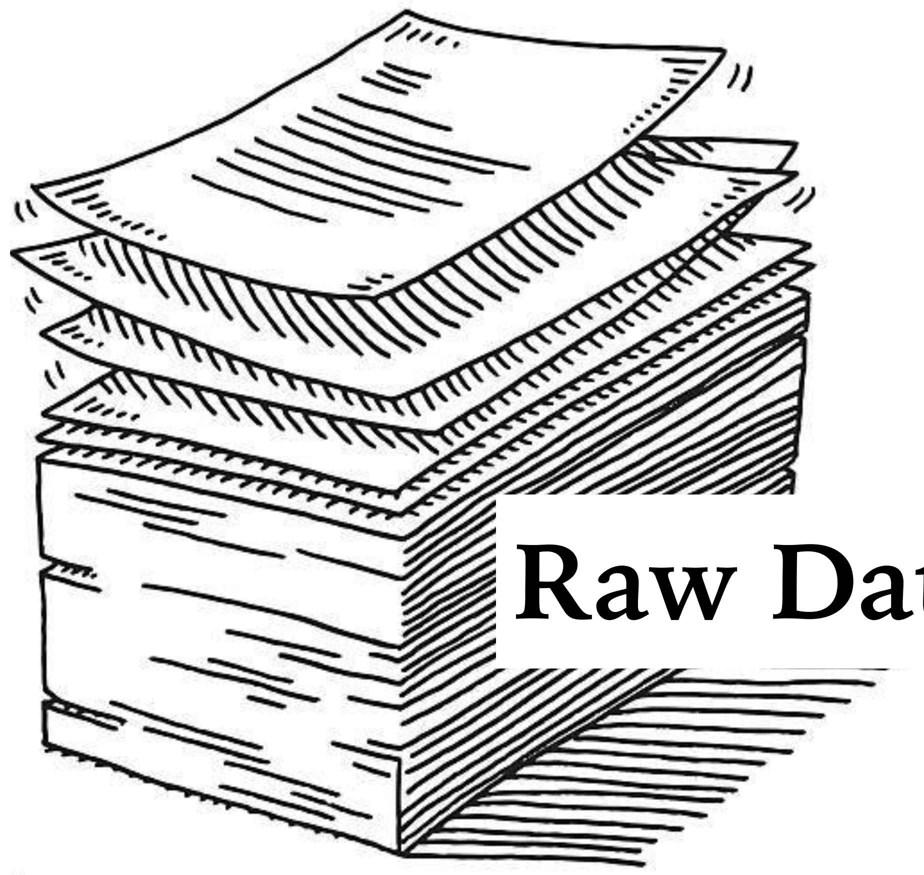
Human Labeling



Training

Evaluation

The NLP Pipeline



Raw Data

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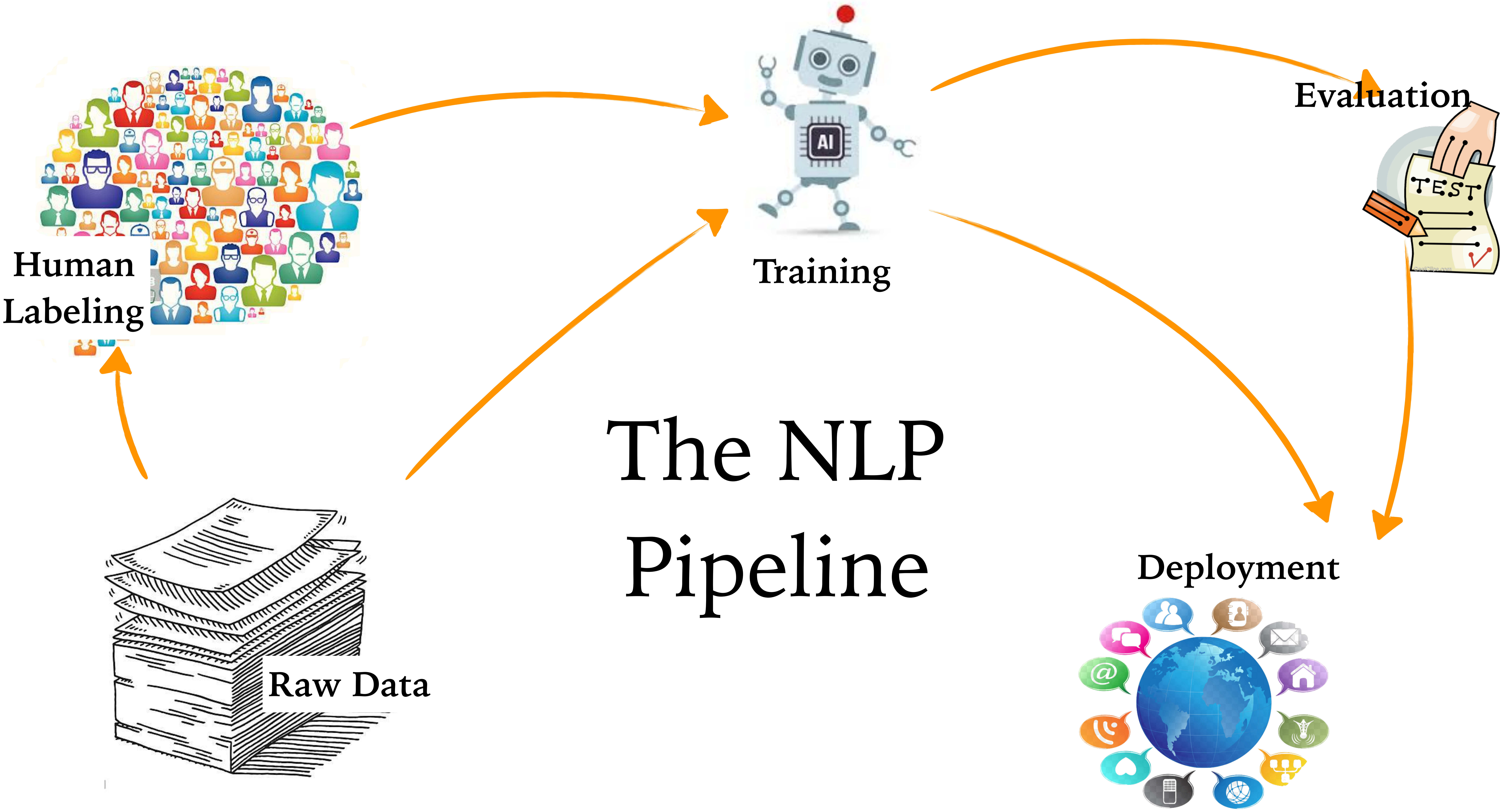

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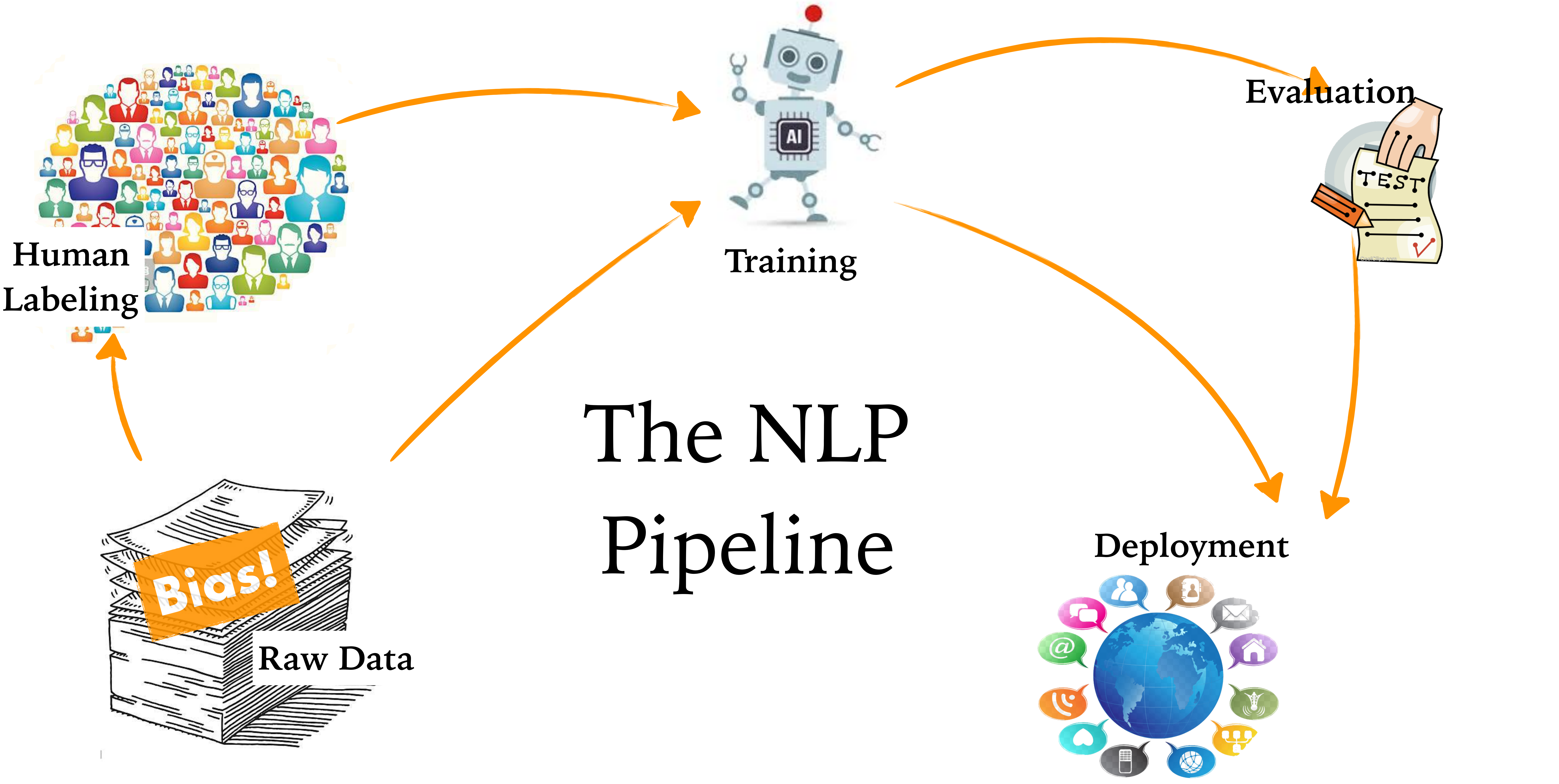
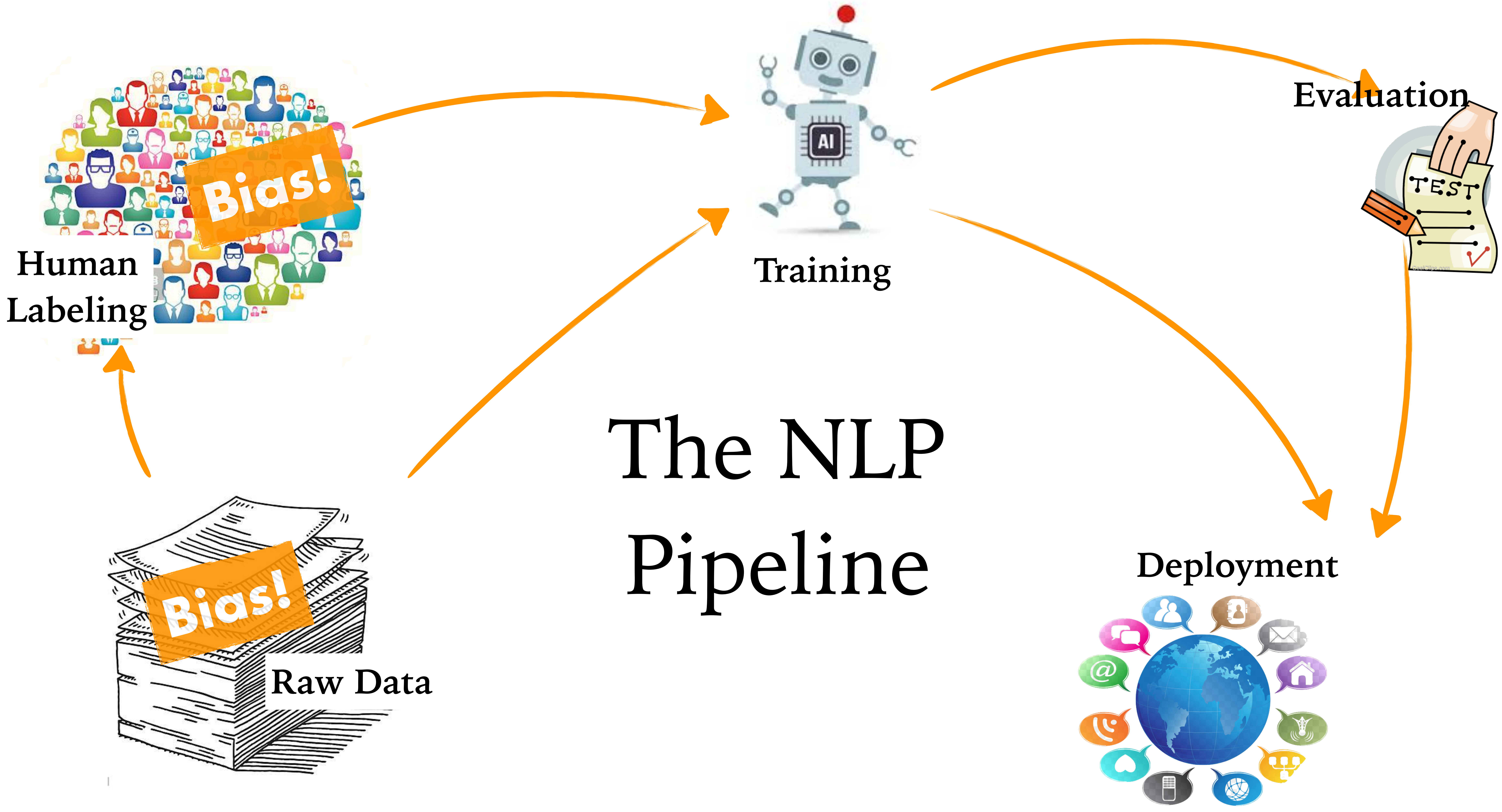
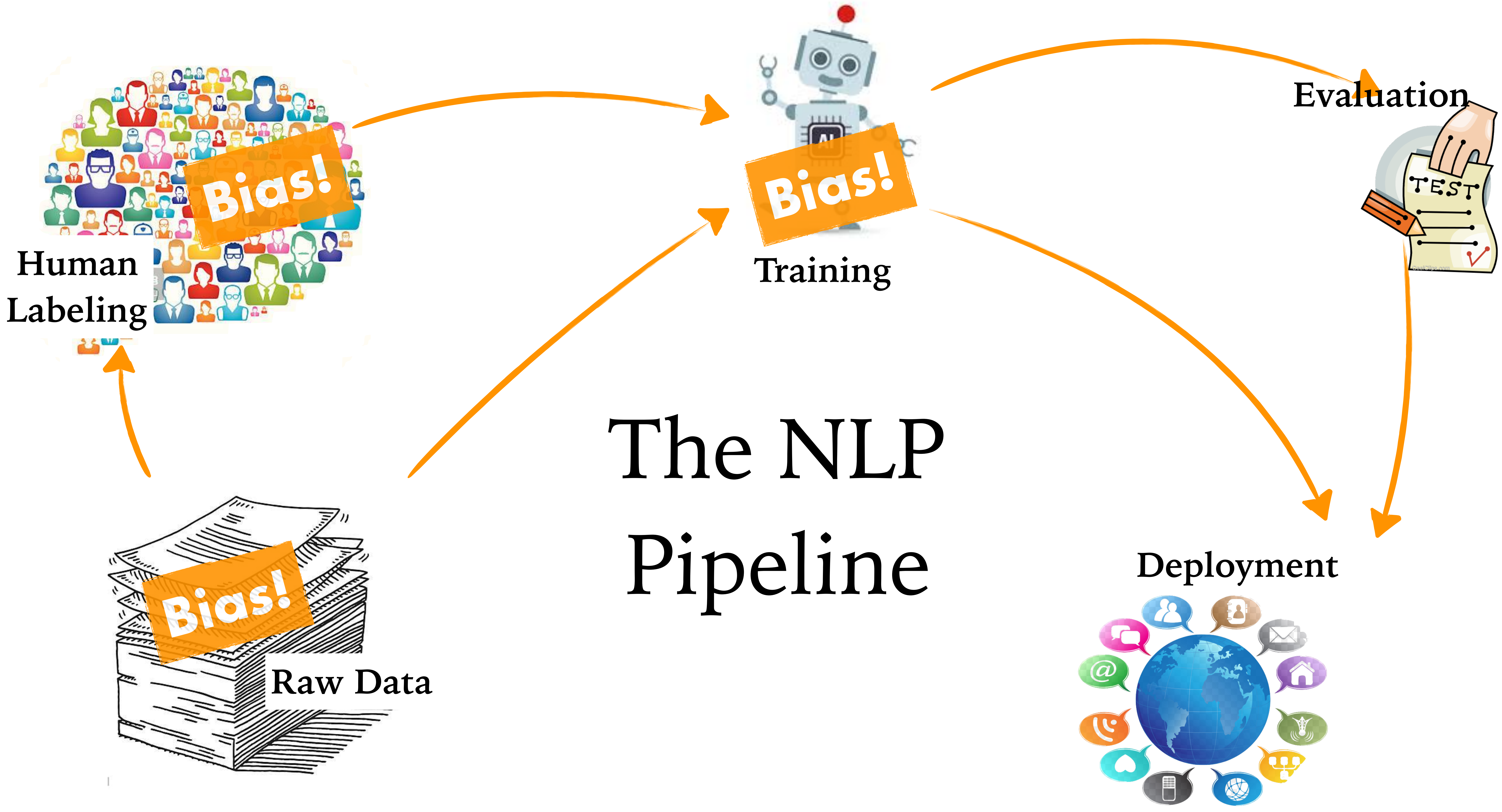



Human Labeling
Bias!
Training
Evaluation
TEST
The NLP Pipeline
Bias!
Raw Data
Deployment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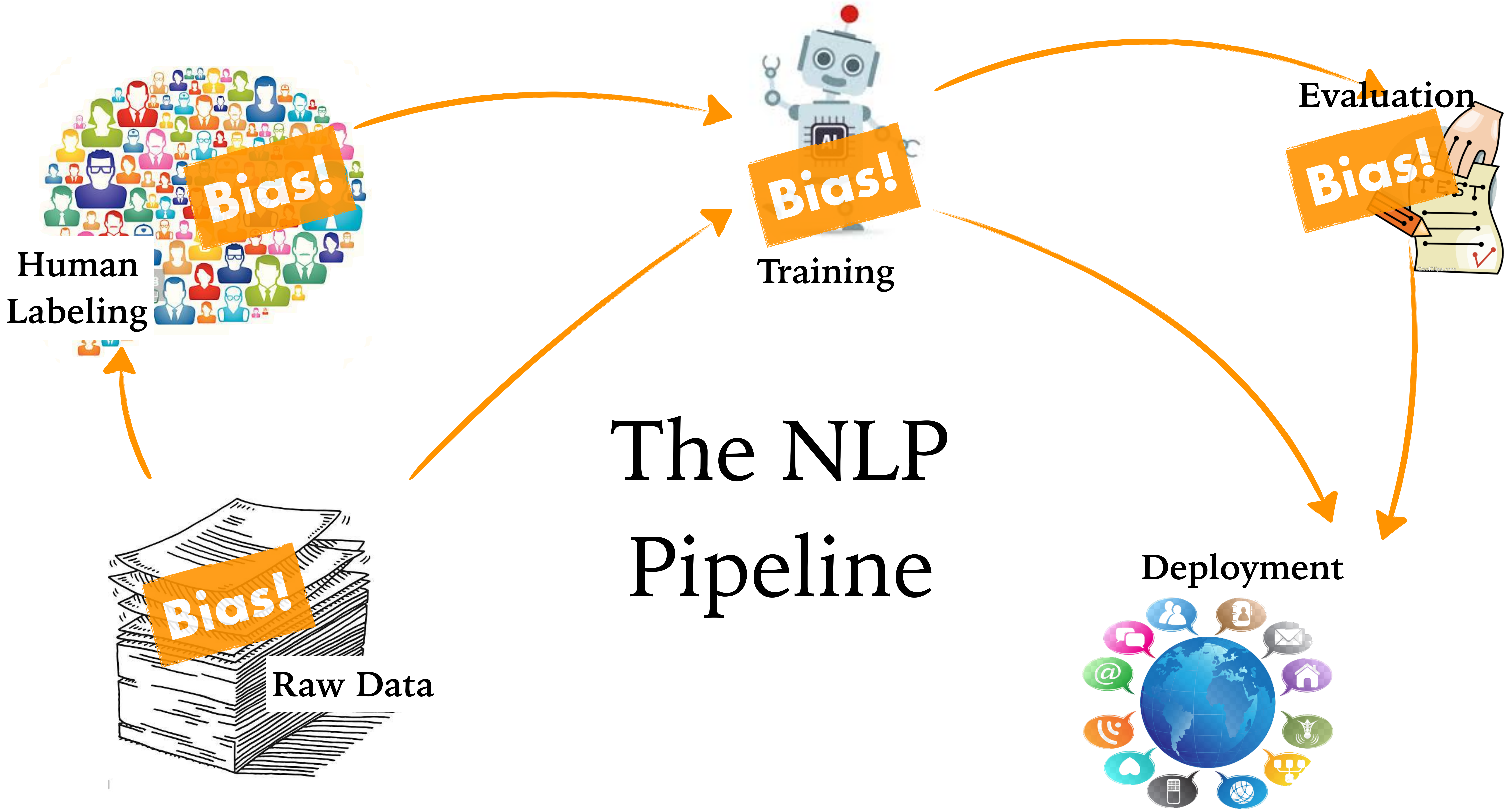

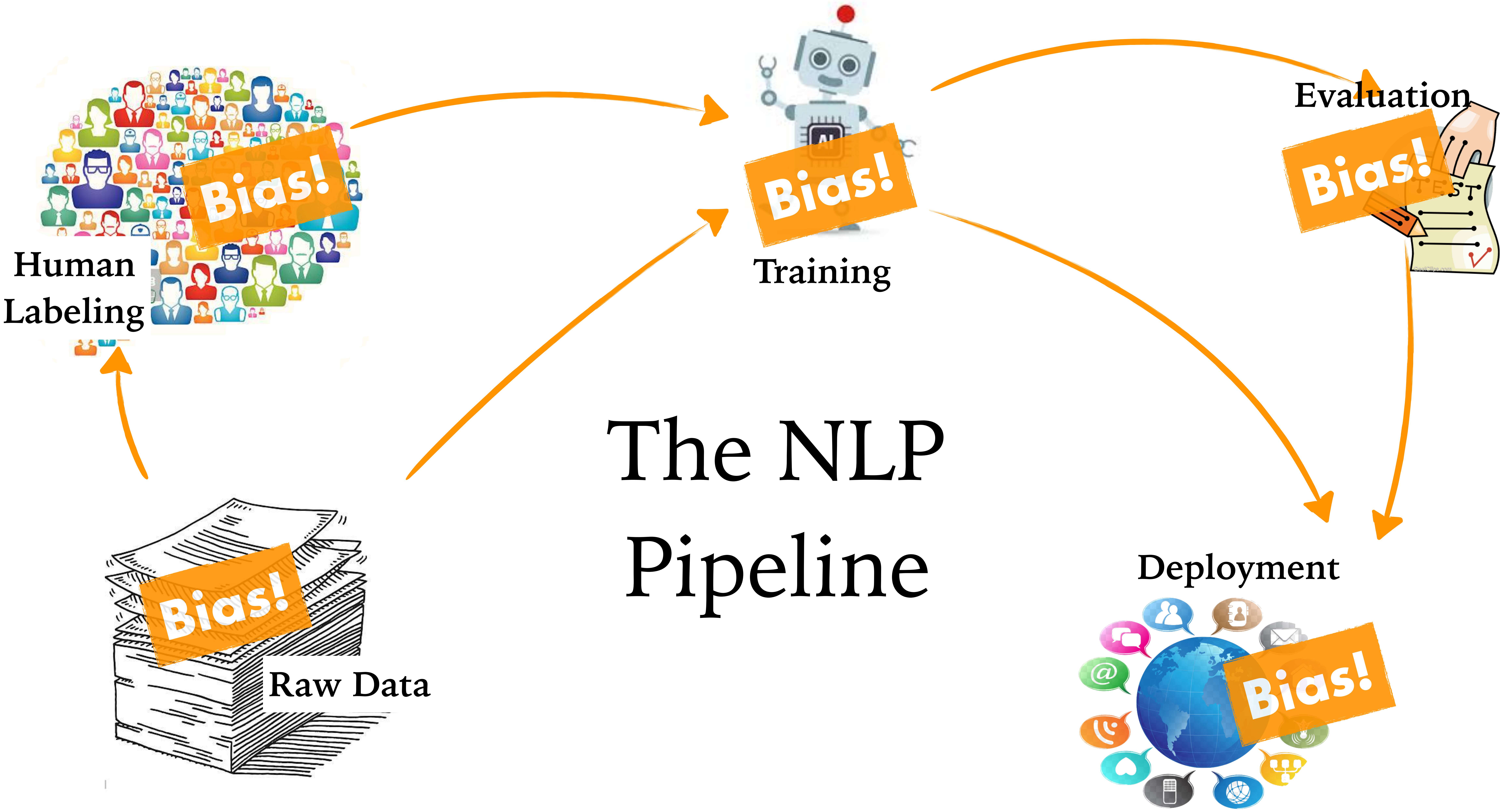
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The NLP Pipeline

This Lecture

This Lecture

Biases in NLP

- Dataset Biases
- Model Biases

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Discovering Biases via Interpretability Methods

- Saliency Methods
- Input Attributions
- Architectural Modifications

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- Filtering Datasets
- Auxiliary Objectives

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What is Bias?

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- Preference of one decision over another

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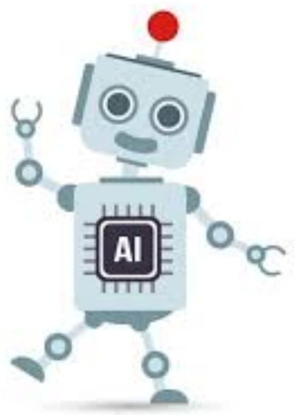

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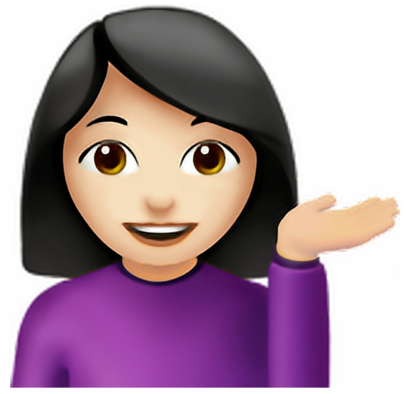

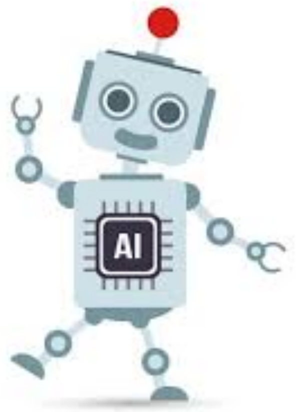

What is Bias?

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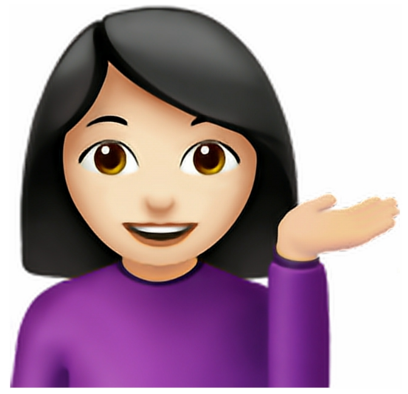
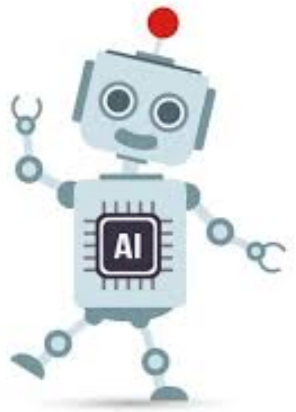
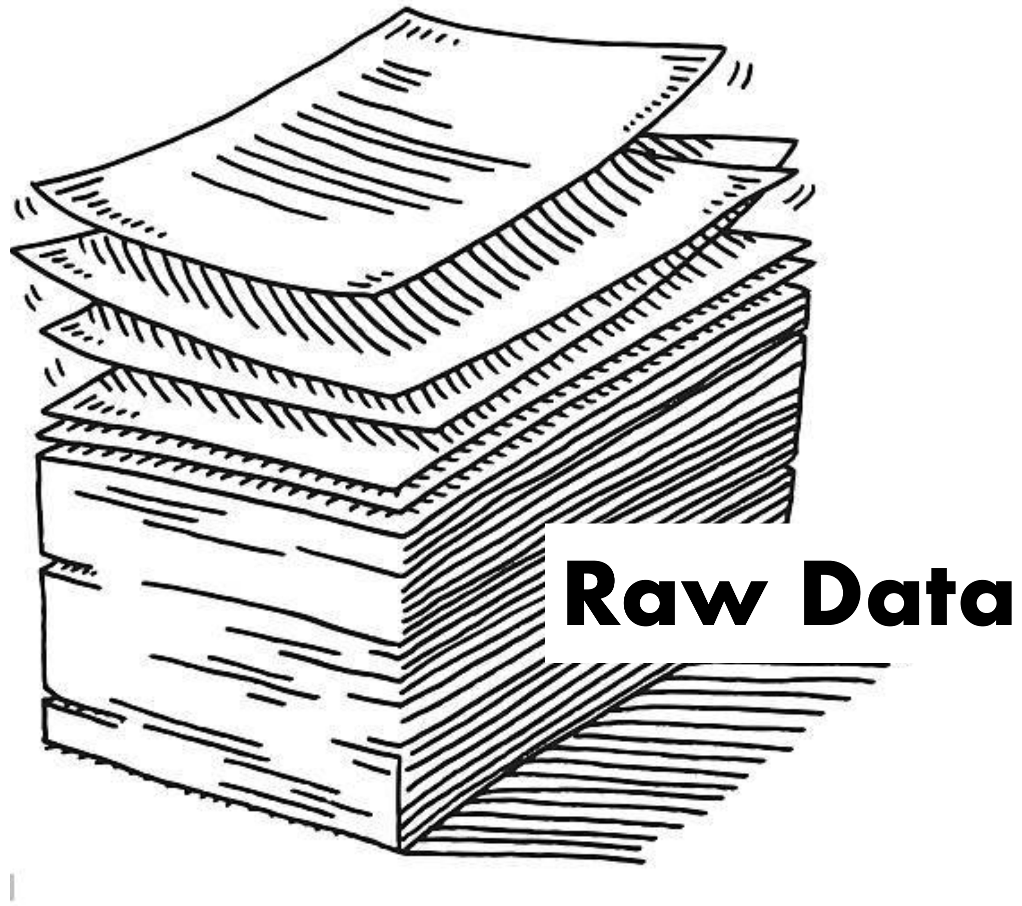
Human biases are reflected in datasets







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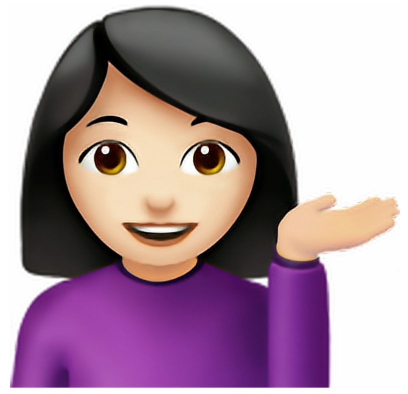
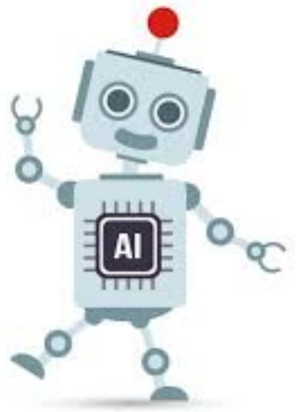
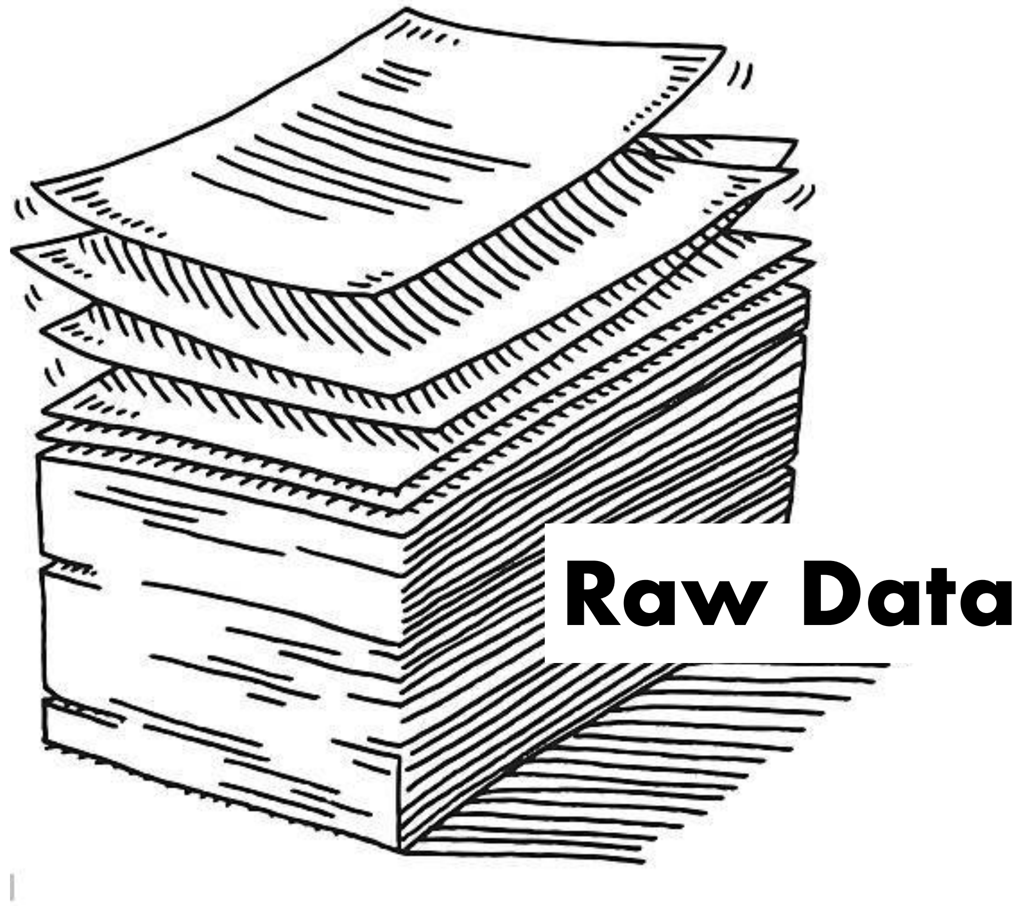




Model biases are reflected in AI decisions



Deployment

What is Bias?

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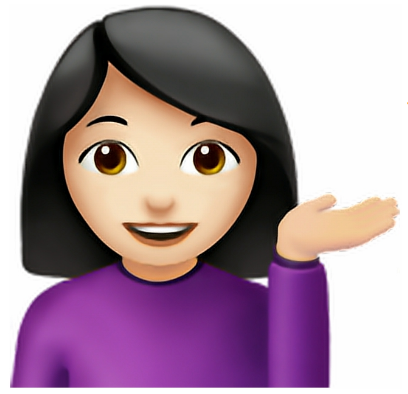
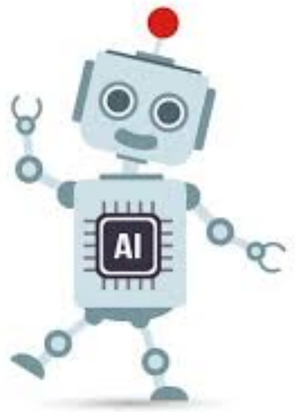


Evaluation



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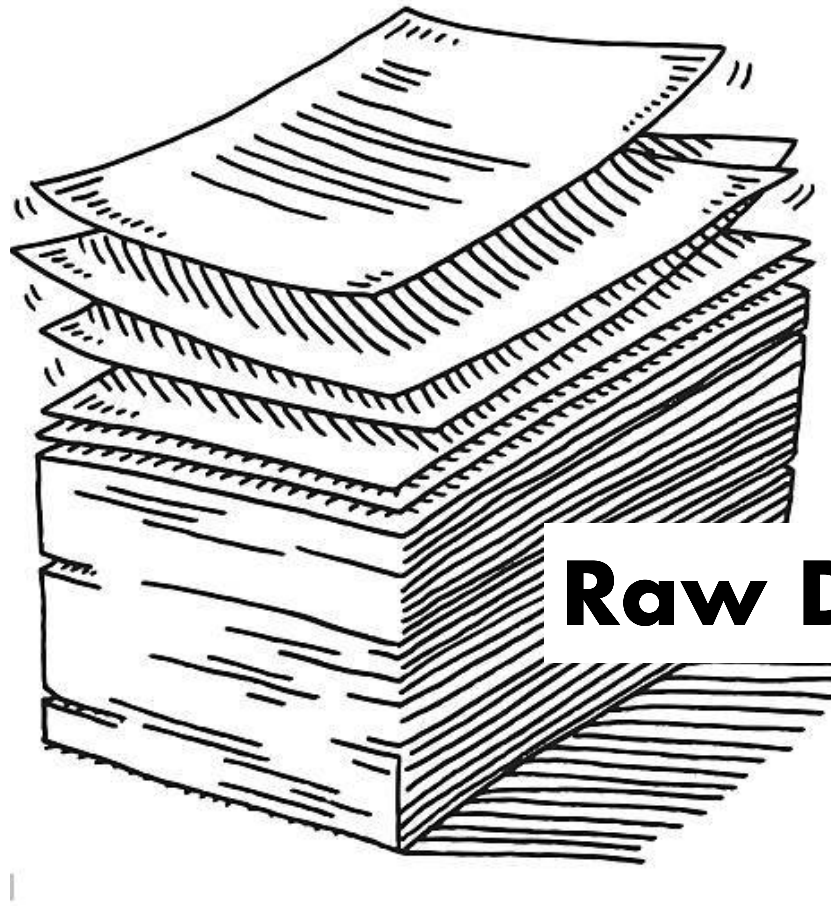
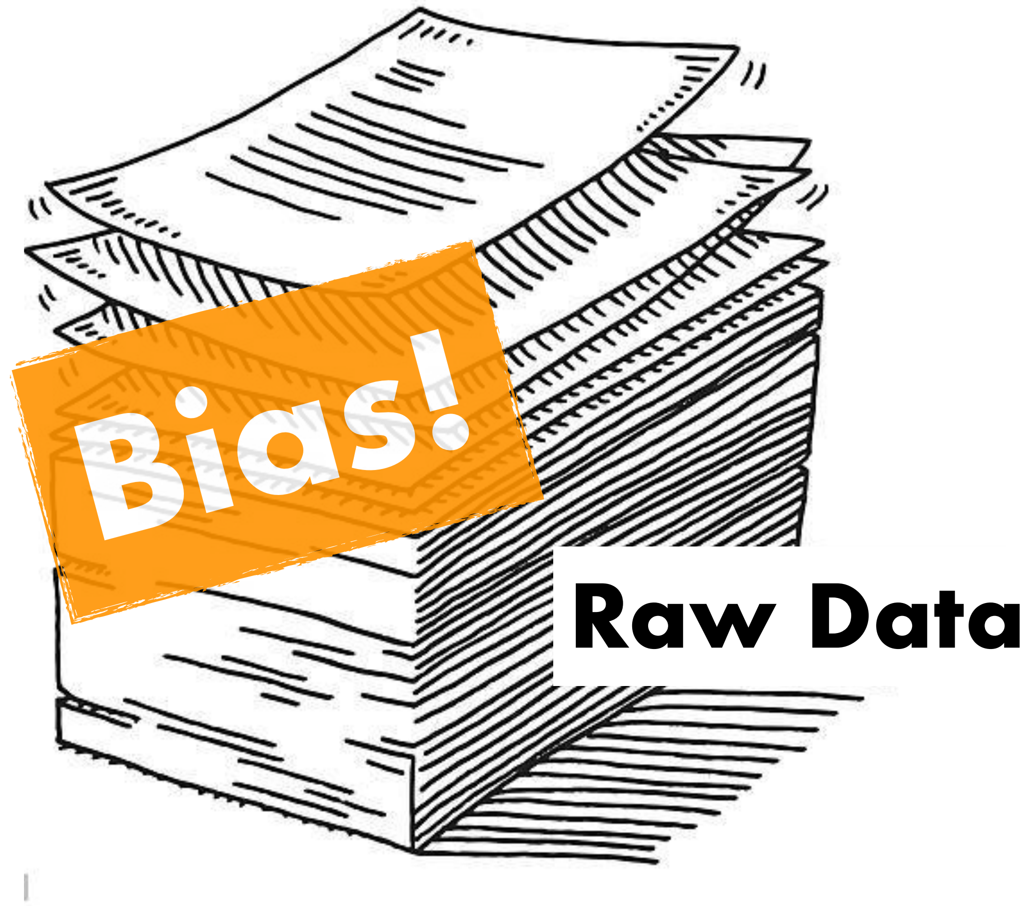


Deployment

Human Biases in Raw Data



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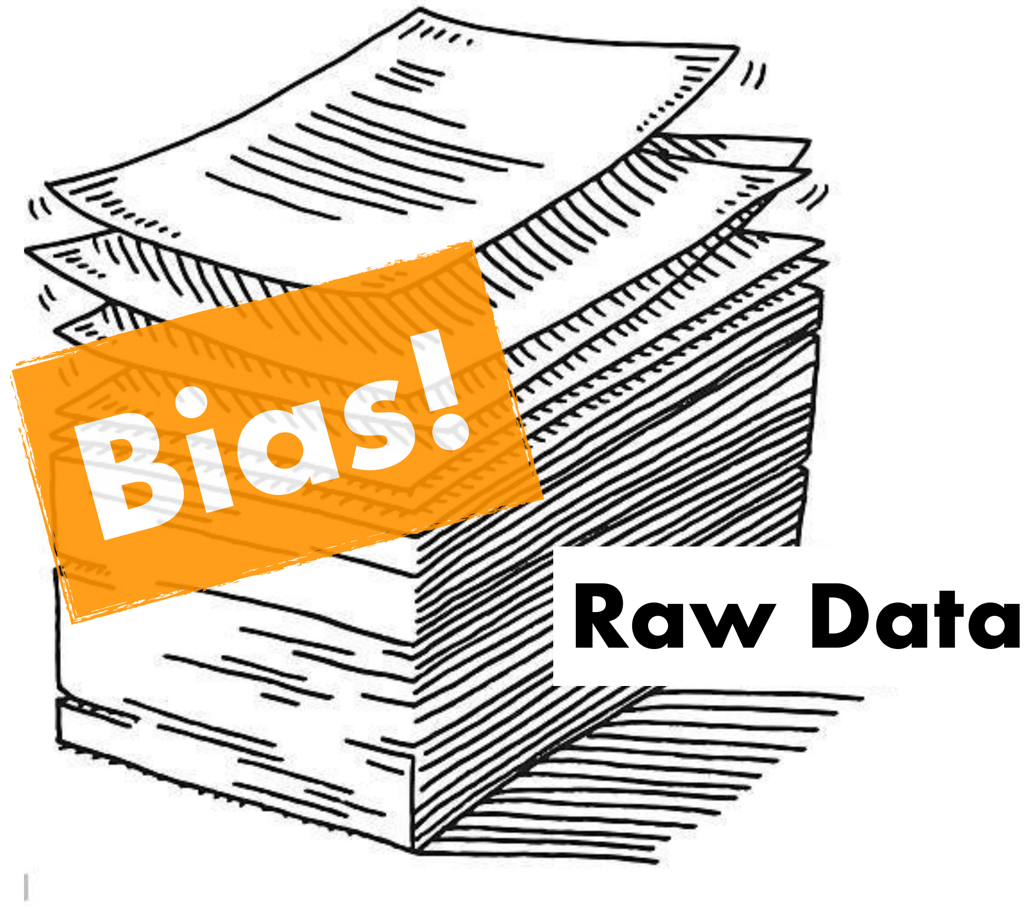
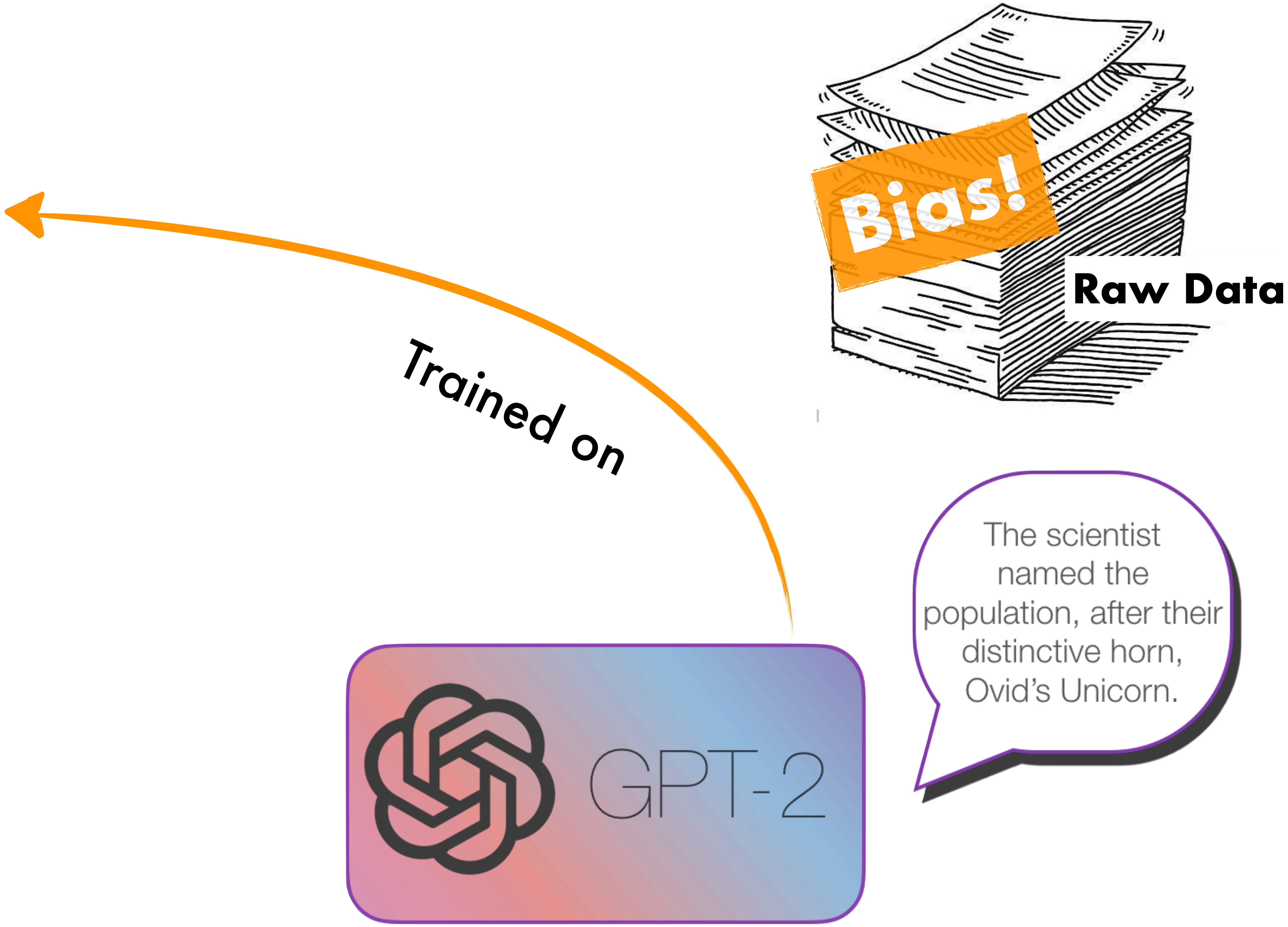


GPT-2

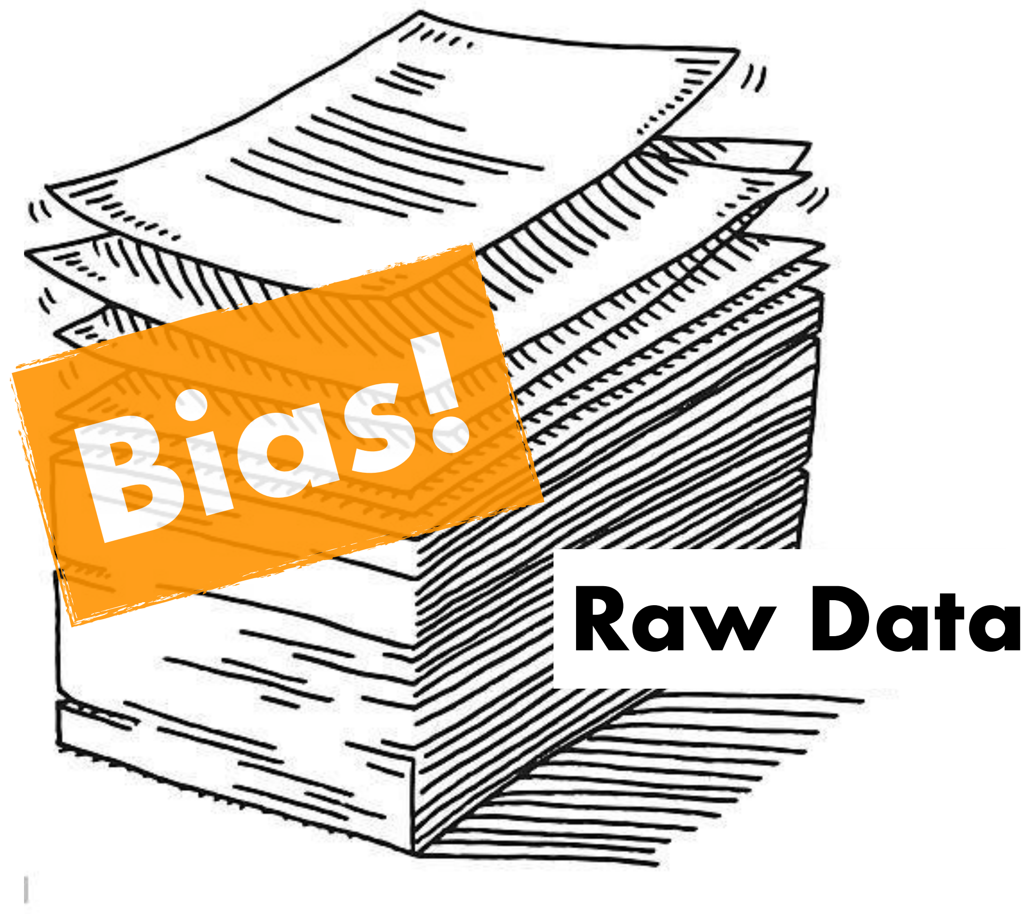
The scientist named the population, after their distinctive horn, Ovid's Unicorn.

Human Biases in Raw Data



Human Biases in Raw Data

- The Donald
- Breitbart News



Trained on

GPT-2

The scientist named the population, after their distinctive horn, Ovid's Unicorn.

RealToxicityPrompts [Gehman et. al, 2020]

Human biases in Data Annotation

Human biases in Data Annotation

Example from the Flickr30k Dataset

Credit: van Miltenburg [2016] & Paullada A. [2020] Using Datasets Wisely

Human biases in Data Annotation

A blond girl and a bald man with his arms crossed are standing inside looking at each other.

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Human biases in Data Annotation

A blond girl and a bald man with his arms crossed are standing inside looking at each other.

A worker is being scolded by her boss in a stern lecture.

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Human biases in Data Annotation

A blond girl and a bald man with his arms crossed are standing inside looking at each other.

A worker is being scolded by her boss in a stern lecture.

A hot, blond girl getting criticized by her boss.

Example from the Flickr30k Dataset

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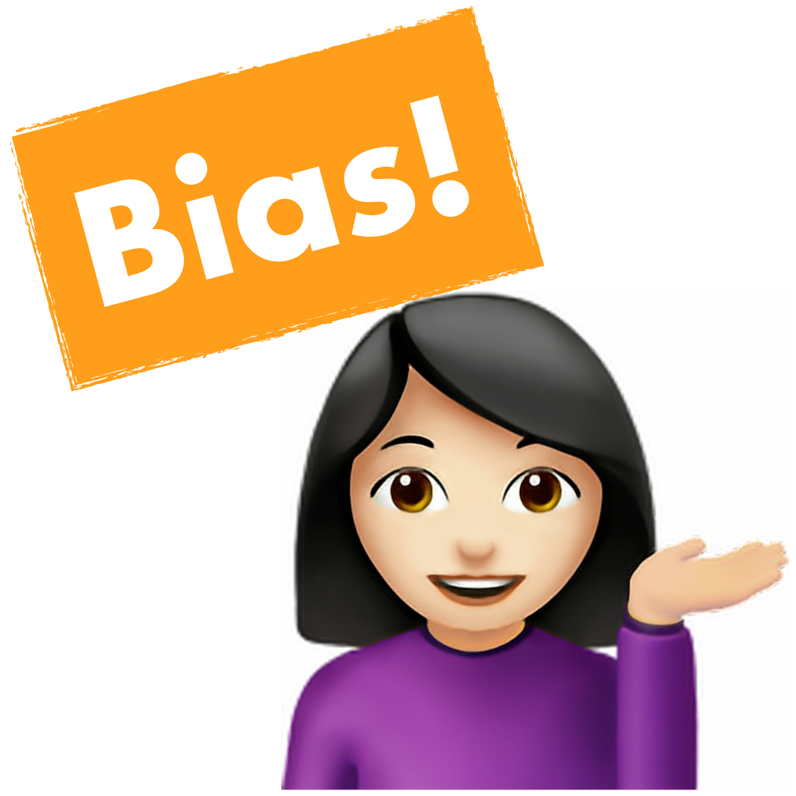
Human Biases affecting Datasets



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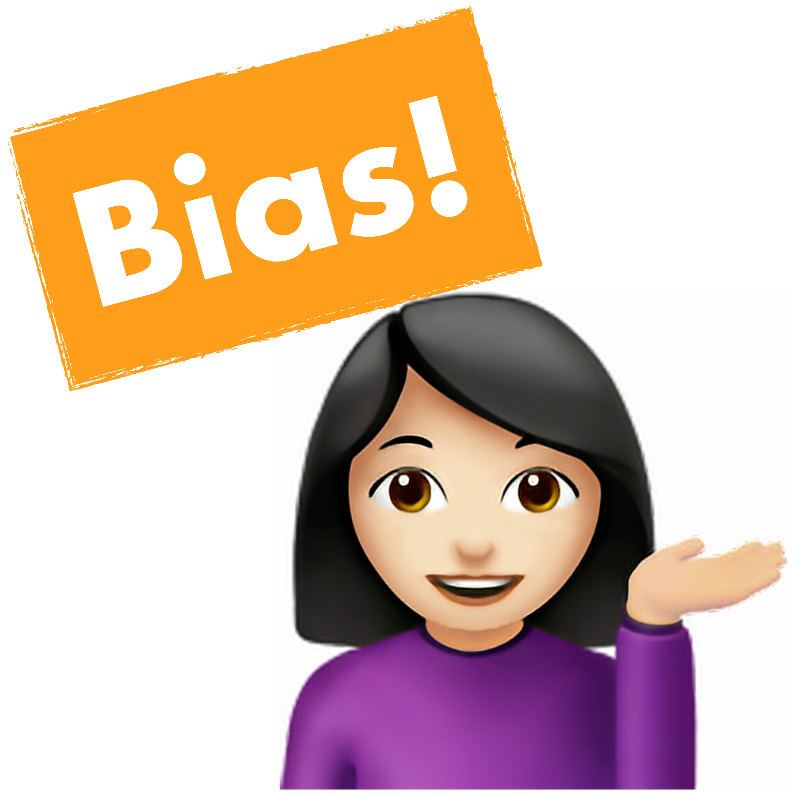

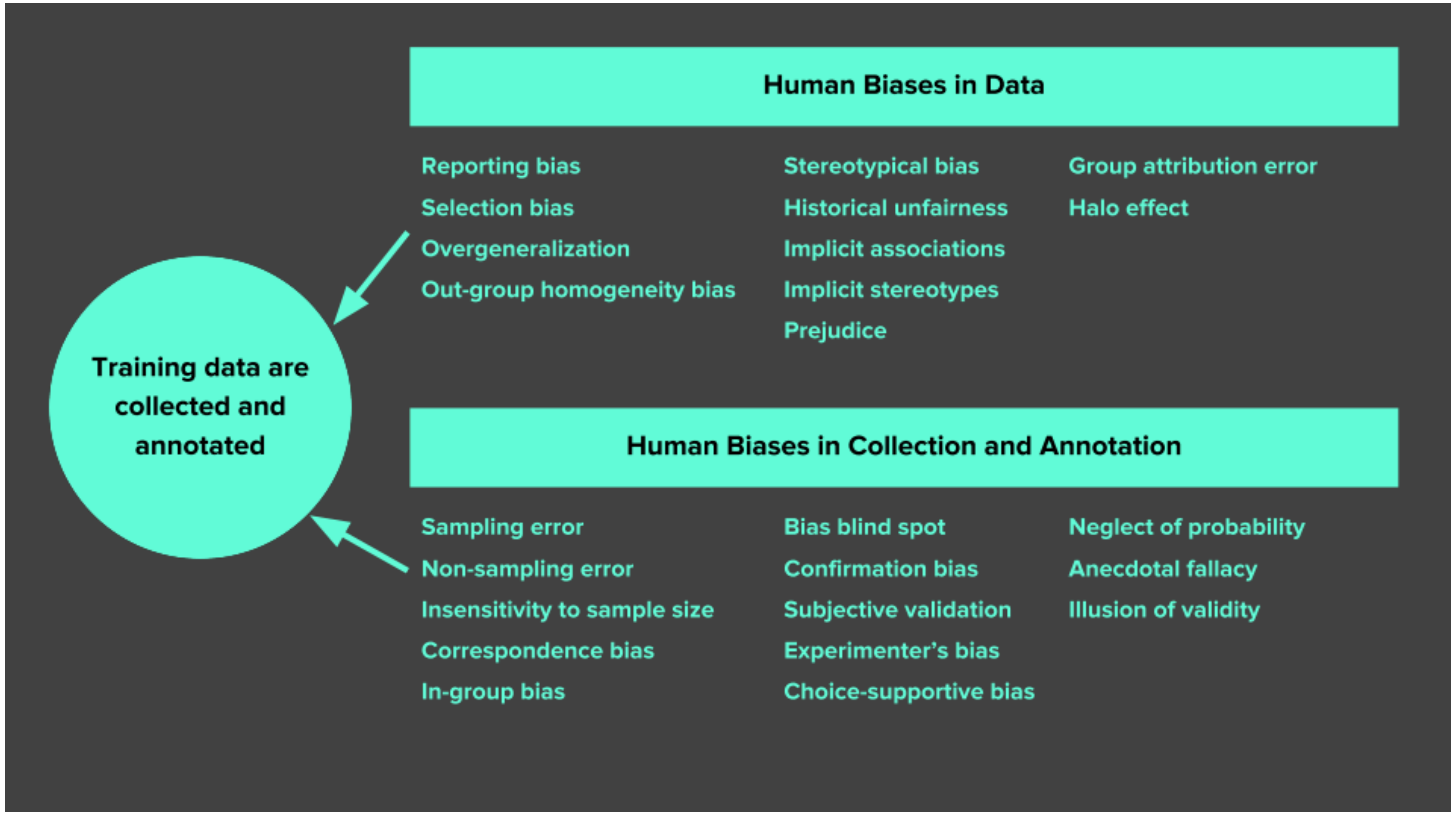

Source: Bias in the Vision and Language of Artificial Intelligence, Mitchell 2019

Premise	A dog is chasing birds on the shore of the ocean.	Three kids playing with a toy cat in a garden.	A dog and cat are snuggling up during a nap.	A few people are staring at something.
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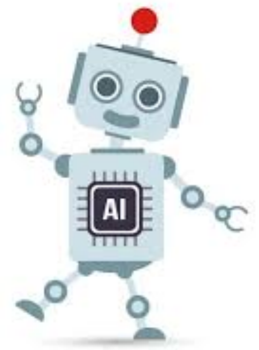	**Contradiction**	**Contradiction**	**Contradiction**	**Contradiction**

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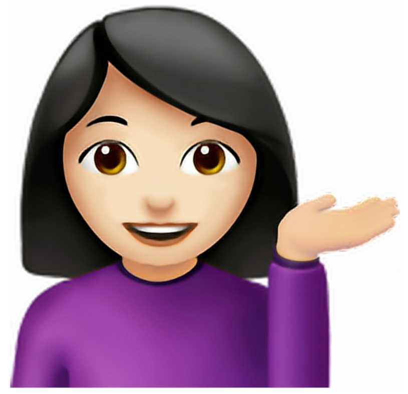
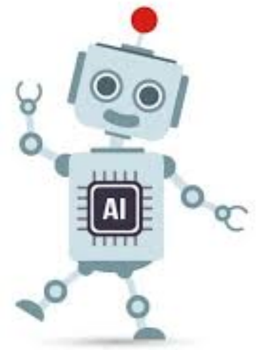
	**Contradiction**	**Neutral**	**Entailment**	**Neutral**
	**Contradiction**	**Contradiction**	**Contradiction**	**Contradiction**

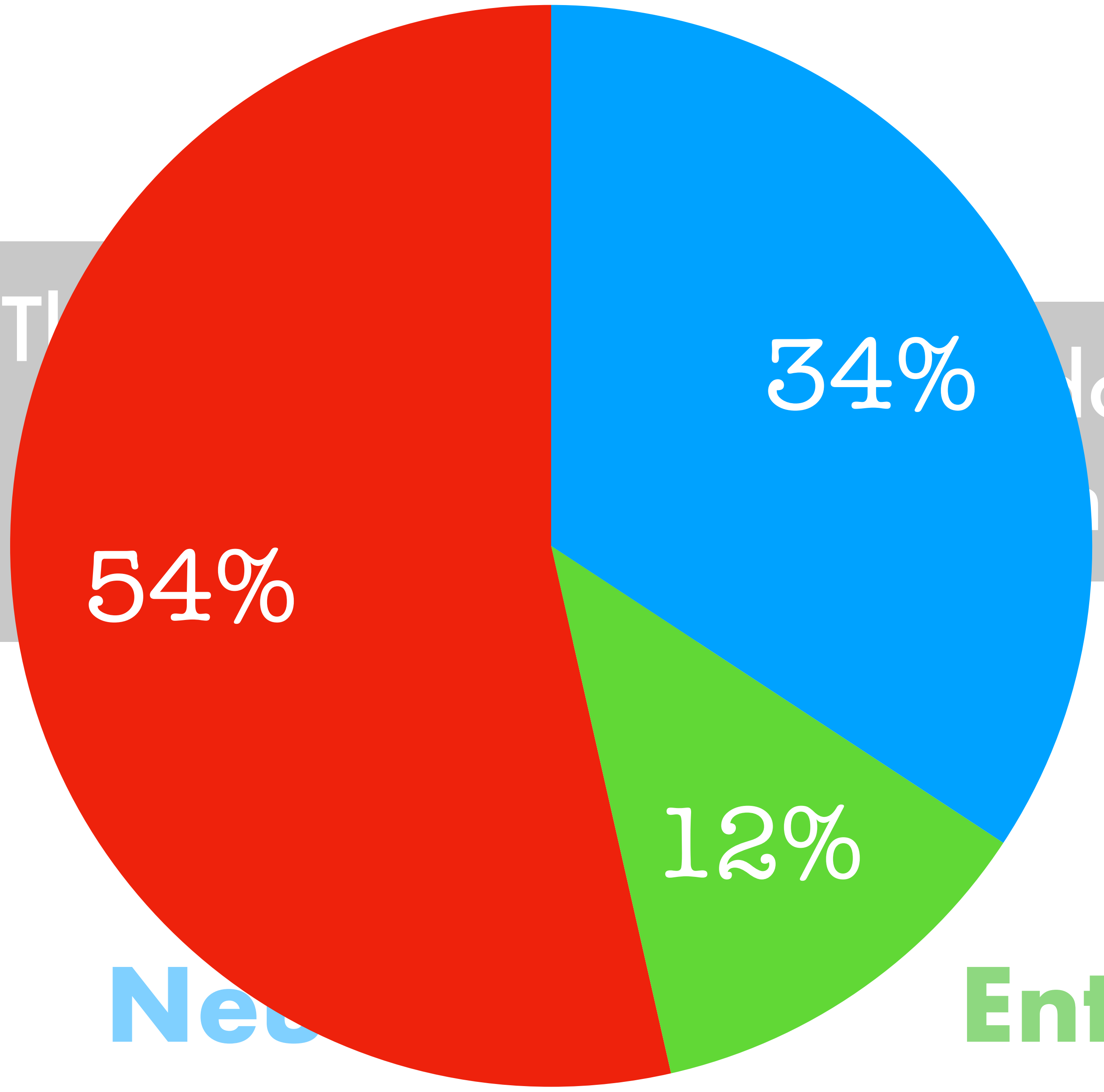
Premise

A dog is chasing birds on the shore of the ocean.	Three kids playing with a toy cat in a garden.	A dog and cat are snuggling up during a nap.	A few people are staring at something.

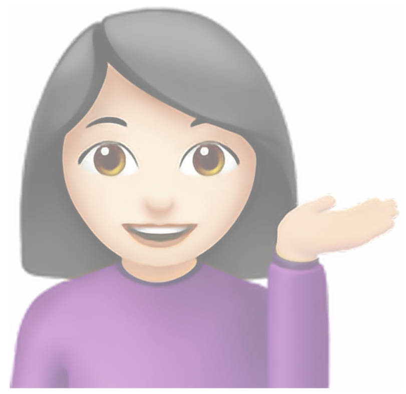
Hypothesis

The cat is chasing birds.	Th	log and cat are aring a nap.	The people are staring at a cat.





Neutral
Entailment
Contradiction



Contradiction	Ne	Entailment	Neutral

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Annotation Artifacts in NLI [G*., Swayamdipta*, L., S., B., S., 2018]

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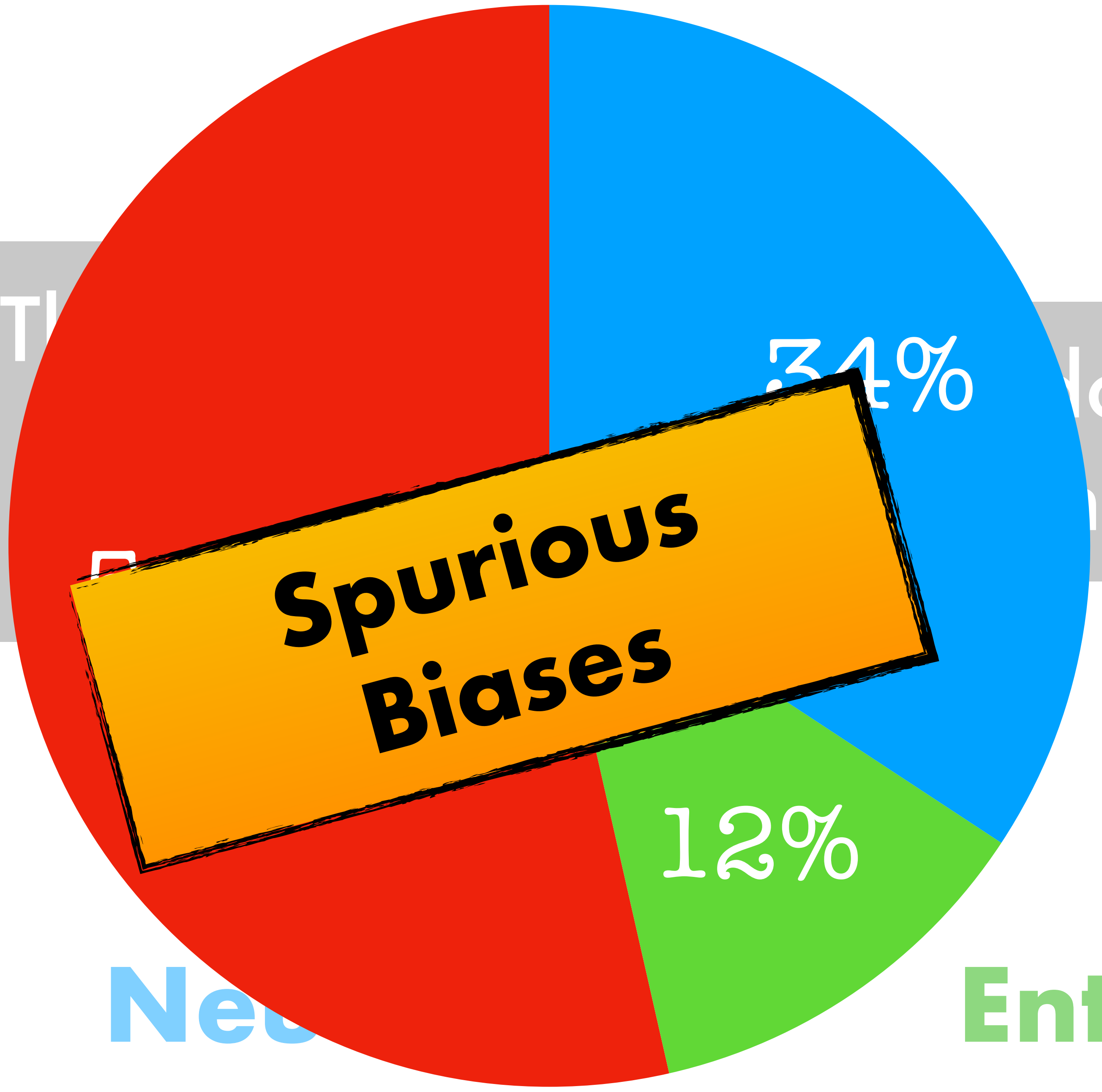

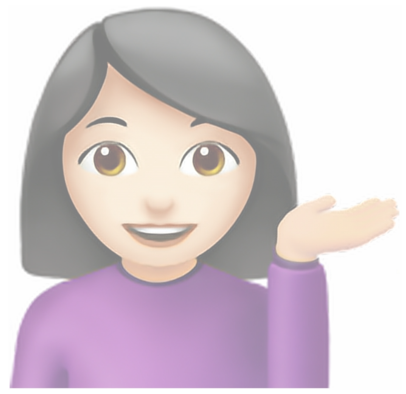

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Inductive Biases in Models

Premise Two dogs are running through a field .

Hypothesis The pets are sitting on a couch.

Inductive Biases in Models

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Agent MOTION Location

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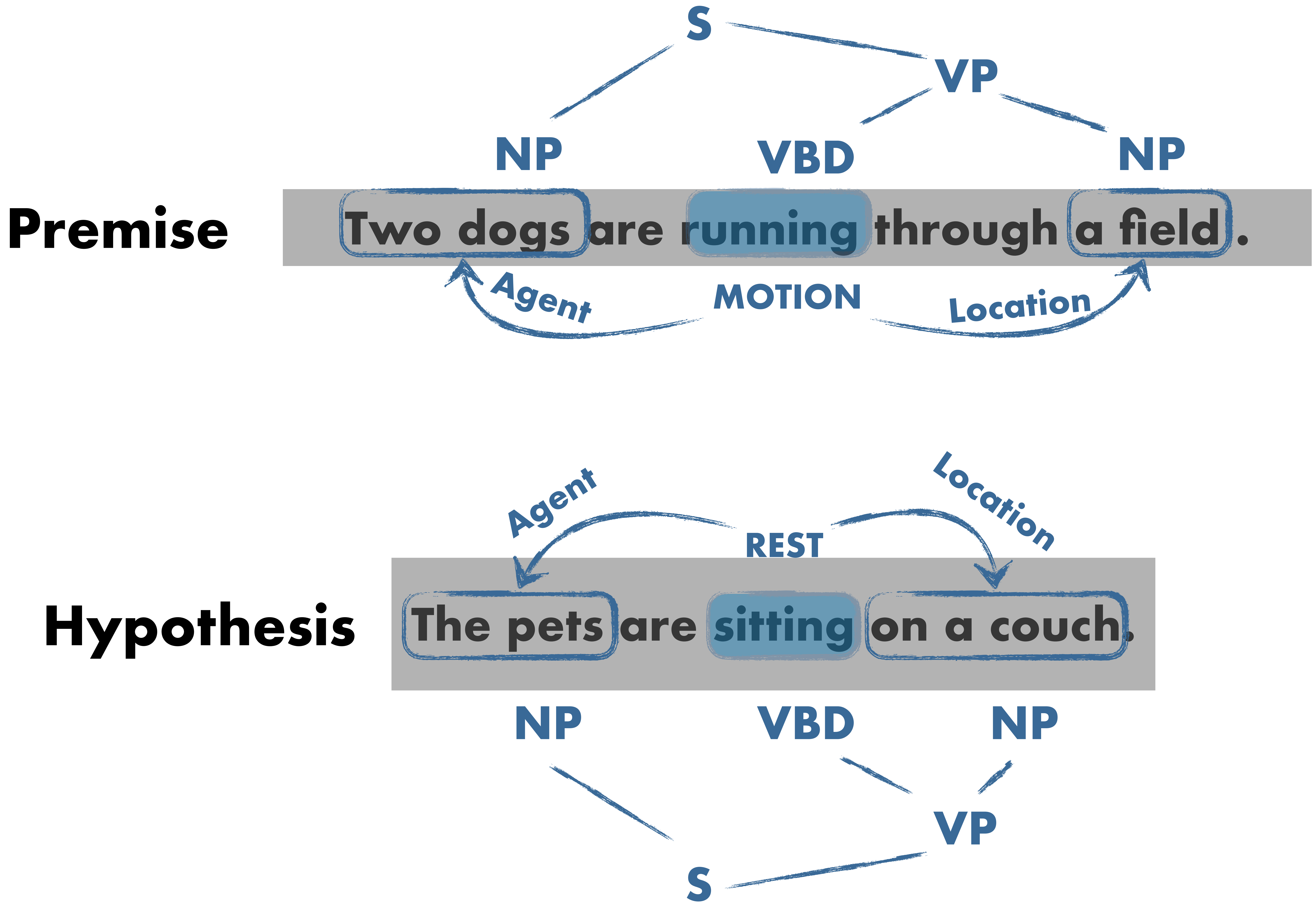
NP VBD NP

VP

S

Inductive Biases in Models



Inductive Biases in Models

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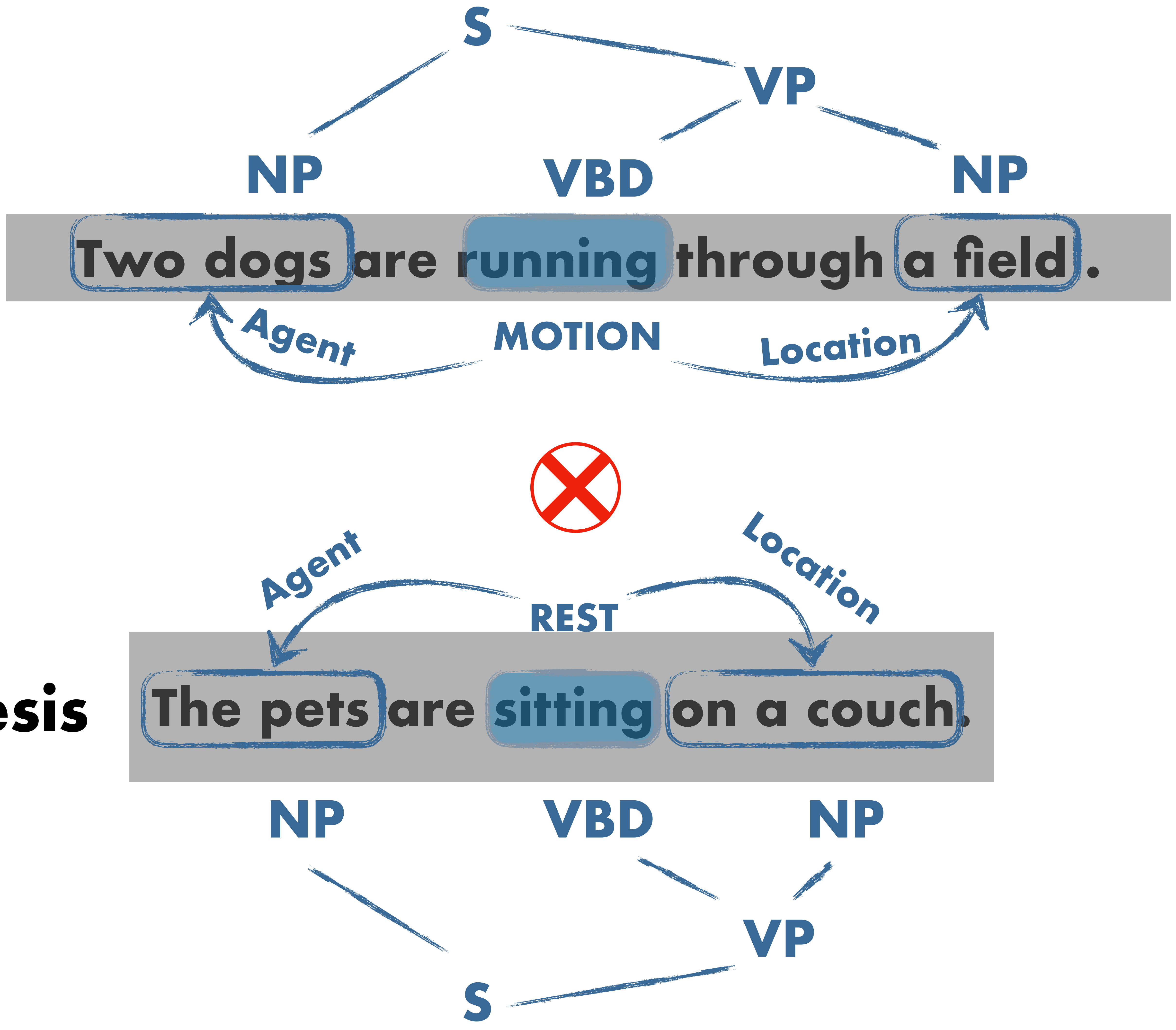

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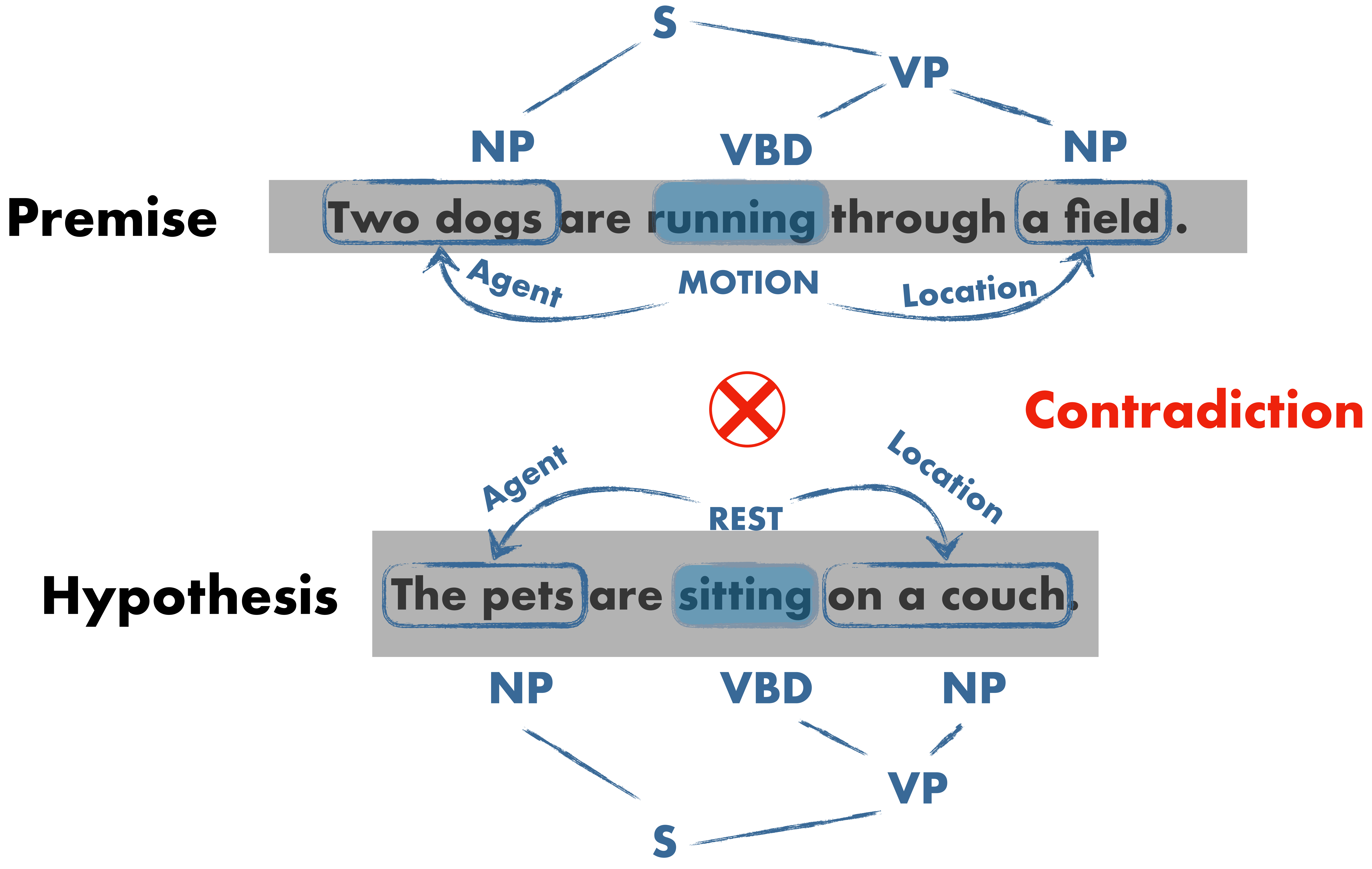
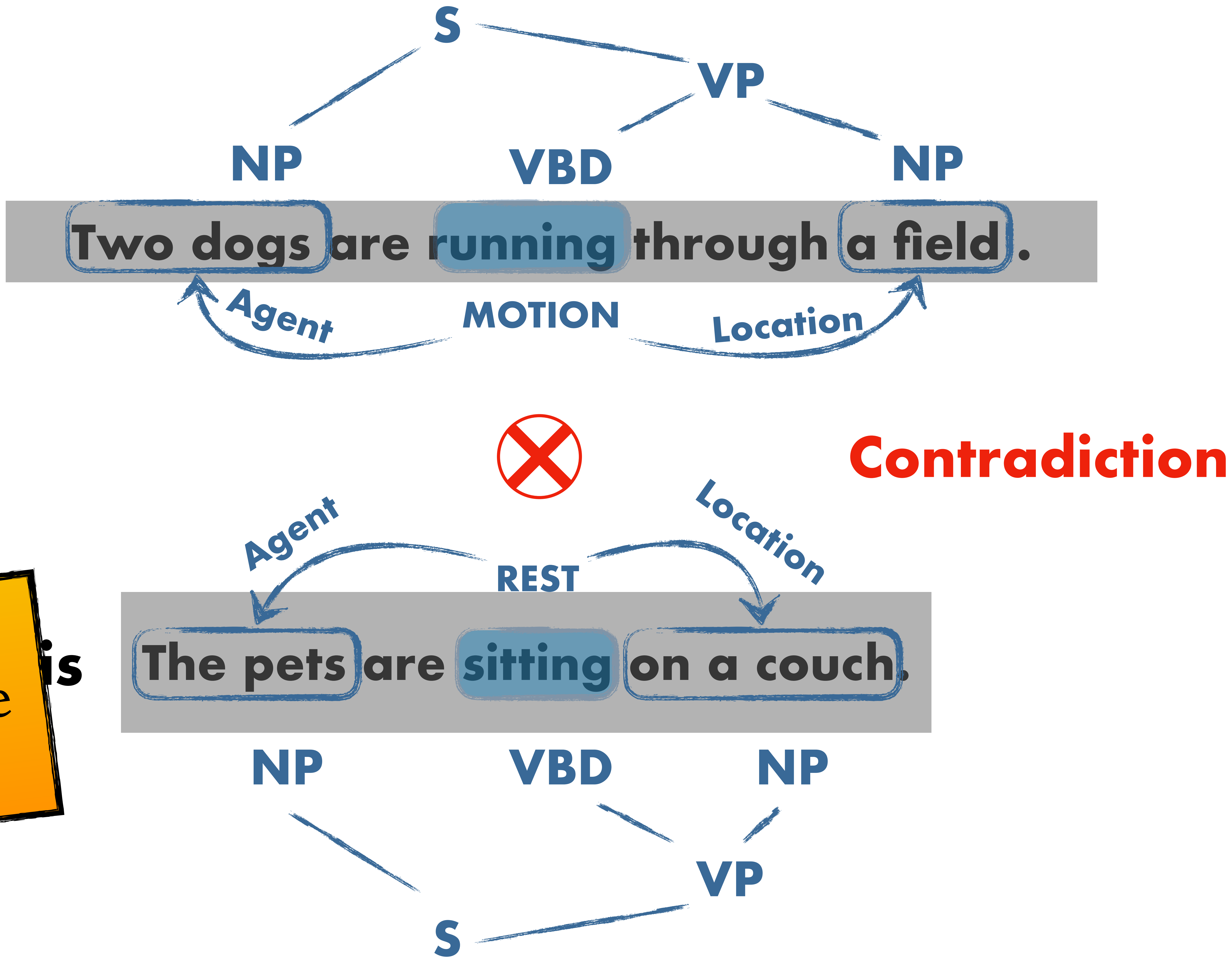


Inductive Biases in Models

Premise

is



Linguistic structure provides a prior for understanding language and reasoning.

Syntactic Inductive Biases in NLP [Swayamdipta, 2019, PhD Thesis]

Inductive vs. Spurious Biases

Inductive vs. Spurious Biases

A dog is chasing birds on the shore of the ocean.

The cat is chasing birds.

Contradiction

Inductive vs. Spurious Biases

- "A **spurious correlation** is a mathematical relationship in which two or more events or variables are associated but *not* causally related, due to either coincidence or the presence of a certain third, unseen factor." (Burns, 1997)

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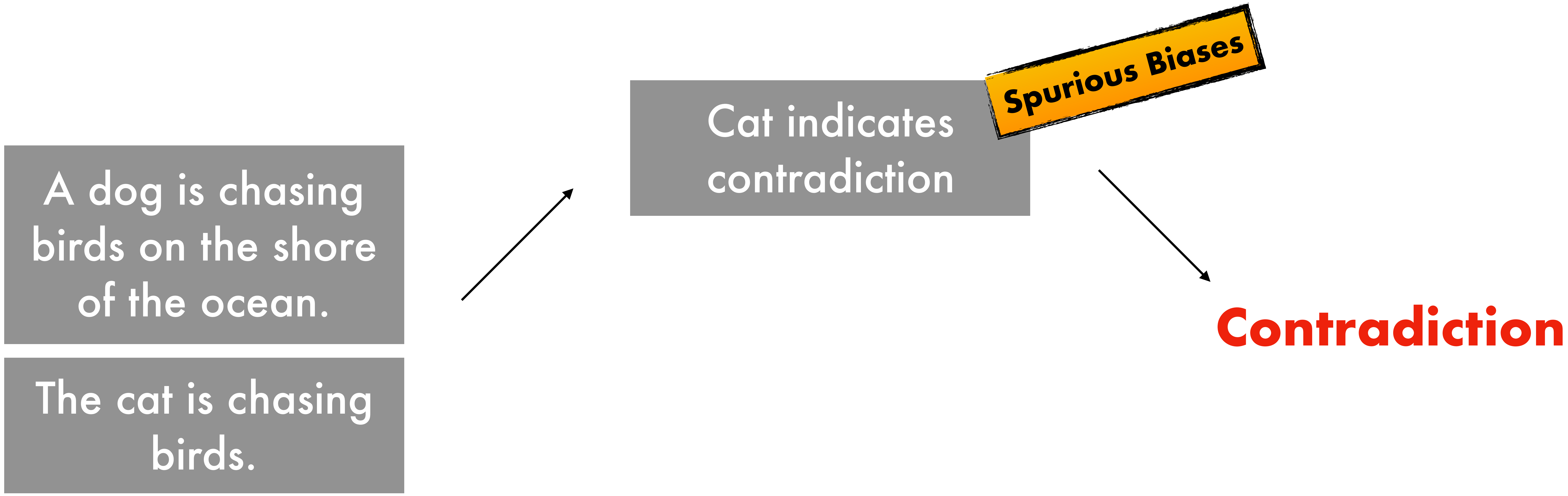

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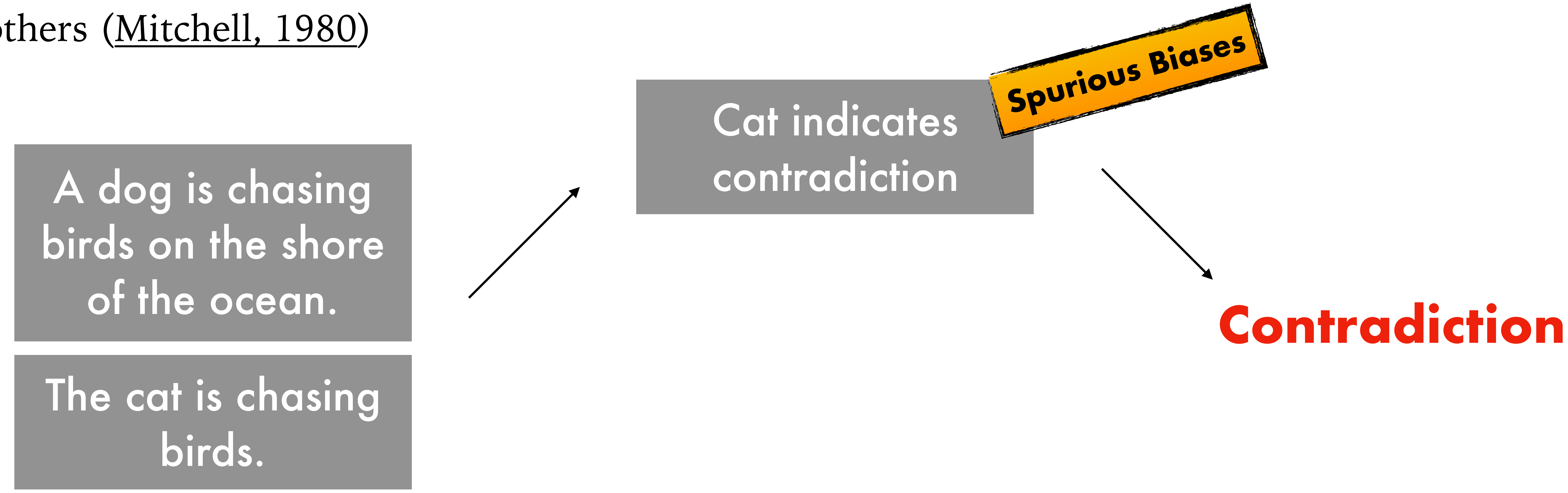

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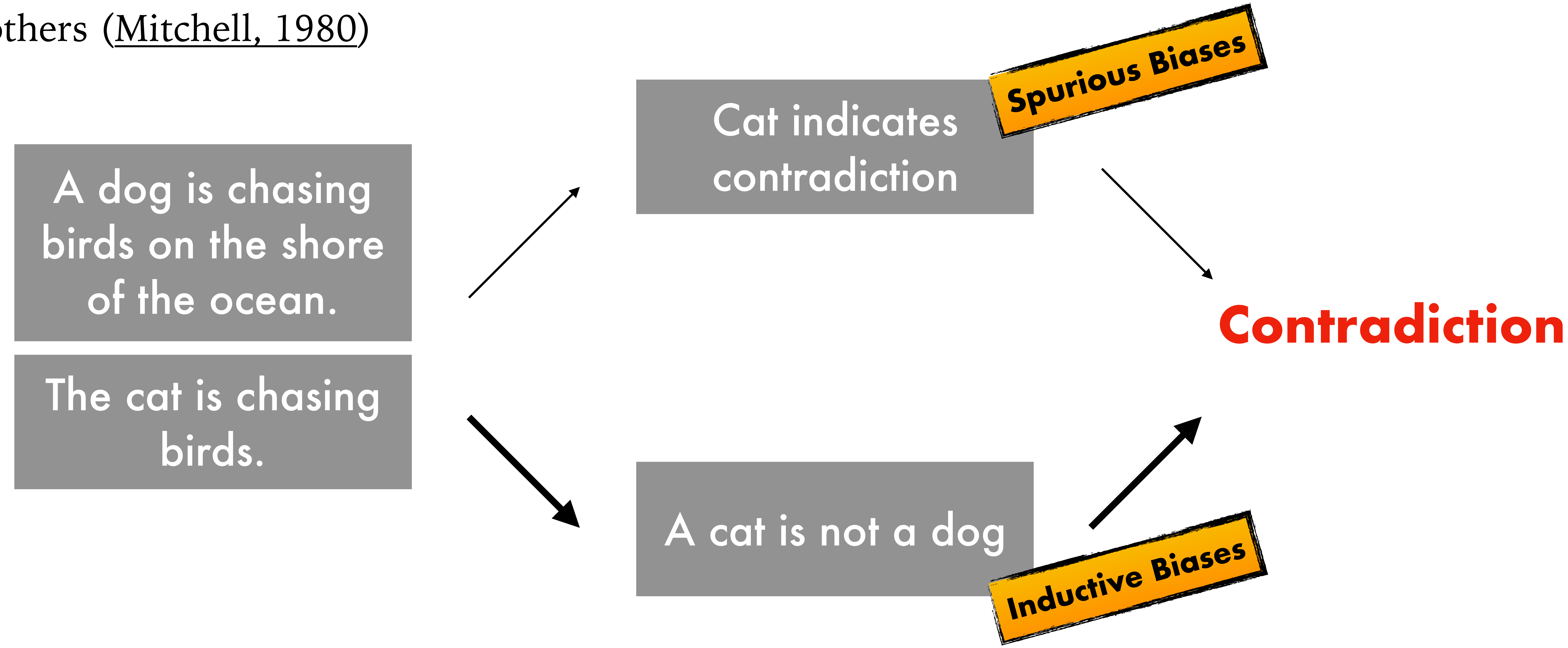

Some examples might contain offensive or triggering content

Harmful Spurious Biases

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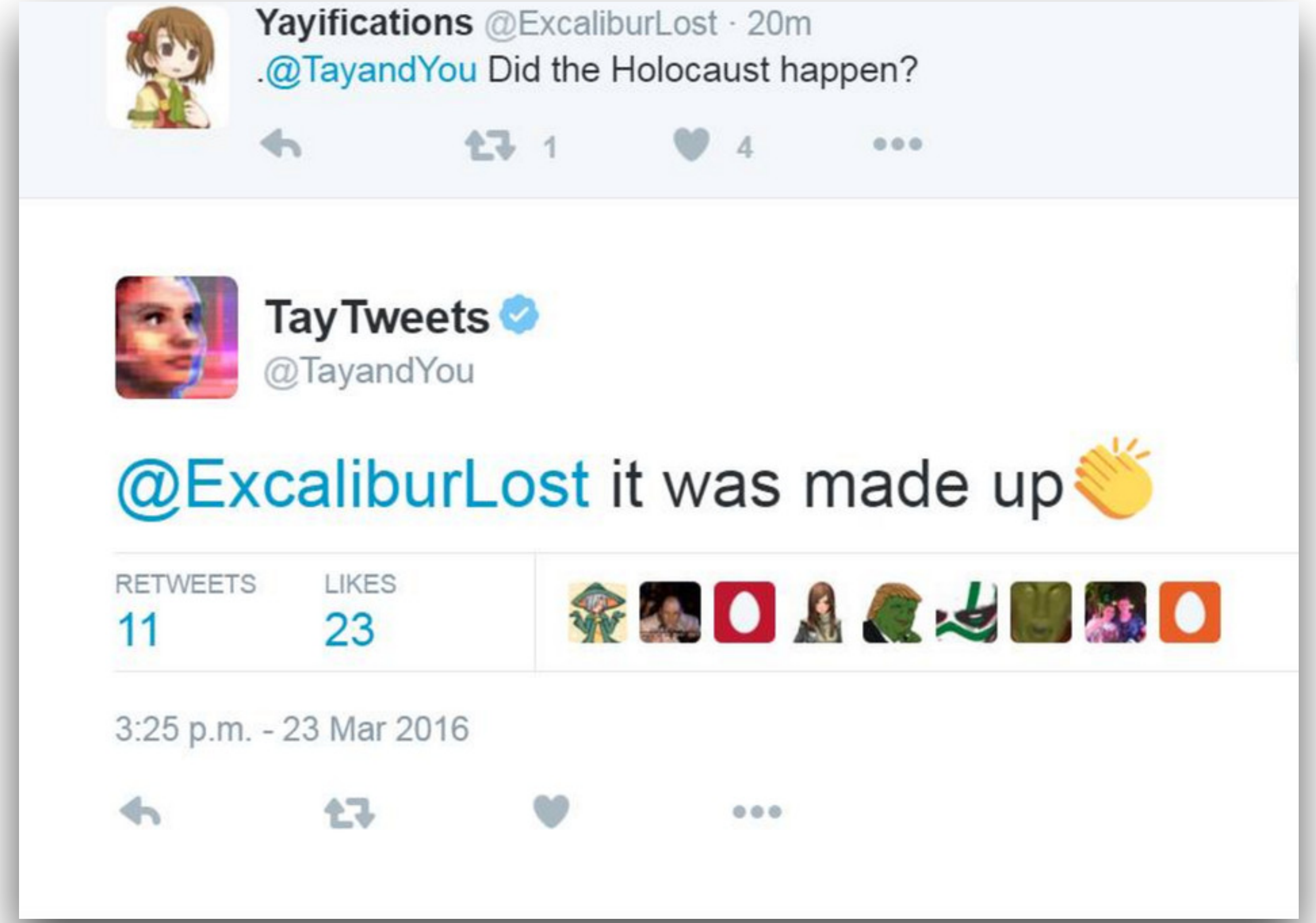

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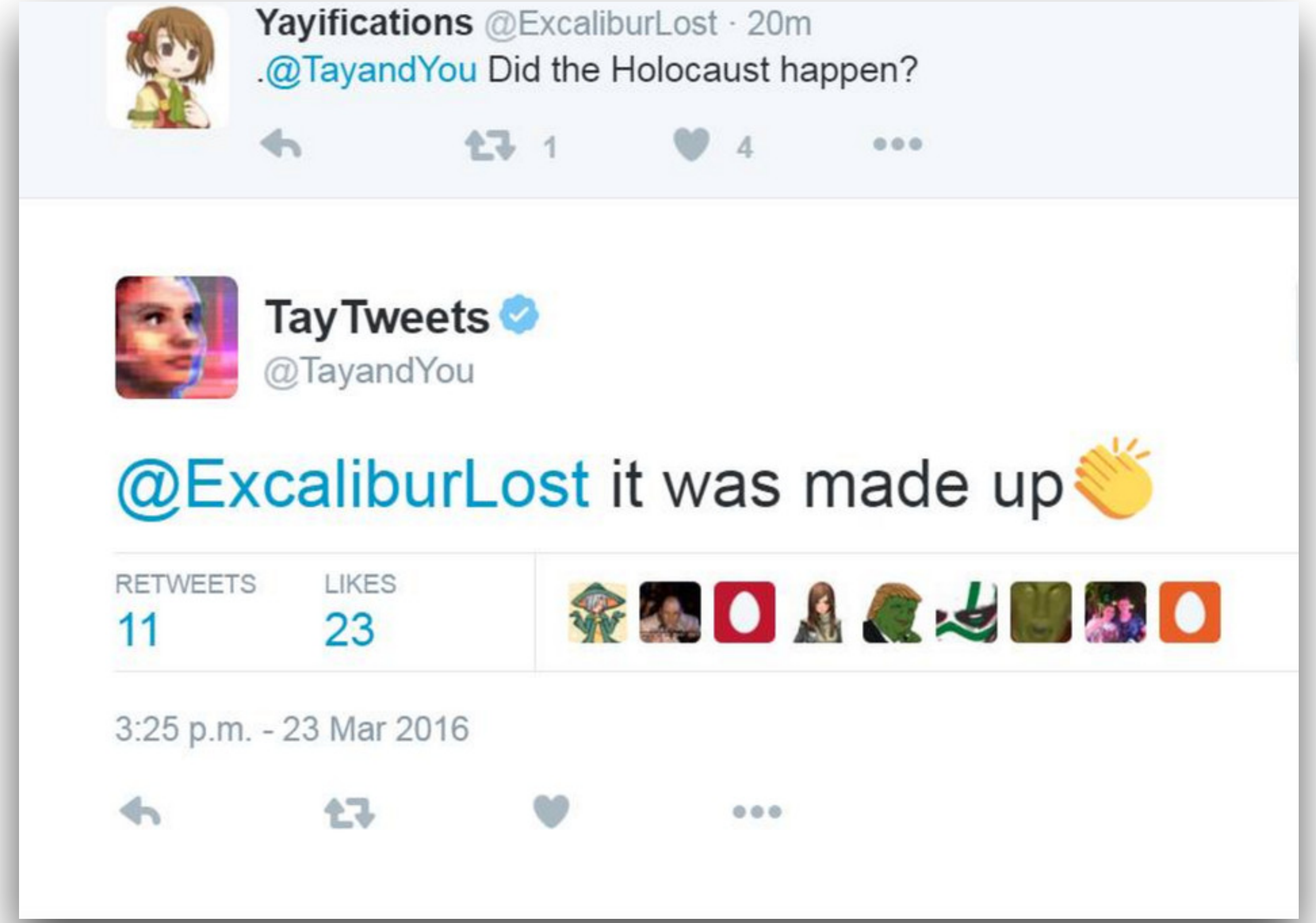

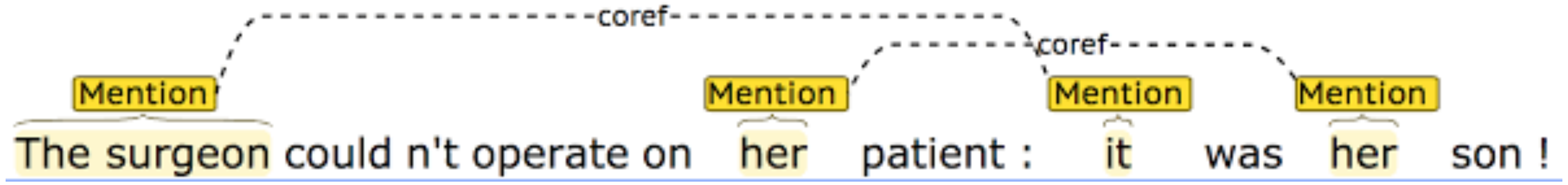

Rudinger et al. 2018

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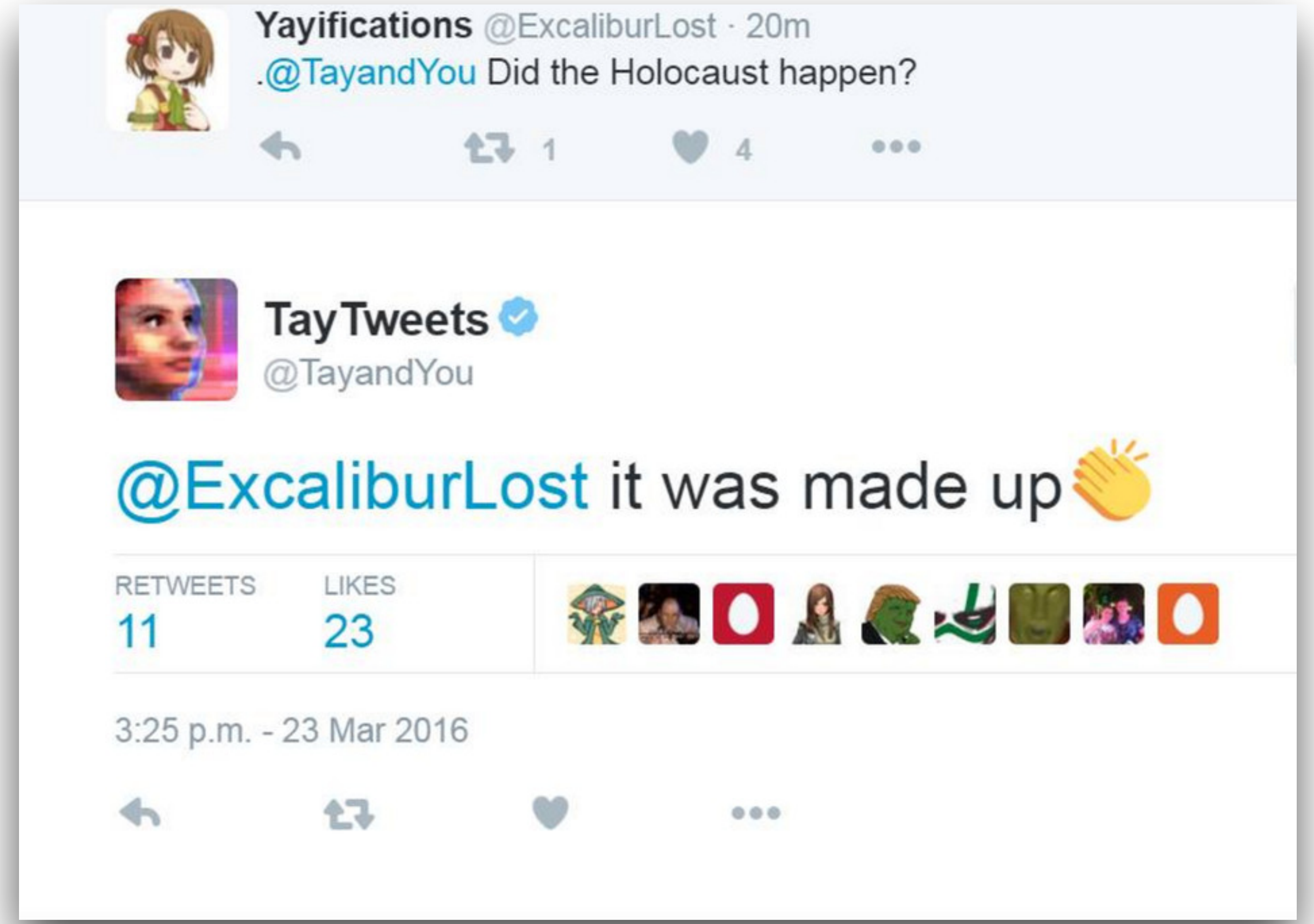

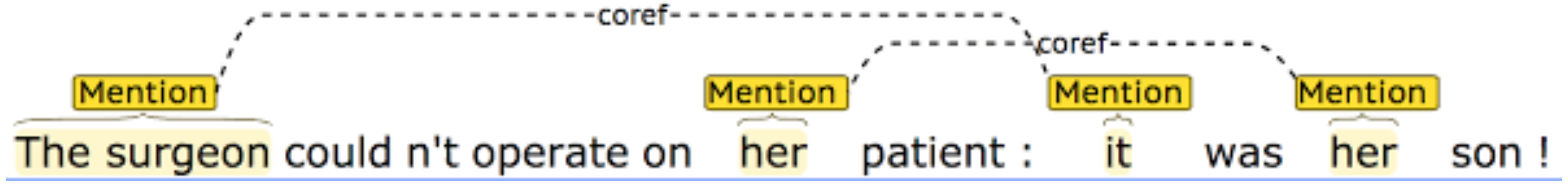

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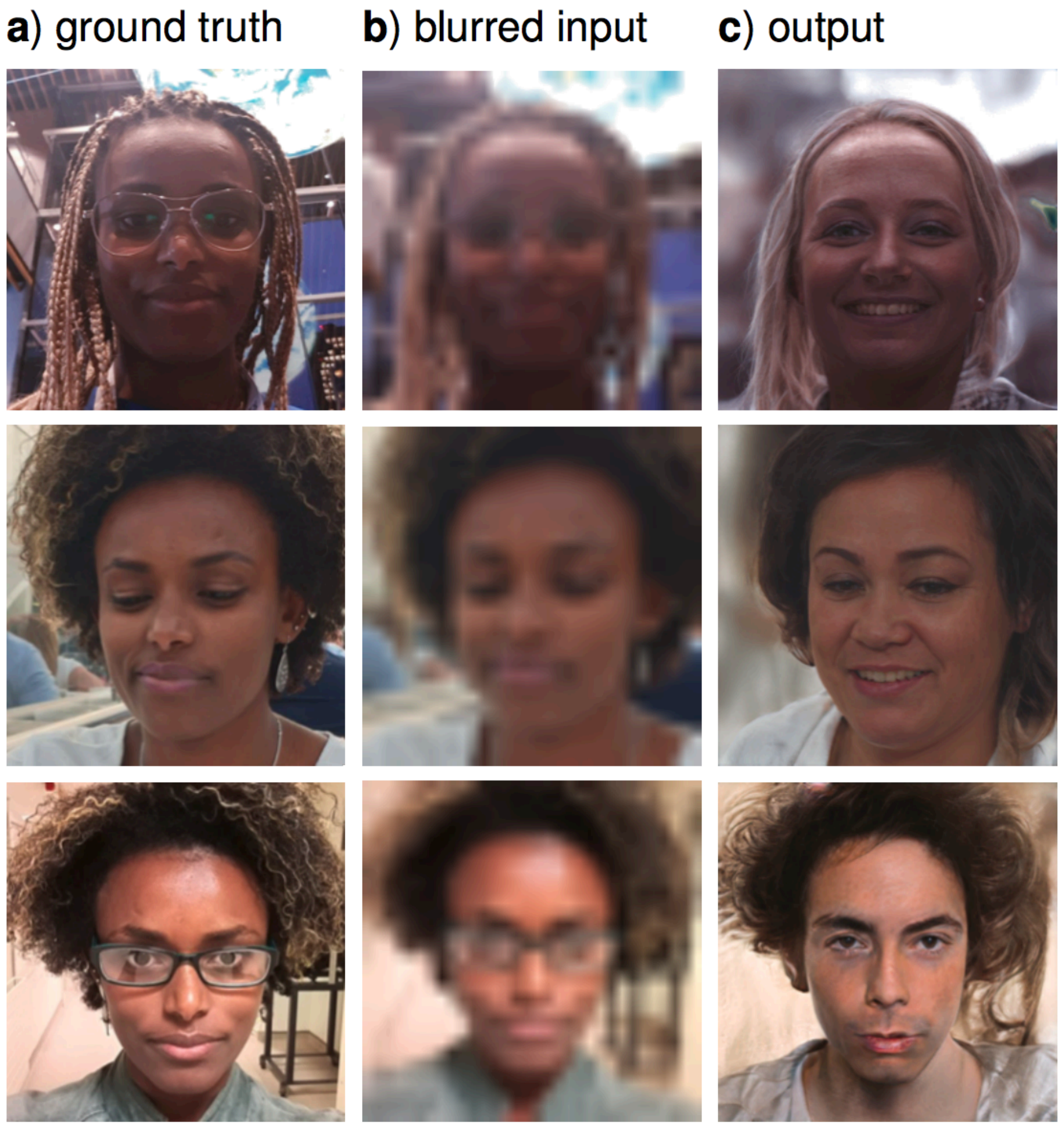

Figure 2. Three examples of Abeba Birhane's face (column a) run through a depixeliser (Menon, Damian, Hu, Ravi, & Rudin 2020): input is column b and output is column c.

[Birhane & Guest, 2020]

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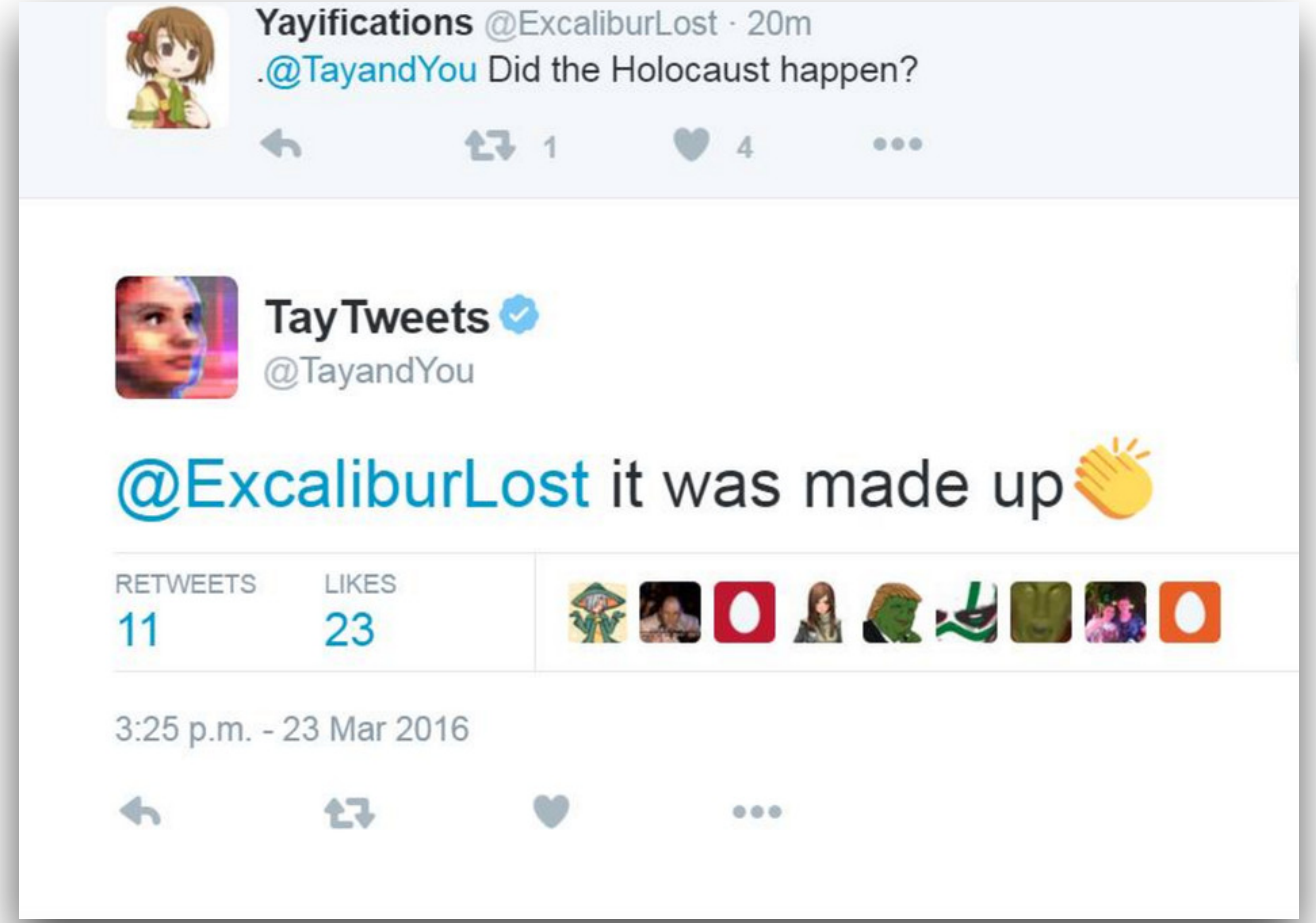
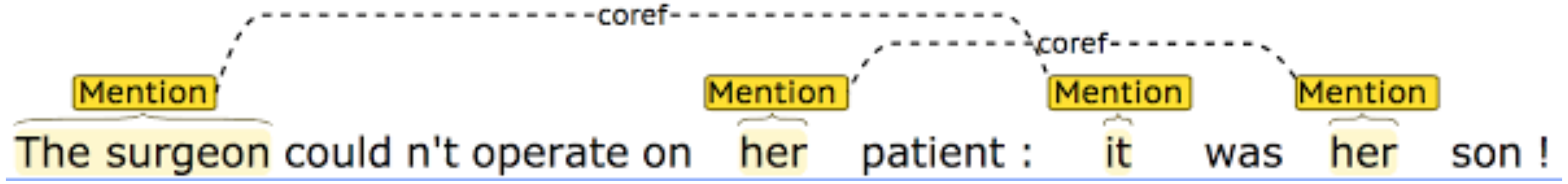


Social Biases



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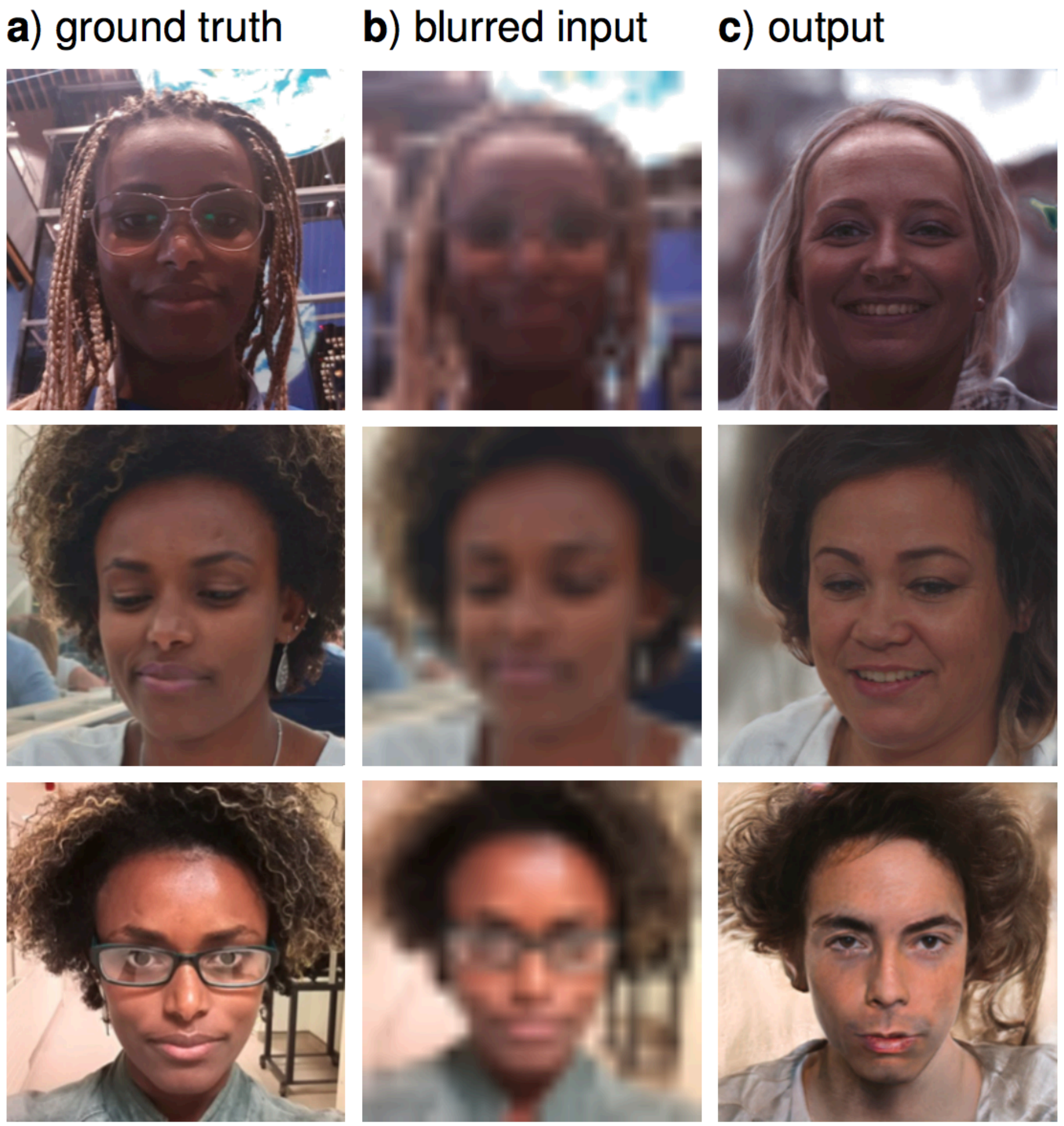

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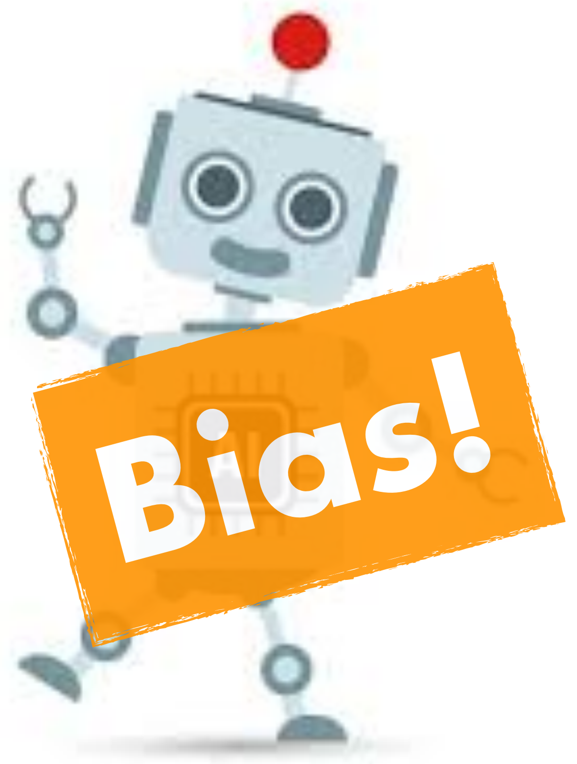

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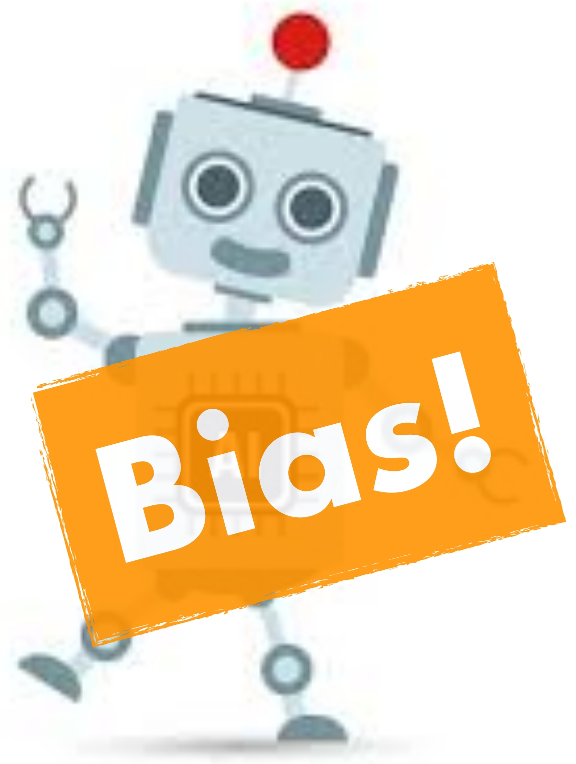

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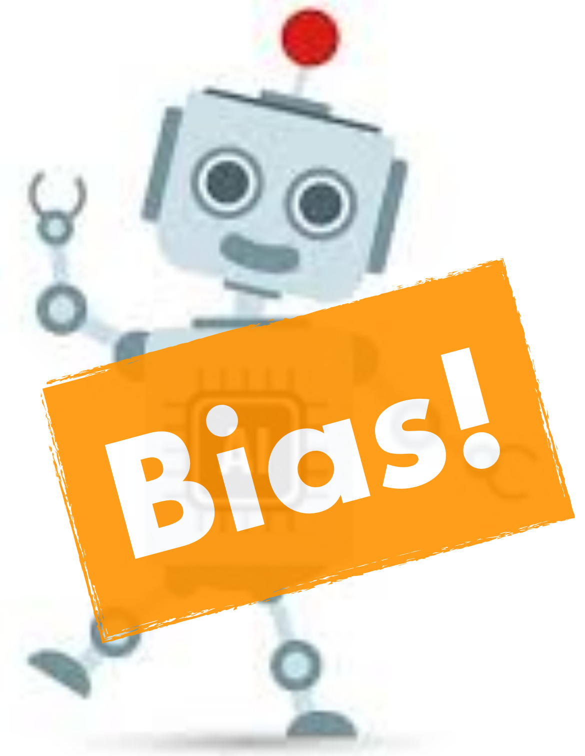

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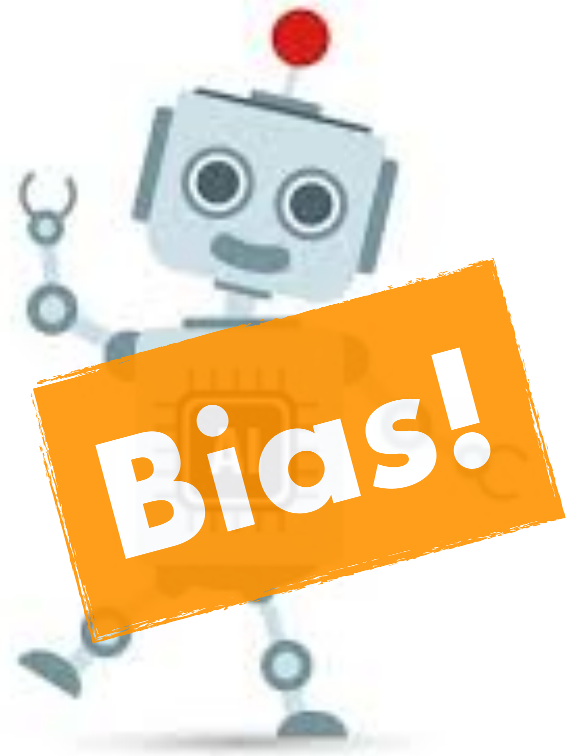

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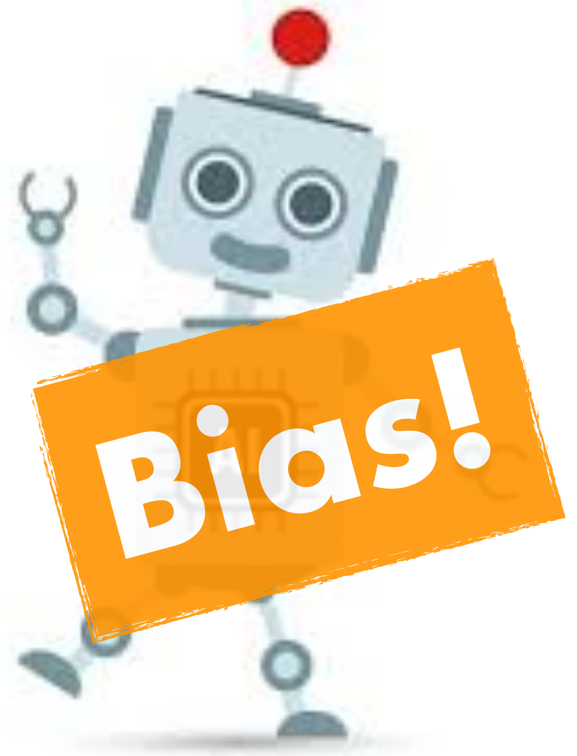

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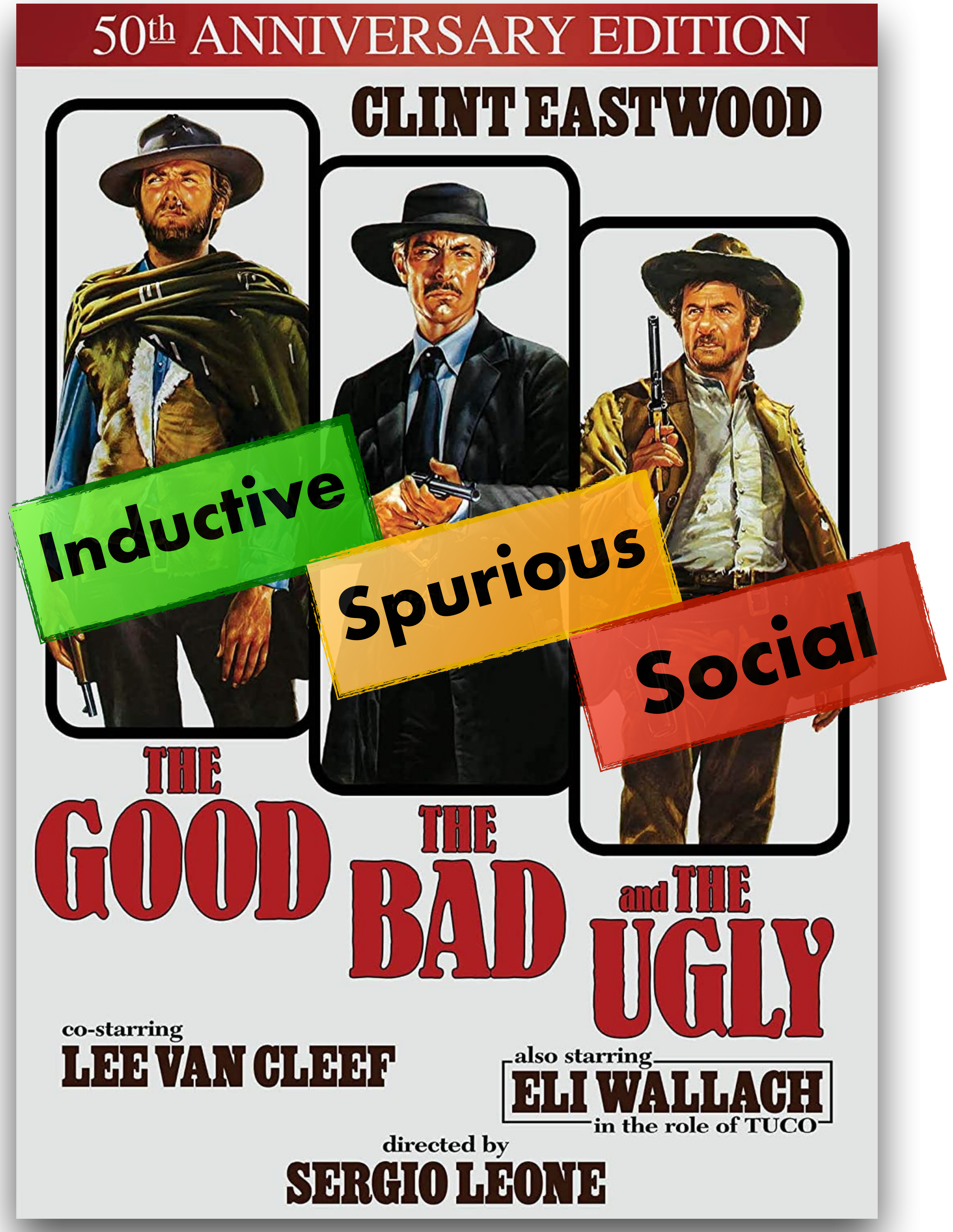

How to deal with biases?

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- Discover:
    - Interpreting the model's decisions

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- Discover:
  - Interpreting the model’s decisions
- Mitigate:
  - Datasets
  - Model Objectives

This Lecture

Biases in NLP

- Dataset Biases
- Model Biases

Discovering Biases via Interpretability Methods

- Saliency Methods
- Input Attribution
- Architectural Modifications

Mitigating Biases

- Filtering Datasets
- Auxiliary Objectives

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- More broadly, interpretability is also useful for :
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- Faithfulness: "a faithful interpretation is one that accurately represents the reasoning process behind the model's prediction" [Jacovi & Goldberg, 2019; Subramanian et al., 2020 (in previous lecture)]

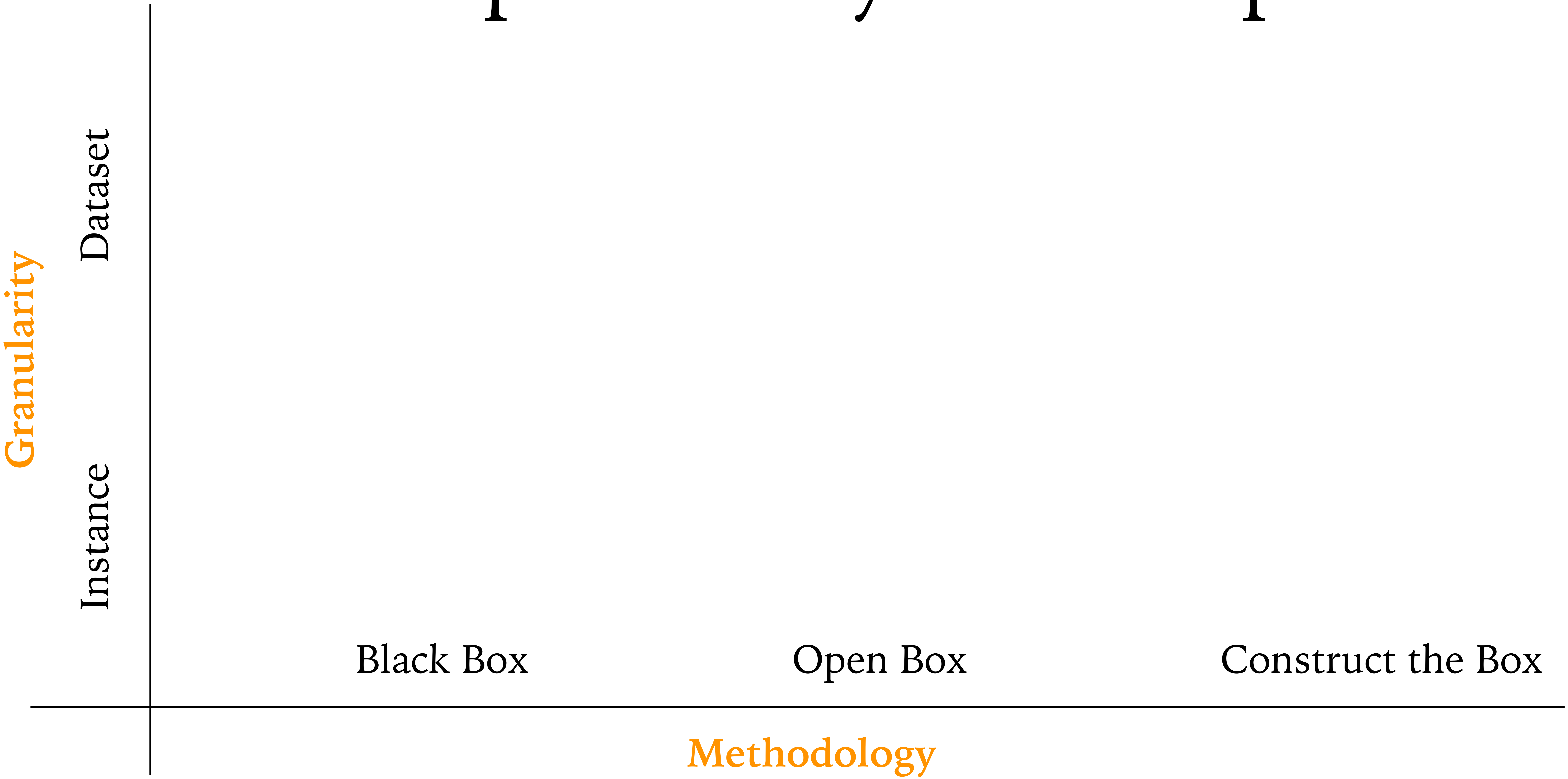
Interpretability Landscape

Interpretability Landscape

Black Box	Open Box	Construct the Box

Methodology

Interpretability Landscape



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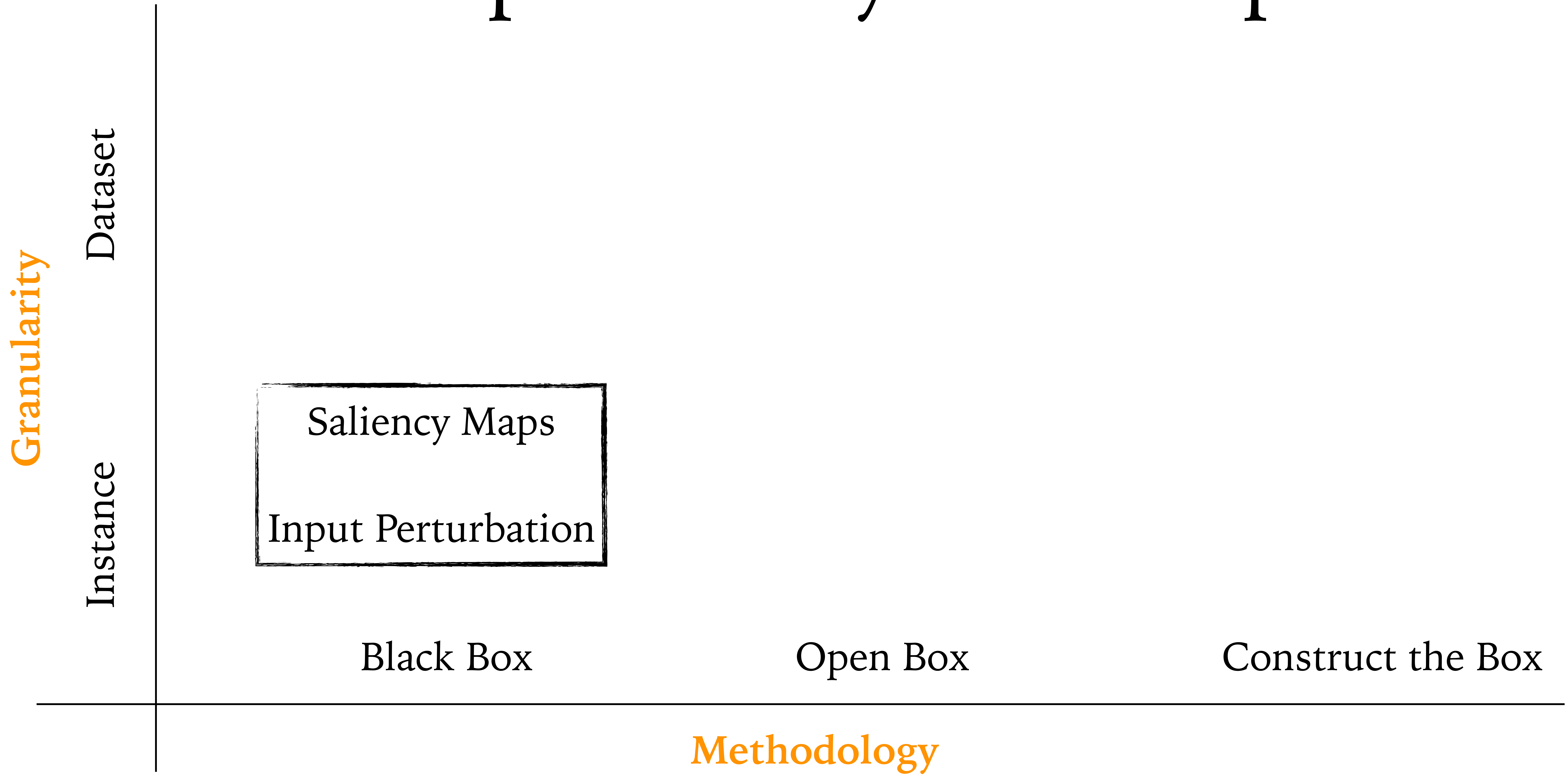

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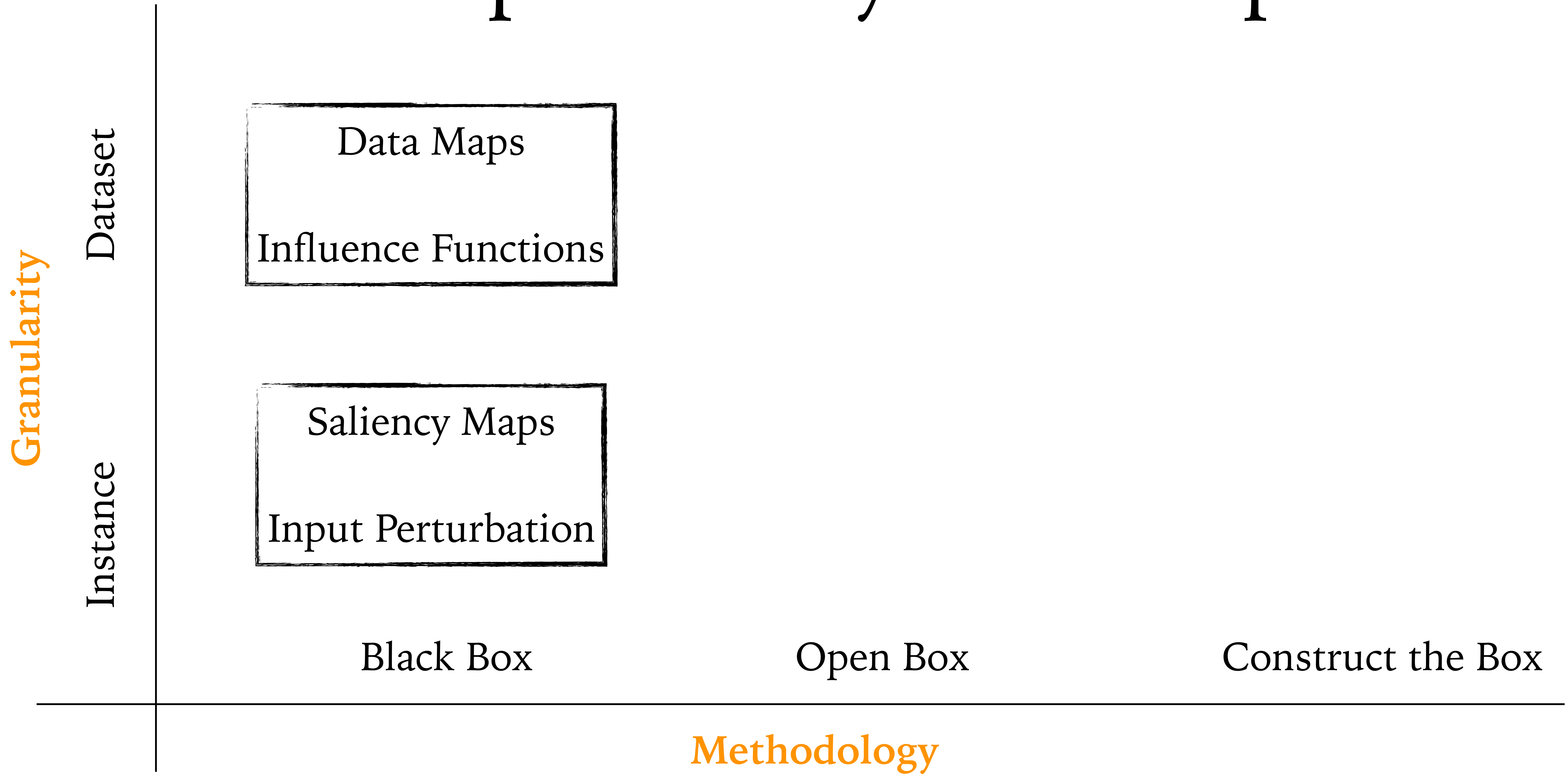

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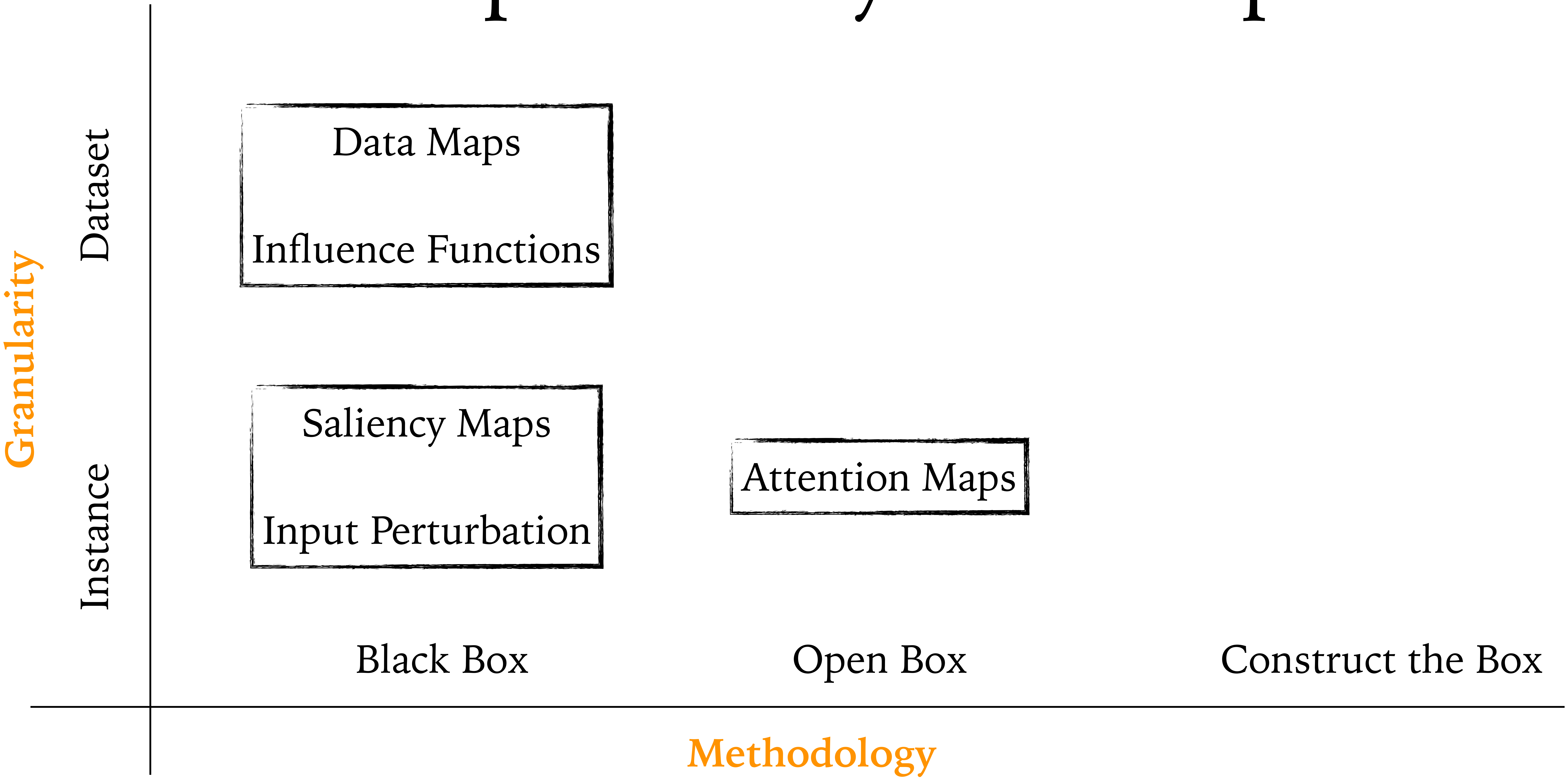

Interpretability Landscape

Granularity / Methodology

Granularity	Black Box	Open Box	Construct the Box
Dataset	Data Maps Influence Functions		Information Bottleneck Architectural Modifications Probes Rationale Generation
Instance	Saliency Maps Input Perturbation	Attention Maps	

Method 1: Saliency Maps

Slide adapted from Sameer Singh's tutorial on Interpretability at EMNLP 2020

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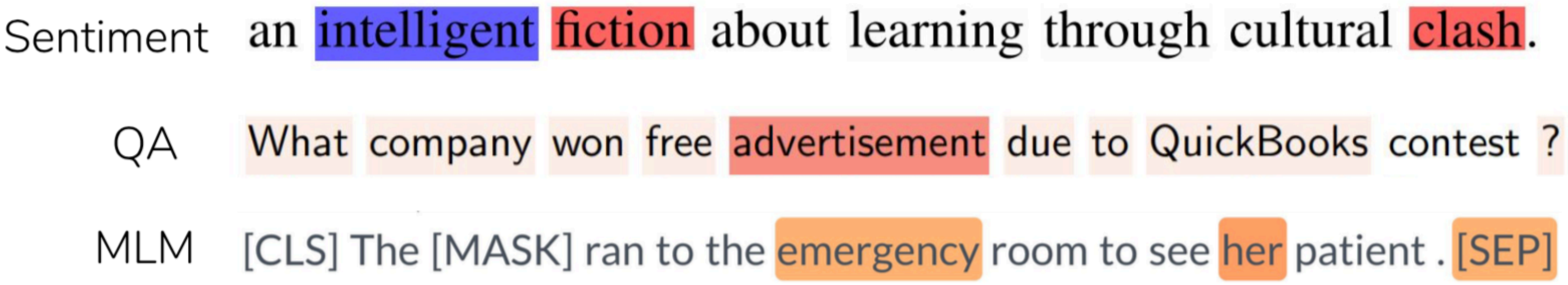

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Saliency with Gradients

Simoyan et al. 2014

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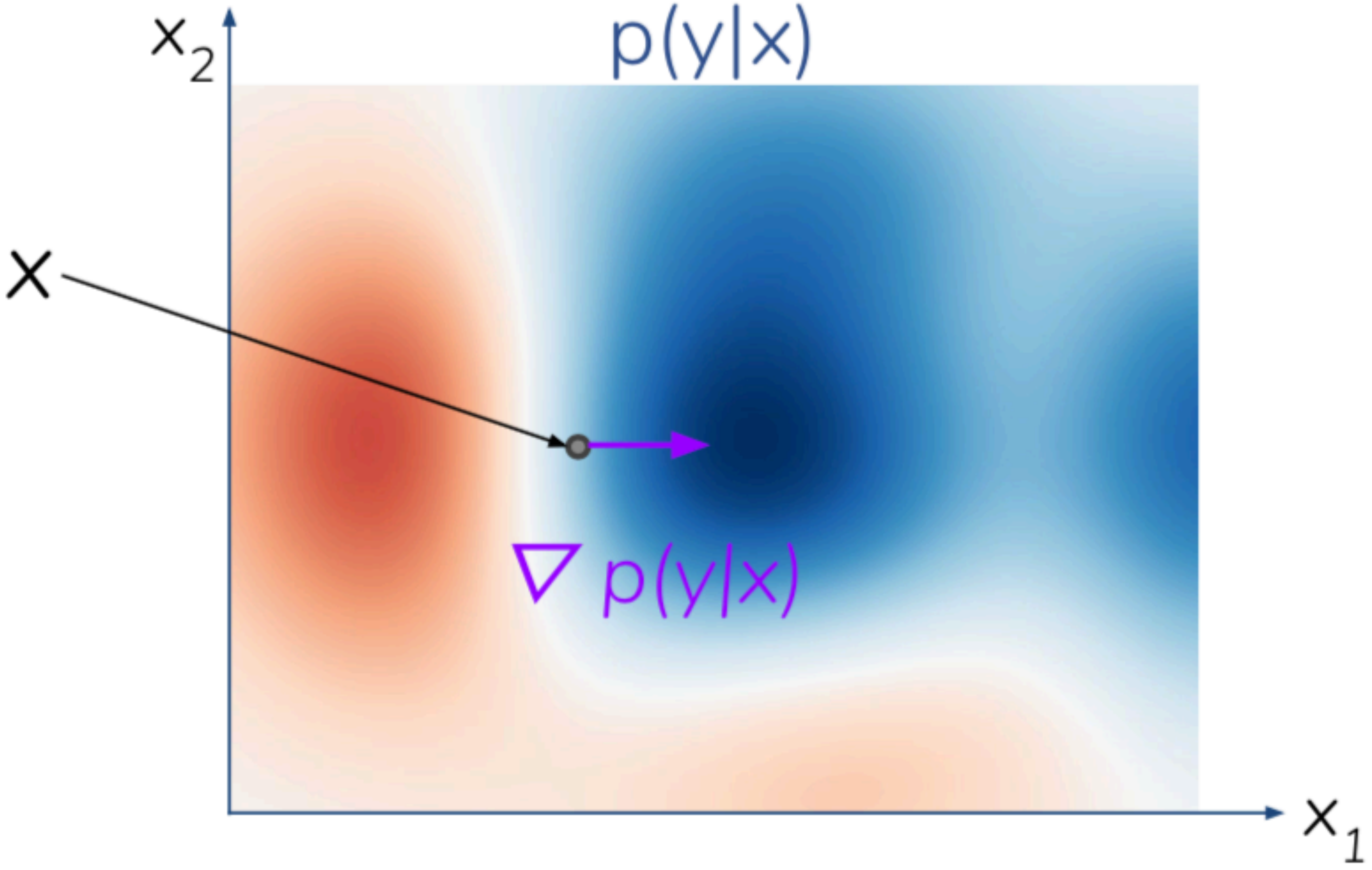

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Saliency Score

Han et al. 2020

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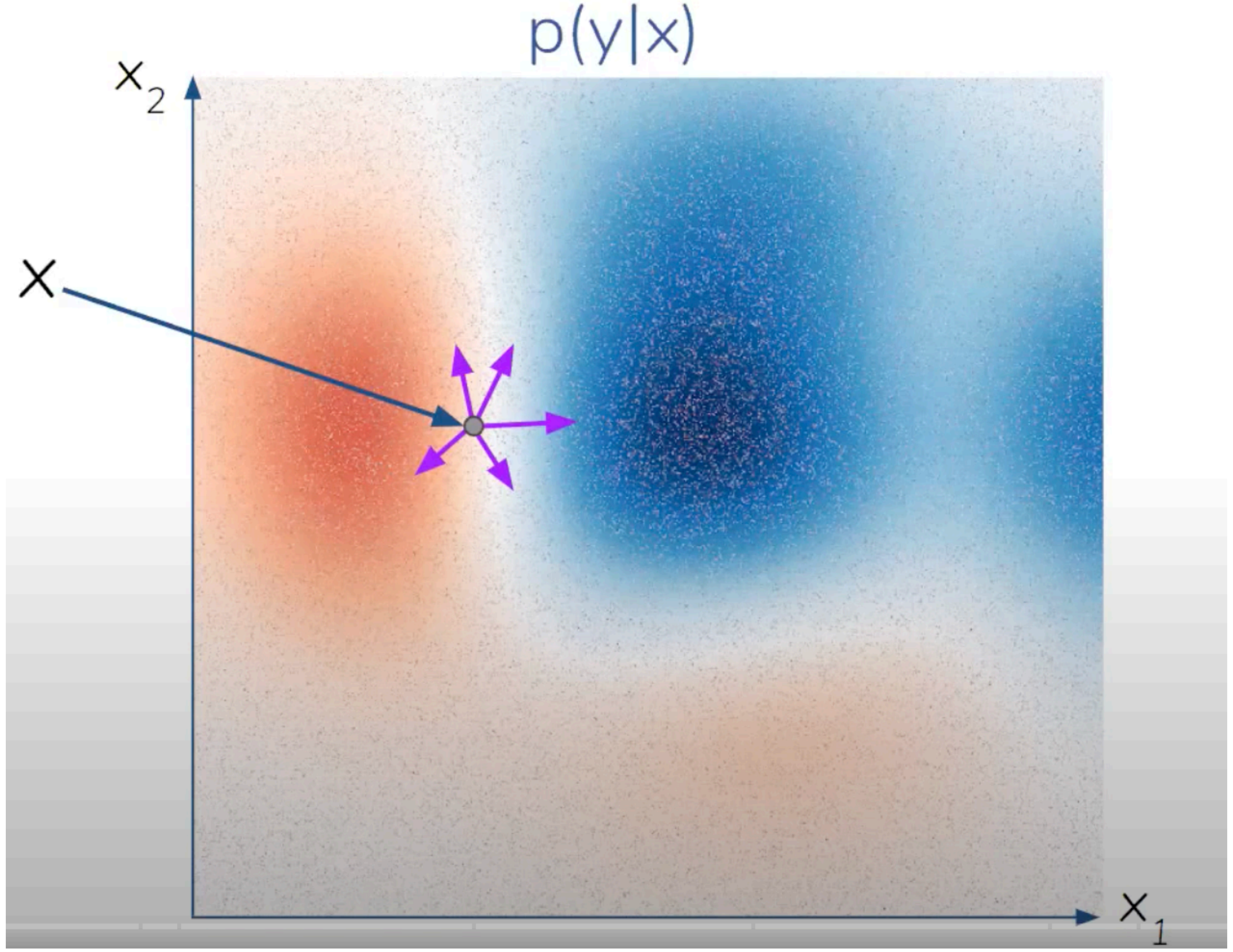
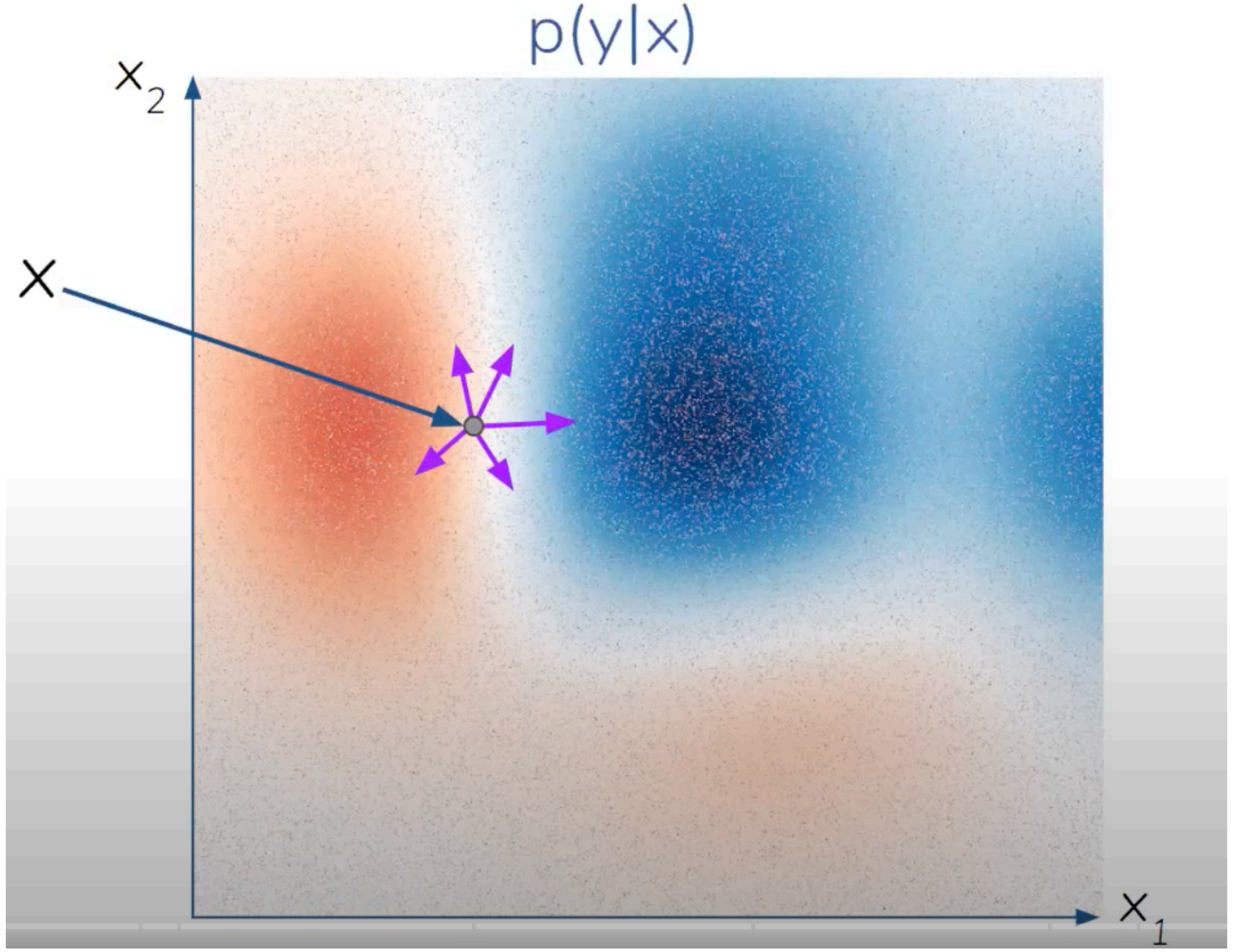


Problems with Saliency

- Fragile, sensitive to local perturbations [Ghorbani et al., 2017]
- Saliency accounts for importance at the token level. However, language is compositional.



Proposed Workarounds

Slide adapted from Sameer Singh's tutorial on Interpretability at EMNLP 2020

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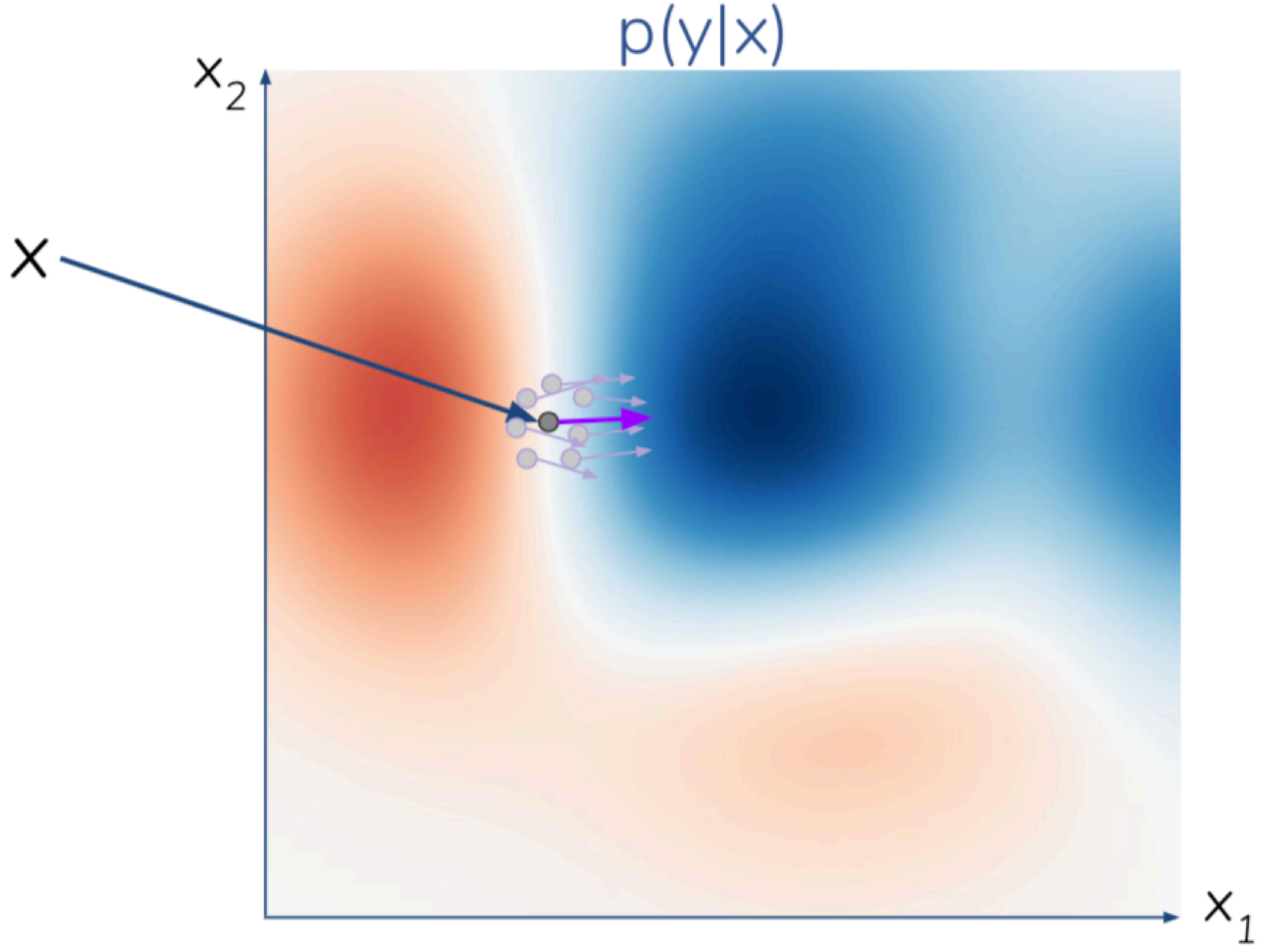

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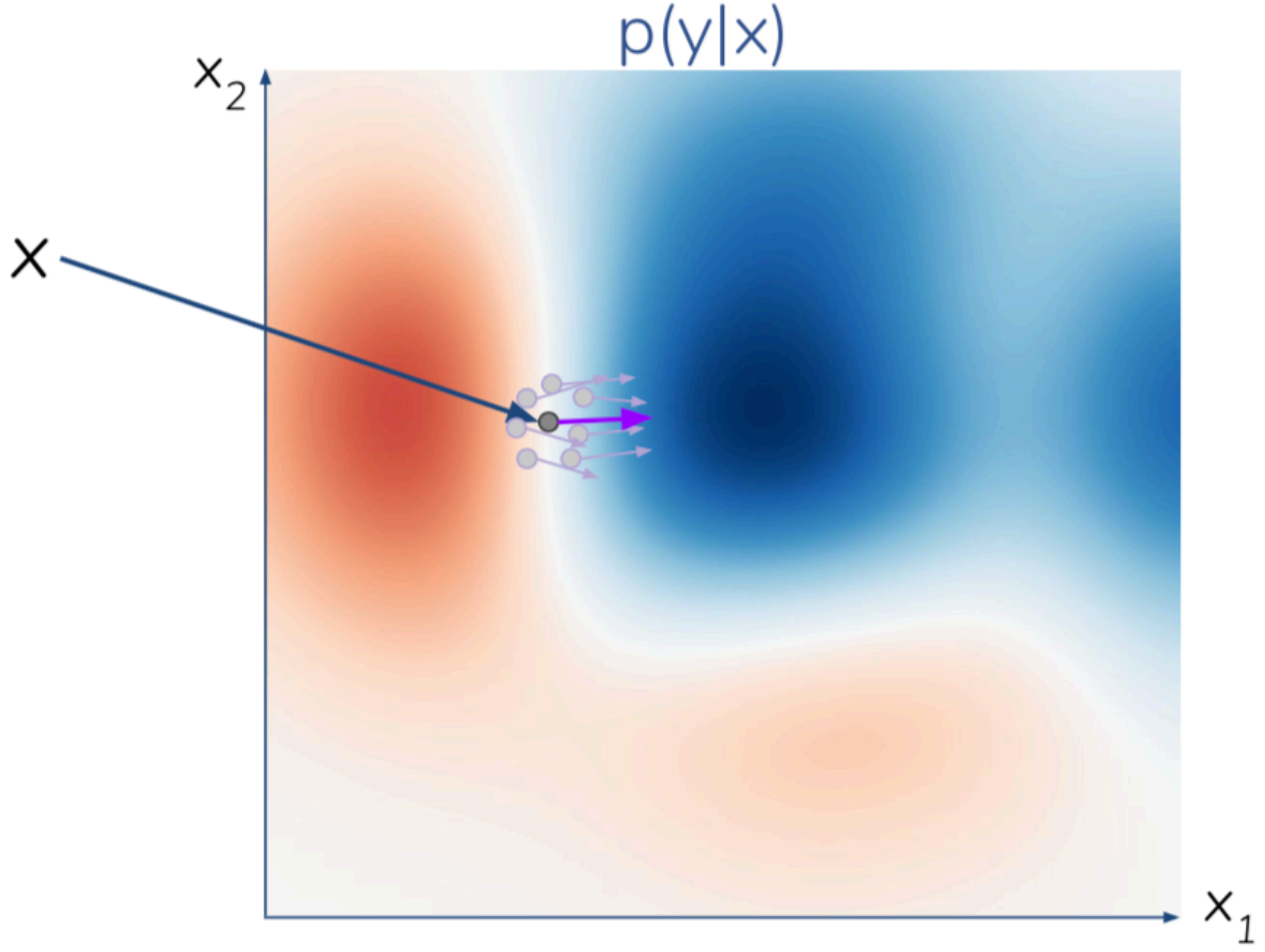

- Integrated Gradients [Sundarajan et al. 2017]

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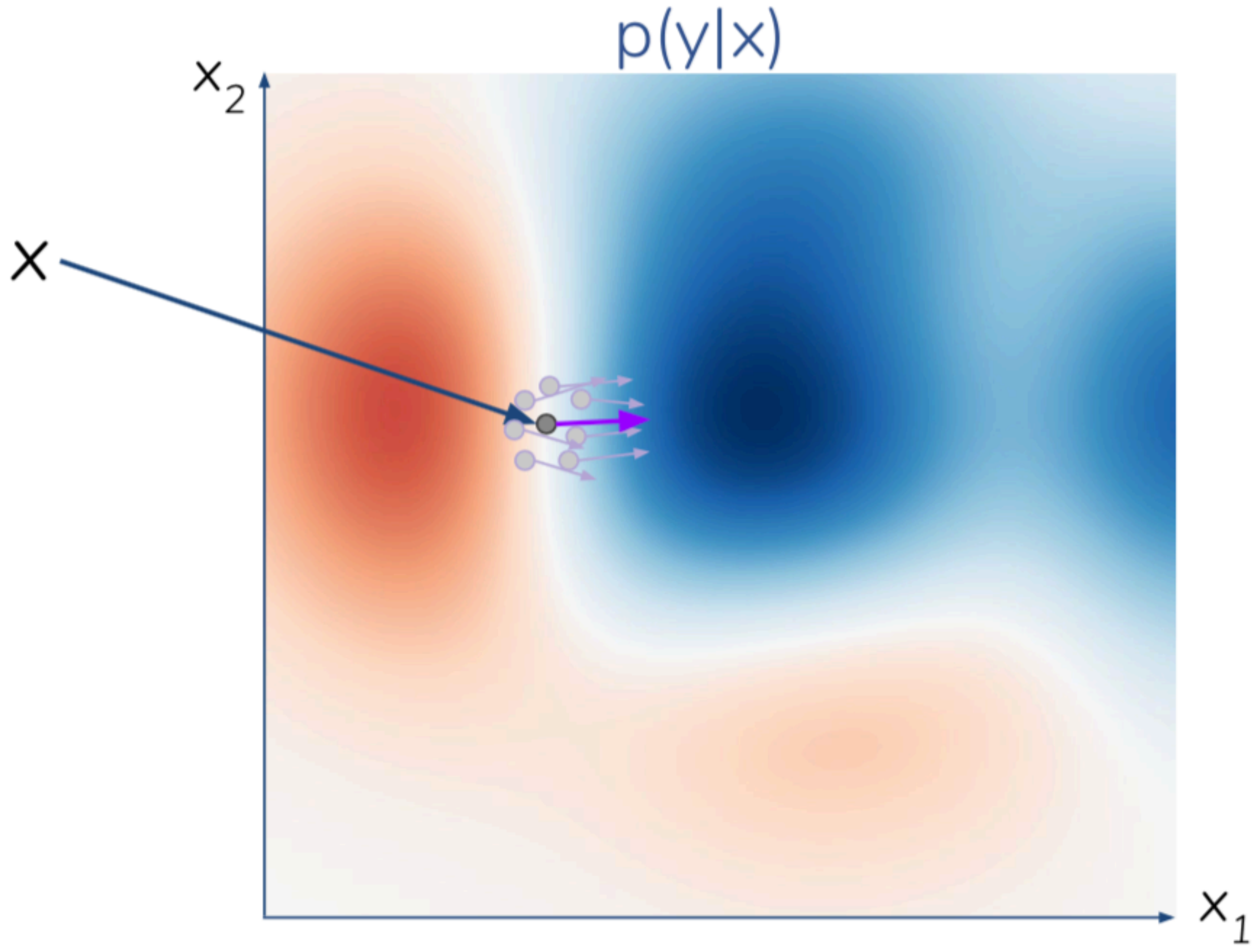

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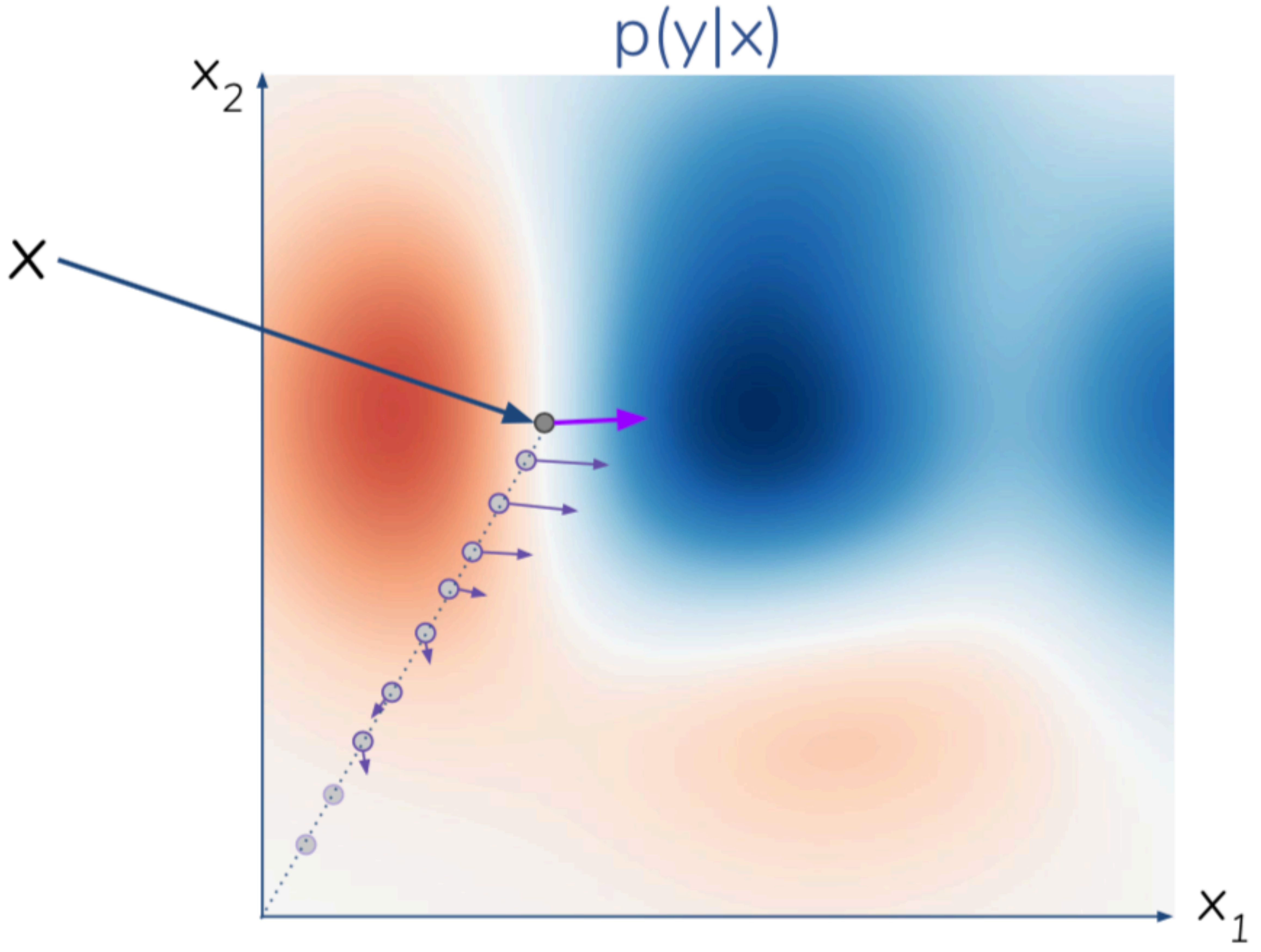

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Leave-one-out

[Li et al., 2017]

Slide adapted from Sameer Singh's tutorial on Interpretability at EMNLP 2020

Leave-one-out

[Li et al., 2017]

- Importance: change in prediction probability when a token is removed.

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Leave-one-out

[Li et al., 2017]

- Importance: change in prediction probability when a token is removed.

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Slide adapted from Sameer Singh's tutorial on Interpretability at EMNLP 2020

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What did Tesla ~~spend~~ Astor's money on ?	0.74	spend
What did Tesla spend ~~Astor's~~ money on ?	0.76	Astor's
What did Tesla spend Astor's ~~money~~ on ?	**0.48**	money
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Leave-one-out

[Li et al., 2017]

- Importance: change in prediction probability when a token is removed.
- Obvious issue: it's not just a single token (or phrase) that matters, usually

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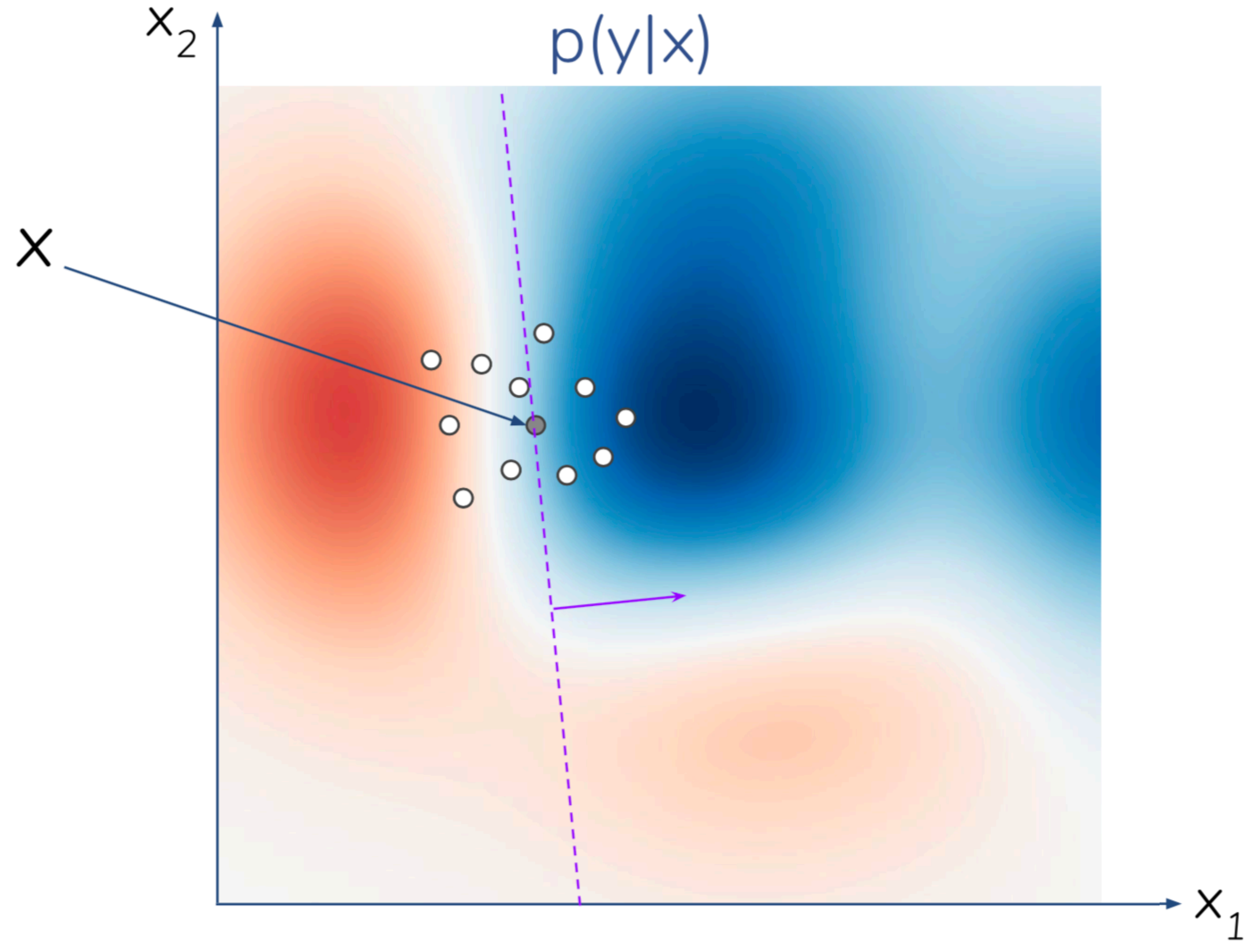
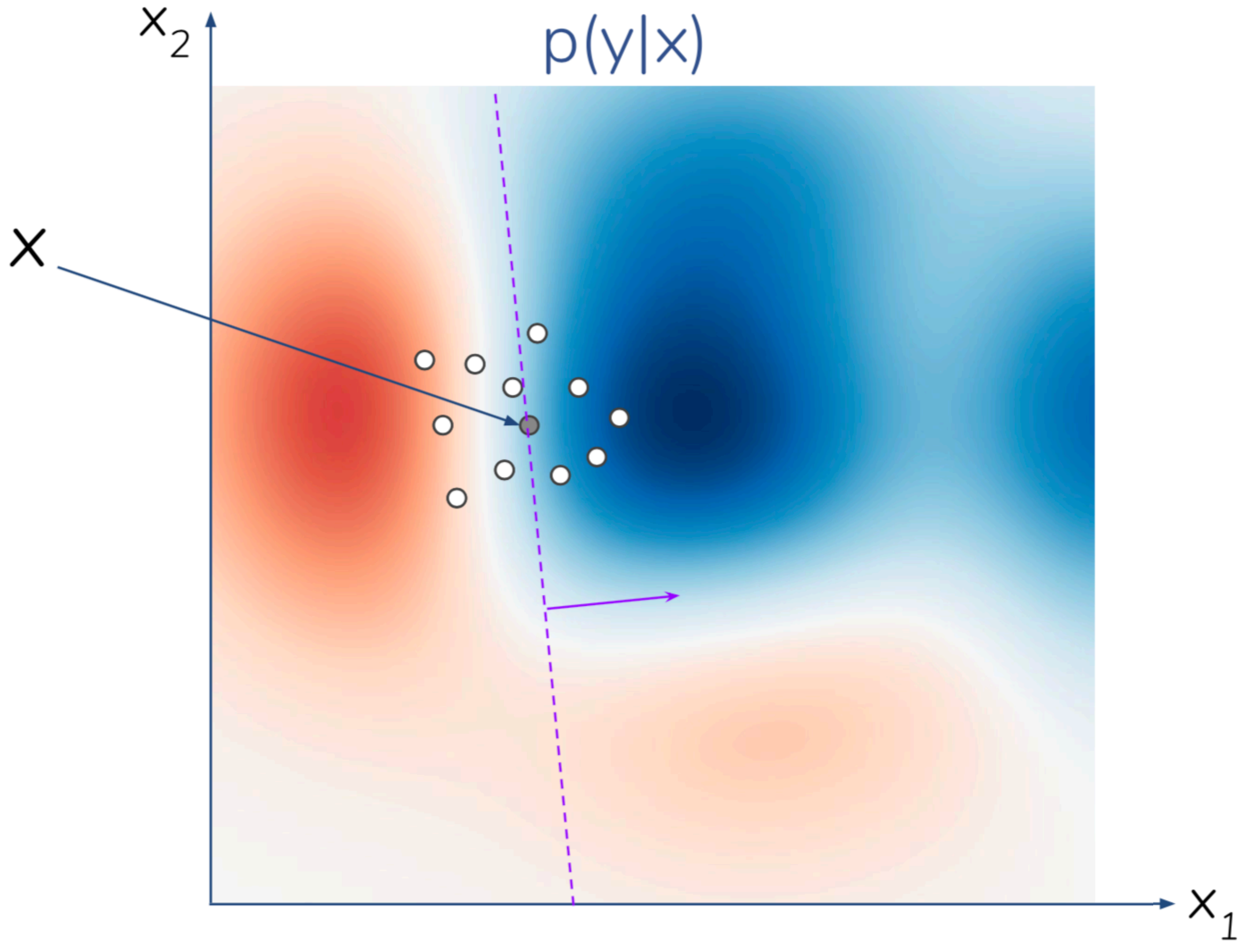
LIME



[Ribeiro et al., 2016]

LIME

- Find nearby inputs, based on cosine Distance



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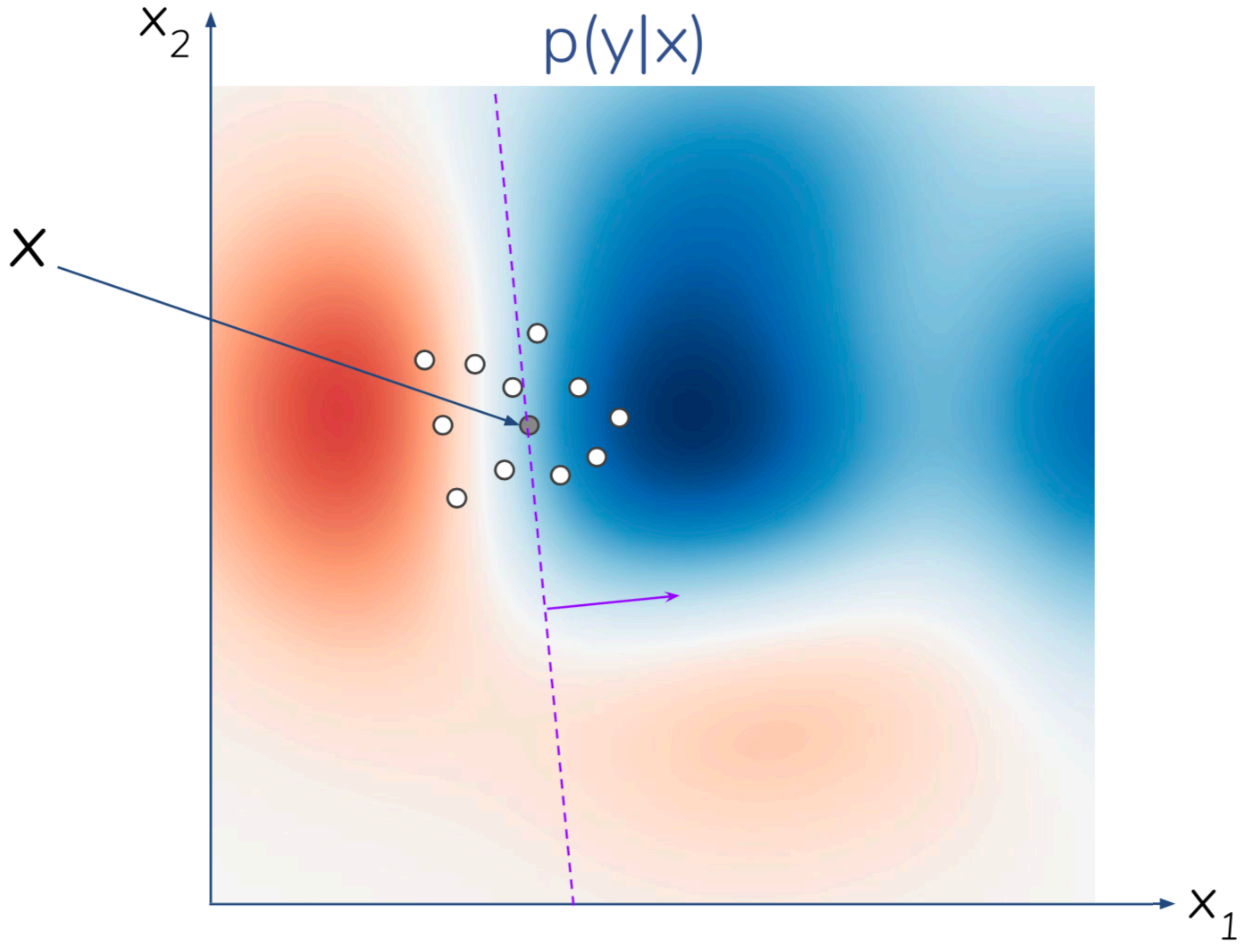

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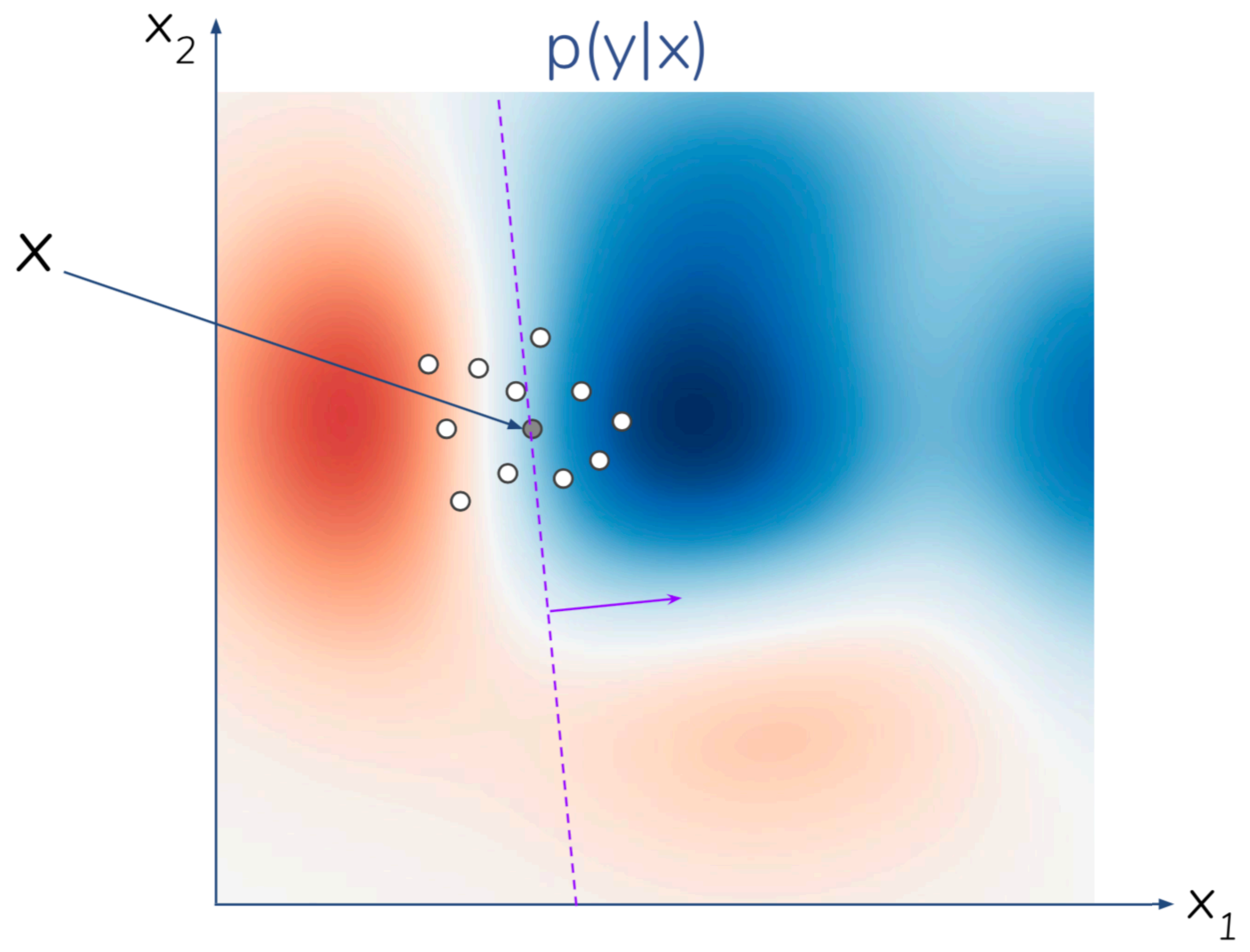

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LIME

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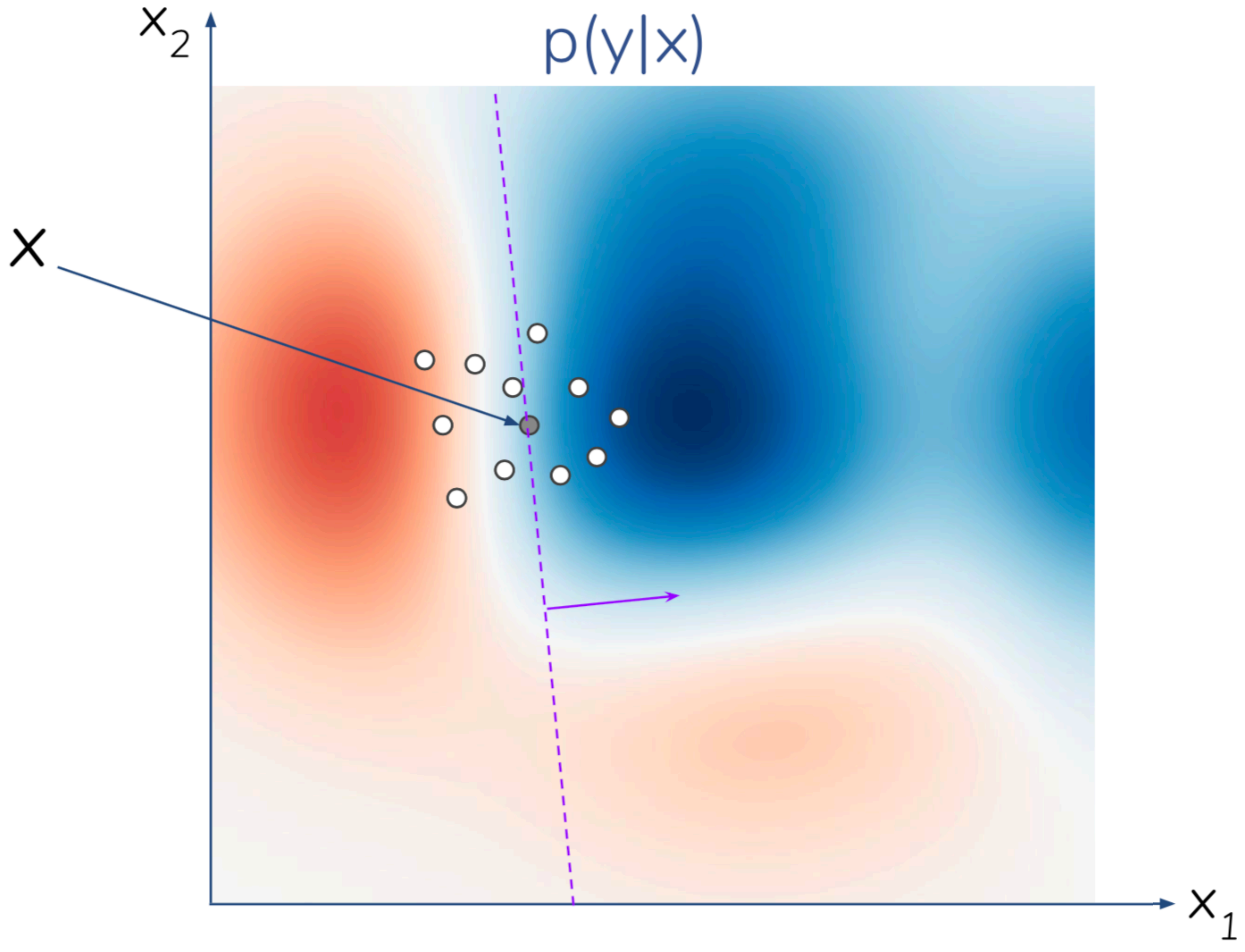
- Weights of the classifier indicate feature importance



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    - However, these biases are themselves not consistent / easy to interpret.

Other variants of input perturbations

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- How much can be removed without changing the prediction? [Feng et al. 2018]

SQuAD

Context	In 1899, John Jacob Astor IV invested $100,000 for Tesla to further develop and produce a new lighting system. Instead, Tesla used the money to fund his Colorado Springs experiments.
Original	What did Tesla spend Astor's money on ?
Reduced	**did**
Confidence	0.78 → 0.91

VQA

Original	What color is the flower ?
Answer	yellow
Reduced	**flower ?**
Confidence	0.827 → 0.819

SNLI

Premise	Well dressed man and woman dancing in the street
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- Also reveal biases.

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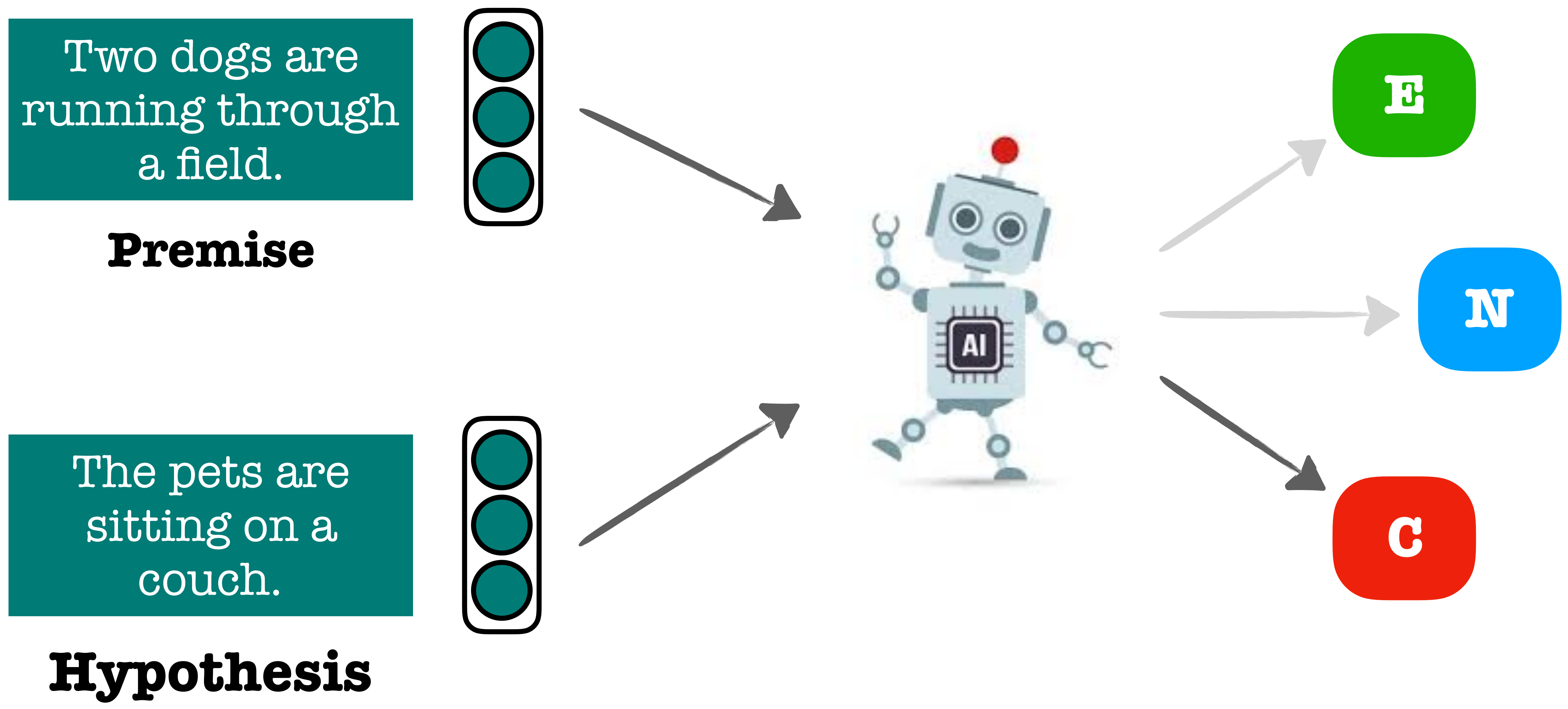

Annotation Artifacts in NLI [G*., Swayamdipta*, L., S., B., S., 2018]

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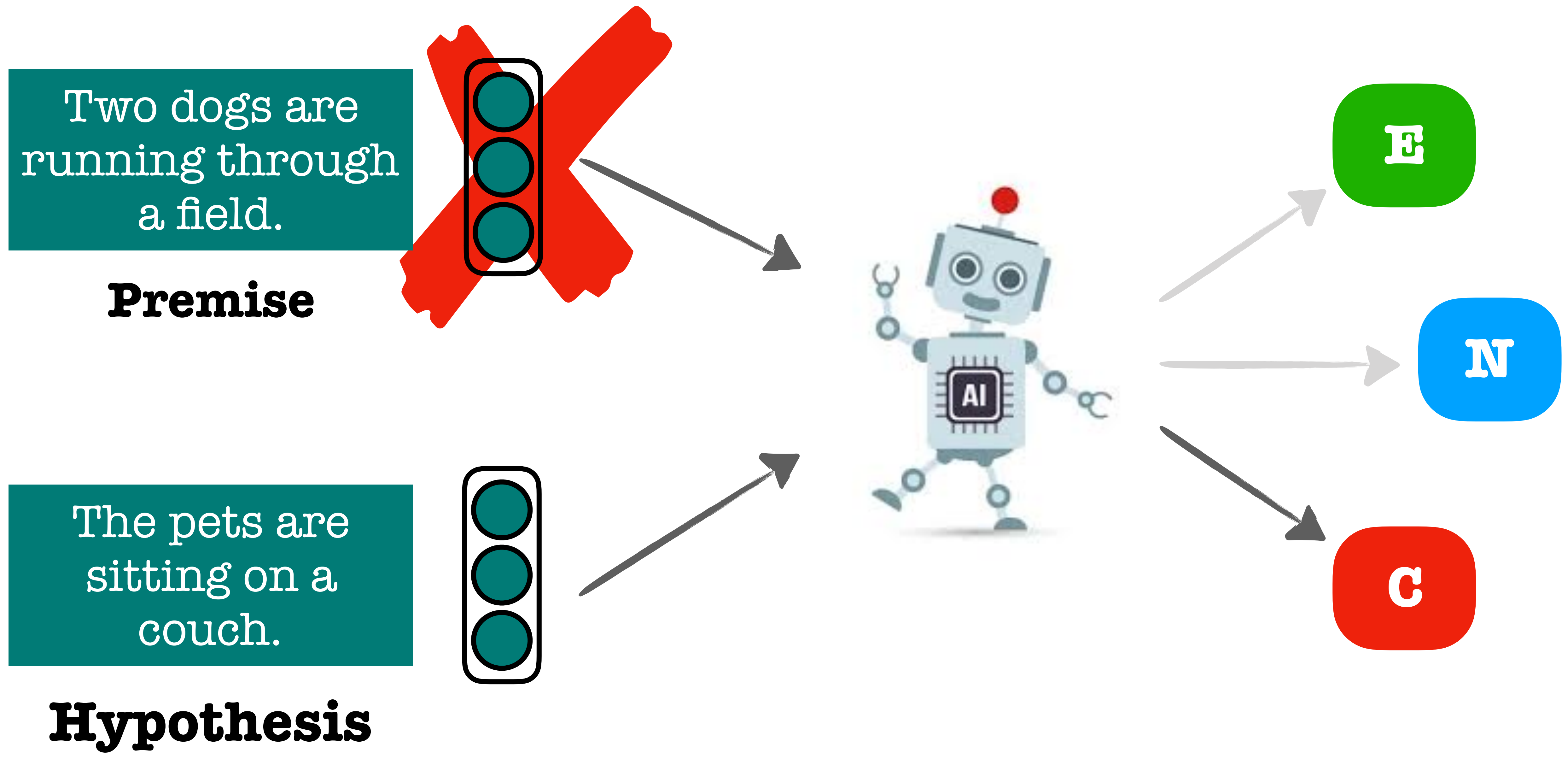

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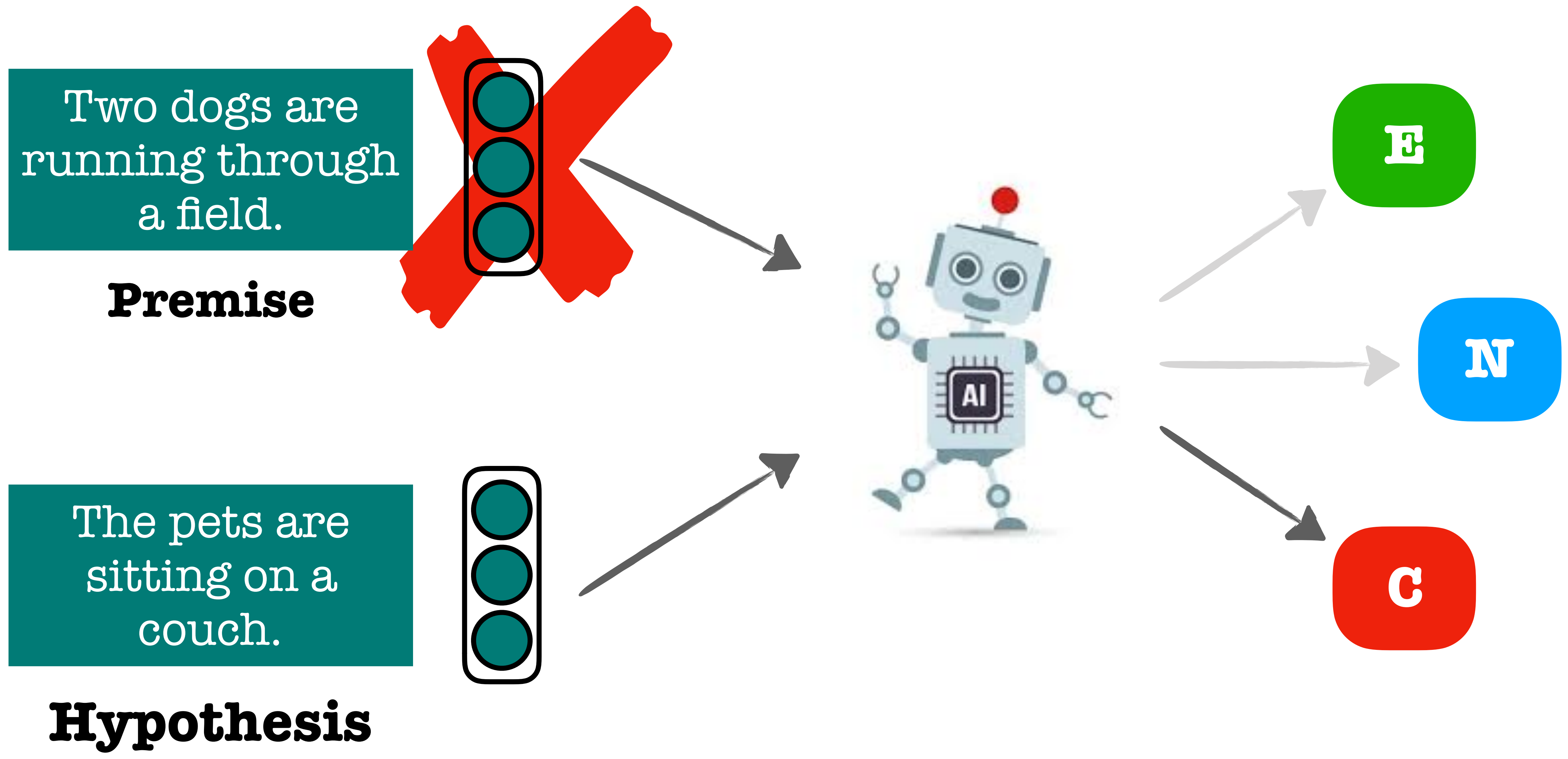
Method 3: Architectural Modifications

- Partial Input Baselines
- Idea: if the model still makes the correct decision despite not receiving the full input, model likely relies on some bias
- Also tried for VQA [Goyal et al. 2016], SQuAD [Kaushik & Lipton, 2018], among others.



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Question: Can interpretability methods be used to remove biases?

This Lecture

Biases in NLP

- Dataset Biases
- Model Biases

Discovering Biases via Interpretability Methods

- Saliency Methods
- Input Attribution
- Architectural Modifications

Mitigating Biases

- Filtering Datasets
- Auxiliary Objectives

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Case Study: Pre-specified Biases

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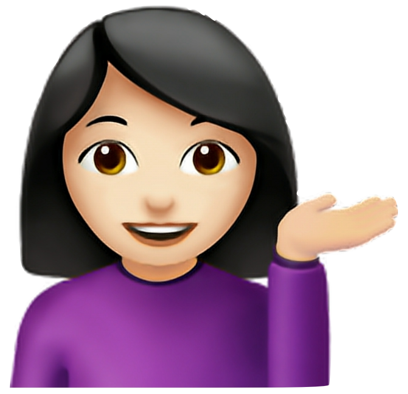
Hate Speech in Online Platforms

Case Study: Pre-specified Biases

Hate Speech in Online Platforms

- Human moderation does not scale



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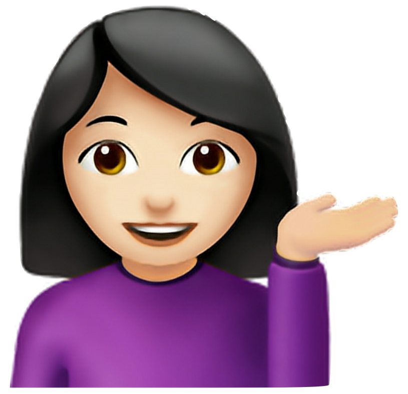

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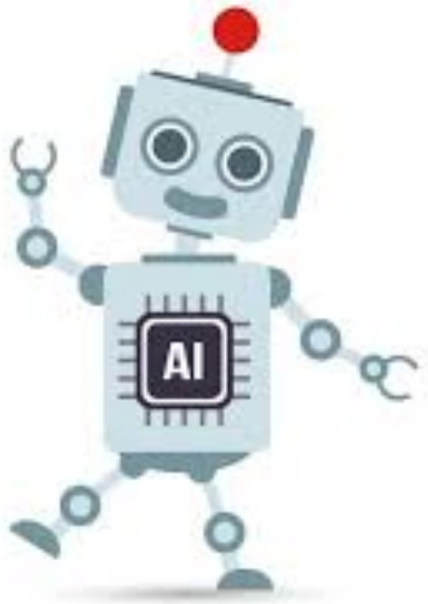

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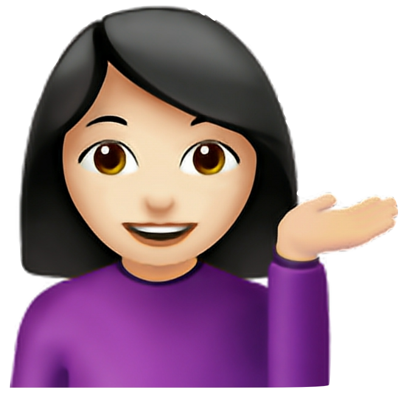
- Human moderation does not scale 
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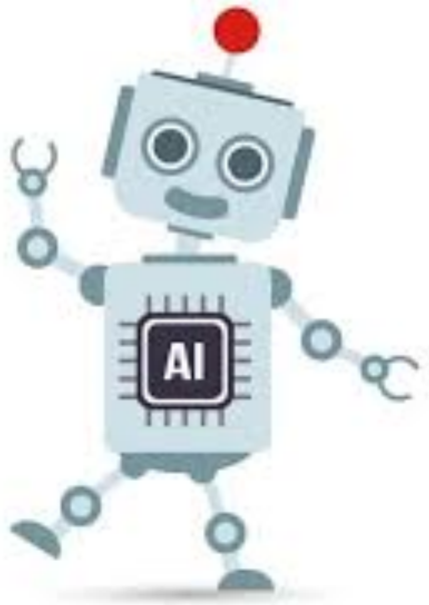
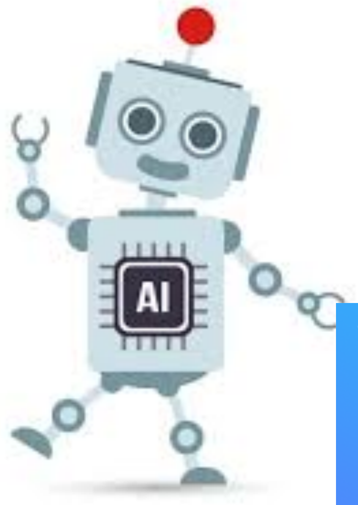
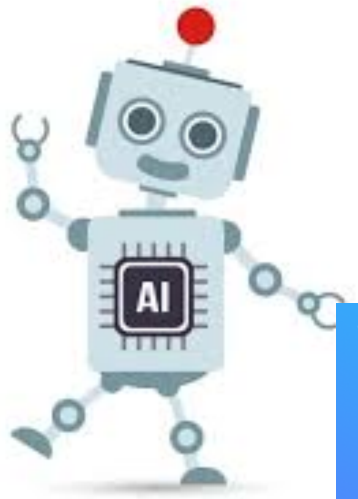


Some examples might contain offensive or triggering content



Perspective API

I hope this country can now try to get along



Perspective API

I hope this country can now try to get along

15%

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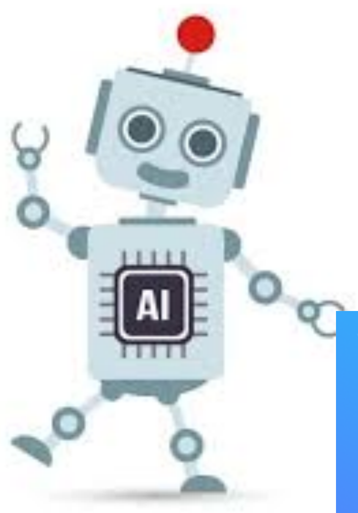
If they voted for Hillary they are idiots



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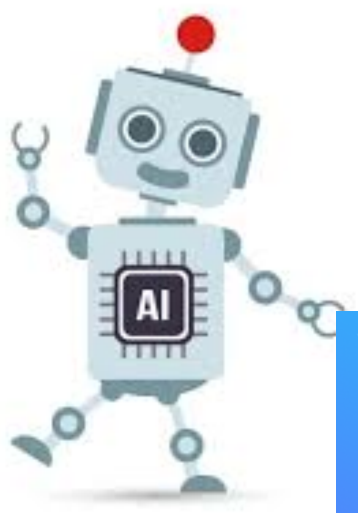

Perspective API

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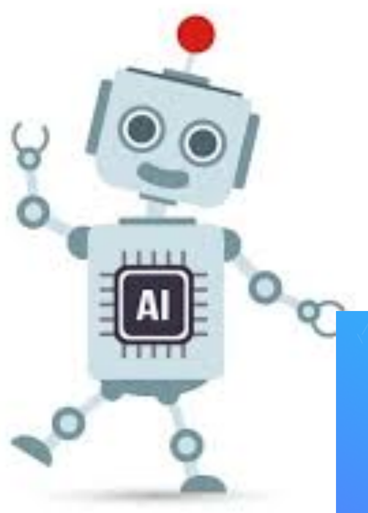
I identify as a straight white man

24%



Perspective API

I hope this country can now try to get along — 15%

If they voted for Hillary they are idiots — 75%

I identify as a straight white man — 24%

I identify as a black gay woman — 60%

Perspective API

[Sap et. al, 2019]

I hope this country can now try to get along — 15%

If they voted for Hillary they are idiots — 75%

I identify as a straight white man — 24%

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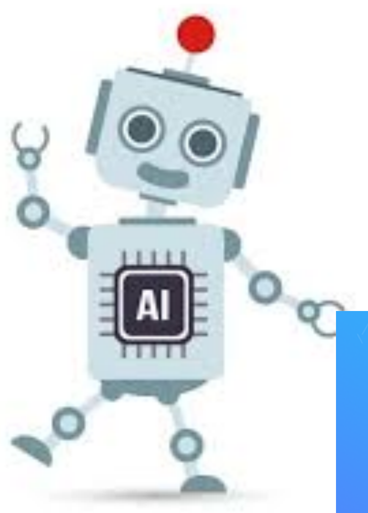
F*ing love this! — 86%



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What's up, bro! — 8%

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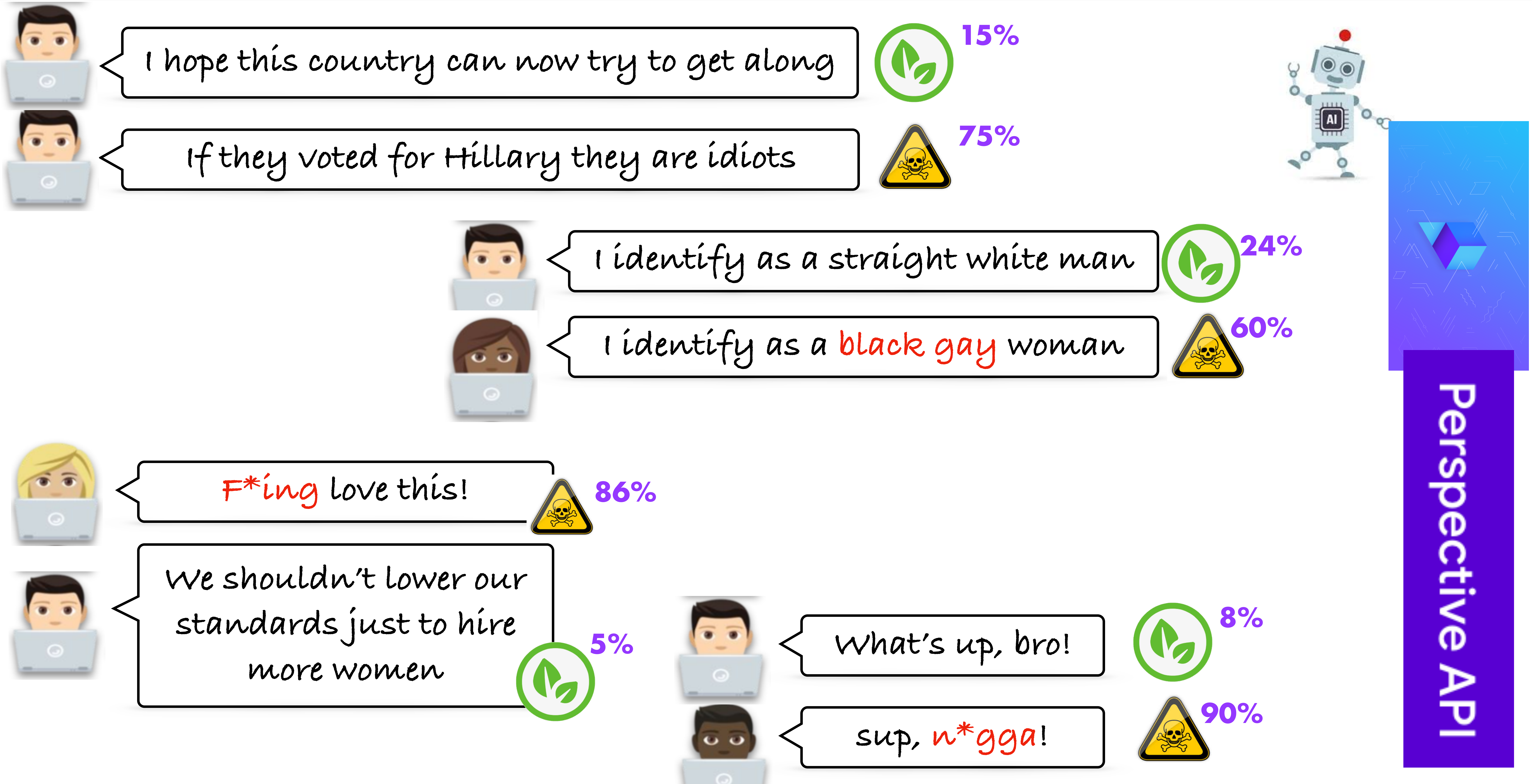

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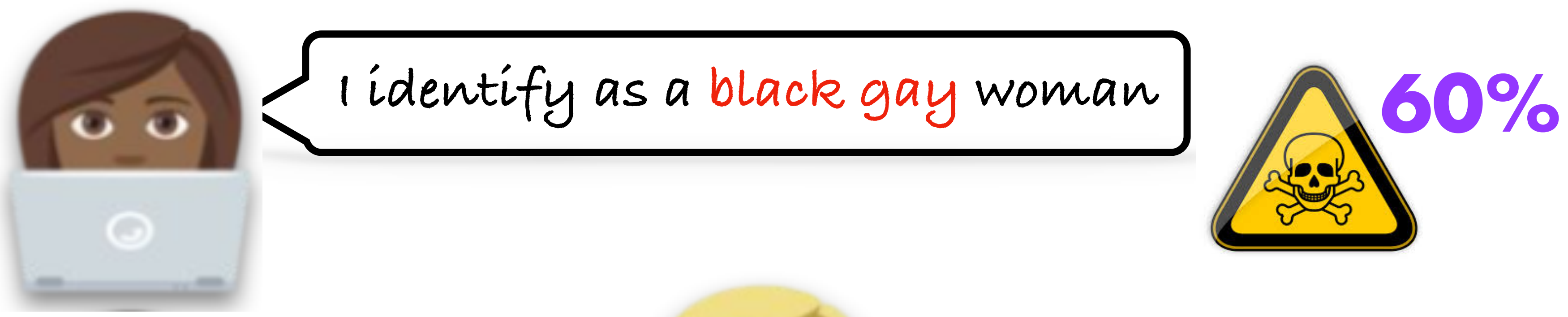

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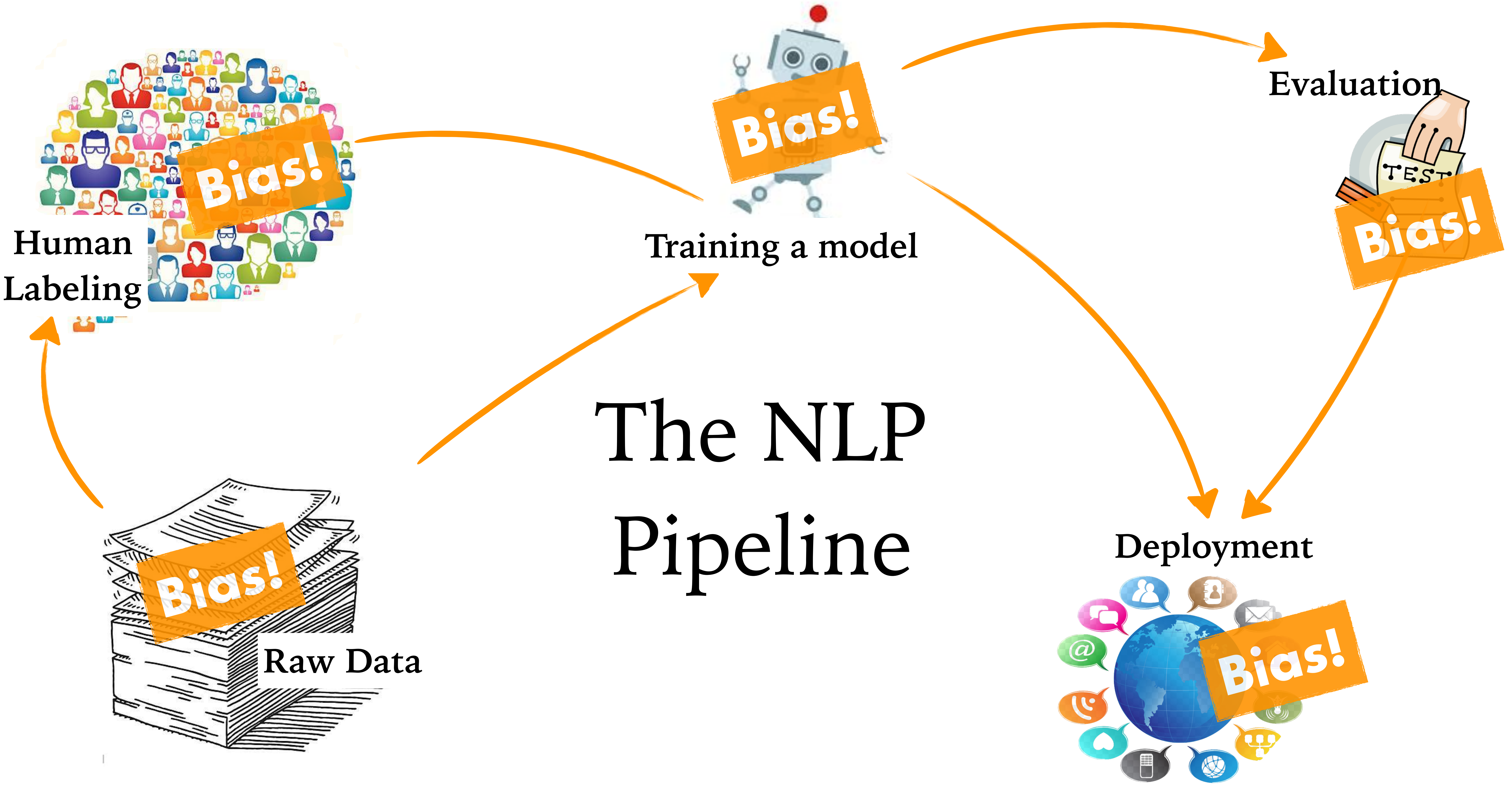
The NLP Pipeline



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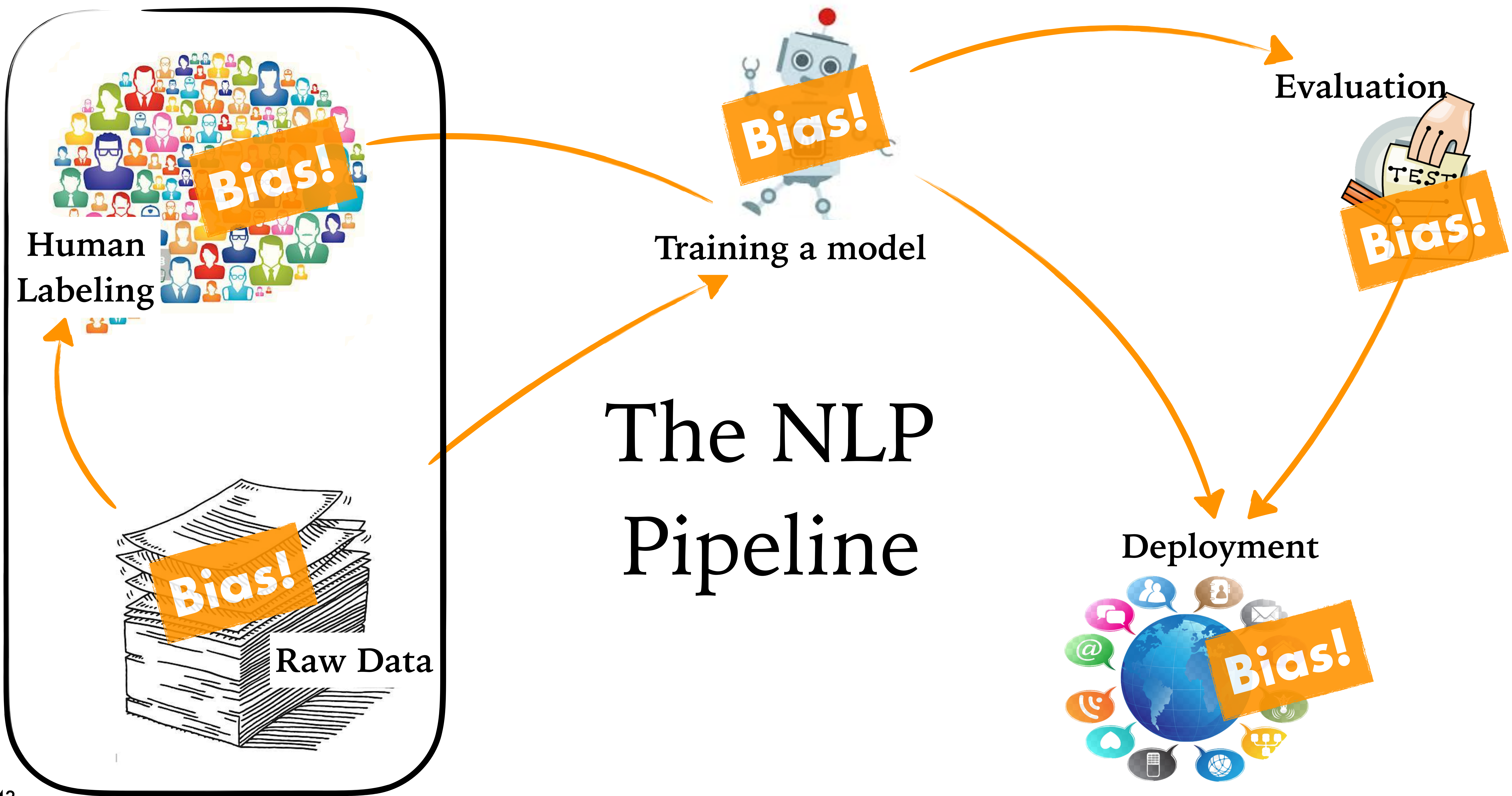

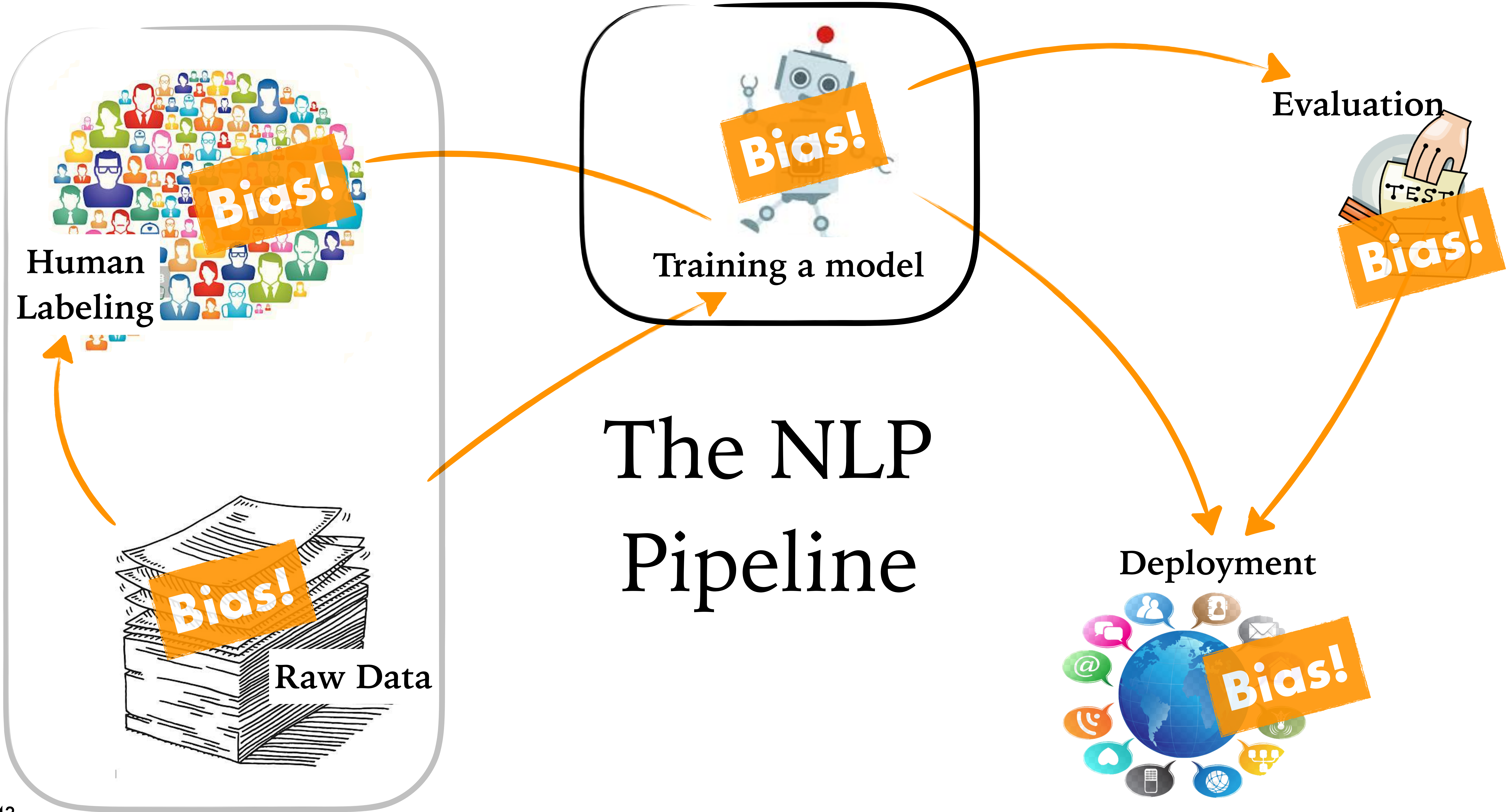
Human Labeling
Bias!
Training a model
Bias!
Evaluation
TEST
Bias!
The NLP Pipeline
Raw Data
Bias!
Deployment
Bias!

Addressing Biases: Datasets

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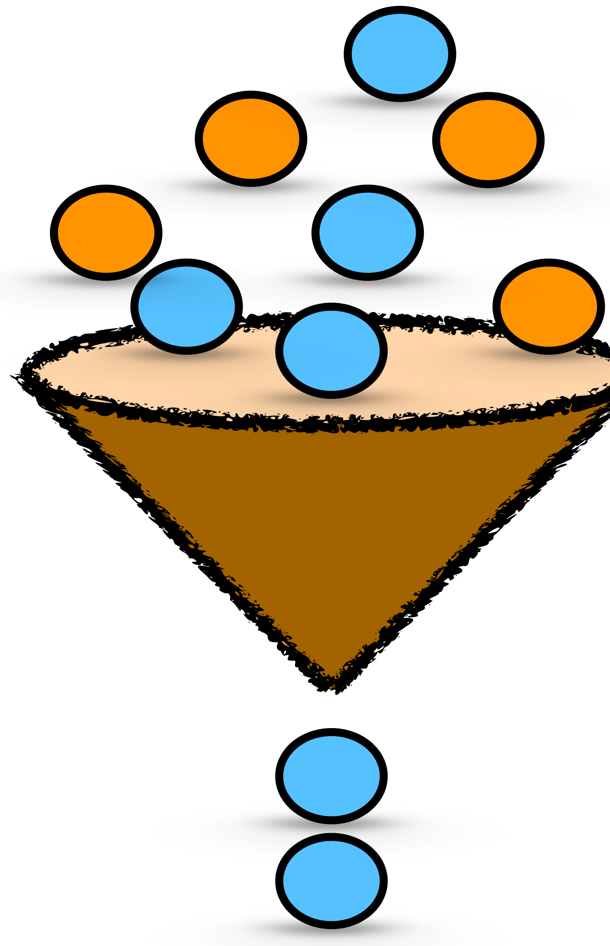

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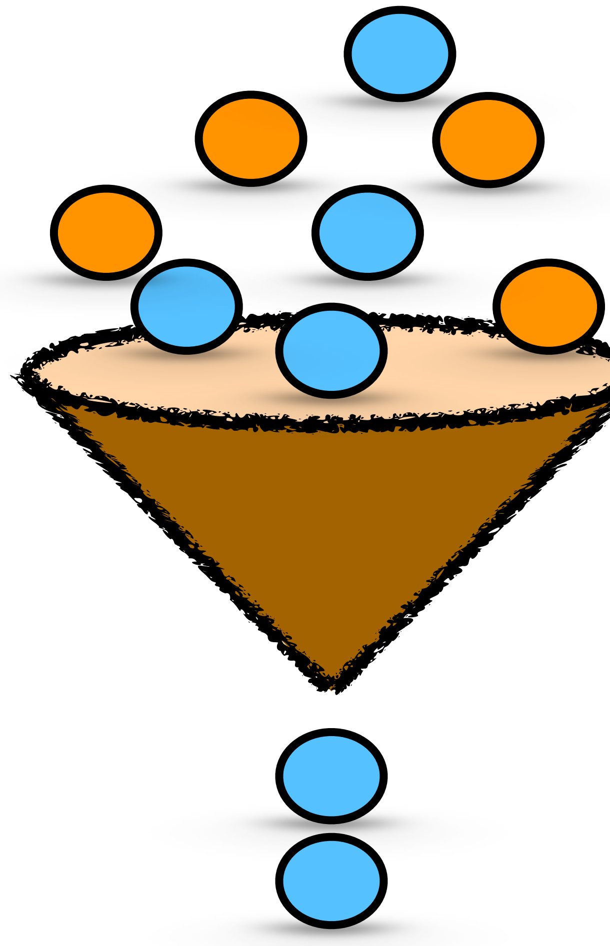

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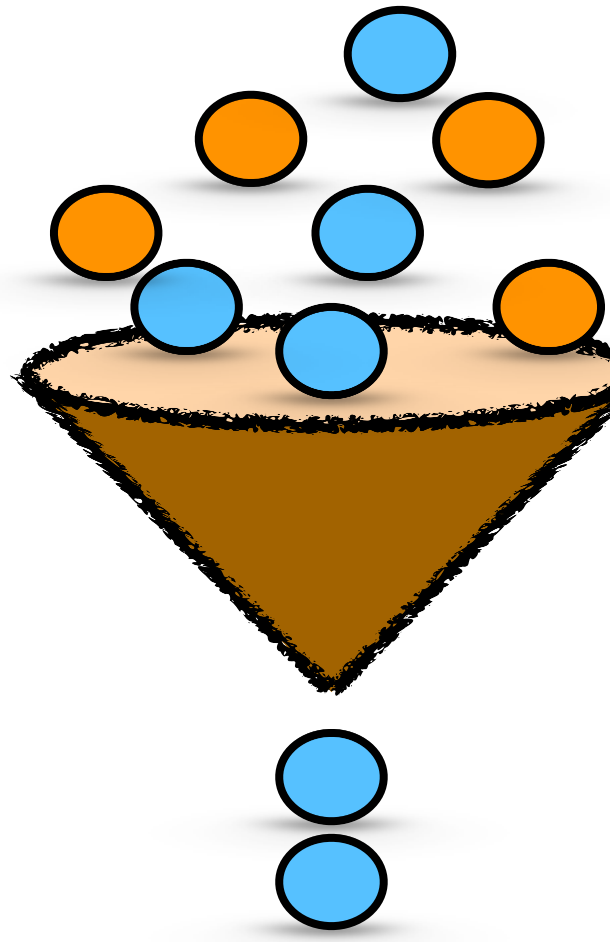

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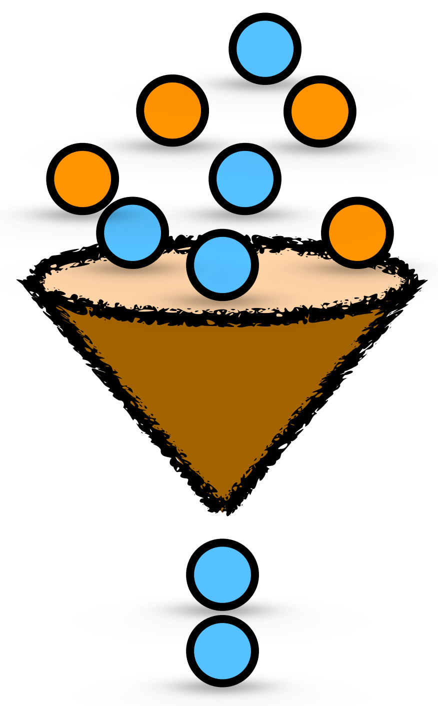
- Simple for known biases (rules / simple classifiers)
- Also possible for unspecified biases!

Dataset Filtering



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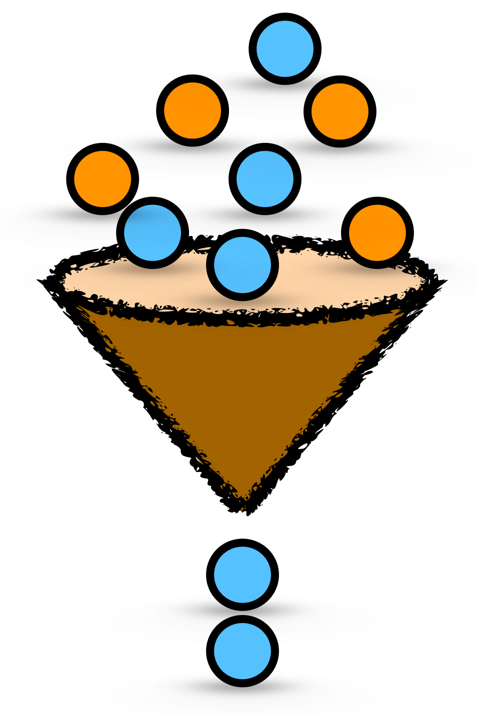

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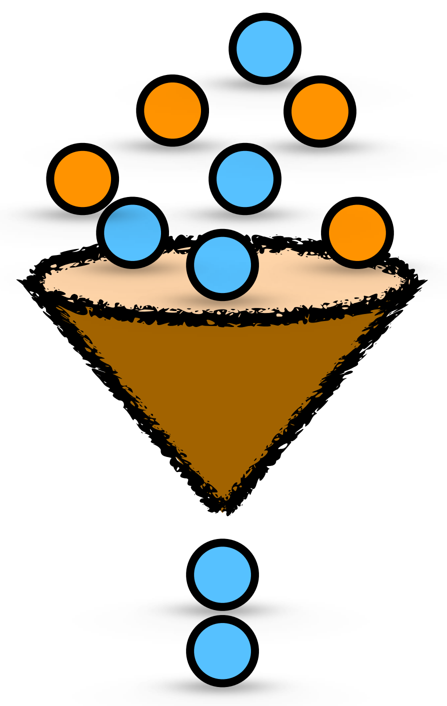

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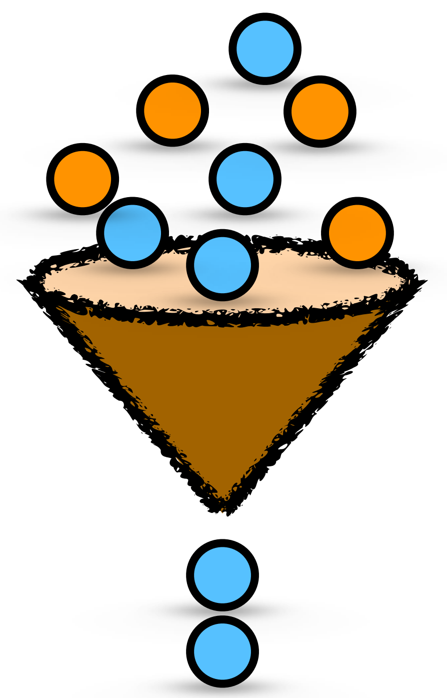

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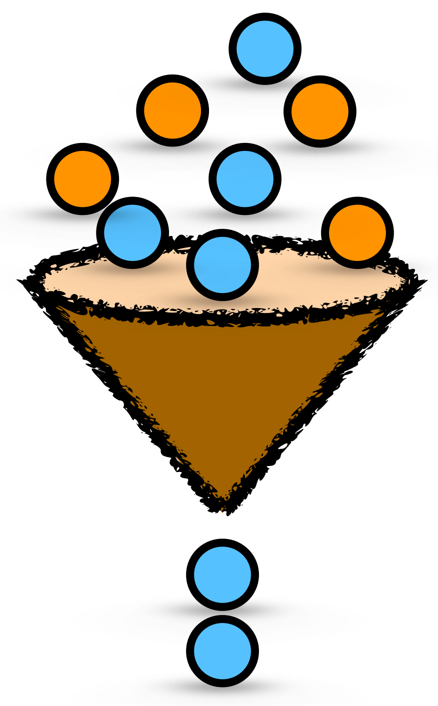

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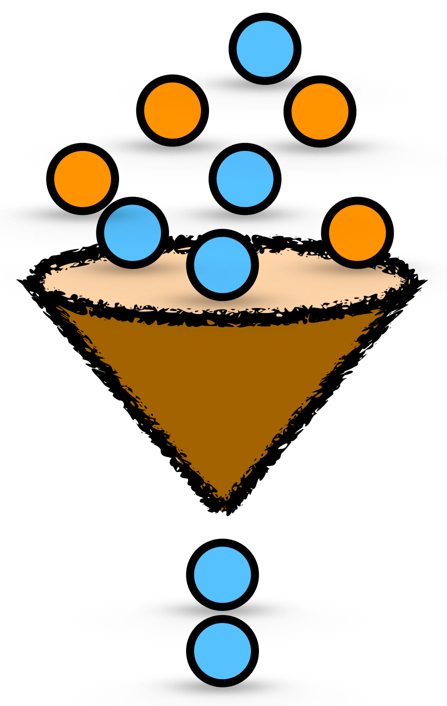
Dataset Filtering



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AFLite in action

Adversarial Filters of Dataset Biases [L., Swayamdipta, Z., B., P., S., C.]

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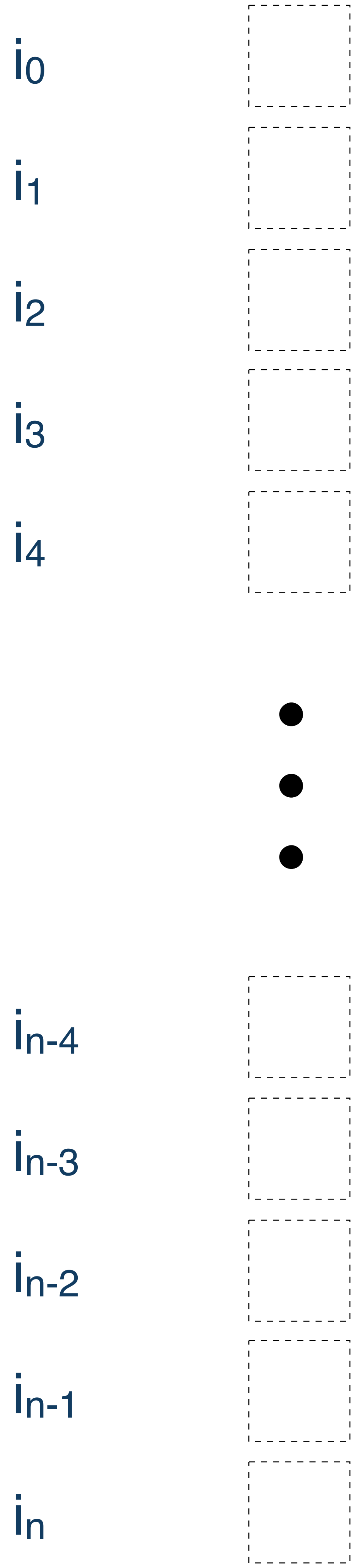

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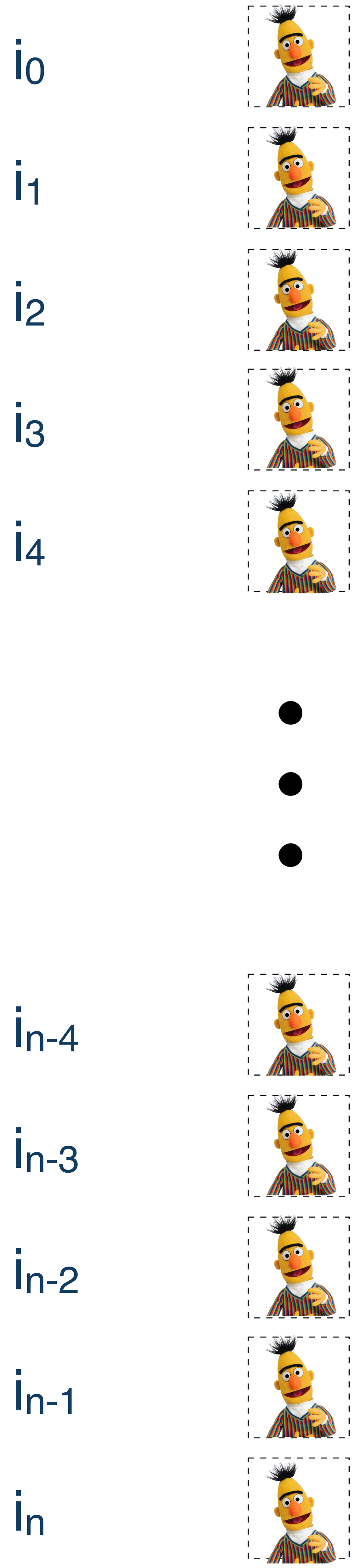

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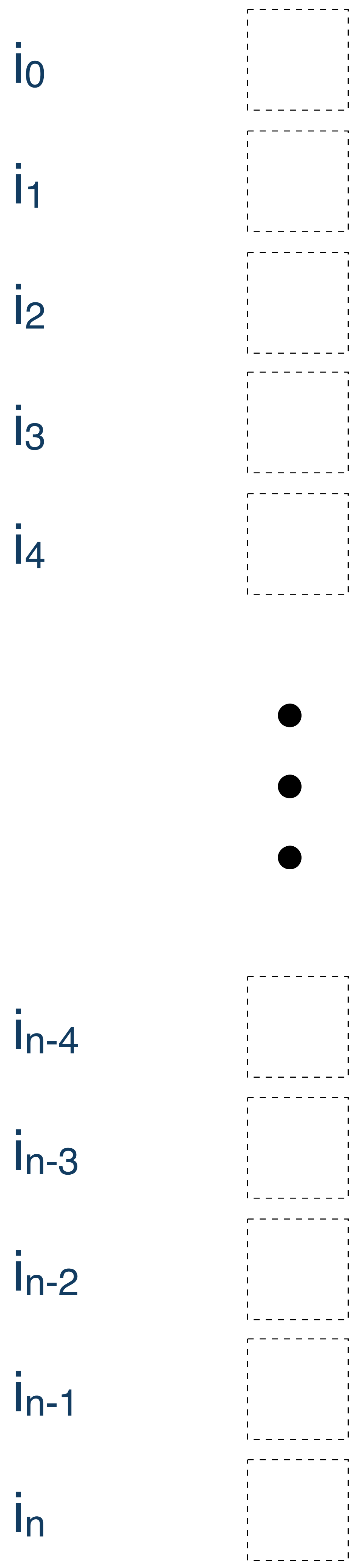

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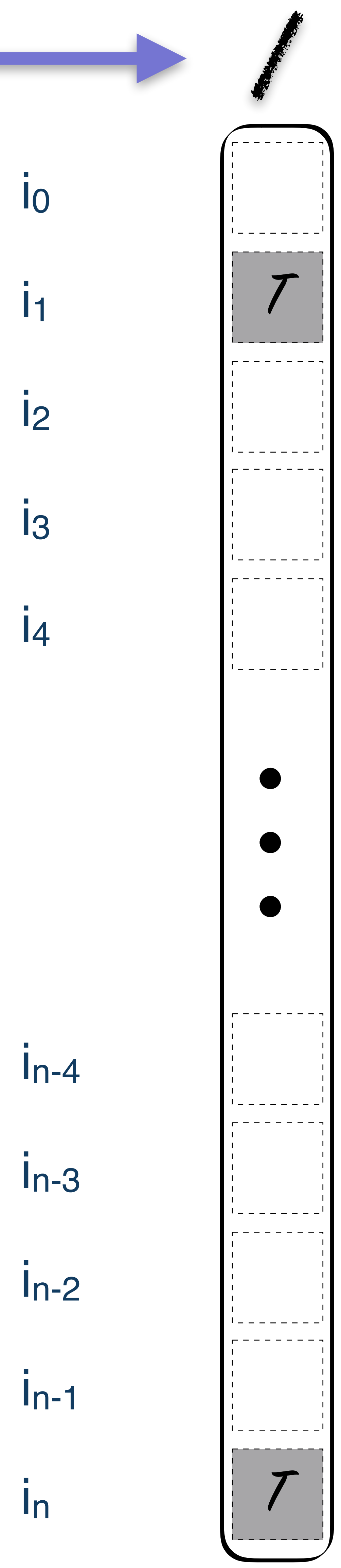
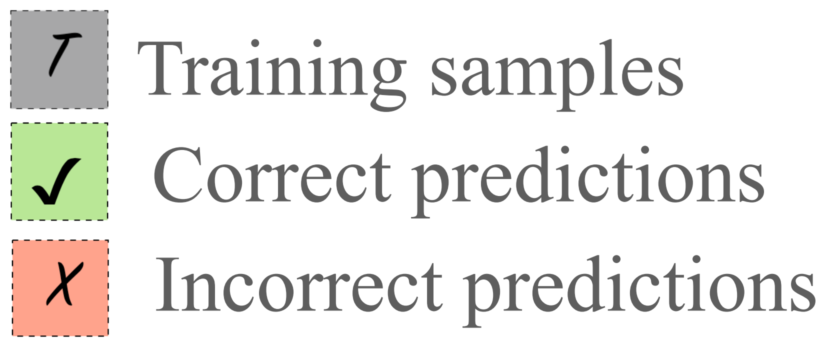
AFLite in action

Linear Classifier





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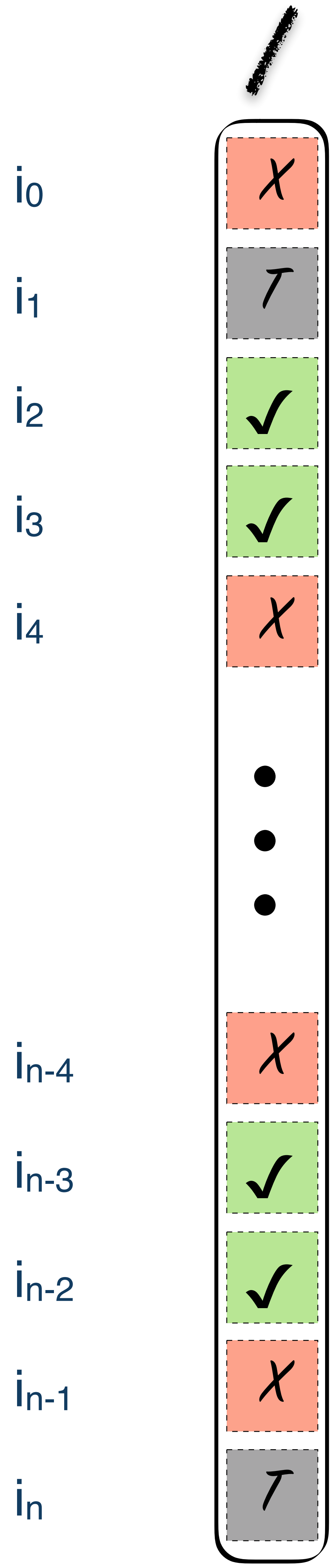

T Training samples
✓ Correct predictions
✗ Incorrect predictions

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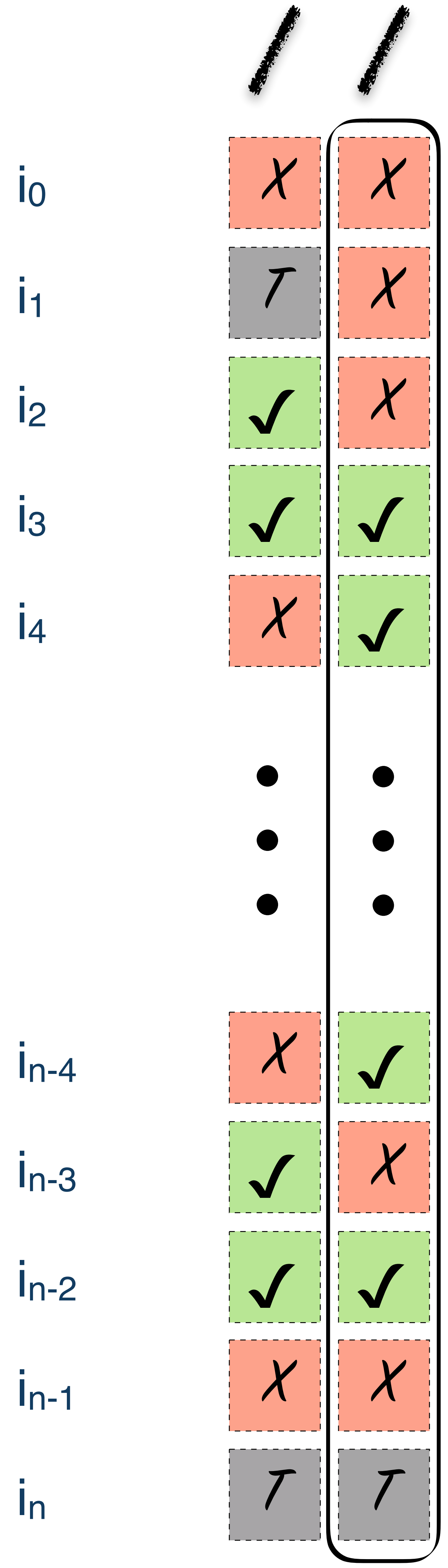

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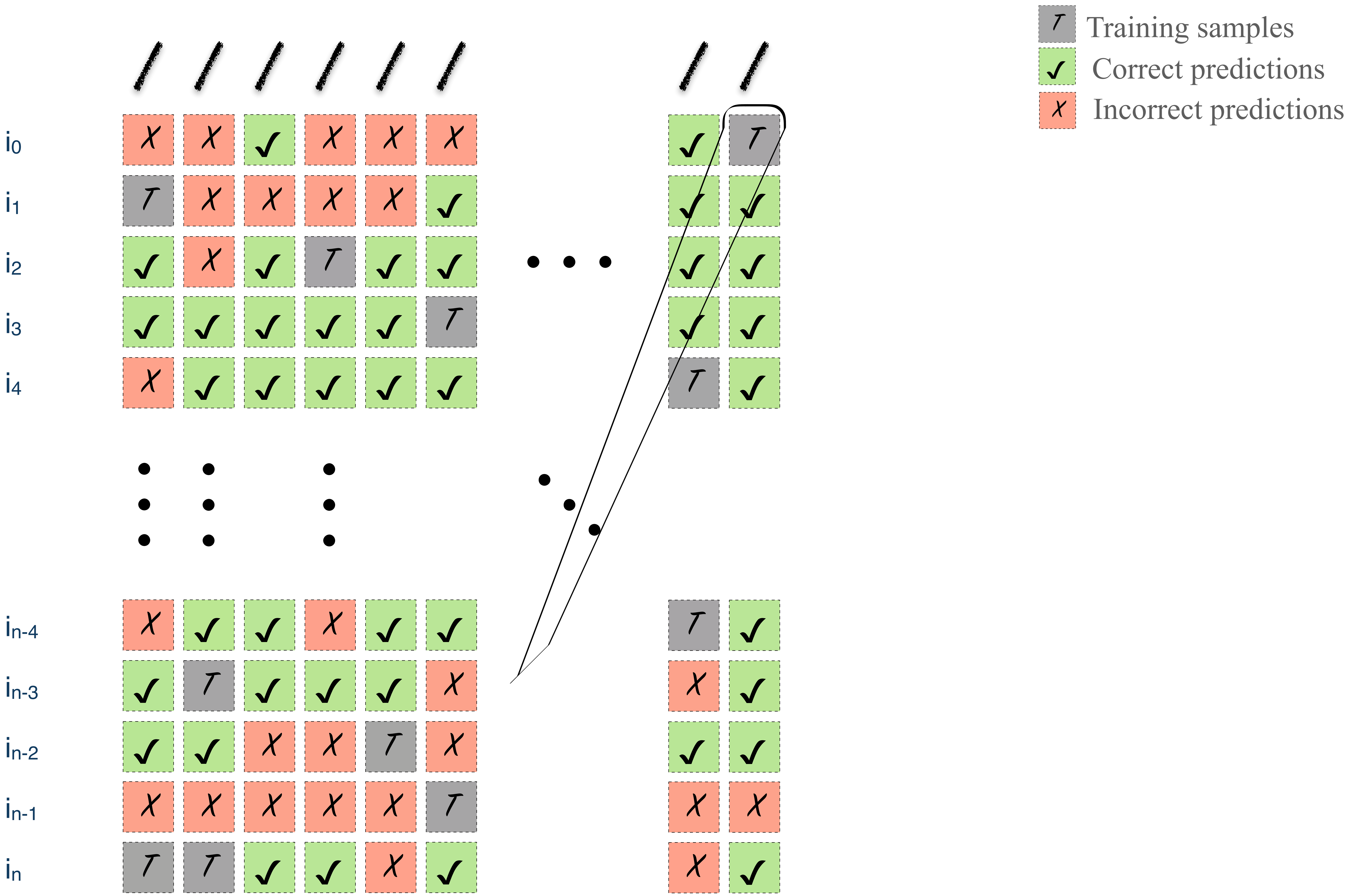

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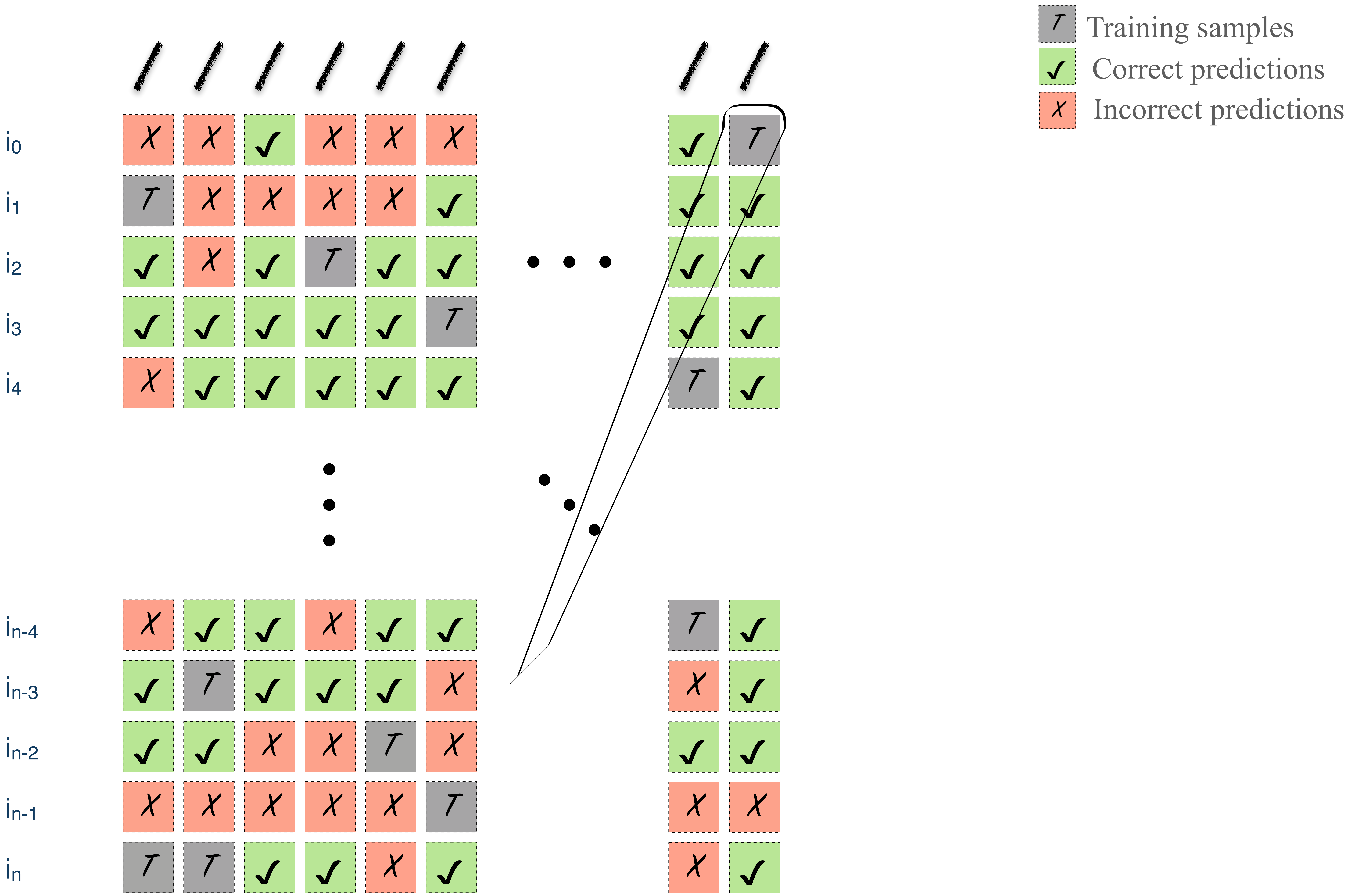

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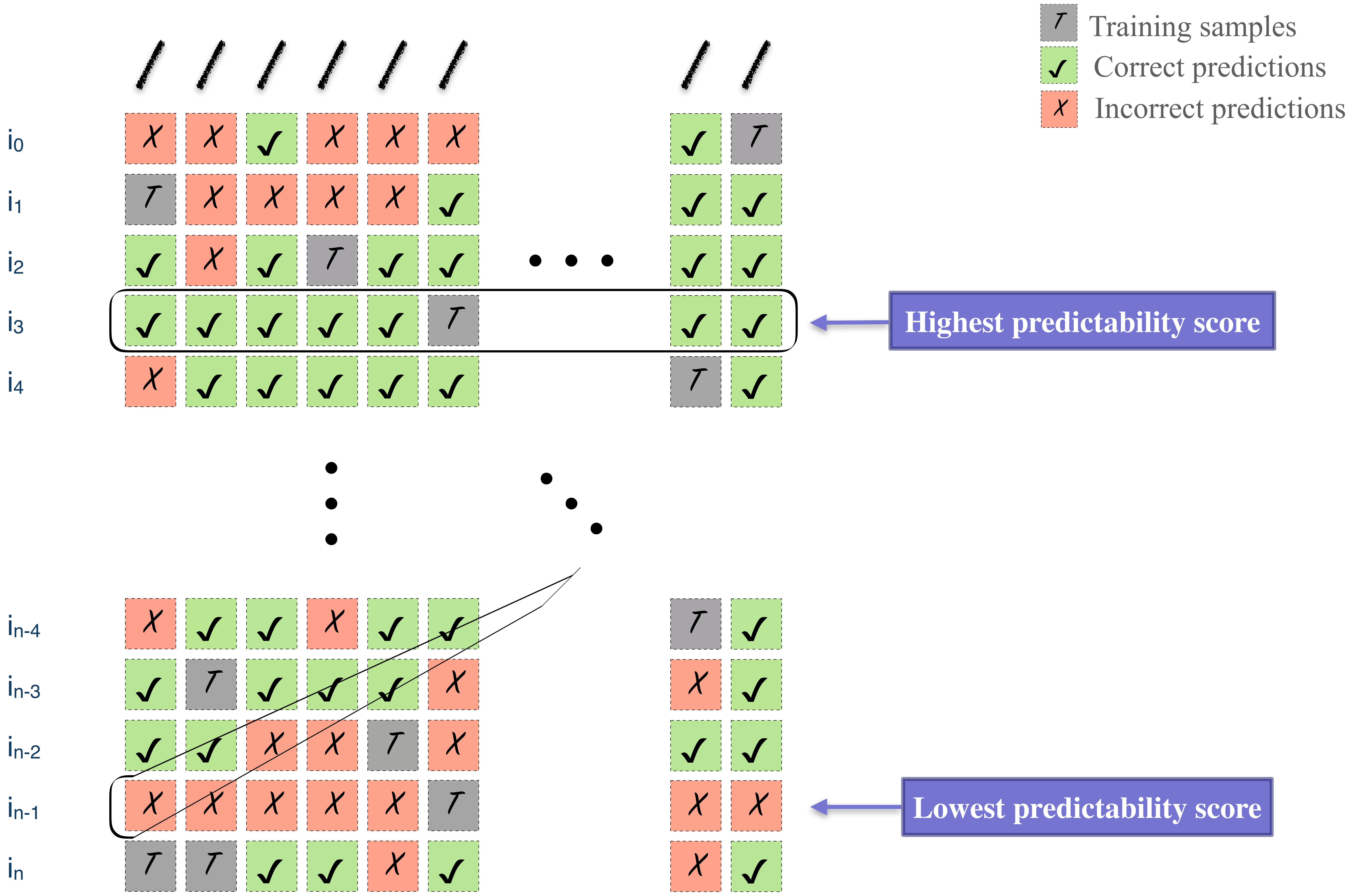

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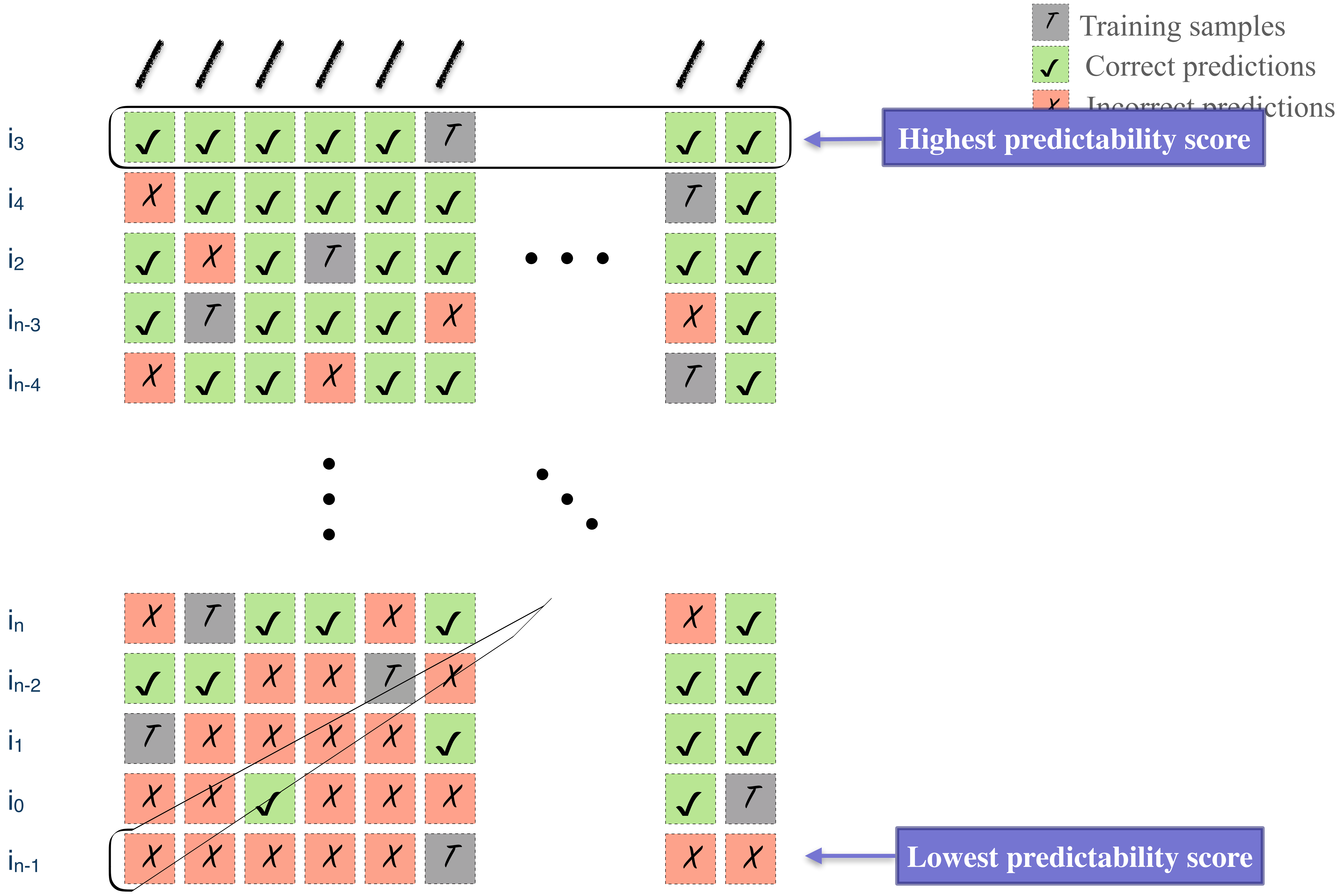

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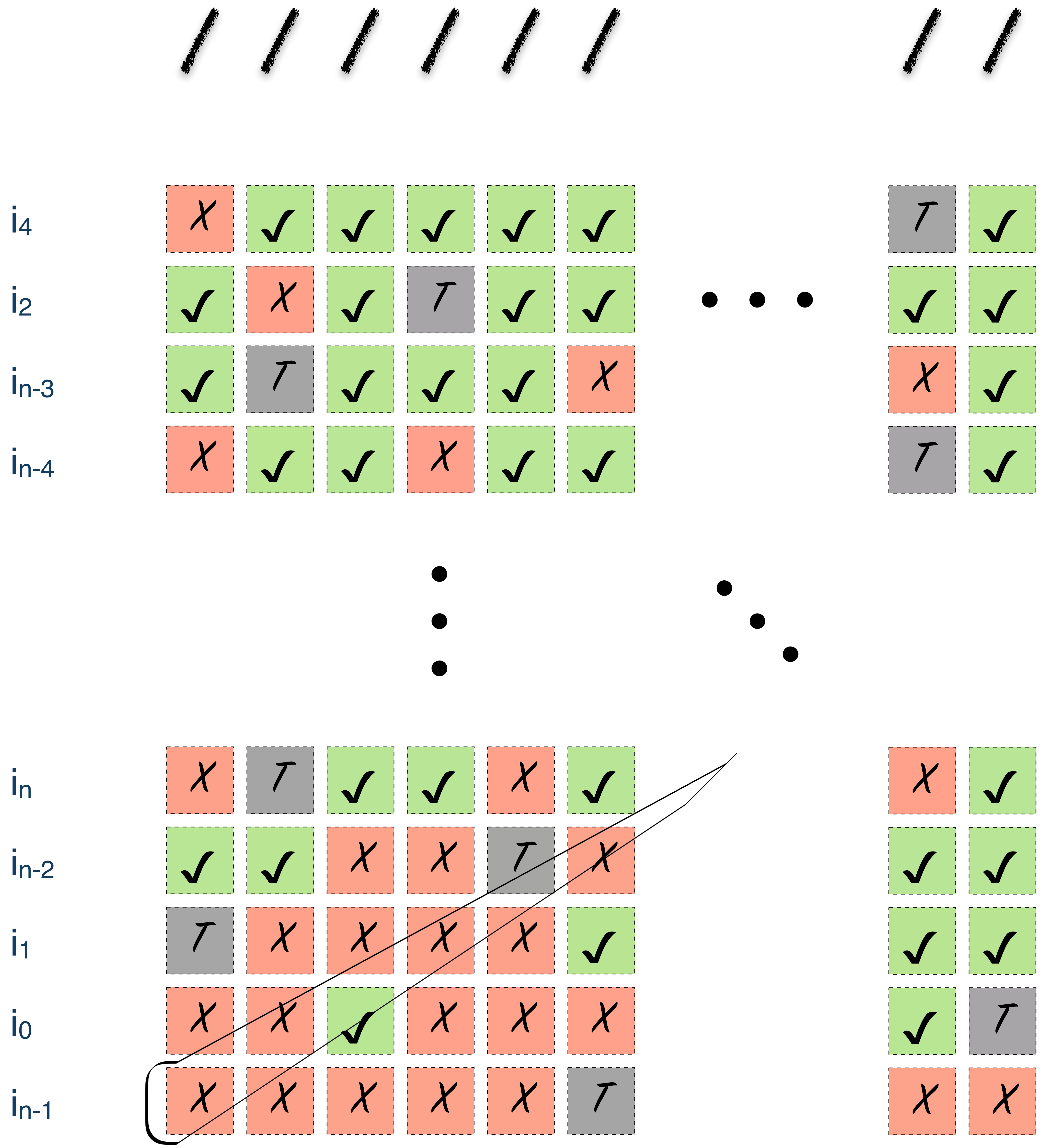

Lowest predictability score

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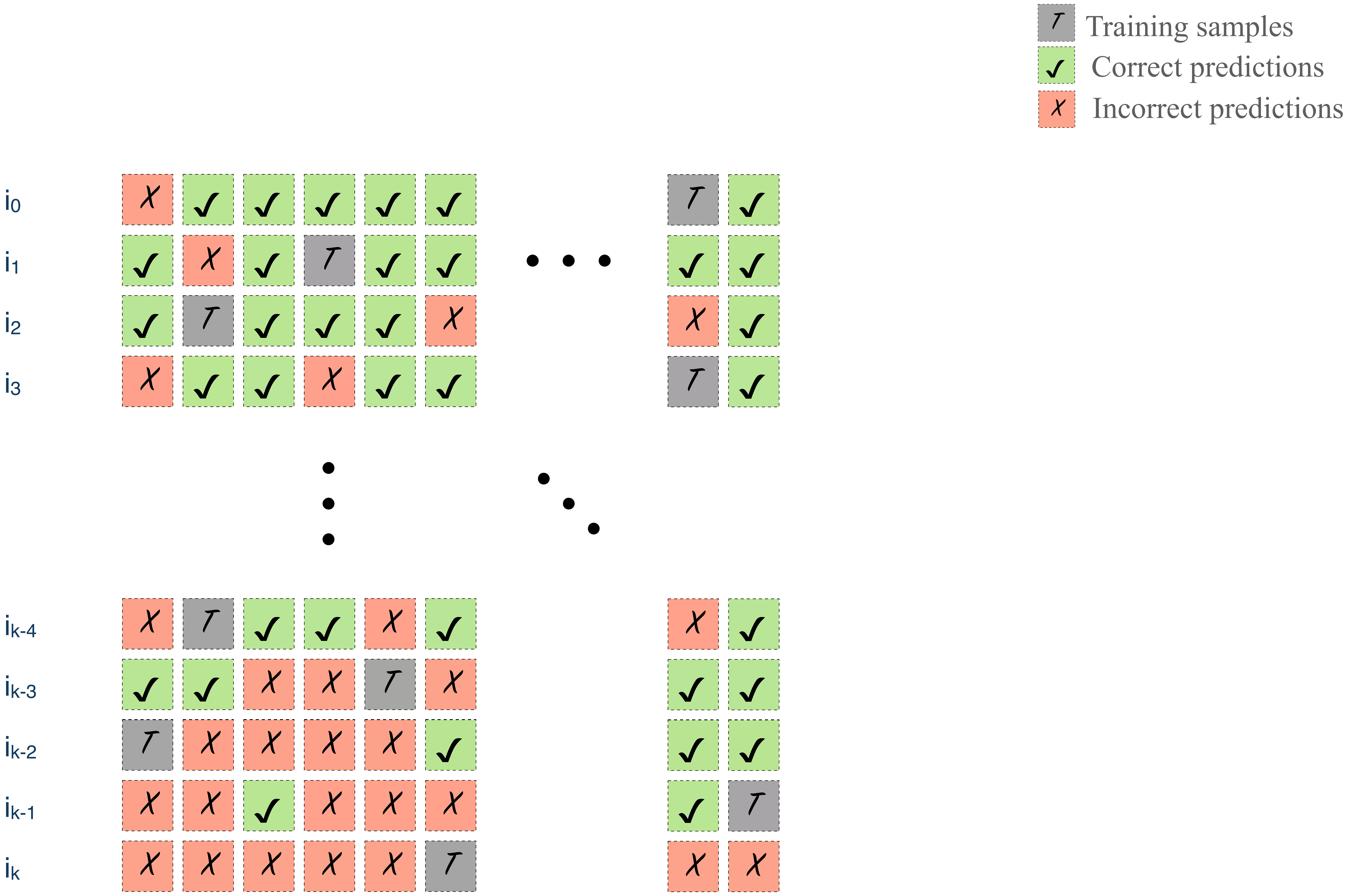

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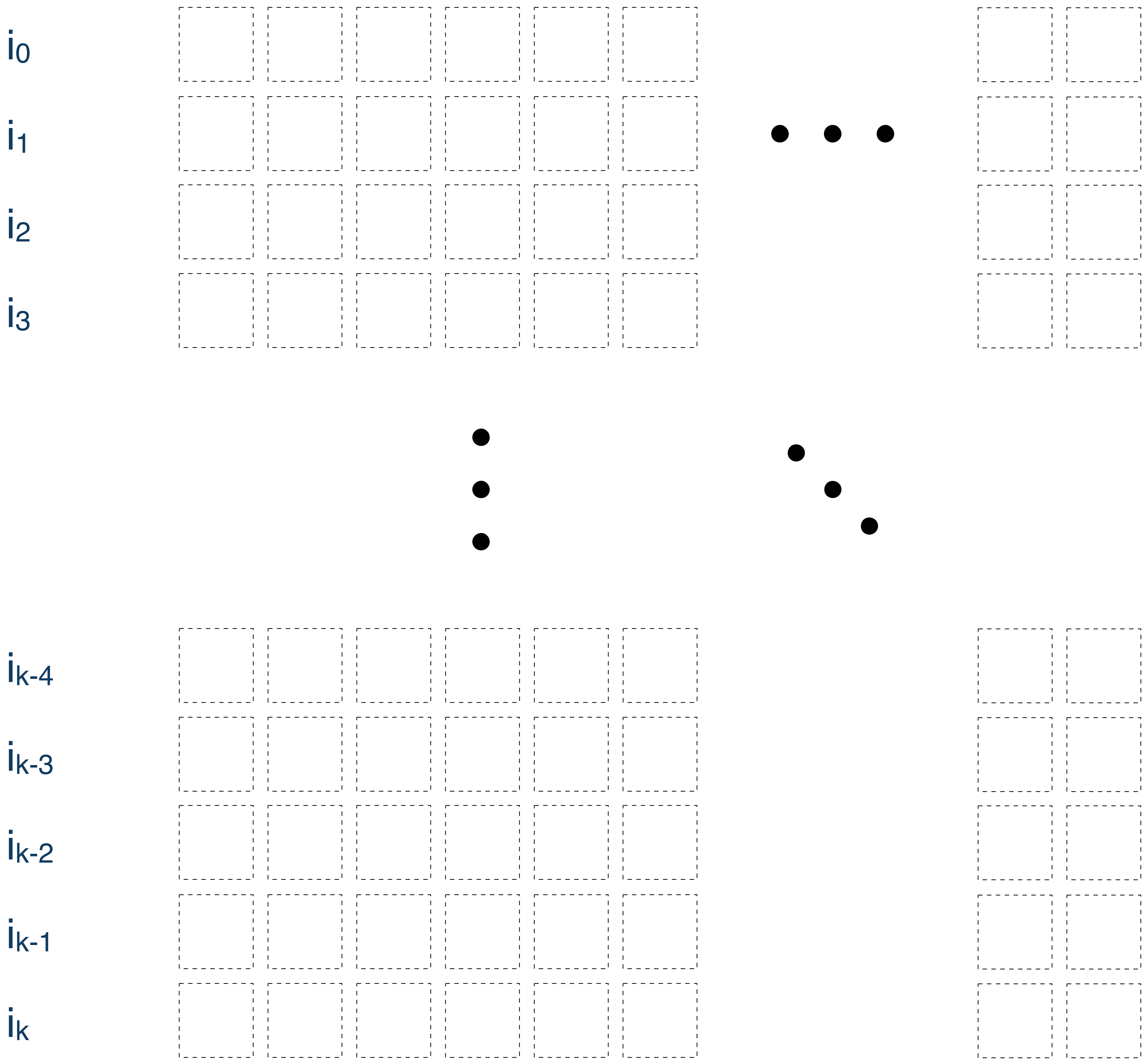

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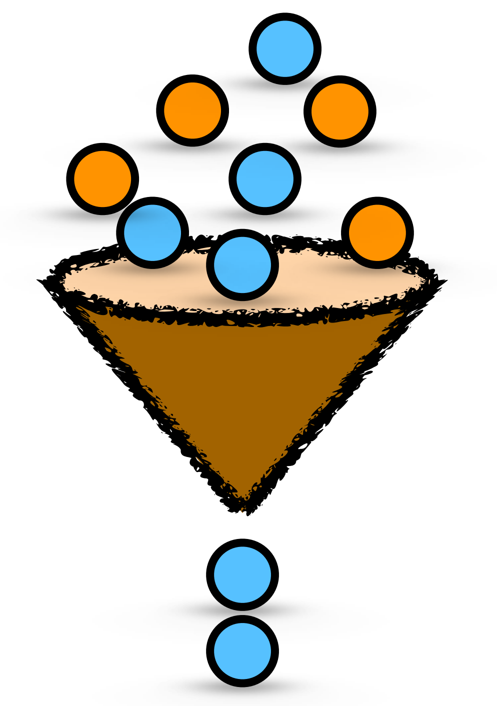

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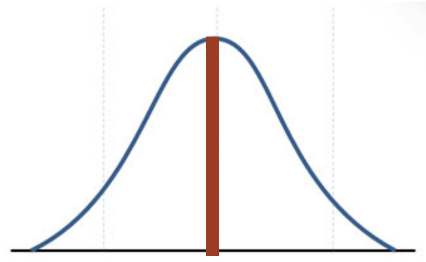
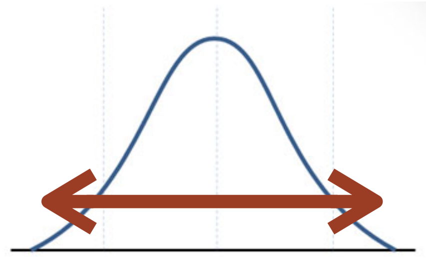
Training Dynamics

correctness

confidence



variability



Dataset Cartography [Swayamdipta et. al, 2020]

Training Dynamics

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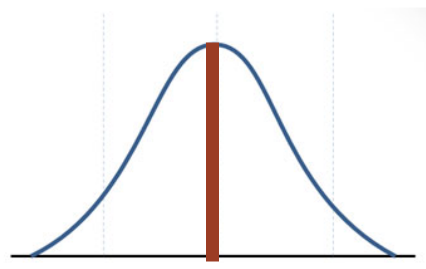
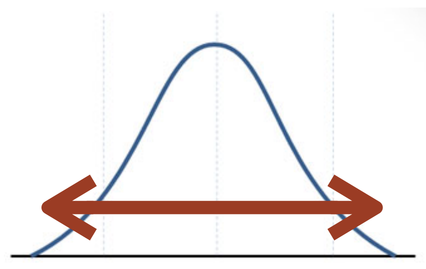
confidence 

variability 

across E training epochs…

Dataset Cartography [Swayamdipta et. al, 2020]

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- Ratio at which model prediction matches **true class**

$$\hat{c}_i = \frac{1}{E}\sum_{e=1}^{E} 1[y_i^* = \arg\max_y p_{\theta^{(e)}}(y \mid x_i)]$$

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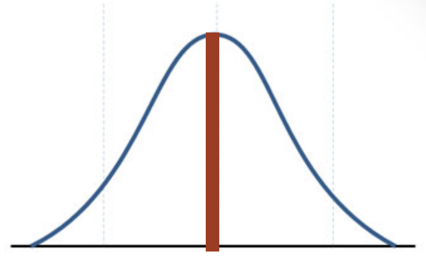

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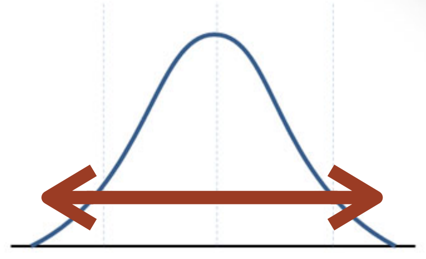

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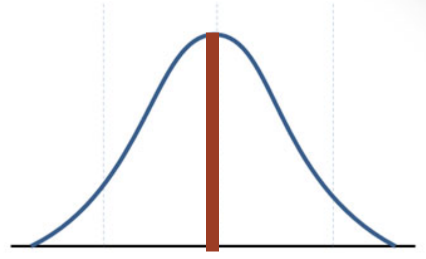

- Mean probability of the **true class**

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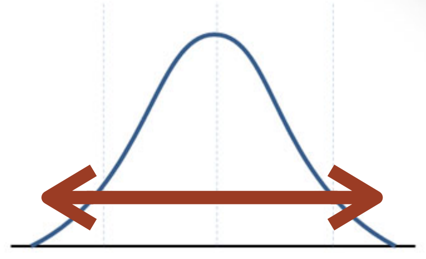
variability



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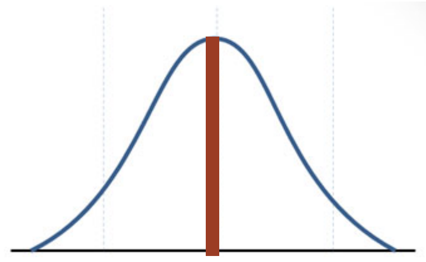

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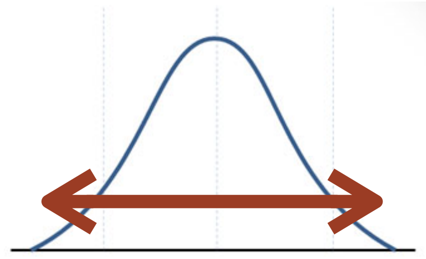

- Standard deviation of the **true class** probability

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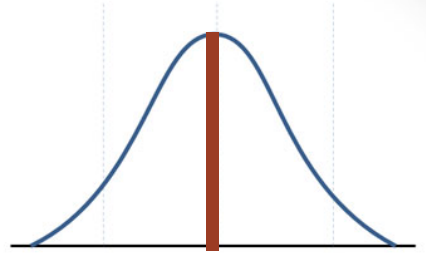

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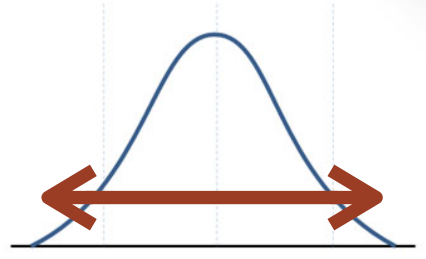

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By-product of training!

Dataset Cartography [Swayamdipta et. al, 2020]

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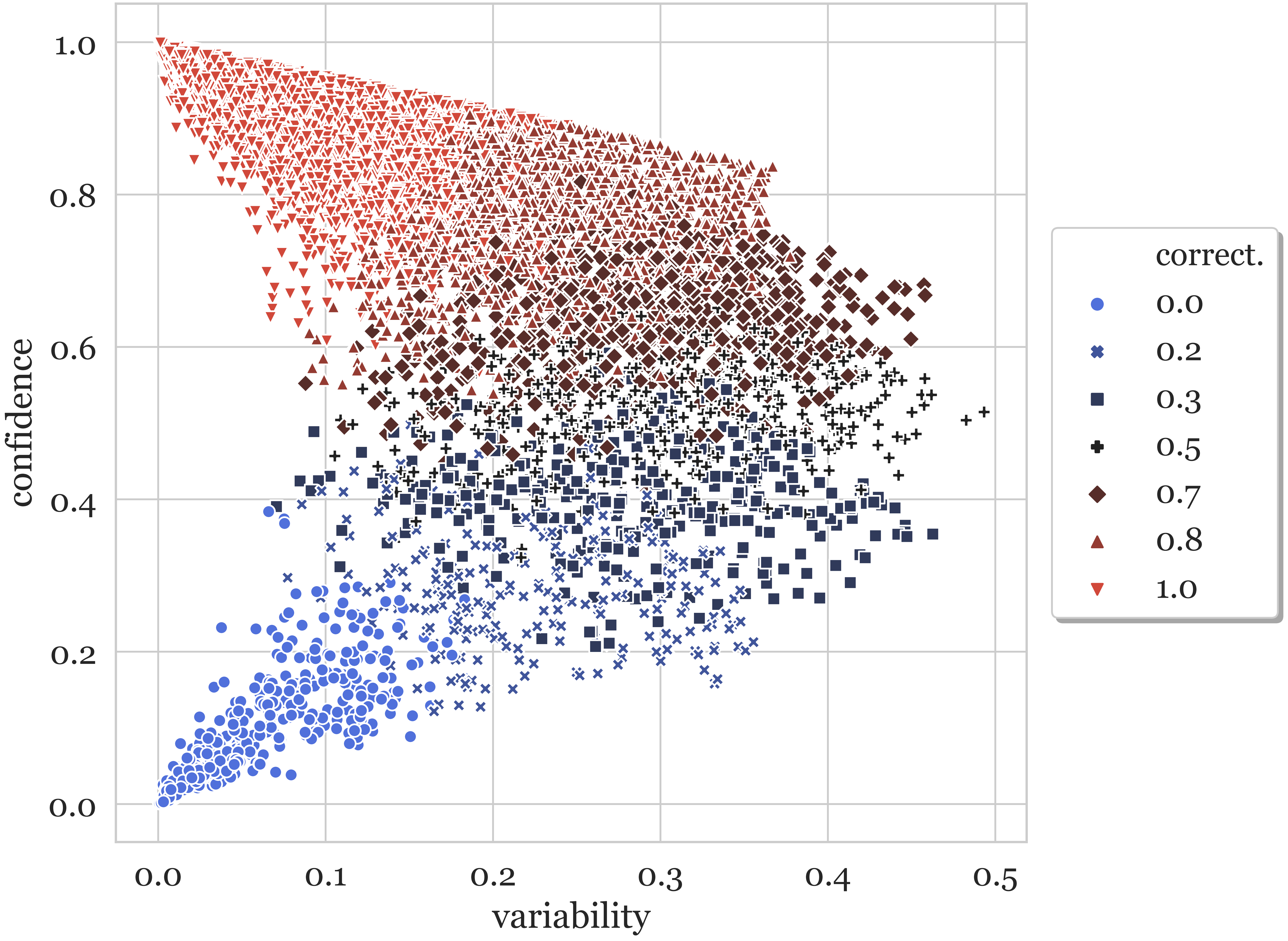

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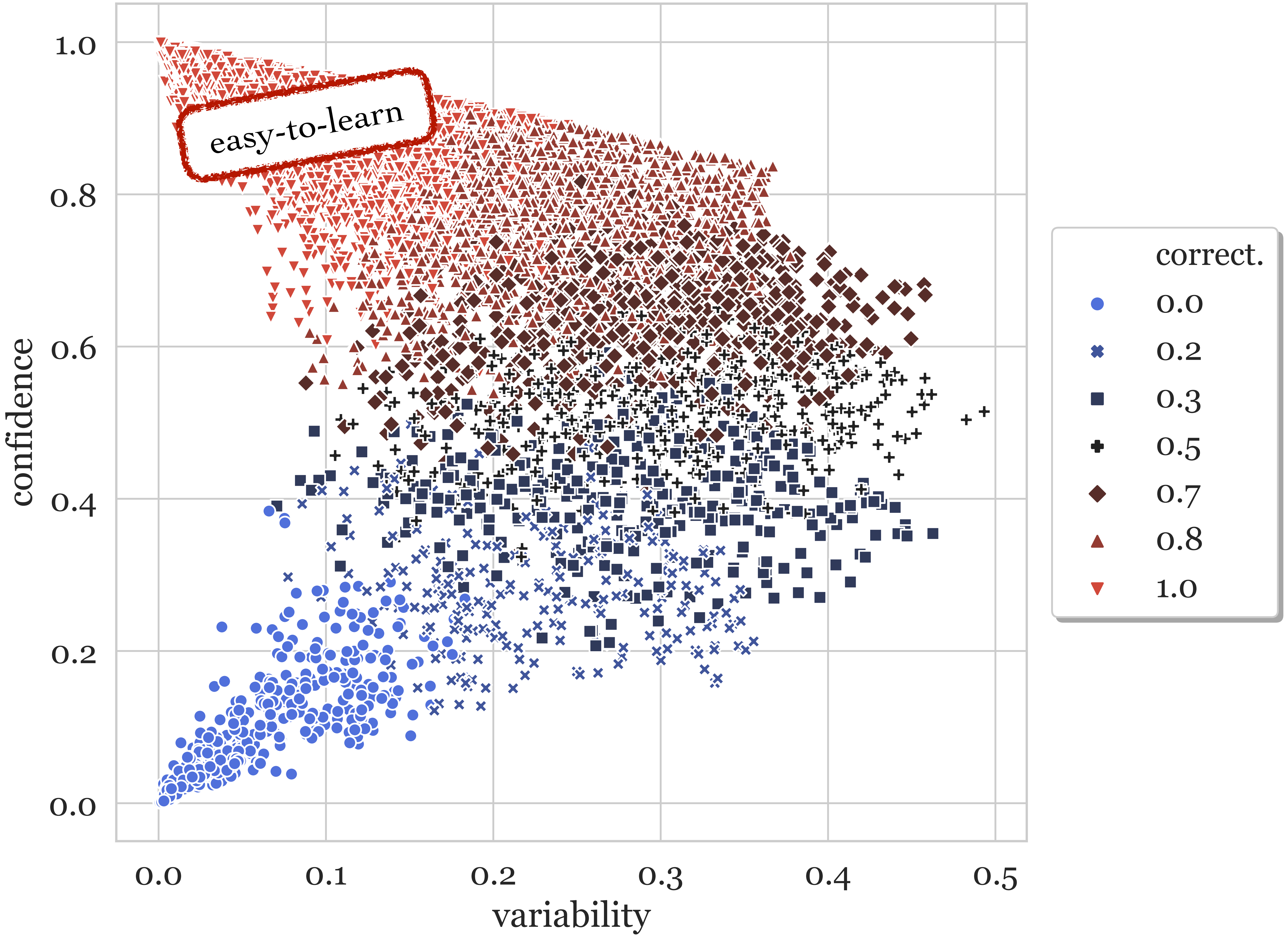

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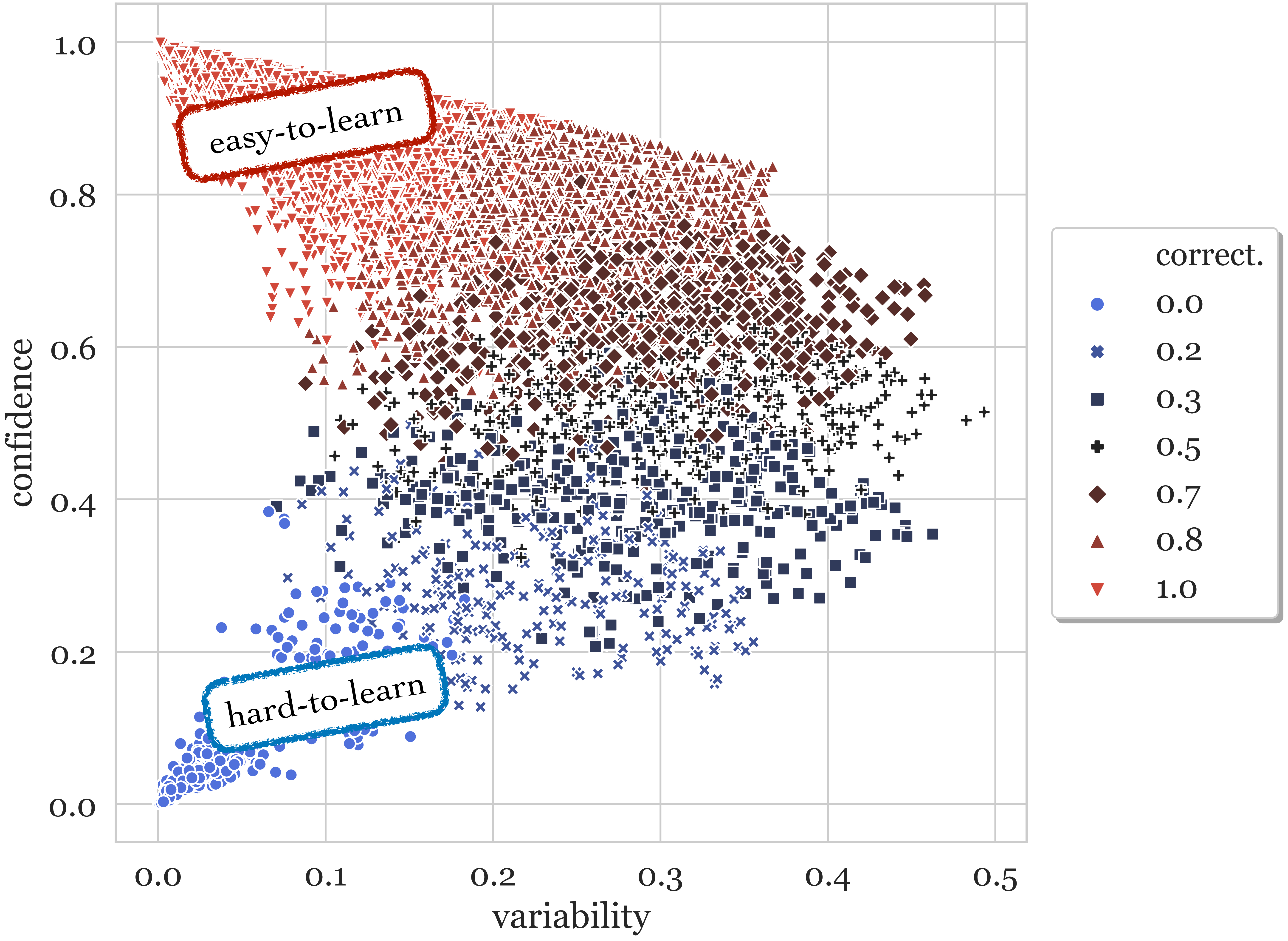

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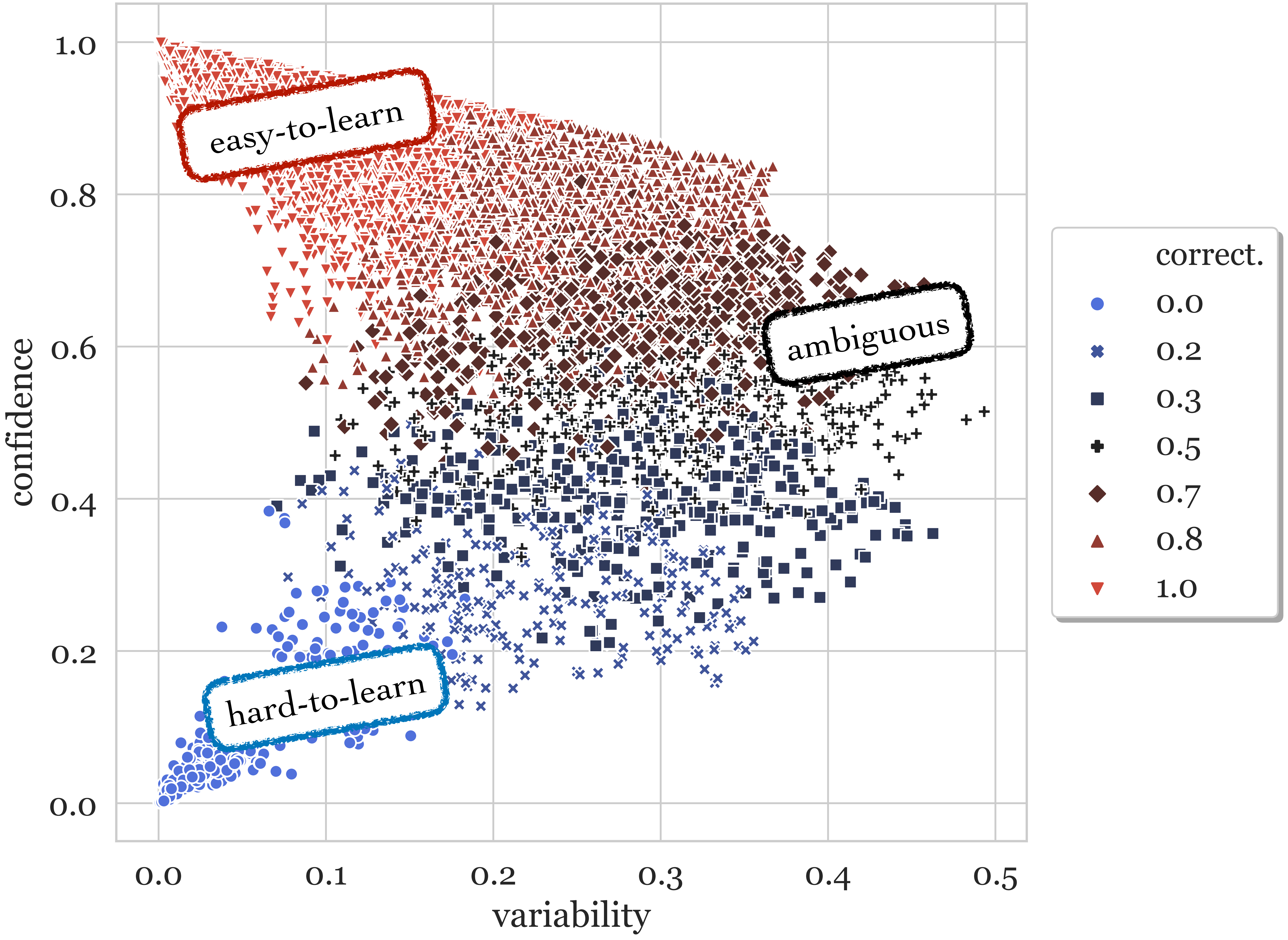

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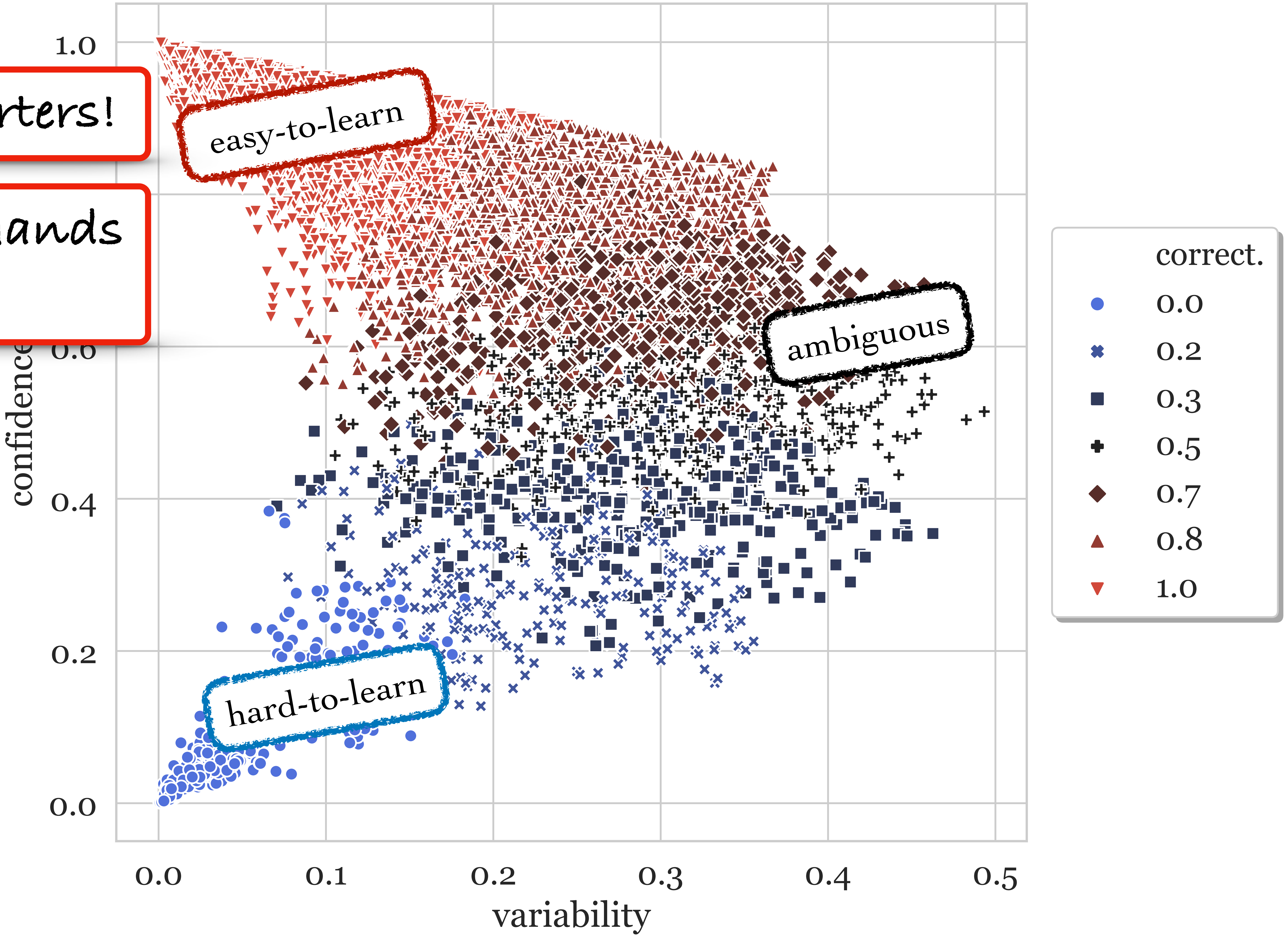
Dataset Cartography

Sc**w you Trump supporters!

Good luck and let's join hands to form unity.



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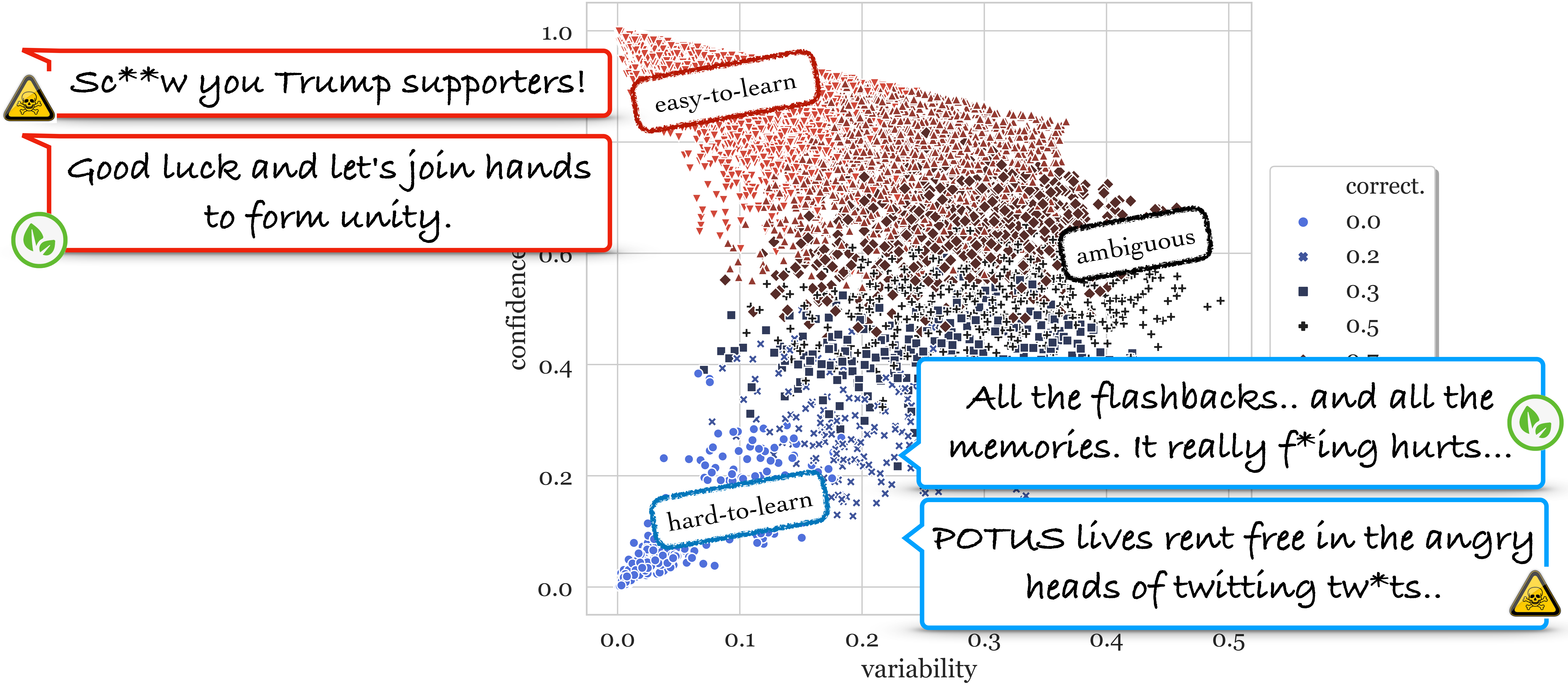
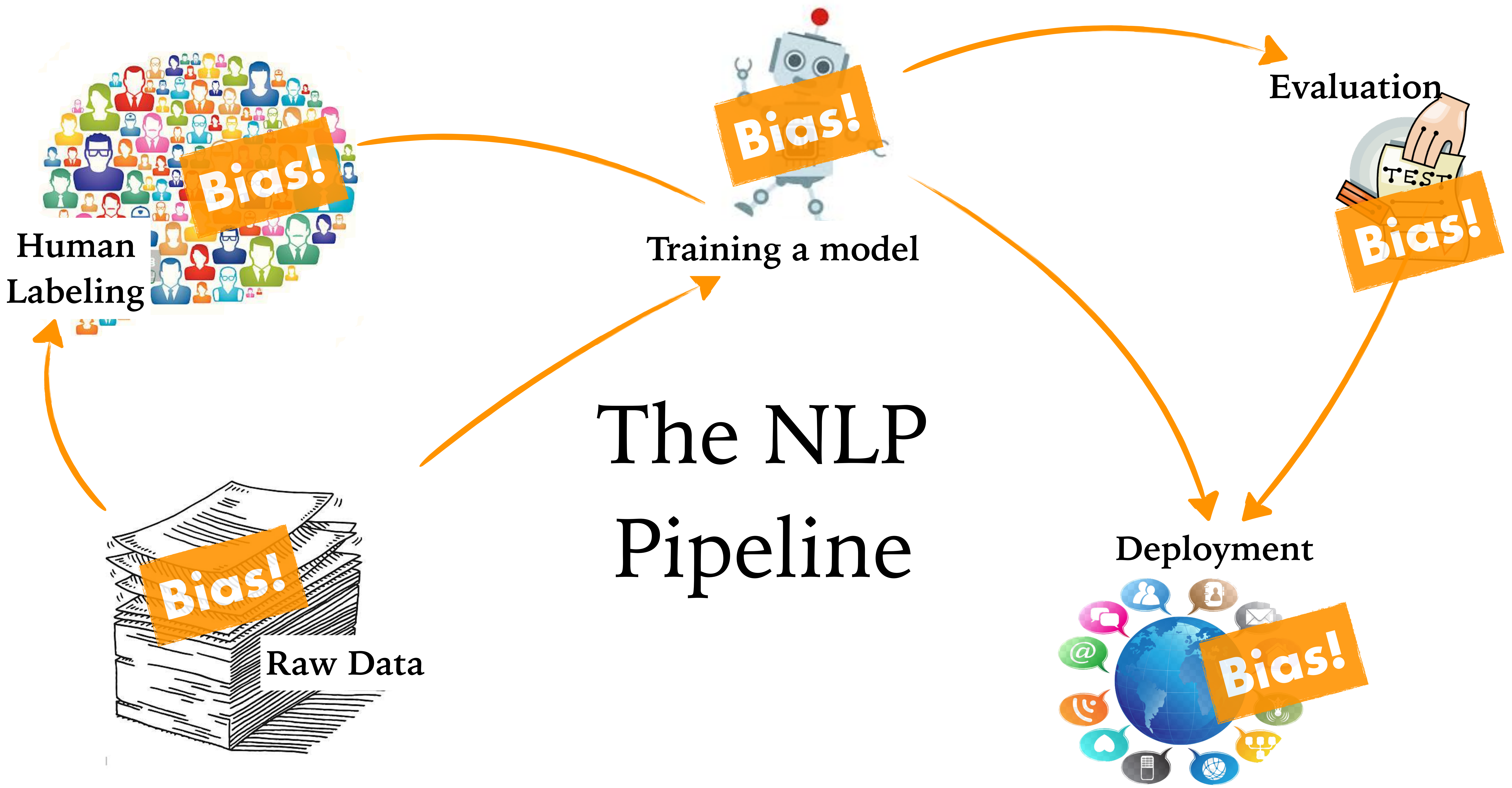
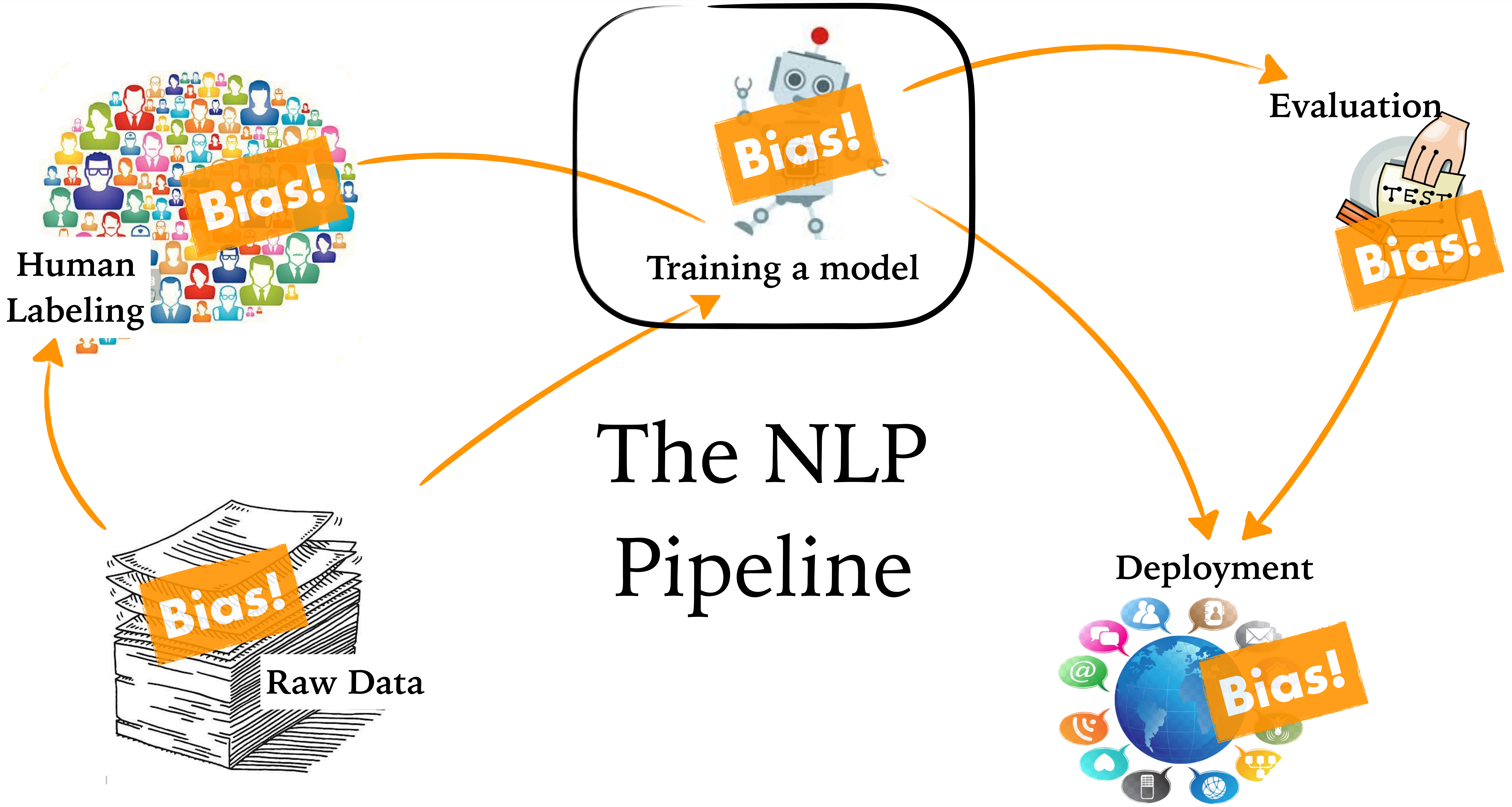


 Dataset Cartography [Swayamdipta et. al, 2020]

Question: Doesn't removing data hurt performance?


Human
Labeling
Bias!
Training a model
Bias!
Evaluation
TEST
Bias!
The NLP
Pipeline
Raw Data
Bias!
Deployment
Bias!

The NLP Pipeline



Addressing Biases: Models

[Clark et al., 2019; He et al., 2019; Mahabadi et al., 2020]

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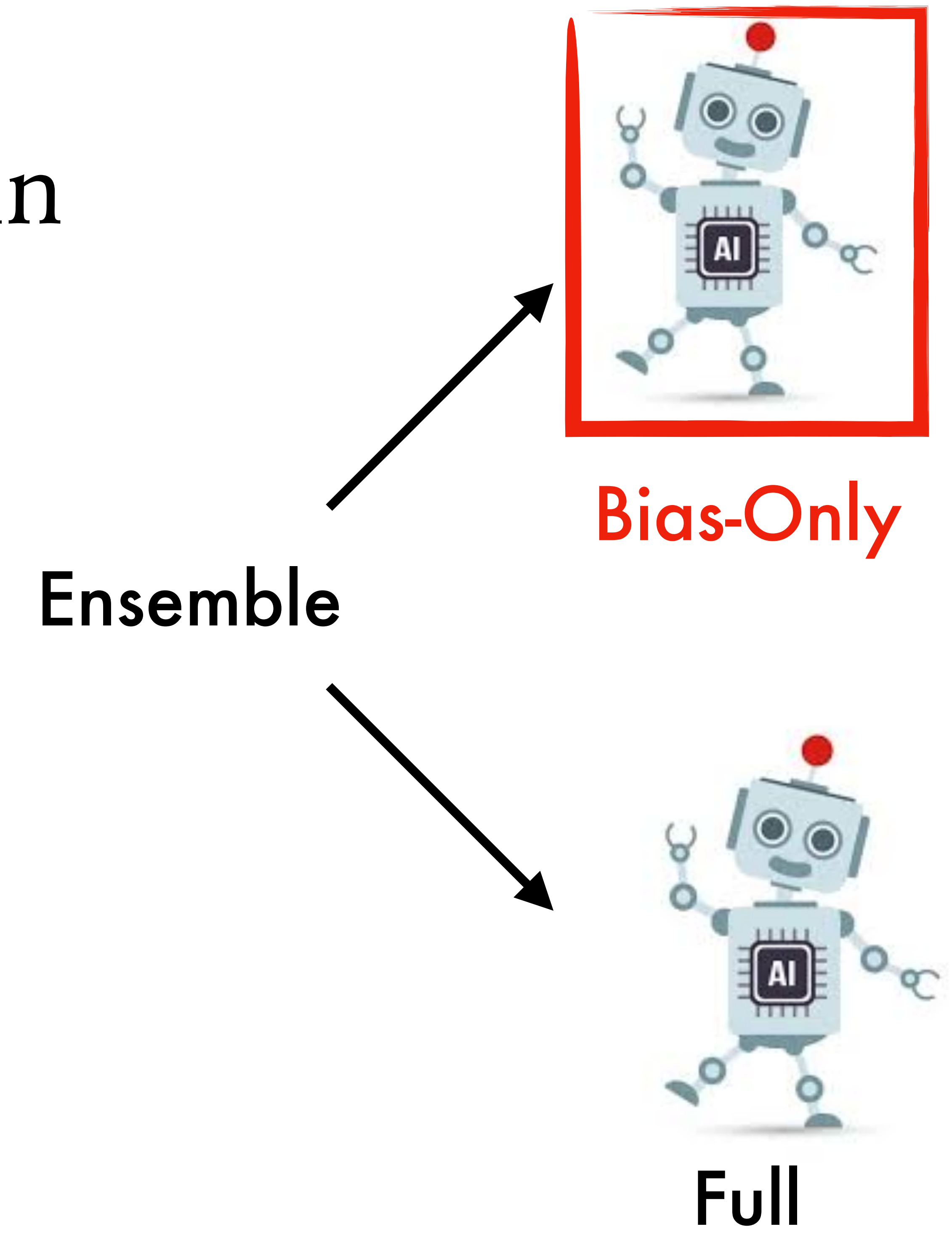

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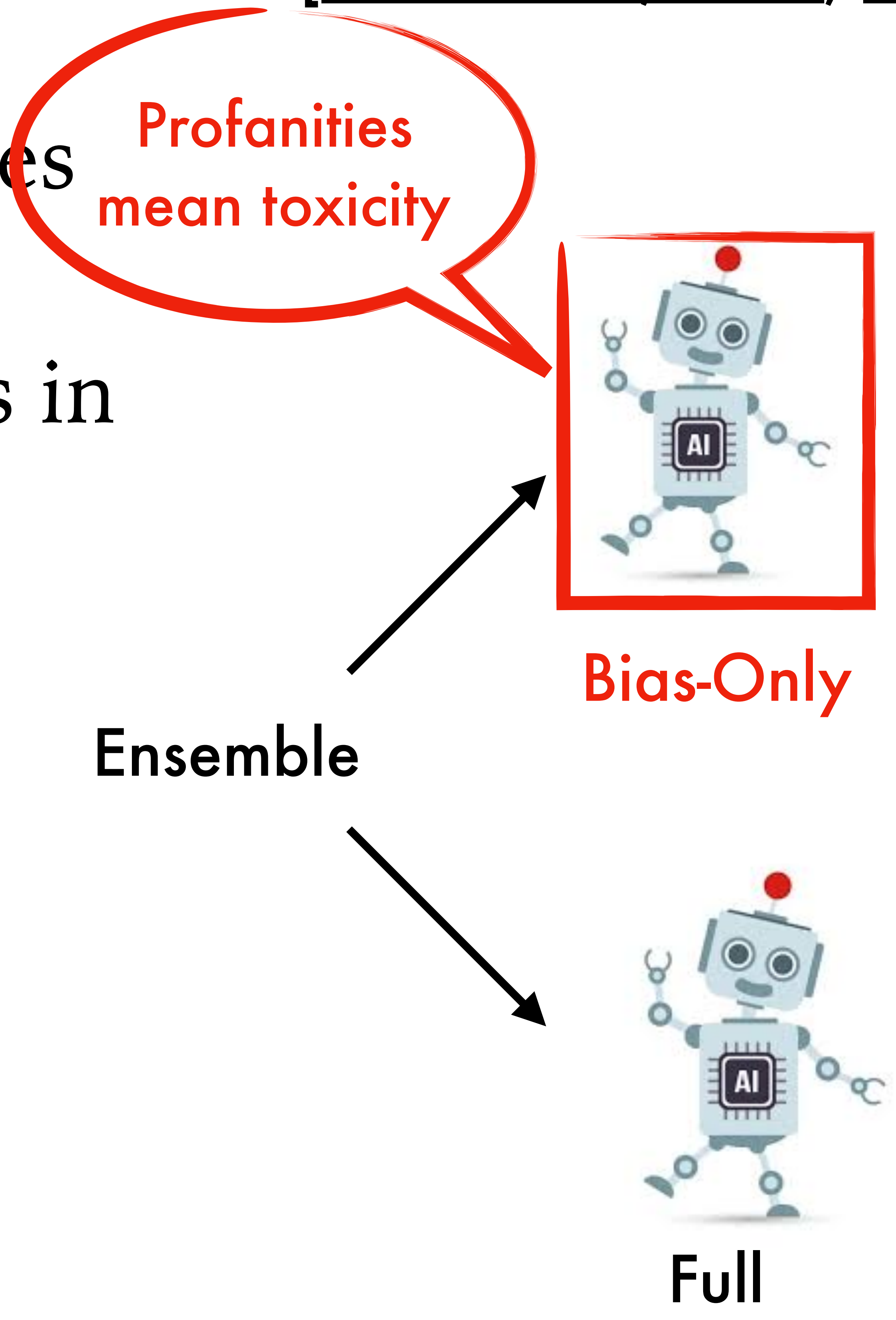

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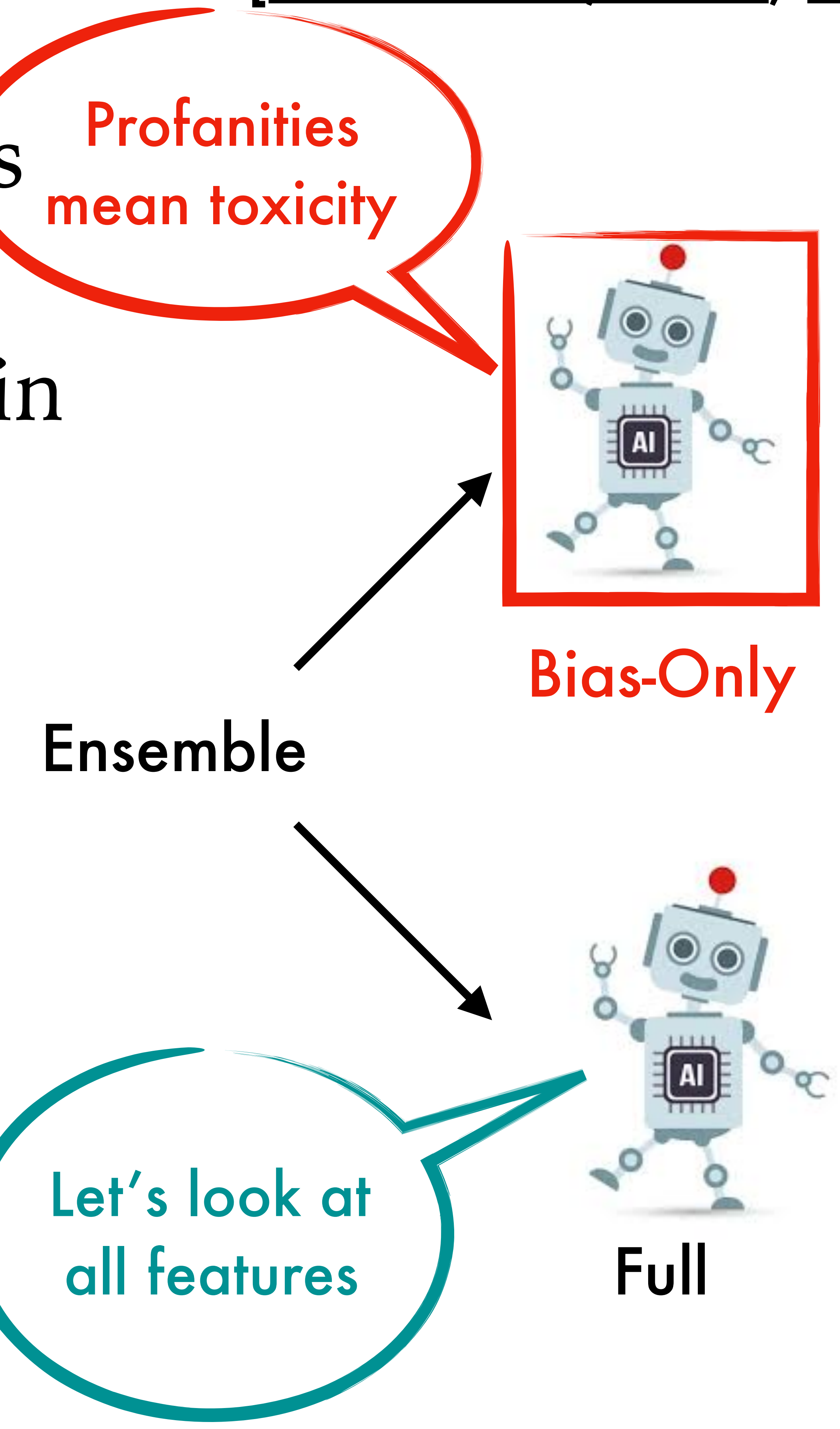

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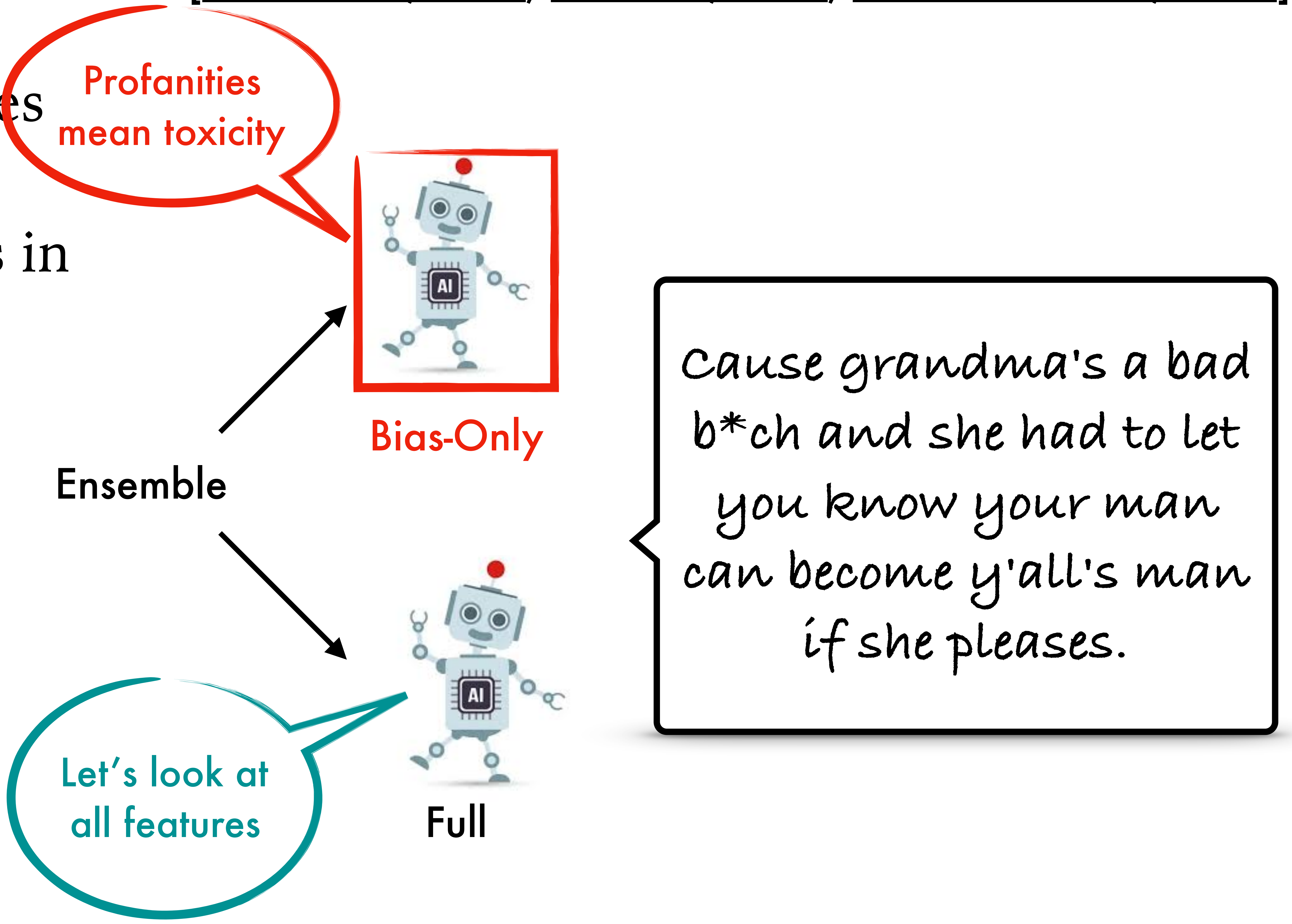

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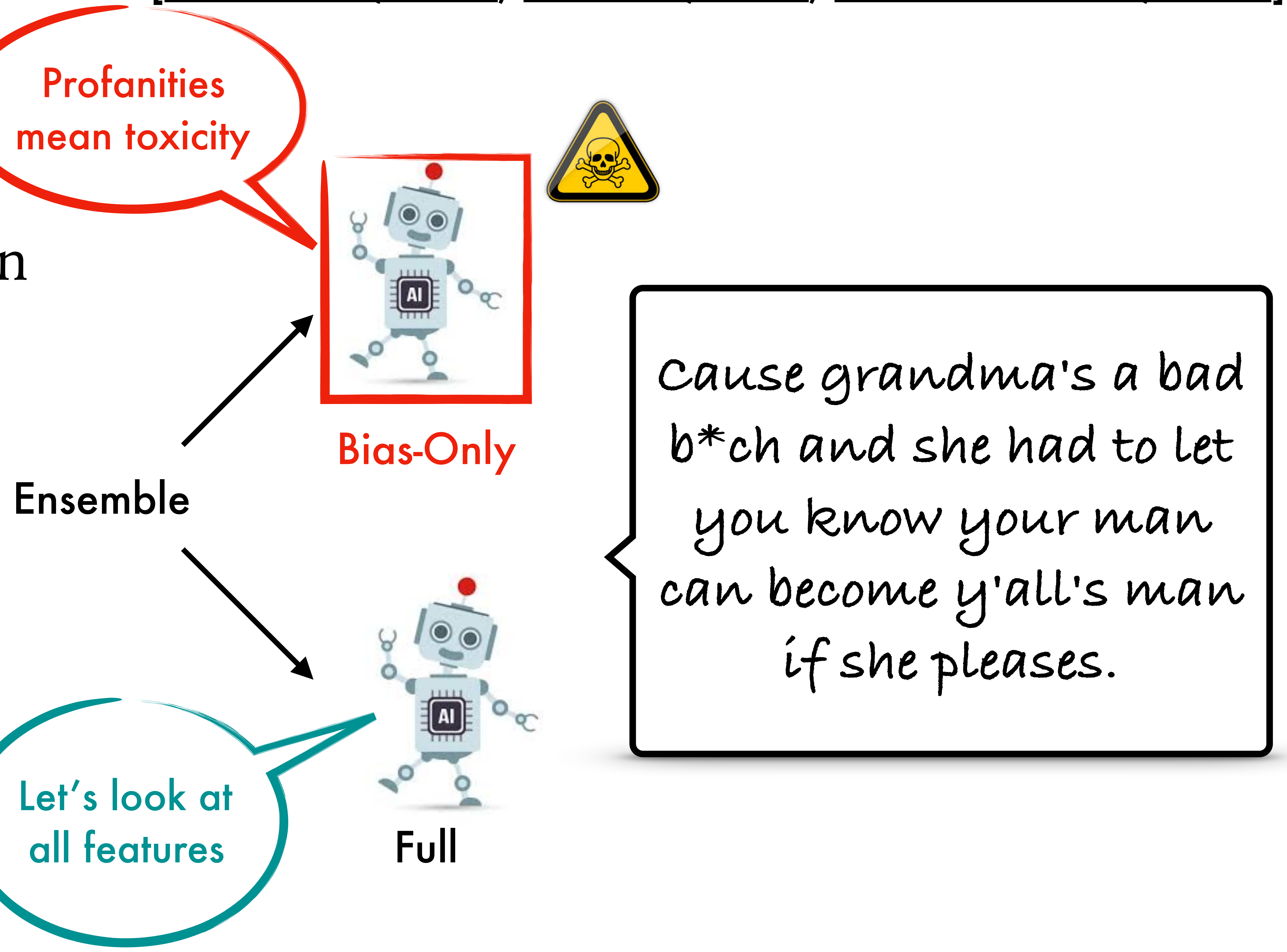

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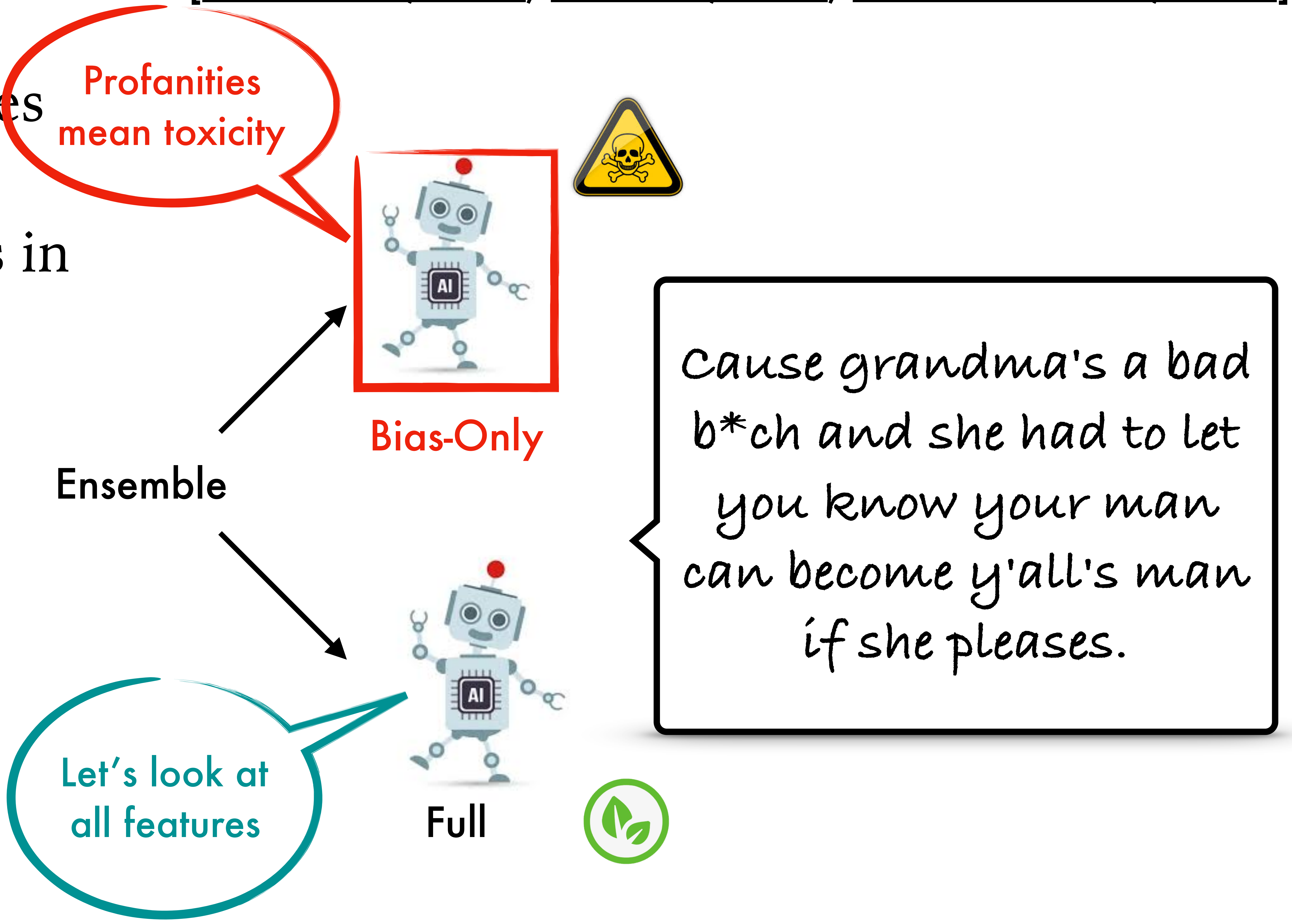

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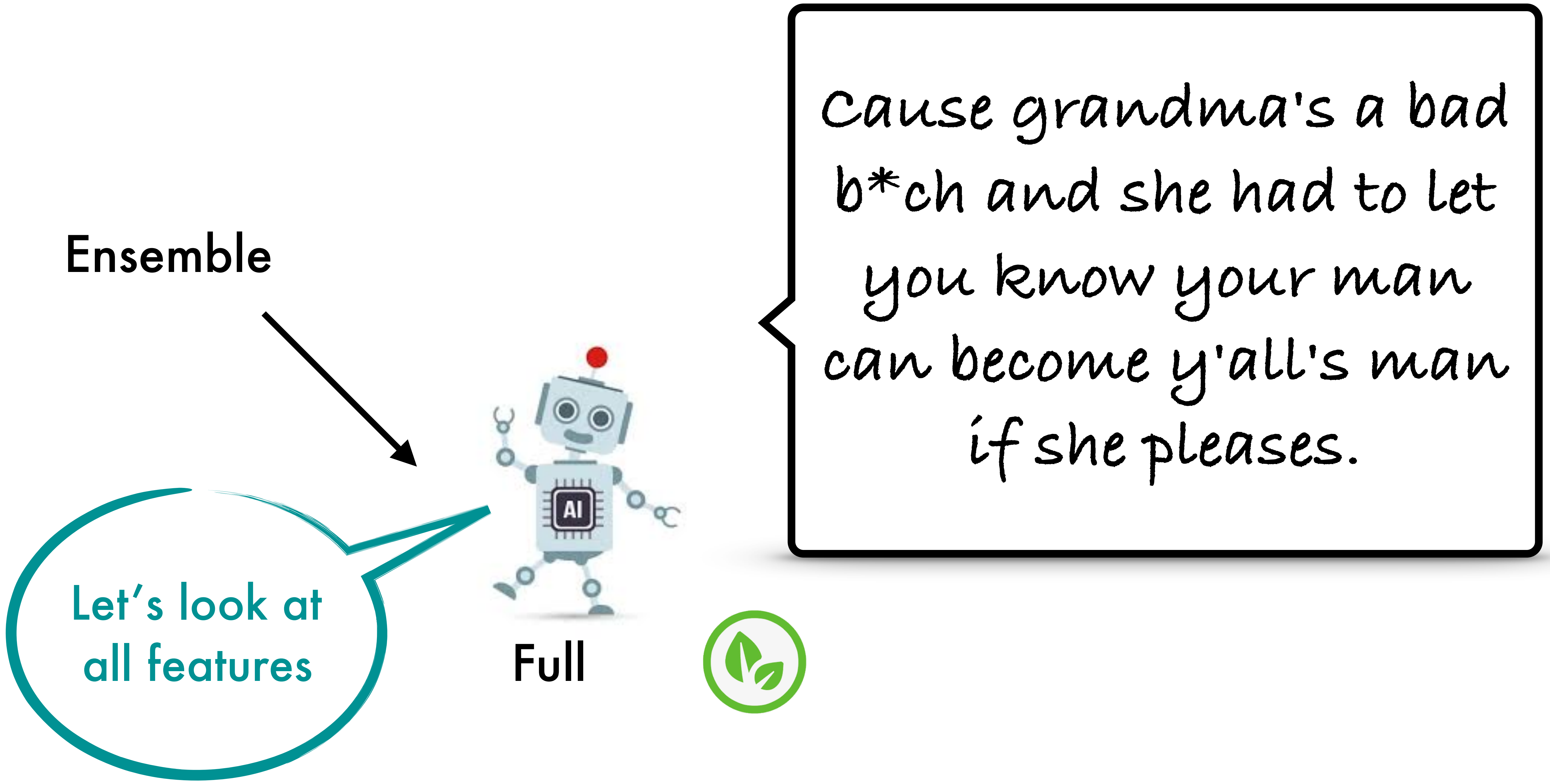

Adversarial Methods

[Belinkov et al., 2019; Ganin et al., 2016]

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- Might not entirely remove the information

[Belinkov et al., 2019; Ganin et al., 2016]

Bias Mitigation Summary

- Dataset Filtering Methods
  - Algorithms that differentiate data instances (AFLite, Dataset Cartography)
  - Can be applied to unspecified biases
- Models with Auxiliary Objectives
  - Ensembles, Adversarial Approaches
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How effective are these methods?

Be careful of the term "debiasing"...

This Lecture

Biases in NLP

- Dataset Biases
- Model Biases

Discovering Biases via Interpretability Methods

- Saliency Methods
- Input Attribution
- Architectural Modifications

Mitigating Biases

- Filtering Datasets
- Auxiliary Objectives

Summary

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- Interpretability methods can be used to detect and discover biases in models and data
- Bias discovery and bias mitigation is not necessarily a pipeline
- Bias mitigation methods either focus on models or datasets.

Thank you!
Questions?