Data:

Collection, Annotation, and Biases

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Announcements

- **Course Feedback:** Indicative Feedback this week! Please fill it out!
- **Assignment 2:** Due Friday, 07/04/2023 at 11:59 AM
  - Office Hours: **today, 11AM**; next week 11 AM
- **Course Project:** Description to be released next week!

Indicative Feedback

- What was some of the feedback you provided about the course?
  - Lectures
  - Exercise sessions
  - Assignments
- What can we do to address those concerns without sacrificing some core components of its content, milestones, and evaluation, etc.

Feedback: Lectures

- “I'd like it better if there were more information completely written on the slides and not abbreviated or only said during the presentation (for example the answers to the questions the teacher ask us).”

I will try to do better!

Feedback: Exercise Sessions

- “**Exercise sessions are way to long**, and require multiple hours to be completed.”

What we can do:

- **Clarification:** Exercise sessions aren’t graded!

- We make them long to cover more applied topics about the course material. I’d rather give you more than you need, so we specifically make them long

- If it feels overwhelming, don’t be afraid to take them a bit slower, particularly since there are no more exercise sessions in the second half of the course. You can pace yourself at a different rate!

Feedback: Exercise Sessions

- “In the exercises session, **I think the presentation of the exercises are a bit useless**, because the exercises instructions are clear. I would perfer going over the solution of the past week exercises […]”

- “I also suggest an overhaul to how exercise sessions are run: **walking us through the workbooks before we've done them is pointless** because they're intelligible on their own.”

- “The notebooks are really of great quality and **I do not feel like presenting the exercises helps in any way**, in fact they make us lose time we could spend asking questions to the TAs head to head.”

Survey Question

Would you prefer that we **not** do the run-through of this week's exercise as the start of session?

Feedback: Assignments

Feedback: Assignments

- “Lastly, **it would be beneficial to divide the assignment into separate .py files rather than Jupyter notebooks**”

- “**The assignment has compatibility issues and a lot of small random bugs.** Filling details on functions and spending my time debugging is not one of my hobbies.”

- “**The schedule for assignments is too tight in my opinion,** the assignments follow one another directly without a break. But my main issue is that the **assignments are released on a Friday night, just to be introduced on the following Wednesday,** so that a big portion of the time given for the assignment is before the introduction.”

What we can do:

- Improvements to assignments;
  - Removed some of the workload (compute-heavy components, such as hyperparameter sweeps; open-ended questions, such as choose your own data augmentation)
  - Re-organized presentation (less code in the workbooks; more code in files)
  - Information sessions (2 per assignment)

- Marks will be normalised if the average is low

Survey Question

Would you prefer that assignments be **due** on Sunday, rather than Friday?

Any other comments?

Today's Outline

- **Lecture**
  - **Quick Recap:** Finetuning
  - **Data Annotation:** Process, Biases, and effect on Fine-tuning
- **A1 Review**
- **Tomorrow:** Exercise Session
  - **Review of Week 5 Exercise Session:** Finetuning pretrained models
  - **Week 6 Exercise Session:** Robustness & Prompting

Some slides adapted from Greg Durrett, Swabha Swayamdipta

Transfer Learning

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)

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.

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, 22 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	-

Is natural language understanding solved?

No! So why is 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 real data
  - synthetic data / could be made up data to suit the algorithm
- 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 to collect a dataset
- Run pilot studies to refine annotation guideline and qualify workers
- 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.
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.

- **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.
Entailment	There are **at least** three **people** 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?

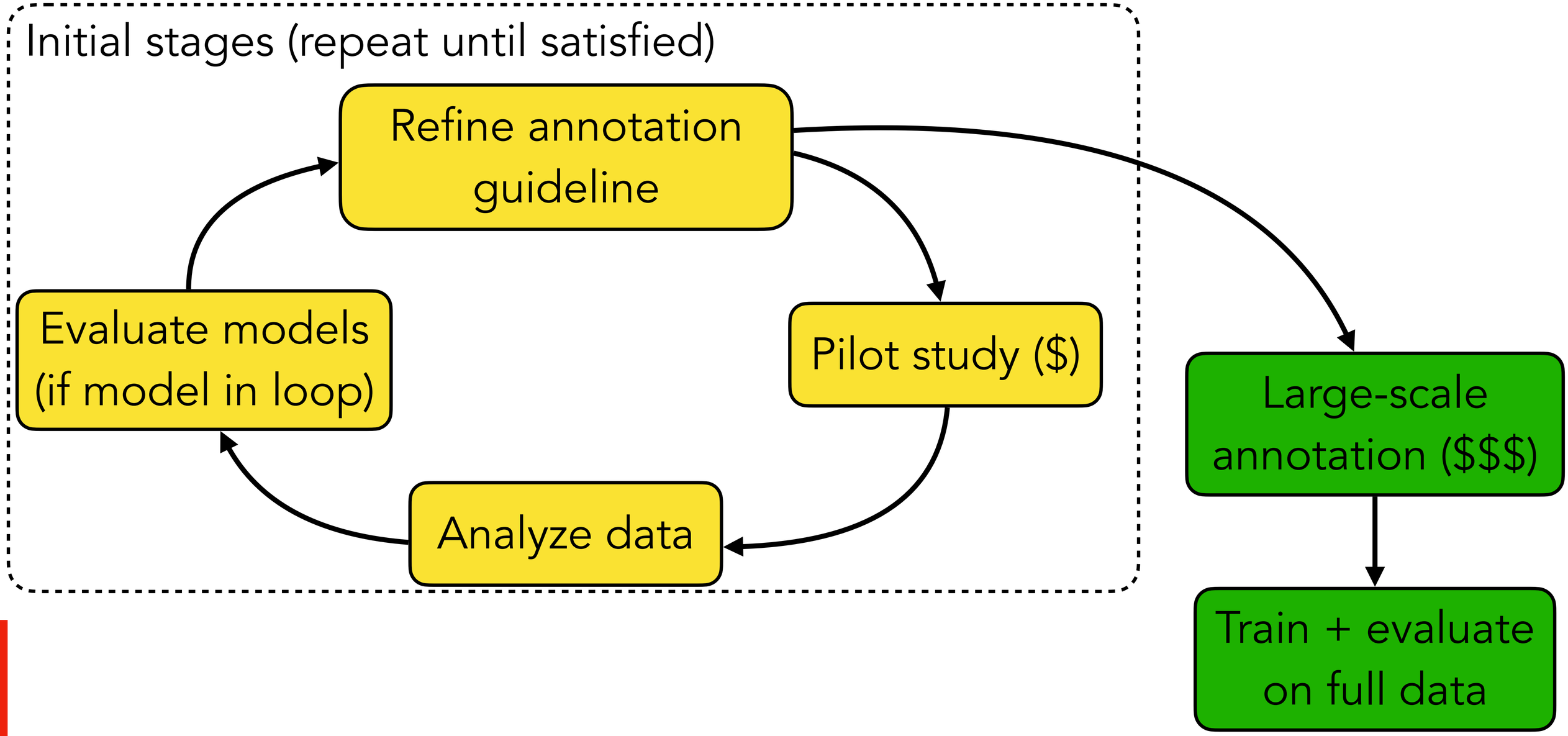
Collect data at scale

- 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
    - Fleiss' Kappa
    - Krippendorf's Alpha
  - Reject the rest

Cohen, 1960; Fleiss, 1971; Krippendorf, 1970

Annotation Lifecycle

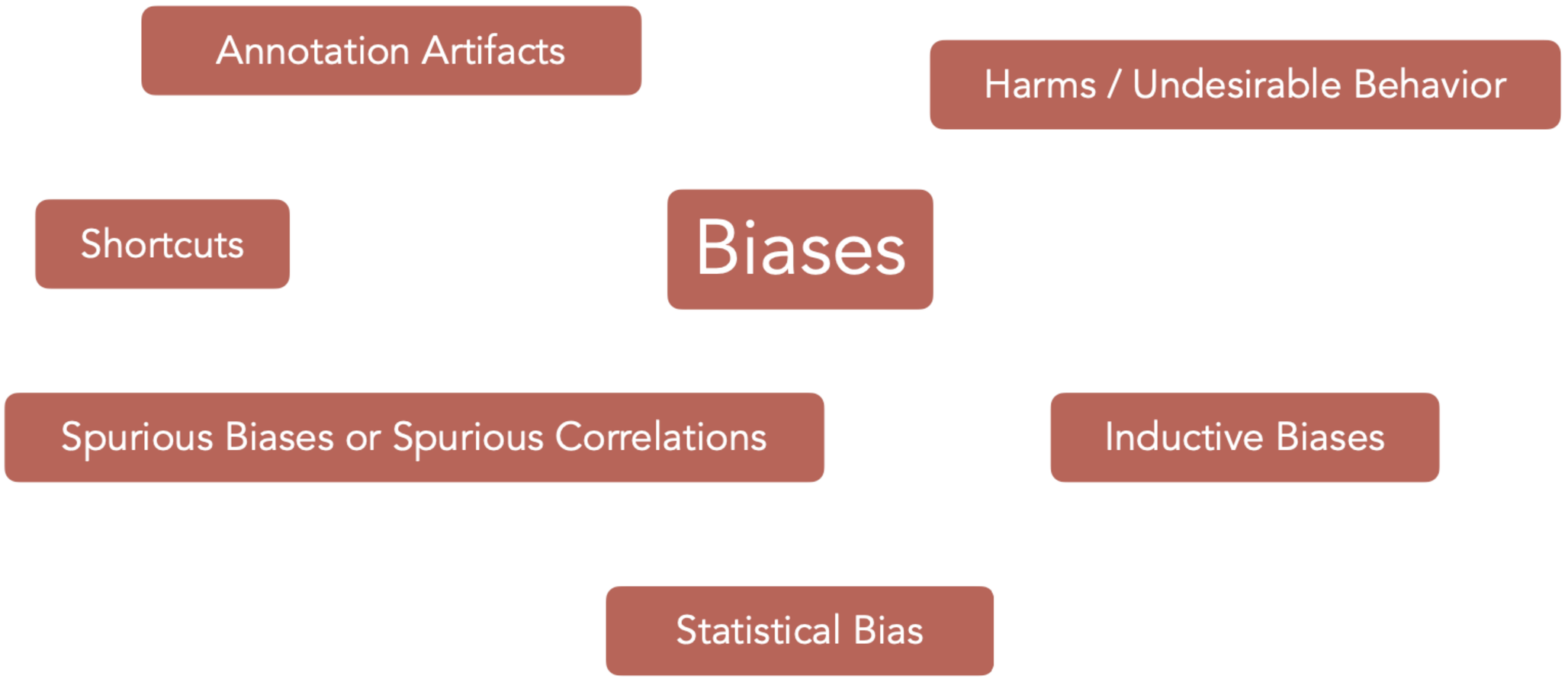


Why do our benchmarks fall short of measuring true NLU performance?

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

Shortcuts

Biases

Spurious Biases or Spurious Correlations

"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)

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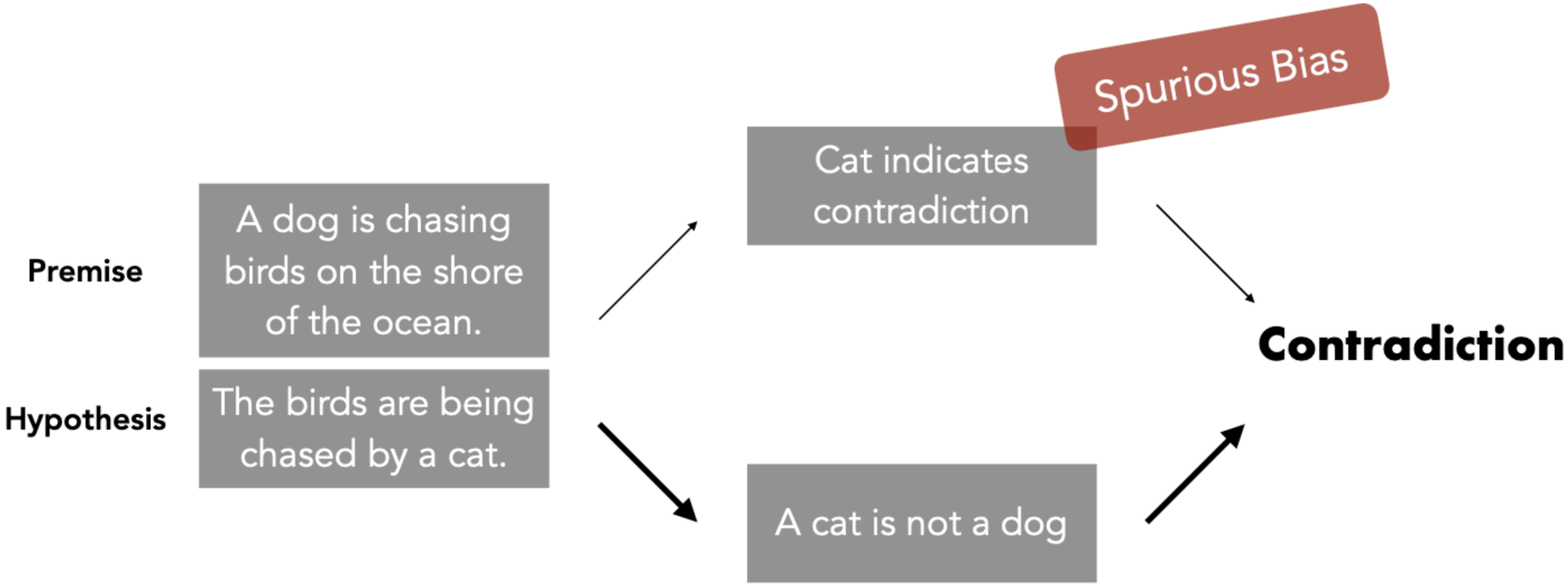
- To create neutral sentences**, annotators add information**
- To create contradictions**, annotators add negation**
- Models can do well even if they **ignore the premise**

	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?

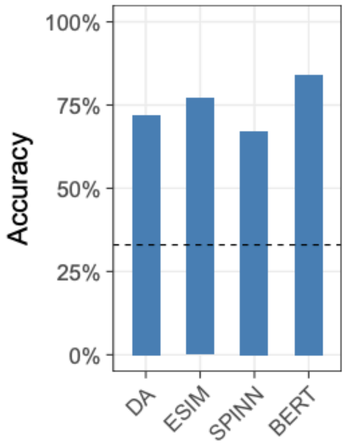
Generalisation Issues

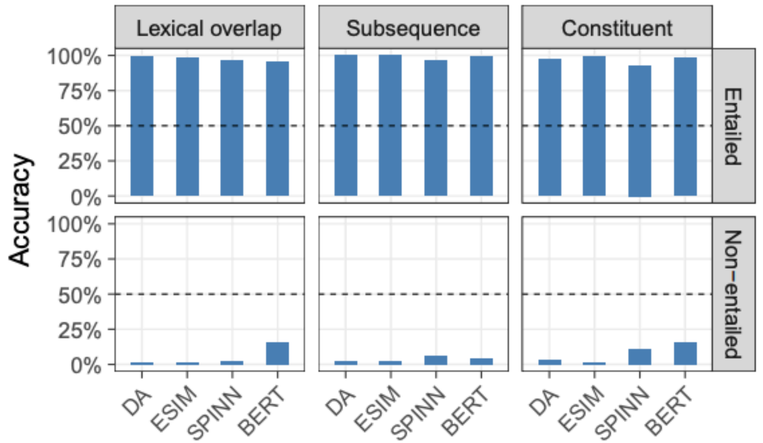
- **Assumption in ML:** samples in train and test sets are drawn from the same distribution
- **Reality:** Future data that must be classified by the model may not come from the same **distribution** of text (i.e., out-of-distribution data)
  - e.g., annotators may be different)
- Models learn simple 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?

- **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

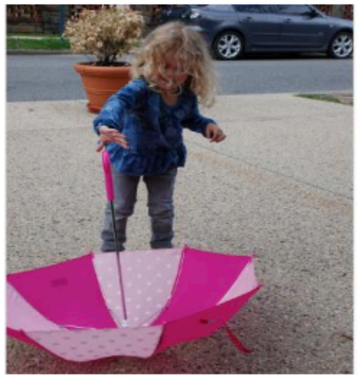
McCoy et al. (2019)

Also a problem in other tasks

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

Is the umbrella upside down?

yes

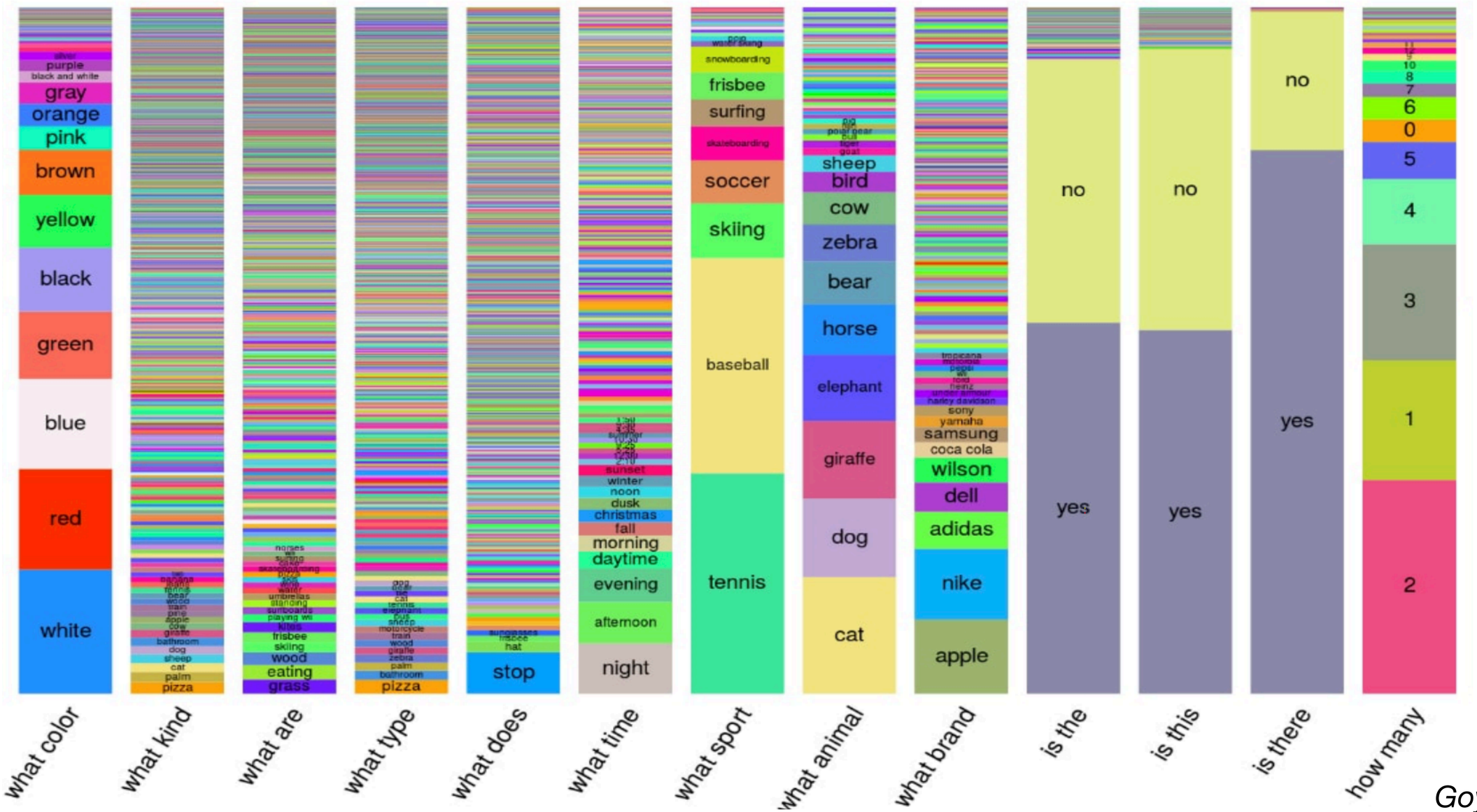


How many children are in the bed?

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
CommonsenseQA	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!

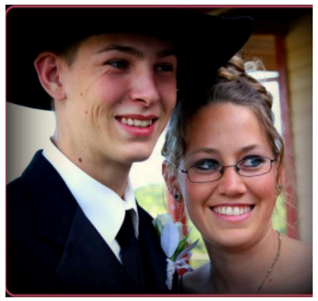
What can we do to build better benchmarks?

Post-hoc: Manual Re-balancing

Who is wearing glasses?

man

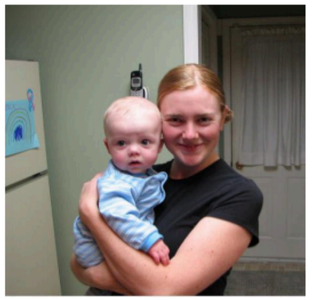
woman



Where is the child sitting?

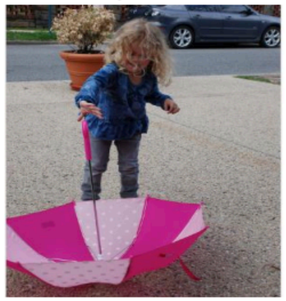
fridge

arms



Is the umbrella upside down?

yes

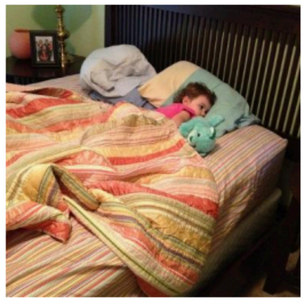


no

How many children are in the bed?

2

1



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

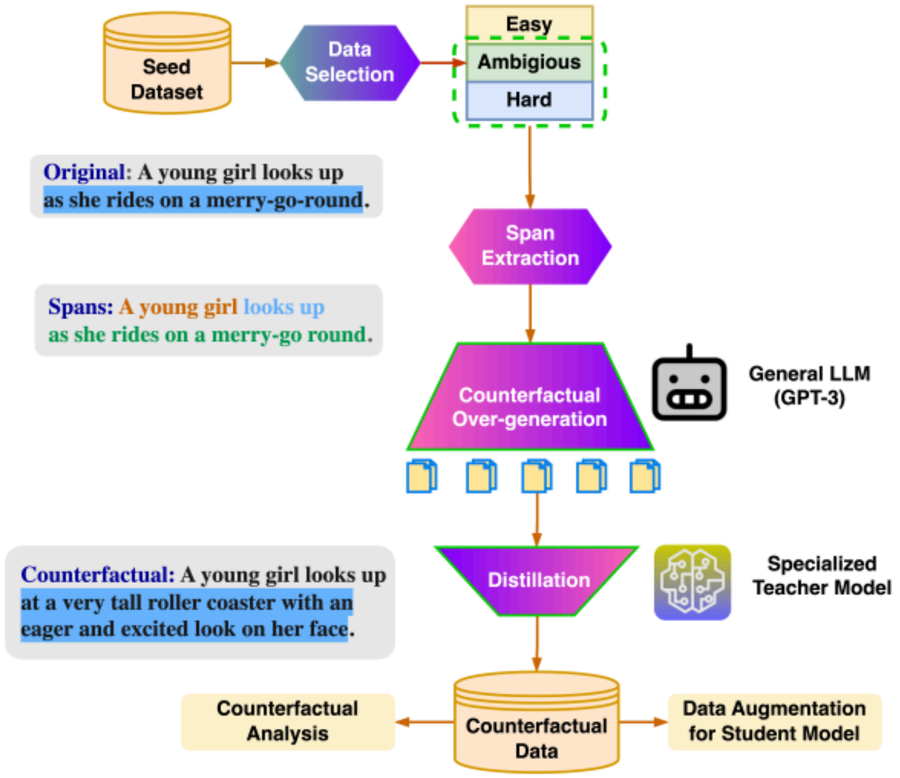
- Perturb examples using known patterns to highlight specific distinctions

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

- 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.

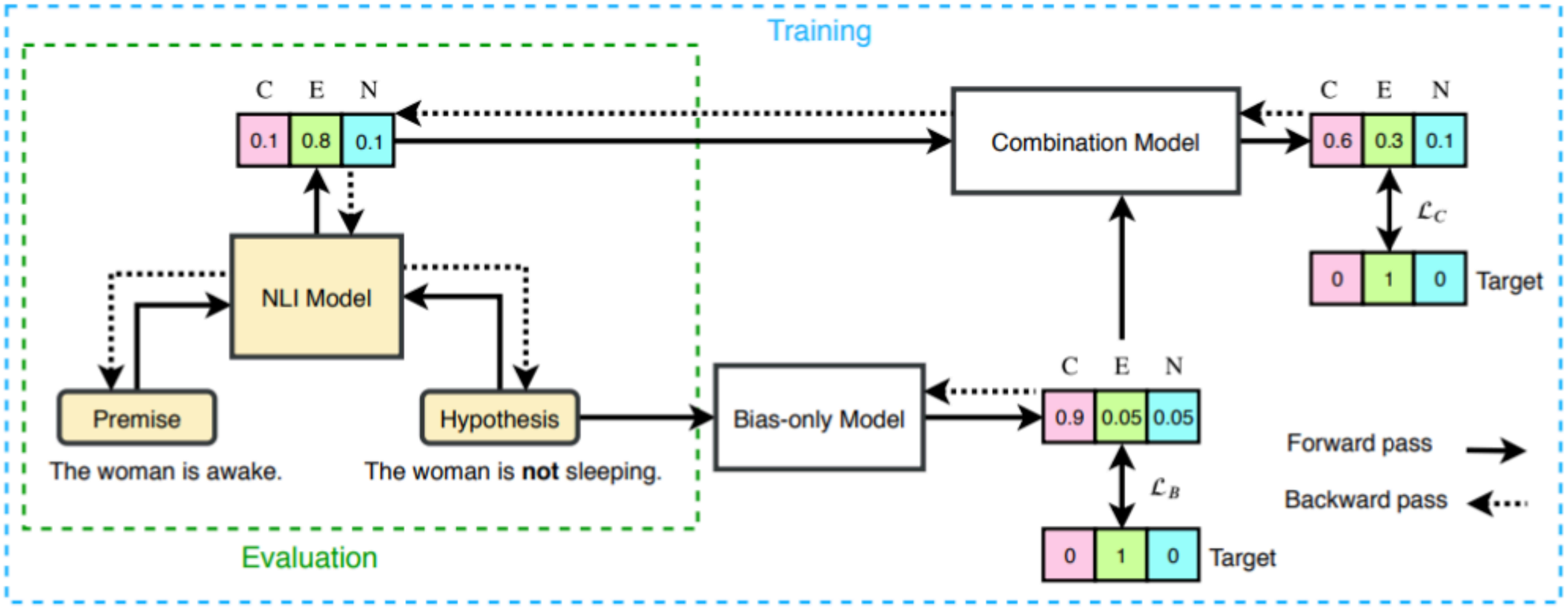


Adversarial Filtering Algorithms

- **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

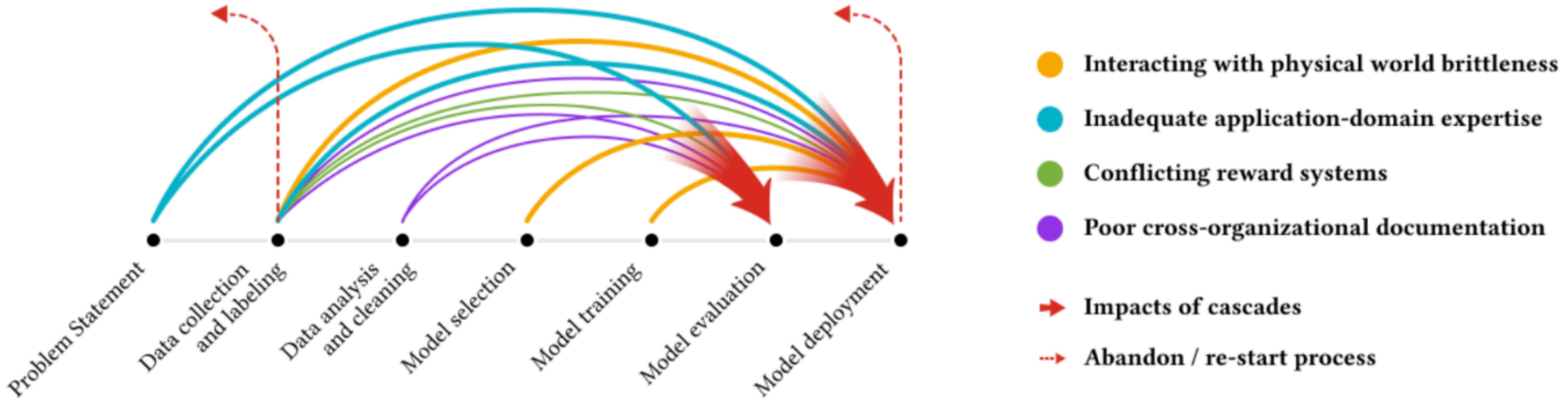


Figure 1: Data cascades in high-stakes AI. Cascades are opaque and protracted, with multiplied, negative impacts. Cascades are triggered in the upstream (*e.g.,* data collection) and have impacts on the downstream (*e.g.,* model deployment). Thick red arrows represent the compounding effects after data 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
- ChatGPT components
  - GPT-3 data: Trained on 400 GB of raw text
  - InstructGPT data: **~45k** examples of instructions and expert-labeled task demonstrations

> **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)