Data:
Collection, Annotation, and Biases

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Announcements

- **Course Feedback:** Indicative Feedback this week! Please fill it out!
- **Midterm:** April 9th confirmed!

Midterm Logistics

- **Date:**
  - Wednesday, April 9th, 2025
  - 11:30 - 13:00
- **Location:** 6 rooms on campus
  - INF 1, AAC 2 31, CE 1 3, CM 1 1, CM 1 2, CM 1 4
  - Each student will be pre-assigned to one of the rooms.
    - **YOUR EXAM COPY WILL BE IN THE ROOM WHERE YOU WERE ASSIGNED.**
    - **YOU MUST GO TO THE CORRECT ROOM.**
    - **NO EXTRA EXAMS WILL BE AVAILABLE IN OTHER ROOMS.**
- **Schedule**
  - **A few days before**: room assignments and seating chart released on Moodle
  - **11:00** on the day of: Exam rooms set up
  - **11:20** on the day of: Exam hall doors open and students take their seat.
  - **11:30** on the day of: Exam begins
  - **During exam**: EPFL ID Cards checked (**don't forget CAMIPRO!**)
  - **13:00** on the day of: Exams collected

Midterm Format

- 30 Multiple Choice QA
  - From **lectures** AND **exercise sessions (up to and including Week 7)**
- Materials
  - 1 double-sided A4 crib sheet allowed
  - Non-programmable calculators allowed
  - CAMIPRO card
- No phones or other electronic devices allowed

Questions ?

Today’s Outline

- **Lecture**
  - **Quick Recap:** Finetuning
  - **Data Annotation:** Process, Biases, and effect on Fine-tuning
- **Tomorrow:** Exercise Session
  - **Review of Week 4 Exercise Session:** Finetuning pretrained models
  - **Week 5 Exercise Session:** Robustness & Prompting

Some slides adapted from Greg Durrett, Swabha Swayamdipta

Transfer Learning

train model to learn useful feature representat° (embeddings) from data, embeddings capture general patterns that can be used as inputs for another model that will be trained for a specific task

Pretraining

Learn embeddings that can be used to seed a downstream model (ELMo)

-or-

Learn a model that can be fine-tuned for many downstream tasks (GPT, BERT)

model designed to be adaptable so that it can be fine-tuned with task-specific data for ≠ problems

Fine-tuning

Design a new model architecture whose embeddings are initialised with pretrained embeddings. Train this model on a task of interest

- or -

Take a pretrained model and train it further on data from a task of interest

Transfer Learning

Pretraining

Uses simple training objectives

Requires tons of data

Resultant model often not useful yet

Slow & expensive; can often only do once

Fine-tuning

Done on smaller datasets

Trained on data with a more complex structure

Resultant model applied to task of interest

Typically cheaper; can afford multiple runs, hyper parameter tuning, etc.

Pretraining: Two Approaches

(Causal, Left-to-right) Language Modeling

I really enjoyed the movie we watched on ____

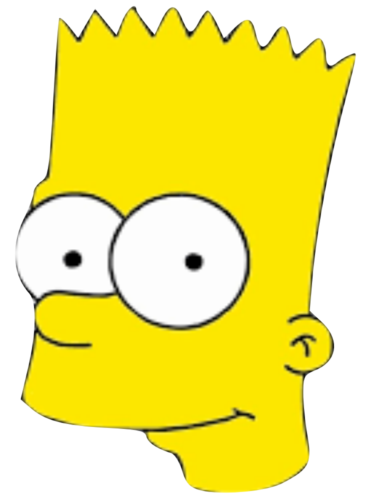
OpenAI

(Radford et al., 2018, 2019, many others)

Masked Language Modeling

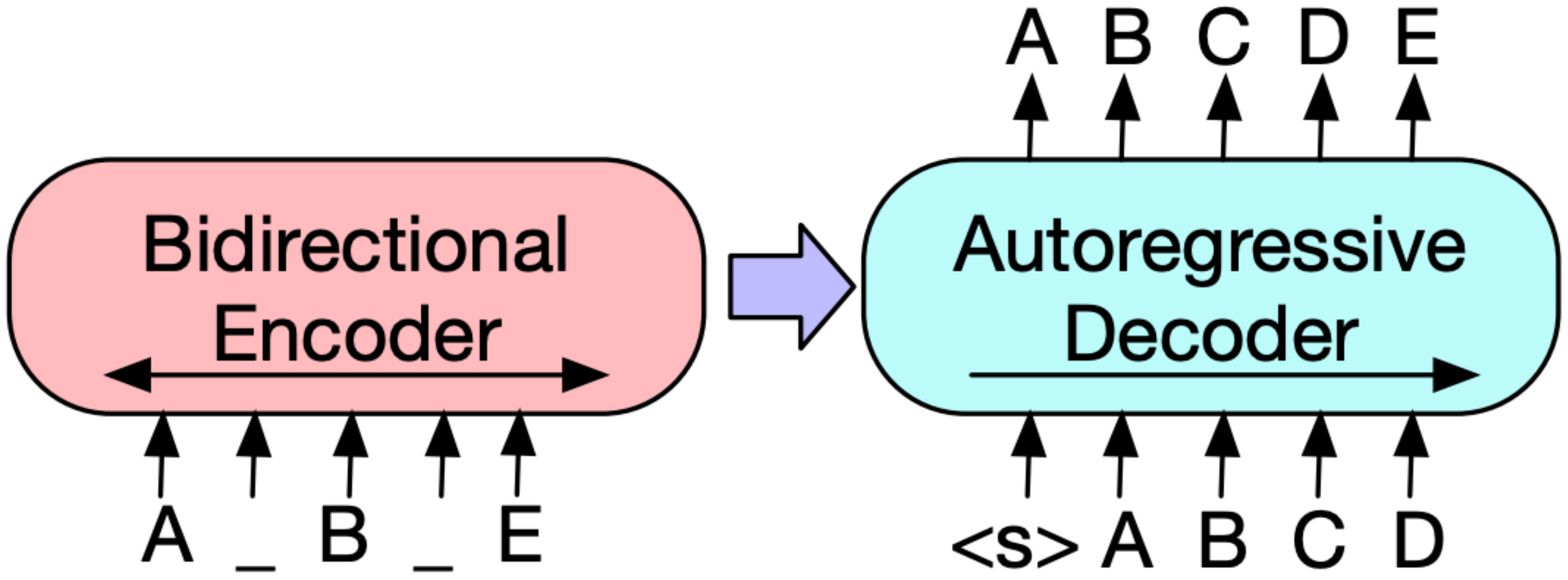
I really enjoyed the ____ we watched on Saturday!

(Devlin et al., 2018; Liu et al., 2020)



BART Pretraining

- Pretraining BART combines elements of BERT and GPT!
- **BERT-style:** input texts corrupted before they are passed to bidirectional encoder
- **GPT-style:** model is trained with a language modelling objective in the decoder: predict the next word!



Lewis et al. (2019)

Recap

- **Contextual representations:** Let us model words and sequences conditioned on the context around them
- **ELMo:** Based on bidirectional LSTMs. **Good for pretrained embeddings.**
- **GPT**: Uses a transformer decoder. **Good for generating text as a language model.**
- **BERT**: Uses a transformer encoder. **Good for classification and sequence labelling.**
- **BART + T5:** Pretraining sequence-to-sequence transformer models. **Extendable to all task types!**

Benchmark Performance: SuperGLUE

	Rank	Name	Model	URL	Score	BoolQ	CB	COPA	MultiRC	ReCoRD	RTE	WiC	WSC	AX-b	AX-g
	1	JDExplore d-team	Vega v2		91.3	90.5	98.6/99.2	99.4	88.2/62.4	94.4/93.9	96.0	77.4	98.6	-0.4	100.0/50.0
+	2	Liam Fedus	ST-MoE-32B		91.2	92.4	96.9/98.0	99.2	89.6/65.8	95.1/94.4	93.5	77.7	96.6	72.3	96.1/94.1
	3	Microsoft Alexander v-team	Turing NLR v5		90.9	92.0	95.9/97.6	98.2	88.4/63.0	96.4/95.9	94.1	77.1	97.3	67.8	93.3/95.5
	4	ERNIE Team - Baidu	ERNIE 3.0		90.6	91.0	98.6/99.2	97.4	88.6/63.2	94.7/94.2	92.6	77.4	97.3	68.6	92.7/94.7
	5	Yi Tay	PaLM 540B		90.4	91.9	94.4/96.0	99.0	88.7/63.6	94.2/93.3	94.1	77.4	95.9	72.9	95.5/90.4
+	6	Zirui Wang	T5 + UDG, Single Model (Google Brain)		90.4	91.4	95.8/97.6	98.0	88.3/63.0	94.2/93.5	93.0	77.9	96.6	69.1	92.7/91.9
+	7	DeBERTa Team - Microsoft	DeBERTa / TuringNLRv4		90.3	90.4	95.7/97.6	98.4	88.2/63.7	94.5/94.1	93.2	77.5	95.9	66.7	93.3/93.8
	8	SuperGLUE Human Baselines	SuperGLUE Human Baselines		89.8	89.0	95.8/98.9	100.0	81.8/51.9	91.7/91.3	93.6	80.0	100.0	76.6	99.3/99.7
+	9	T5 Team - Google	T5		89.3	91.2	93.9/96.8	94.8	88.1/63.3	94.1/93.4	92.5	76.9	93.8	65.6	92.7/91.9

T5 model at #9

Humans at #8

7 models better than humans!!!

On GLUE, 20+ models better than humans!!!

Rank	Name	Model	URL	Score	CoLA	SST-2	MRPC	STS-B	QQP	MNLI-m	MNLI-mm	QNLI	RTE	WNLI	AX
1	Microsoft Alexander v-team	Turing ULR v6		91.3	73.3	97.5	94.2/92.3	93.5/93.1	76.4/90.9	92.5	92.1	96.7	93.6	97.9	55.4
2	JDExplore d-team	Vega v1		91.3	73.8	97.9	94.5/92.6	93.5/93.1	76.7/91.1	92.1	91.9	96.7	92.4	97.9	51.4
3	Microsoft Alexander v-team	Turing NLR v5		91.2	72.6	97.6	93.8/91.7	93.7/93.3	76.4/91.1	92.6	92.4	97.9	94.1	95.9	57.0
4	DIRL Team	DeBERTa + CLEVER		91.1	74.7	97.6	93.3/91.1	93.4/93.1	76.5/91.0	92.1	91.8	96.7	93.2	96.6	53.3
5	ERNIE Team - Baidu	ERNIE		91.1	75.5	97.8	93.9/91.8	93.0/92.6	75.2/90.9	92.3	91.7	97.3	92.6	95.9	51.7
6	AliceMind & DIRL	StructBERT + CLEVER		91.0	75.3	97.7	93.9/91.9	93.5/93.1	75.6/90.8	91.7	91.5	97.4	92.5	95.2	49.1
7	DeBERTa Team - Microsoft	DeBERTa / TuringNLRv4		90.8	71.5	97.5	94.0/92.0	92.9/92.6	76.2/90.8	91.9	91.6	99.2	93.2	94.5	53.2
8	HFL iFLYTEK	MacALBERT + DKM		90.7	74.8	97.0	94.5/92.6	92.8/92.6	74.7/90.6	91.3	91.1	97.8	92.0	94.5	52.6
9	PING-AN Omni-Sinitic	ALBERT + DAAF + NAS		90.6	73.5	97.2	94.0/92.0	93.0/92.4	76.1/91.0	91.6	91.3	97.5	91.7	94.5	51.2
10	T5 Team - Google	T5		90.3	71.6	97.5	92.8/90.4	93.1/92.8	75.1/90.6	92.2	91.9	96.9	92.8	94.5	53.1
11	Microsoft D365 AI & MSR AI & GATECH	MT-DNN-SMART		89.9	69.5	97.5	93.7/91.6	92.9/92.5	73.9/90.2	91.0	90.8	99.2	89.7	94.5	50.2
12	Huawei Noah's Ark Lab	NEZHA-Large		89.8	71.7	97.3	93.3/91.0	92.4/91.9	75.2/90.7	91.5	91.3	96.2	90.3	94.5	47.9
13	LG AI Research	ANNA		89.8	68.7	97.0	92.7/90.1	93.0/92.8	75.3/90.5	91.8	91.6	96.0	91.8	95.9	51.8
14	Zihang Dai	Funnel-Transformer (Ensemble B10-10-10H1024)		89.7	70.5	97.5	93.4/91.2	92.6/92.3	75.4/90.7	91.4	91.1	95.8	90.0	94.5	51.6
15	ELECTRA Team	ELECTRA-Large + Standard Tricks		89.4	71.7	97.1	93.1/90.7	92.9/92.5	75.6/90.8	91.3	90.8	95.8	89.8	91.8	50.7
16	David Kim	2digit LANet		89.3	71.8	97.3	92.4/89.6	93.0/92.7	75.5/90.5	91.8	91.6	96.4	91.1	88.4	54.6
17	倪仕文	DropAttack-RoBERTa-large		88.8	70.3	96.7	92.6/90.1	92.1/91.8	75.1/90.5	91.1	90.9	95.3	89.9	89.7	48.2
18	Microsoft D365 AI & UMD	FreeLB-RoBERTa (ensemble)		88.4	68.0	96.8	93.1/90.8	92.3/92.1	74.8/90.3	91.1	90.7	95.6	88.7	89.0	50.1
19	Junjie Yang	HIRE-RoBERTa		88.3	68.6	97.1	93.0/90.7	92.4/92.0	74.3/90.2	90.7	90.4	95.5	87.9	89.0	49.3
20	Shiwen Ni	ELECTRA-large-M (bert4keras)		88.3	69.3	95.8	92.2/89.6	91.2/91.1	75.1/90.5	91.1	90.9	93.8	87.9	91.8	48.2
21	Facebook AI	RoBERTa		88.1	67.8	96.7	92.3/89.8	92.2/91.9	74.3/90.2	90.8	90.2	95.4	88.2	89.0	48.7
22	Microsoft D365 AI & MSR AI	MT-DNN-ensemble		87.6	68.4	96.5	92.7/90.3	91.1/90.7	73.7/89.9	87.9	87.4	96.0	86.3	89.0	42.8
23	GLUE Human Baselines	GLUE Human Baselines		87.1	66.4	97.8	86.3/80.8	92.7/92.6	59.5/80.4	92.0	92.8	91.2	93.6	95.9	-

Was natural language understanding solved?

No! So why was this happening?

Where does our data come from?

What is a benchmark?

- What is a benchmark?
  - A **benchmark** is a collection of **datasets** (or a single dataset) designed to evaluate the performance of a model
- What is a dataset?
  - A **dataset** is a manifestation of a **task** using various input-output pairs
- What is a task?
  - A **task** is an instantiation of a problem, consisting of an input space (what does the typical input look like?) and an output space (what are the labels?) that define the mapping between them

What is a benchmark?

	Rank	Name	Model	URL	Score	BoolQ	CB	COPA	MultiRC	ReCoRD	RTE	WiC	WSC	AX-b	AX-g
	1	JDExplore d-team	Vega v2		91.3	90.5	98.6/99.2	99.4	88.2/62.4	94.4/93.9	96.0	77.4	98.6	-0.4	100.0/50.0
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+	9	T5 Team - Google	T5		89.3	91.2	93.9/96.8	94.8	88.1/63.3	94.1/93.4	92.5	76.9	93.8	65.6	92.7/91.9

BoolQ, COPA, MultiRC, RTE, WiC, etc.

Why do we use benchmarks?

- **Benchmark performance is important to measure algorithmic innovation**
- Benchmarks are historically real data
  - synthetic data / could be made up data to suit the algorithm
  - Modern benchmarks are often created using machine-generated data (potential bias issues we'll discuss)
- Benchmarks are universal
  - All researchers and practitioners evaluate on the same examples (clear victor)
  - **Alternative**: cherry picking test data with specific properties that makes the algorithm effective.
- Diverse benchmarks from different domains suggest algorithms are general

How do we build benchmarks?

- Define the task
- Design an annotation guideline (or prompt) to collect a dataset
- Run pilot studies to refine annotation guideline (and qualify workers for human collection)
- Analyse the initial data
- Collect data at scale

Define the Task

- **Example:** Natural Language Inferences (also known as textual entailment)

Premise	A woman selling bamboo sticks talking to two men on a loading dock.
Entailment	There are **at least** three **people** on a loading dock.
Neutral	A woman is selling bamboo sticks **to help provide for her family.**
Contradiction	A woman is **not** taking money for any of her sticks.

- Three-class classification task over pairs of sentences
  - Entailment: The **premise implies** the **hypothesis**
  - Neutral: The **premise** is **unrelated** to the **hypothesis**
  - Contradiction: The **premise contradicts** the **hypothesis**

How do you define the task?

Gururangan et al. (2018)

What is the problem to solve?

Premise	A woman selling bamboo sticks talking to two men on a loading dock.
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- **What marks a true entailment?**
  - **Hypernymy:** A woman is doing X
    - A person is doing X
  - **Quantification:** Everyone is doing X
    - Someone is doing X
  - **Temporal:** Someone is doing X all day
    - Someone is doing X at noon
  - **etc.**

- **What marks a contradiction?**
  - **Negation:** A woman is doing X
    - A woman is not doing X
  - **Quantification:** Everyone is doing X
    - Noone is doing X
  - **Less easy to define!**

Gururangan et al. (2018)

Design an Annotation Guideline

Premise	A woman selling bamboo sticks talking to two men on a loading dock.
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We will show you the caption for a photo. We will not show you the photo. Using only the caption and what you know about the world:

- Write one alternate caption that is **definitely** a **true** description of the photo. *Example: For the caption "Two dogs are running through a field." you could write "There are animals outdoors."*
- Write one alternate caption that **might be** a **true** description of the photo. *Example: For the caption "Two dogs are running through a field." you could write "Some puppies are running to catch a stick."*
- Write one alternate caption that is **definitely** a **false** description of the photo. *Example: For the caption "Two dogs are running through a field." you could write "The pets are sitting on a couch." This is different from the* maybe correct *category because it's impossible for the dogs to be both running and sitting.*

How do you define the task to annotators?

Gururangan et al. (2018)

Run pilot studies

- Typically done with experts at first (people on your team)
- Refine annotation guidelines based on feedback
- Run more pilot studies with crowdworkers (the individuals who will actually produce the data)
- Analyse the initial data (**do annotators understand the task?**)
- Qualify best crowd workers to do the task at scale
  - Produce high-quality data (need to annotated examples yourself that you evaluate their responses against)
  - Better to make the task interesting and creative so that they remain engaged throughout the process!

Why do we need to qualify workers?

Collect data at scale

- Once a good set of qualified workers is gathered, collect the data at scale
- How do we ensure the quality of the data?
  - Pay well!
  - Collect multiple labels per example
  - Disqualify workers who often disagree with other workers. **Be careful!**
  - Keep data points with high inter-annotator agreement
    - Cohen's Kappa = measures agreement between two raters, adjusts for the fact that some agreement could occur just by chance (YES/NO)
    - Fleiss' Kappa = measures agreement between more than two raters + assumes fixed categories (ex: Good, Avg, Bad)
    - Krippendorf's Alpha = " " " " any # of raters, works for incomplete data (some raters not rating all items) + with any scale type (not just categorical)
  - Reject the rest

Metric	Number of Raters	Data Type	Handles Missing Data?
Cohen's Kappa	2	Categorical (nominal, ordinal)	No
Fleiss' Kappa	3+	Categorical (nominal, ordinal)	No
Krippendorff's Alpha	2+	Any (nominal, ordinal, interval, ratio)	Yes

Cohen, 1960; Fleiss, 1971; Krippendorf, 1970

Annotation Lifecycle

= questioning why existing evaluat° methods (benchmarks) are not fully capturing the actual capabilities of Natural Language Understanding (NLU) systems

GLUE, SuperGlue (= benchmarks) => have limitat° + don't fully assess the system's abilities
True NLU performance => system's real ability to understand + reason about language beyond just pattern matching or memo data

Why do our benchmarks fall short of measuring true NLU performance?

Many small reasons, but the unreliability of our data is at the heart of it!

Let's take a look!

Biases

Annotation Artifacts

Harms / Undesirable Behavior

Shortcuts

Biases

Spurious Biases or Spurious Correlations

Inductive Biases

Statistical Bias

Biases

Annotation Artifacts

Harms / Undesirable Behavior

Shortcuts

Biases

Spurious Biases or Spurious Correlations

Term	Definition	Example
Annotation Artifacts	Systematic patterns in labeled data due to annotation methods.	Sentences with *"great"* always labeled as positive in sentiment datasets.
Shortcuts	Simple heuristics learned instead of real understanding.	NLI models associating *"not"* with contradiction.
Biases	Systematic unfairness or misrepresentation in data.	Job screening model favoring male candidates.
Spurious Biases/Correlations	Accidental patterns in data that models exploit incorrectly.	X-ray models detecting hospital-specific markers instead of disease.
Harms / Undesirable Behavior	Negative outcomes due to model limitations.	A chatbot generating offensive language.
Inductive Biases	Built-in assumptions that guide learning.	CNNs assuming nearby pixels are related.
Statistical Biases	Systematic errors in data collection or analysis.	Online surveys underrepresenting older populations.

Example: Ice Cream Sales & Drowning Incidents

- Data might show that **ice cream sales and drowning incidents** are highly correlated.
- However, **eating ice cream does not cause drowning** (and vice versa).
- Instead, **a third unseen factor—hot weather—**is influencing both:
  - On hot days, **more people buy ice cream**.
  - On hot days, **more people go swimming**, increasing the risk of drowning.

This is a **spurious correlation** because the two variables (ice cream sales and drowning) are **associated**, but the real cause is **temperature**, not a direct relationship between the two.

"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

Design an annotation guideline

Premise	A woman selling bamboo sticks talking to two men on a loading dock.
Entailment	There are **at least** three **people** on a loading dock.
Neutral	A woman is selling bamboo sticks **to help provide for her family.**
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What do you think annotators will do?

Gururangan et al. (2018)

Annotation Artifacts

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- To create neutral sentences, **annotators add information**
- To create contradictions, **annotators add negation**

Gururangan et al. (2018)

Annotation Artifacts

Premise	A woman selling bamboo sticks talking to two men on a loading dock.
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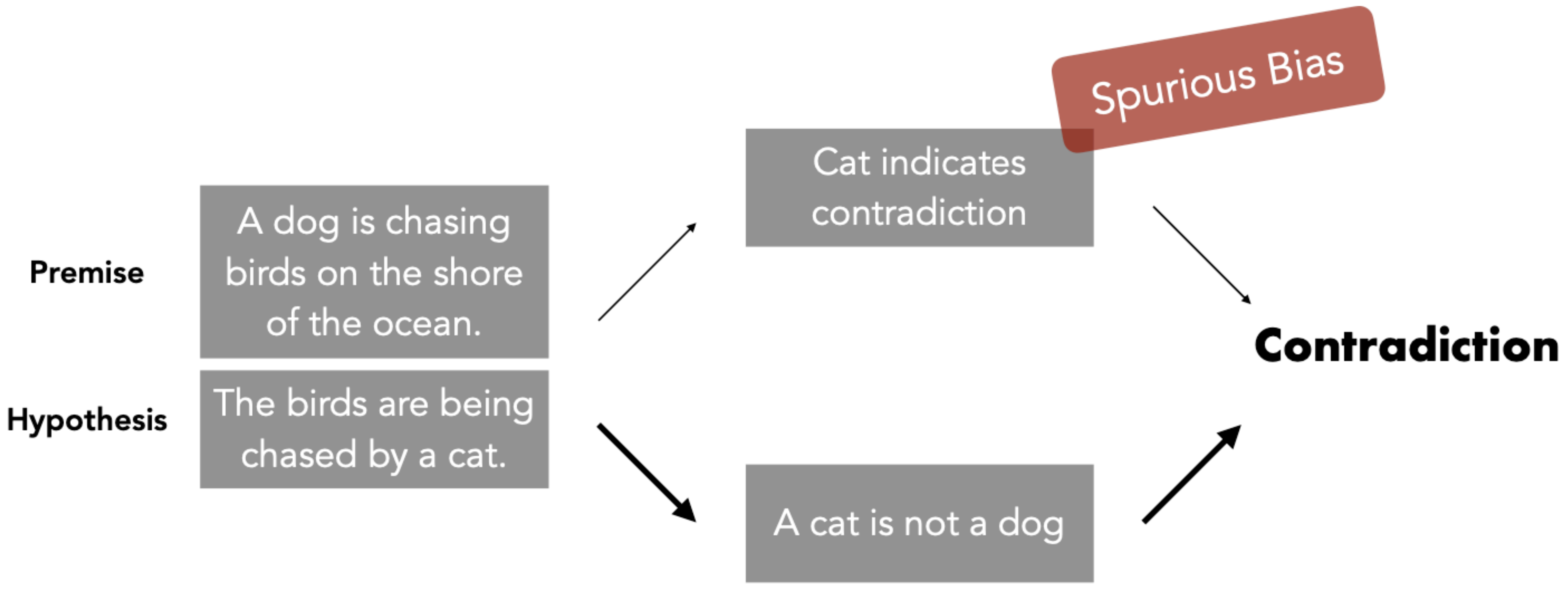
- To create neutral sentences, **annotators add information**
- To create contradictions, **annotators add negation**
- Models can do well even if they **ignore the premise**

	Hypothesis-only	Random	Improvement
SNLI	69.17	33.82	+35.35
MNLI-1	55.52	35.45	+20.07
MNLI-2	55.18	35.22	+19.96

Gururangan et al. (2018)

Sometimes even simpler patterns



Gururangan et al. (2018)

Which patterns?

	Entailment		Neutral		Contradiction	
SNLI	outdoors	2.8%	tall	0.7%	nobody	0.1%
	least	0.2%	first	0.6%	sleeping	3.2%
	instrument	0.5%	competition	0.7%	no	1.2%
	outside	8.0%	sad	0.5%	tv	0.4%
	animal	0.7%	favorite	0.4%	cat	1.3%
MNLI	some	1.6%	also	1.4%	never	5.0%
	yes	0.1%	because	4.1%	no	7.6%
	something	0.9%	popular	0.7%	nothing	1.4%
	sometimes	0.2%	many	2.2%	any	4.1%
	various	0.1%	most	1.8%	none	0.1%

Table 4: Top 5 words by PMI(*word*, *class*), along with the proportion of *class* training samples containing *word*. MultiNLI is abbreviated to MNLI.

Words most associated with labels shouldn't be indicative

Gururangan et al. (2018)

Why might it be a problem that the annotation artefacts exist?

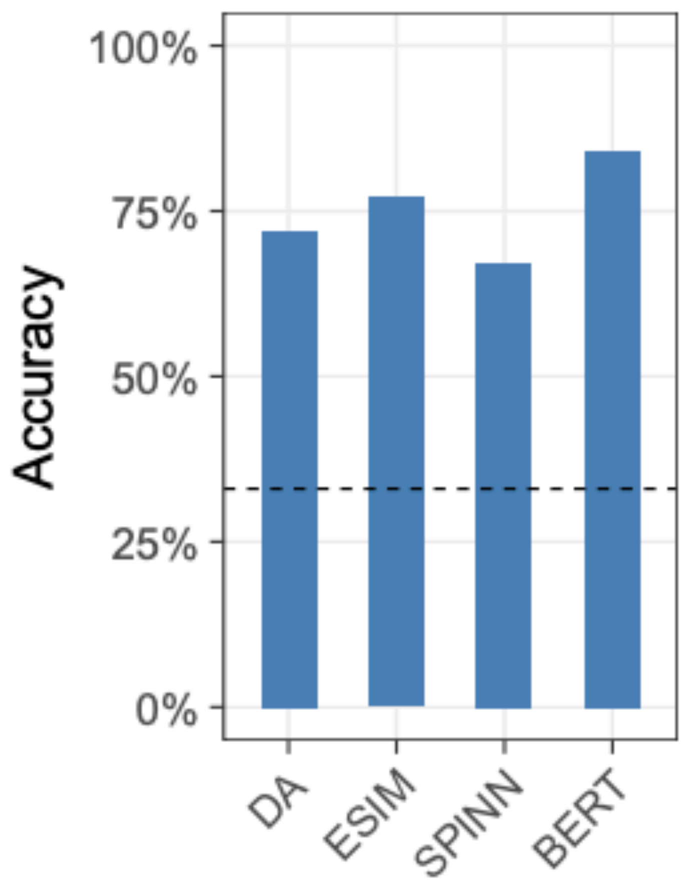
Generalisation Issues

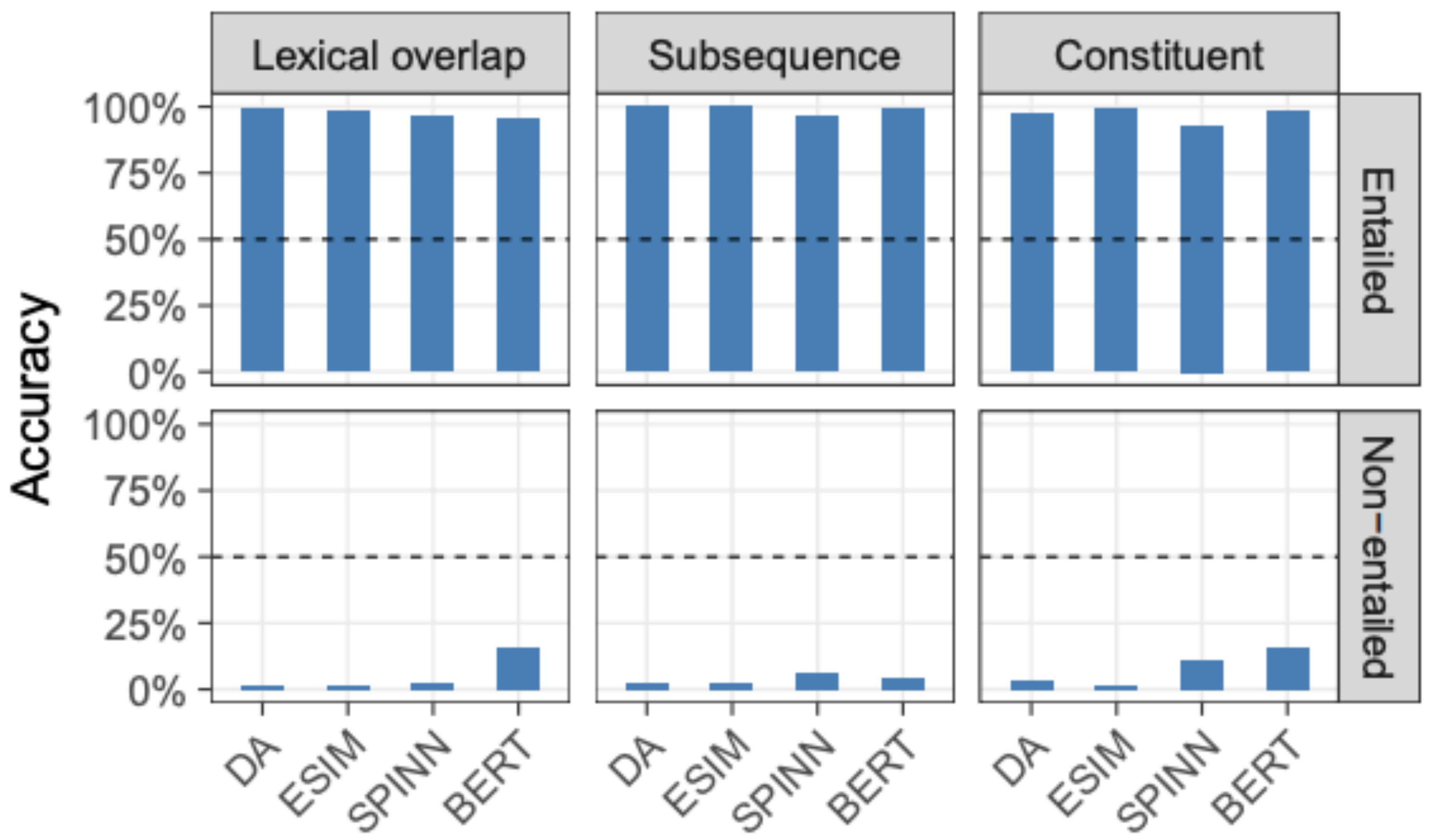
- **Assumption in ML:** samples in train and test sets are drawn from the same distribution
- **Reality:** Future data that must be classified by the model may not come from the same **distribution** of text (i.e., out-of-distribution data)
  - e.g., annotators may be different
- Models learn simple patterns that are merely shortcut heuristics for the hard task we actually want them to learn
  - e.g., natural language inference is very hard
  - seeing negation words is easier
- Models won't generalise to new examples that don't have these patterns
  - Need to understand when models are exploiting these patterns

What happens out-of-distribution?

- **Example:** Develop various syntactic heuristics to express relationships using out-of-distribution language

Heuristic	Premise	Hypothesis	Label
Lexical overlap heuristic	The banker near the judge saw the actor.	The banker saw the actor.	E
	The lawyer was advised by the actor.	The actor advised the lawyer.	E
	The doctors visited the lawyer.	The lawyer visited the doctors.	N
	The judge by the actor stopped the banker.	The banker stopped the actor.	N
Subsequence heuristic	The artist and the student called the judge.	The student called the judge.	E
	Angry tourists helped the lawyer.	Tourists helped the lawyer.	E
	The judges heard the actors resigned.	The judges heard the actors.	N
	The senator near the lawyer danced.	The lawyer danced.	N
Constituent heuristic	Before the actor slept, the senator ran.	The actor slept.	E
	The lawyer knew that the judges shouted.	The judges shouted.	E
	If the actor slept, the judge saw the artist.	The actor slept.	N
	The lawyers resigned, or the artist slept.	The artist slept.	N





100% performance when labels of OOD examples are same as ID bias. 0% otherwise

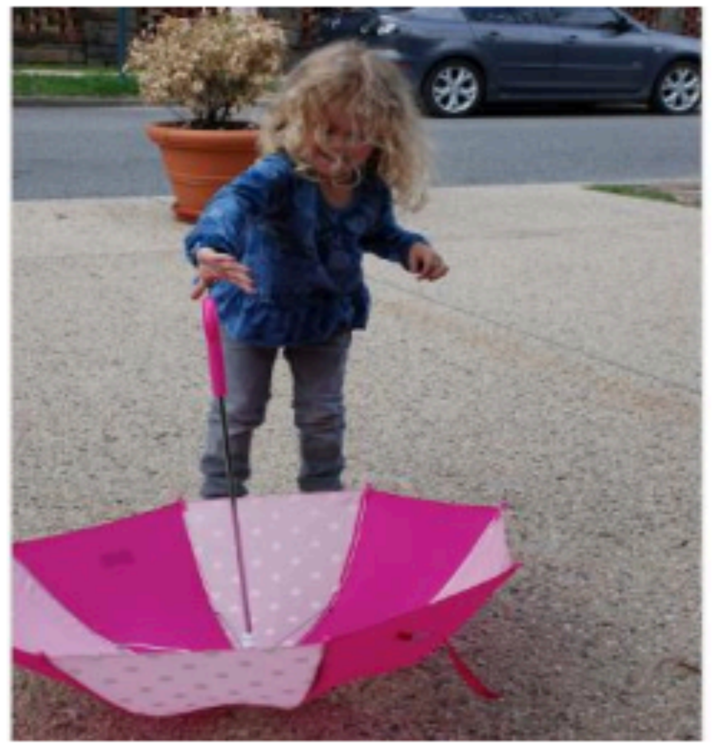
McCoy et al. (2019)

Also a problem in other tasks

- **Visual question answering:** answer questions about a given image

Is the umbrella upside down?

yes

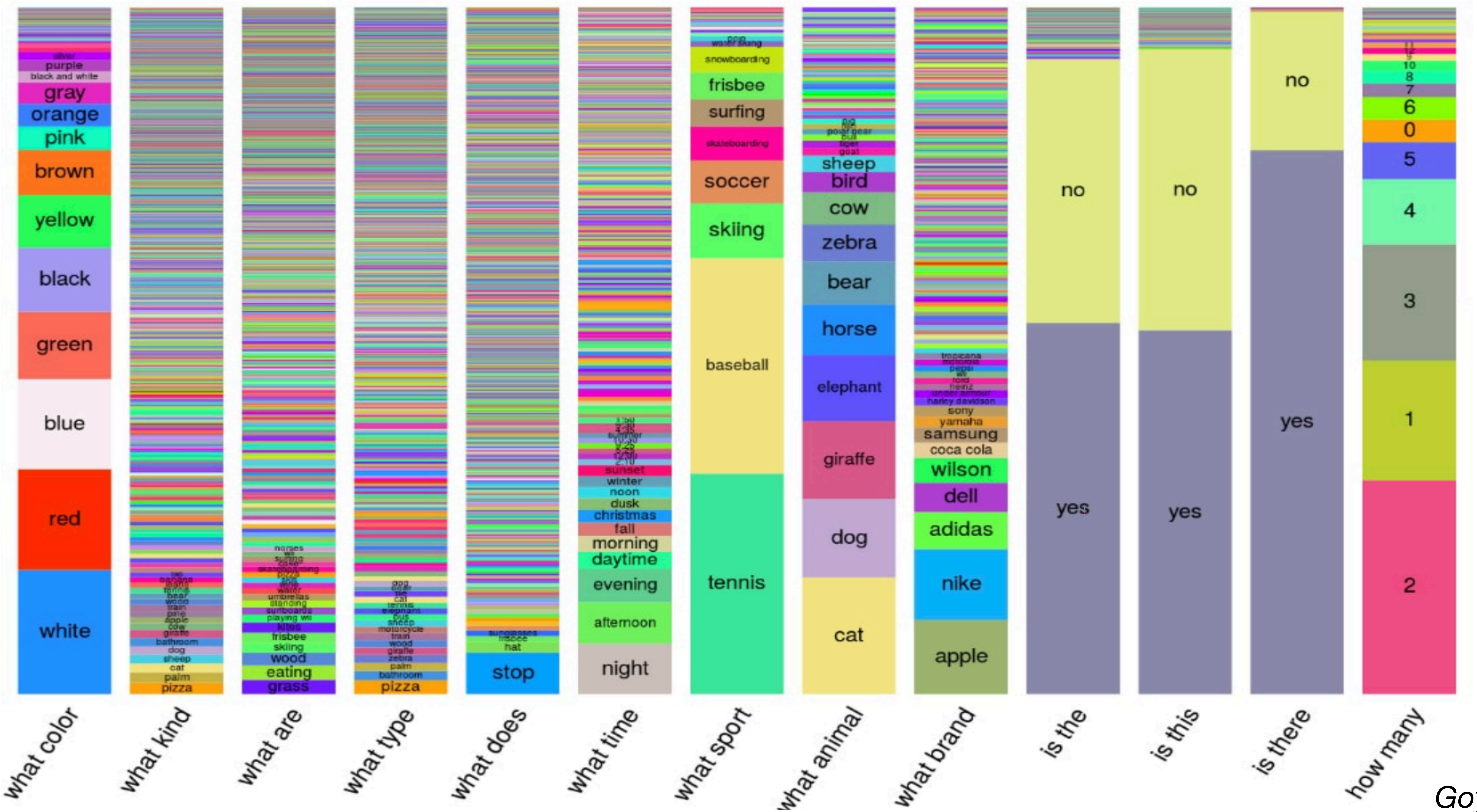


How many children are in the bed?

2

Goyal et al. (2018)

Annotation Artifacts



Goyal et al. (2018)

Annotator Bias

Dataset	# examples	# annotators	Ex / ann
MNLI (matched) [1]	402517	380	1143.32
OpenBookQA [2]	5457	84	64.96
CommonsenseQA [3]	11096	132	84.06

- Crowdsourced datasets are largely created by surprisingly few annotators
- Incentives may push annotators to use heuristics to annotate data rapidly

Does knowing the annotator improve model performance?

Geva et al., 2019

Annotator Bias

Dataset	Unknown annotator	Known annotator
OpenBookQA	52.2	56.4
Commonsense QA	53.6	55.3
MNLI	82.9	84.5

- Knowing the annotator of an example makes the model more likely to classify an example correctly!

why because models may have learnt the biases / patterns of annotator

What can we do to build better benchmarks?

Post-hoc: Manual Re-balancing

Re-balance datasets so that certain answers are not predictable only from the question

Goyal et al. (2018)

Intentional Design: Contrast Sets

- Construct *controlled* datasets that test specific dimensions of what we want in the first place

- Perturb examples using known patterns to highlight specific distinctions

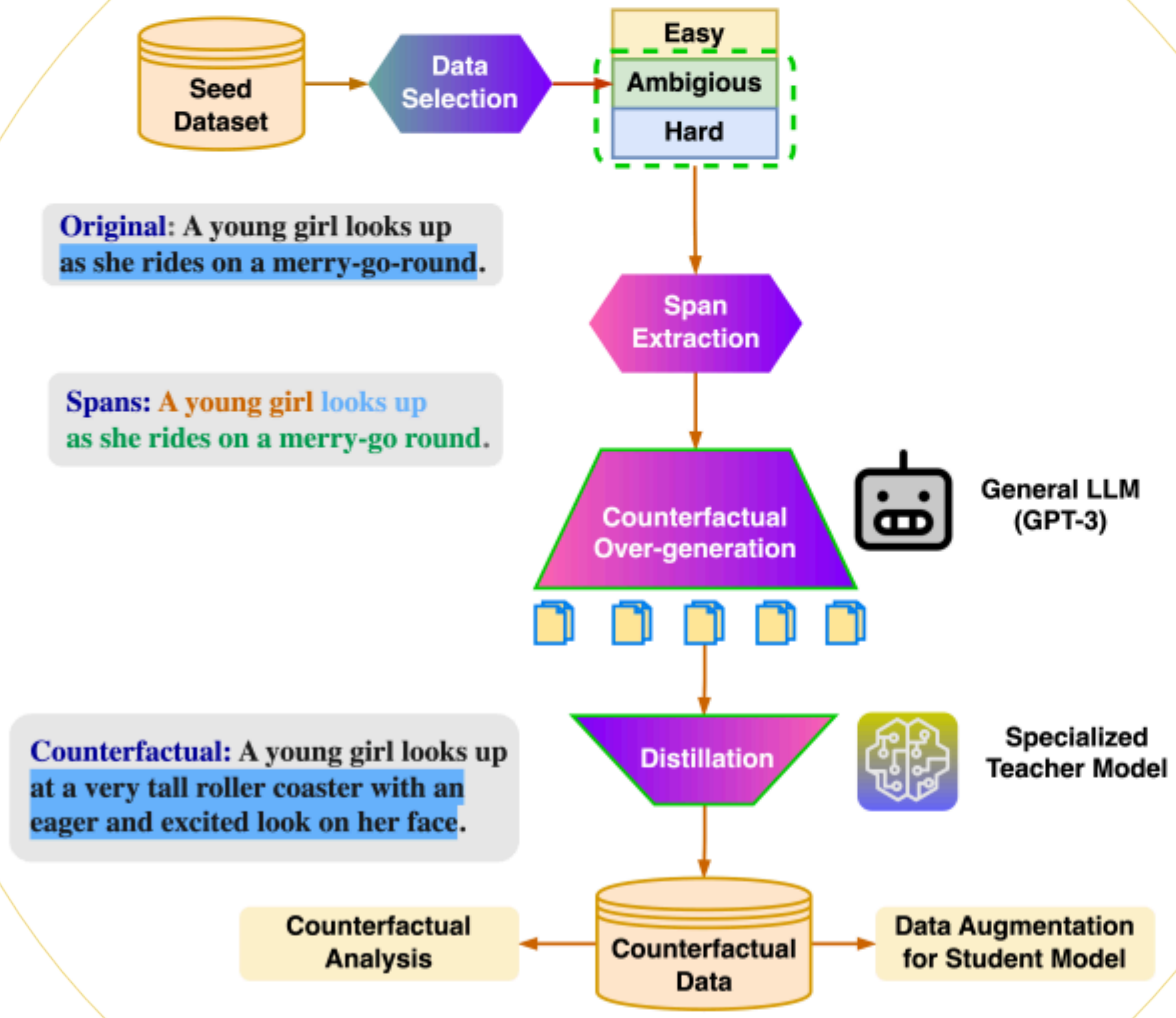
Original (Negative): I had quite high hopes for this film, even though it got a bad review in the paper. I was extremely tolerant, and sat through the entire film. I felt quite sick by the end.
New (Positive): I had quite high hopes for this film, even though it got a bad review in the paper. I was extremely amused, and sat through the entire film. I felt quite happy by the end.

Gardner et al. (2020)

Data Augmentation

don't really get it

- Add new examples to the training dataset that demonstrate new contexts for the model to learn from
- Model learns better via exposure to more diverse training data
- Many different approaches
  - Wei et al., 2019; Kaushik et al., 2019; Yang et al., 2020; Liu et al., 2022; Chen et al., 2022, etc.



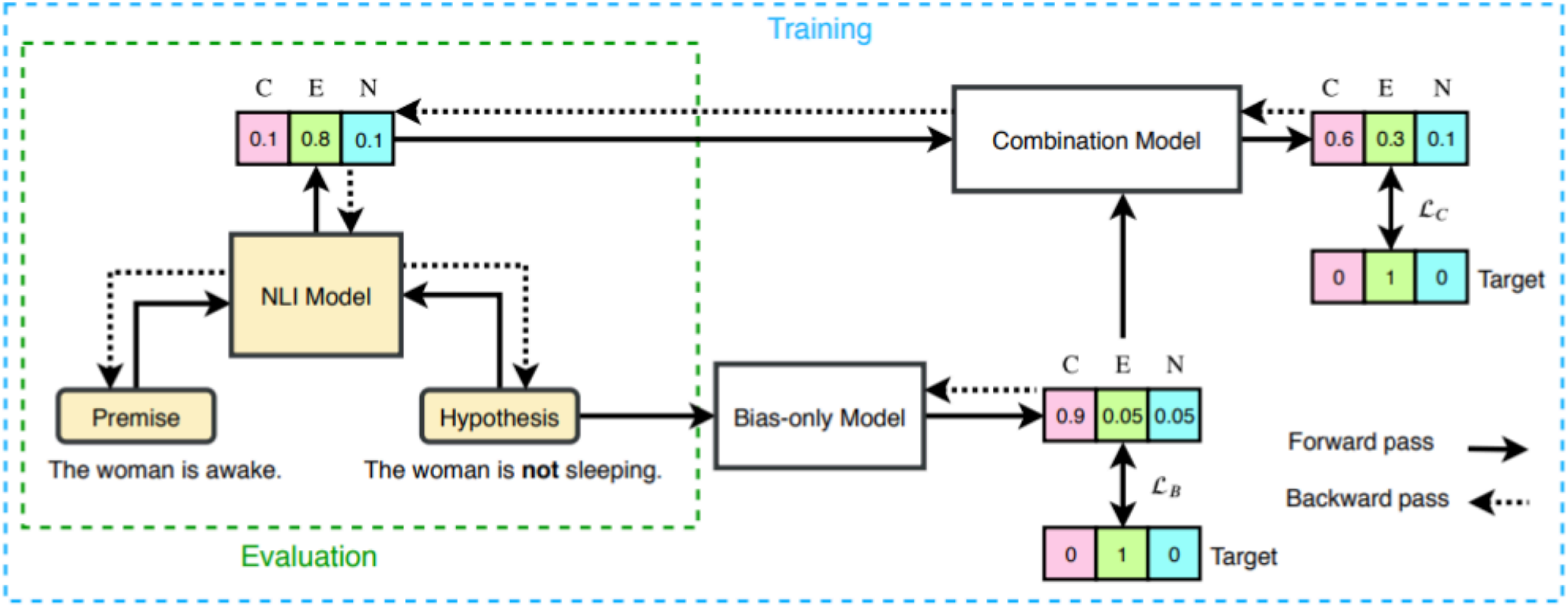
Adversarial Filtering Algorithms

= make dataset more challenging + robust

- **Motivation:** Biased examples can be learned through easy shortcuts
- **Goal:** To avoid shortcuts, remove the easy examples from the dataset
- **Method:** Train a classier on different splits of the data and evaluate validation examples
  - similar to cross-validation
  - Remove examples that are easily solved by a particular model

Zellers et al., 2018; Swayamdipta et al., 2020

Bias Mitigation in Models



- Train a bias-only model in an ensemble with your actual model
- Biased examples will be learned by the bias-only model; the actual model won't need to learn the shortcuts to do well on those examples

Mahabadi et al., 2020

What should we know about our dataset?

- **Datasheets for Datasets:** Framework for recording data details
- **Motivation**:
  - why was it collected?
  - Who created it?
  - Who funded it?
- **Composition:**
  - how were the labels decided?
  - are there official (train/test/dev) splits?
  - Is there confidential or sensitive data? Are the data subjects identifiable? (More in Week 11)

Gebru et al. (2021)

Data Cascades

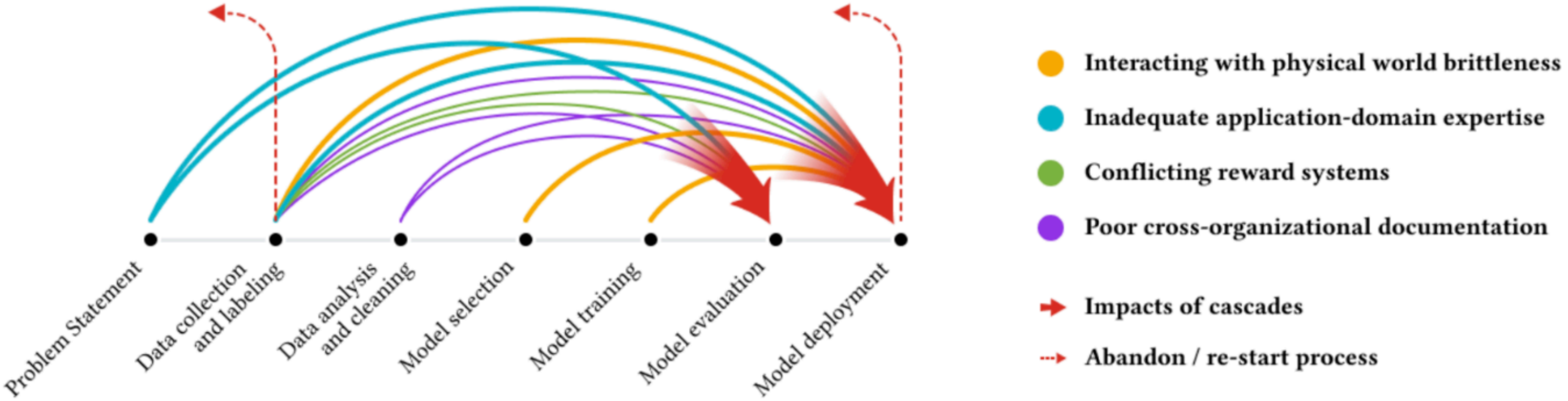


Figure 1: Data cascades in high-stakes AI. Cascades are opaque and protracted, with multiplied, negative impacts. Cascades are triggered in the upstream (*e.g.*, data collection) and have impacts on the downstream (*e.g.*, model deployment). Thick red arrows represent the compounding effects after data cascades start to become visible; dotted red arrows represent abandoning or re-starting of the ML data process. Indicators are mostly visible in model evaluation, as system metrics, and as malfunctioning or user feedback.

Sambasivan et al., 2021

Recap

- Pretrained models fine-tuned on downstream tasks achieve **incredible performance** on benchmarks designed to measure language understanding
- Benchmarks are made up of datasets that are human-constructed
- Humans make “mistakes” when designing datasets, allowing models to shortcut true understanding of the task in favour of easily learnable heuristics
- Designing challenging evaluations remains a primary goal natural language processing systems

Final Note

- Good data, aligned with real human tasks, is the future of NLP
- Synthetic data has the potential to unleash capabilities in this space, but suffers from many of the same issues
  - LLMs recognise outputs of other models (self-recognition)
  - LLMs often have mundane and low-diversity outputs (like humans!)
- ChatGPT components
  - GPT-3 data: Trained on 400 GB of raw text
  - InstructGPT data: **~45k** examples of instructions and expert-labeled task demonstrations

Ouyang et al. (2022)

Final Note

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  - C
  - Ir

Public NLP datasets are not reflective of how our language models are used. We compare GPT-3 fine-tuned on our human preference data (i.e. InstructGPT) to GPT-3 fine-tuned on two different compilations of public NLP tasks: the FLAN (Wei et al., 2021) and T0 (Sanh et al., 2021) (in particular, the T0++ variant). These datasets consist of a variety of NLP tasks, combined with natural language instructions for each task. On our API prompt distribution, our FLAN and T0 models perform slightly worse than our SFT baseline, and labelers significantly prefer InstructGPT to these models (InstructGPT has a 73.4 $\pm$2% winrate vs. our baseline, compared to 26.8 $\pm$2% and 29.8 $\pm$2% for our version of T0 and FLAN, respectively).

Ouyang et al. (2022)