Commonsense benchmarks

Or how to measure that your model is actually doing some commonsense reasoning

How do you know that a model is doing commonsense reasoning?

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Unsupervised:

- Observe behavior,
- Probe representations,
- etc.

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Benchmarks:
knowledge-specific tests (with training data)

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Benchmarks:
knowledge-specific tests
(with training data)

QA format: easy to evaluate
(e.g., accuracy)

Step 1: Determine type of reasoning

Abductive NLI

Physical IQa

Social IQa

VCR

HELLA SWAG

https://leaderboard.allenai.org/

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Reasoning about Social Situations

Social
IQa

Reasoning about Social Situations

Alex spilt food all over the floor and it made a huge mess.

What will Alex want to do next?

Social IQa

Reasoning about Social Situations

Alex spilt food all over the floor and it made a huge mess.

What will Alex want to do next?

run around in the mess

mop up the mess

Social IQa

Reasoning about Social Situations

Alex spilt food all over the floor and it made a huge mess.

What will Alex want to do next?

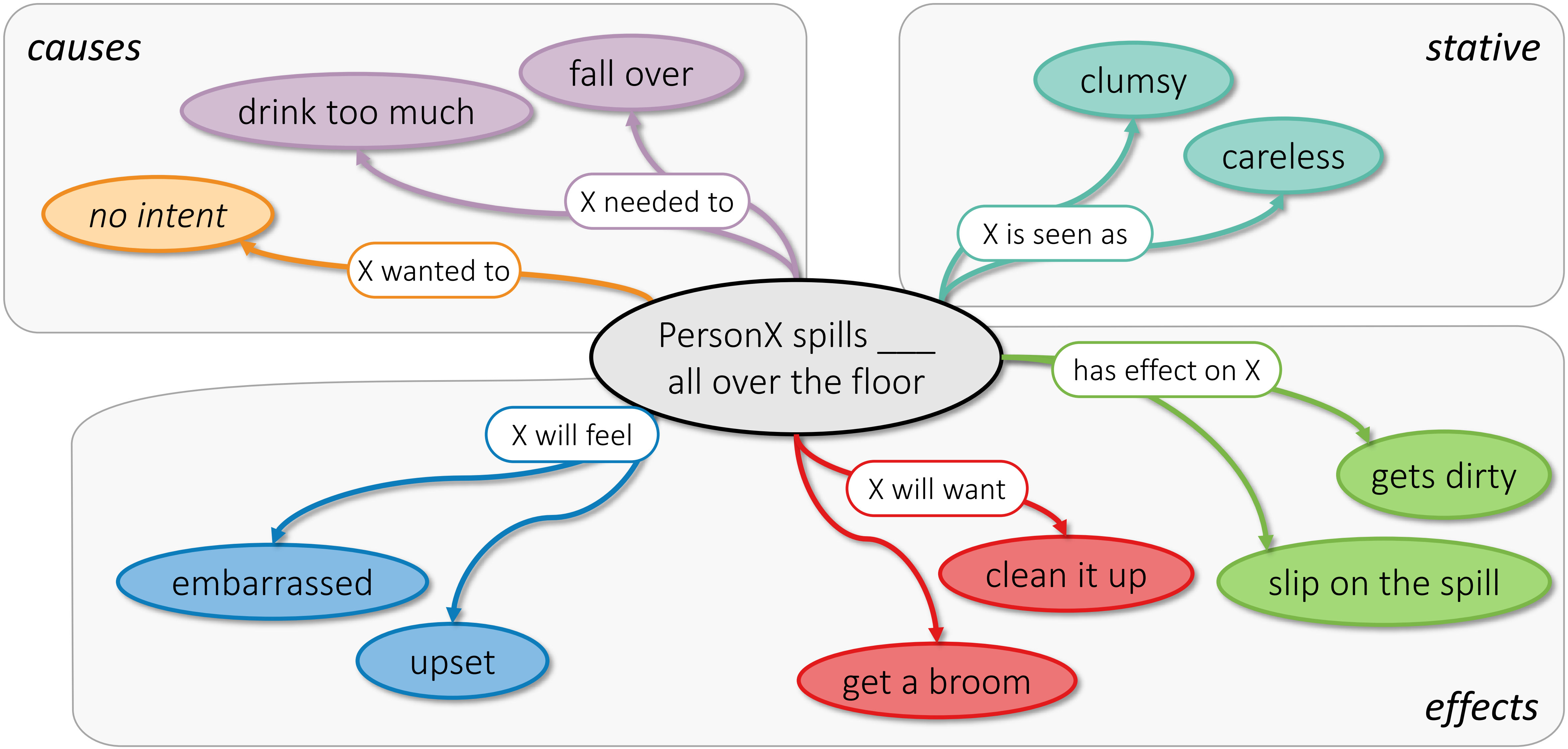
run around in the mess

less likely

mop up the mess

more likely

Knowledge tested in SOCIAL IQA: ATOMIC



Step 2: Choosing a benchmark size

	Small scale	**Large scale**
Creation	Expert-curated	Crowdsourced/automatic
Coverage	Limited coverage	Large coverage
Training	Dev/test only	Training/dev/test
Budget	Expert time costs	Crowdsourcing costs

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Winograd Schema Challenge (WSC),
Choice of Plausible Alternatives (COPA)

Small commonsense benchmarks

Winograd Schema Challenge (WSC)
273 examples

Choice of Plausible Alternatives (COPA)
500 dev, 500 test

The city councilmen refused the demonstrators a permit because ***they*** **advocated** violence. Who is "***they***"?

(a) The city councilmen
(b) The demonstrators

The city councilmen refused the demonstrators a permit because ***they*** **feared** violence. Who is "***they***"?

(a) The city councilmen
(b) The demonstrators

Small commonsense benchmarks

Winograd Schema Challenge (WSC)
273 examples

Choice of Plausible Alternatives (COPA)
500 dev, 500 test

I hung up the phone.
What was the **cause** of this?

(a) The caller said goodbye to me.
(b) The caller identified himself to me.

The toddler became cranky.
What happened as a **result**?

(a) Her mother put her down for a nap.
(b) Her mother fixed her hair into pigtails.

Step 2: Choosing a QA benchmark size

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Challenge: do to collect positive/negative answers?

Challenge of collecting unlikely answers

Goal: negative answers have to be ***plausible but unlikely***

- Automatic matching?
  - Random negative sampling won’t work, too topically different
  - “smart” negative sampling isn’t effective either
- Need better solution… maybe we can ask crowd workers?

Collecting answers from crowdworders

Context and Question

Alex spilt food all over the floor and it made a huge mess.

What happens next

What will Alex want to do next?

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amazon mturk Requester

Free Text Response

Handwritten ✓ and ✗ Answers

- ✓ mop up
- ✓ give up and order take out
- ✗ leave the mess
- ✗ run around in the mess

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Free Text Response

Handwritten ✓ and ✗ Answers

✓ mop up
✓ give up and order take out
✗ leave the mess
✗ run around in the mess

Problem: handwritten unlikely answers are **too easy to detect**

Problem: annotation artifacts

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- Models can exploit artifacts in handwritten incorrect answers
  - Exaggerations, off-topic, overly emotional, etc.
  - See Schwartz et al. 2017, Gururangan et al. 2018, Zellers et al. 2018, etc.
- Seemingly “super-human” performance by large pretrained LMs (BERT, GPT, etc.)

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How to make unlikely answers **robust to annotation artifacts**?

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SOCIAL IQA:
switch questions in annotation

How to make unlikely answers **robust to annotation artifacts**?

Social IQa:
switch questions in annotation

HellaSwag & AF-lite:
Adversarial filtering of artifacts

Question-Switching Answers (SOCIAL IQA)

Original Question

Alex spilt food all over the floor and it made a huge mess.

WHAT HAPPENS NEXT

What will Alex want to do next?

✓ mop up
✓ give up and order take out
✗
✗

Question-Switching Answers (SOCIAL IQA)

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Alex spilt food all over the floor and it made a huge mess.

WHAT HAPPENS NEXT

What will Alex want to do next?

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✗
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Question-Switching Answer

WHAT HAPPENED BEFORE

What did Alex need to do before this?

Question-Switching Answers (SOCIAL IQA)

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Alex spilt food all over the floor and it made a huge mess.

WHAT HAPPENS NEXT

What will Alex want to do next?

- ✓ mop up
- ✓ give up and order take out
- ✗
- ✗

Question-Switching Answer

WHAT HAPPENED BEFORE

What did Alex need to do before this?

- ✓ have slippery hands
- ✓ get ready to eat

Question-Switching Answers (Social IQa)

Original Question

Alex spilt food all over the floor and it made a huge mess.

What happens next

What will Alex want to do next?

✓ mop up
✓ give up and order take out
✗ have slippery hands
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Question-Switching Answer

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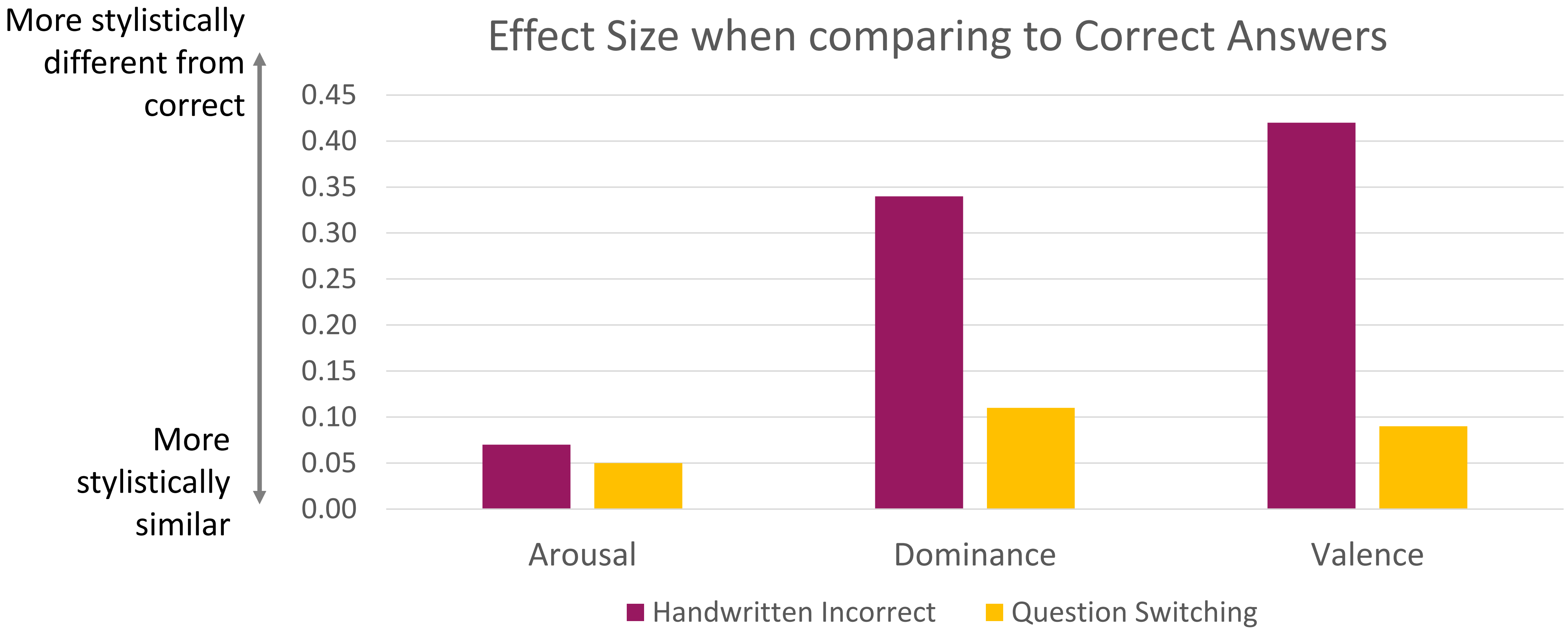
Comparing incorrect/correct answers’ styles



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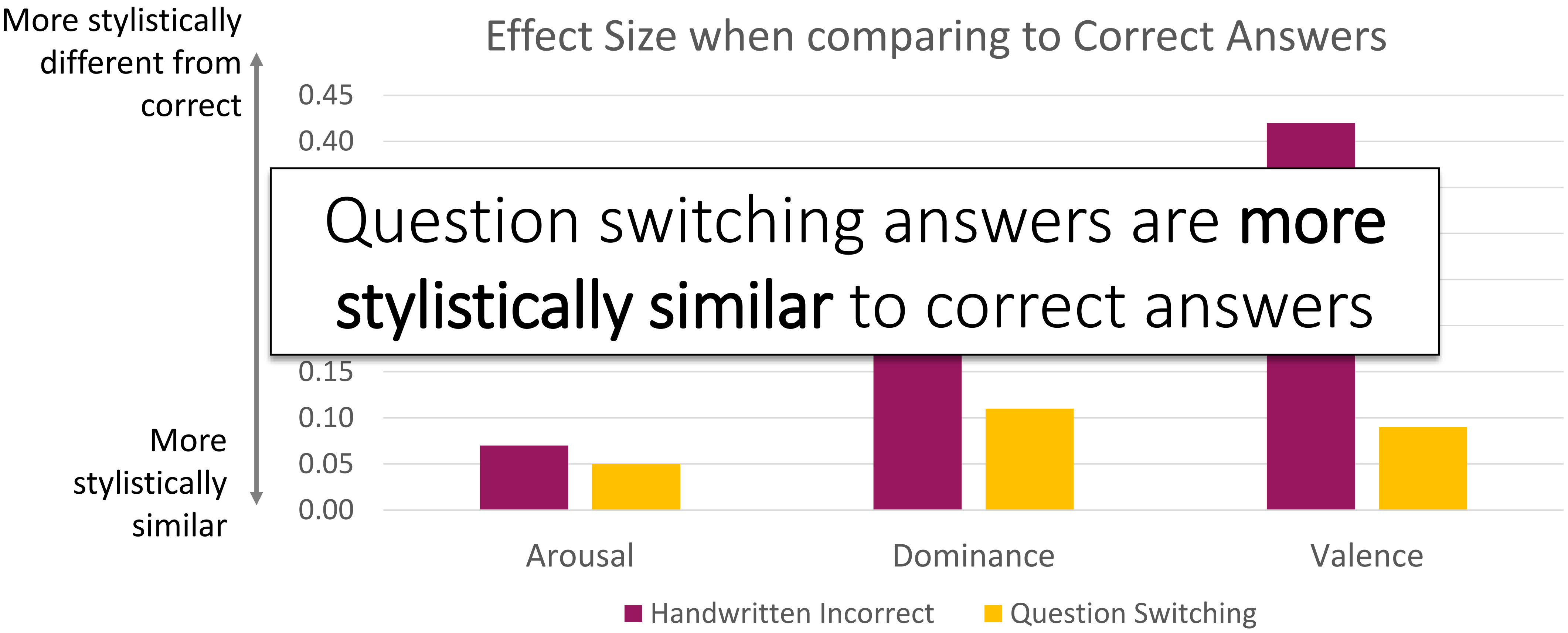

Adversarial Filtering (lite)

Goal: remove examples with exploitable artifacts or spurious correlations

- Use pre-trained representations
- Iteratively remove data that's easiest to predict by a linear classifier (e.g., logistic)
- Robust examples remain

HellaSwag (Zellers et al., 2019)
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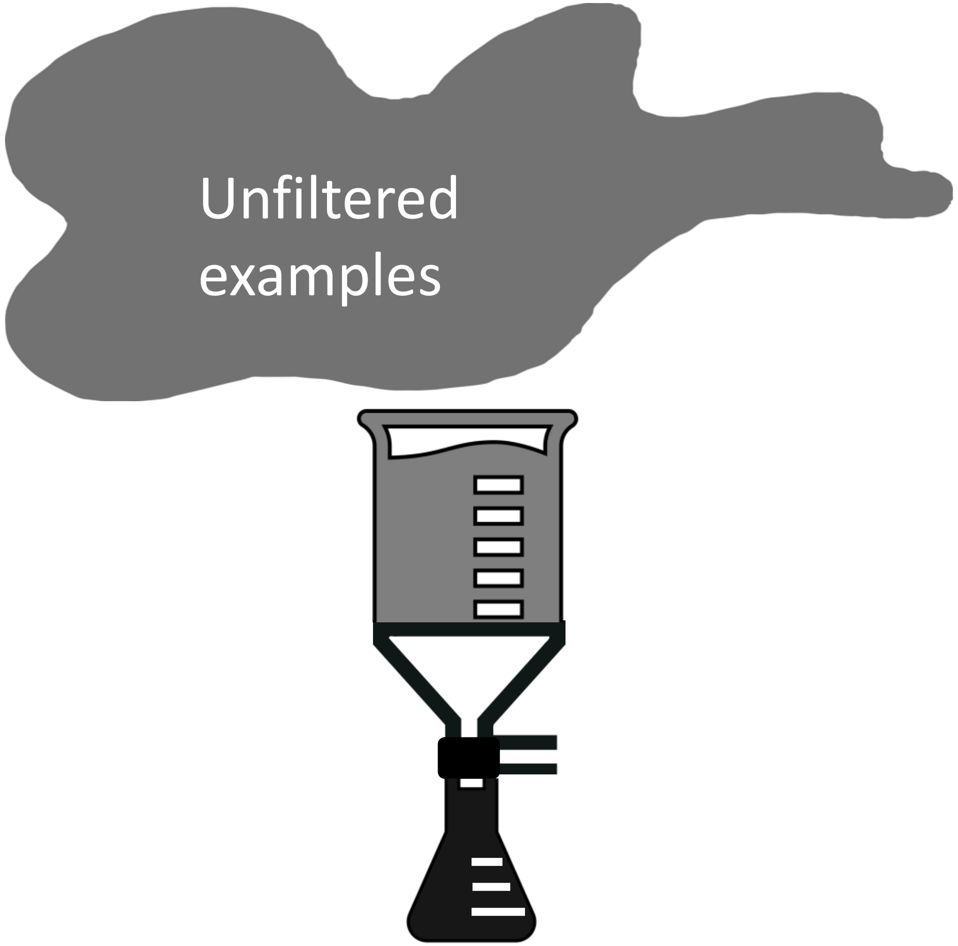

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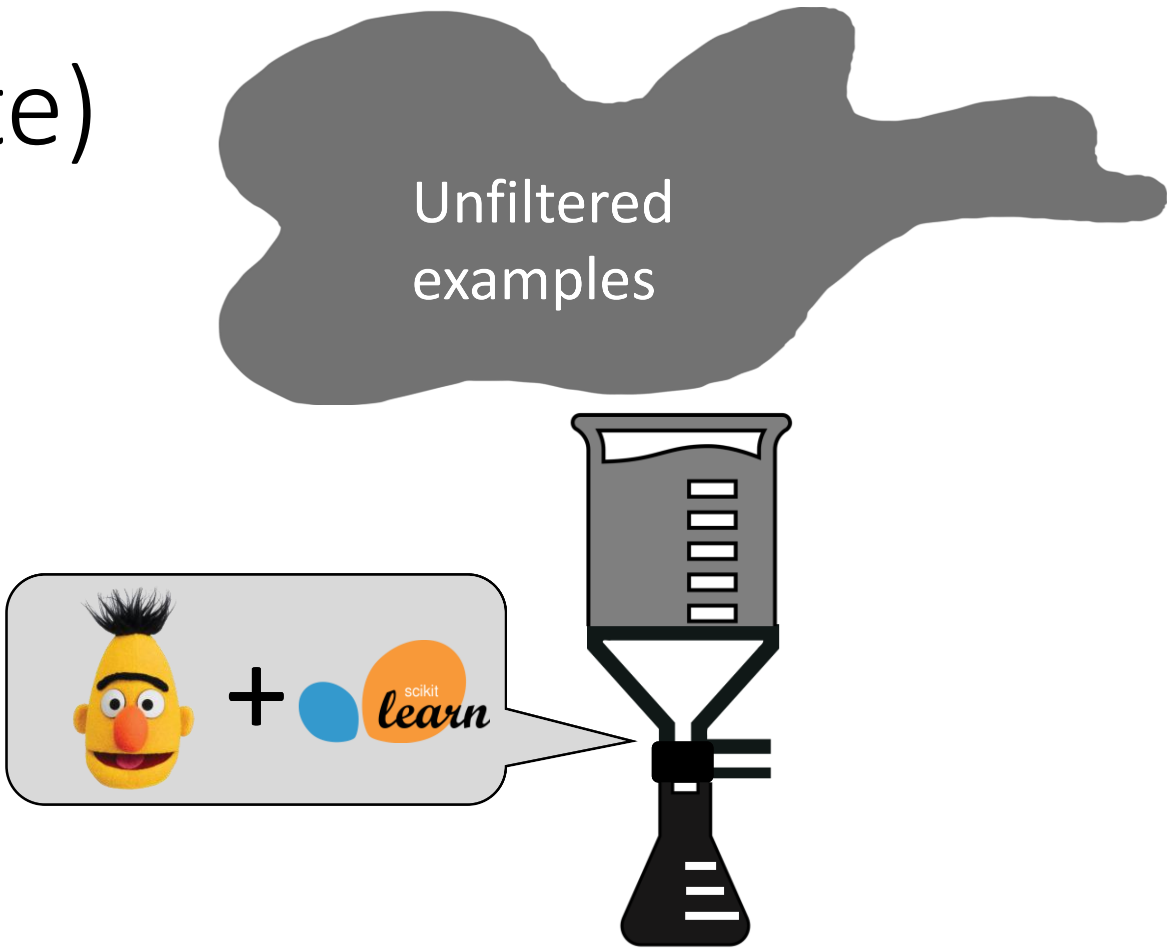

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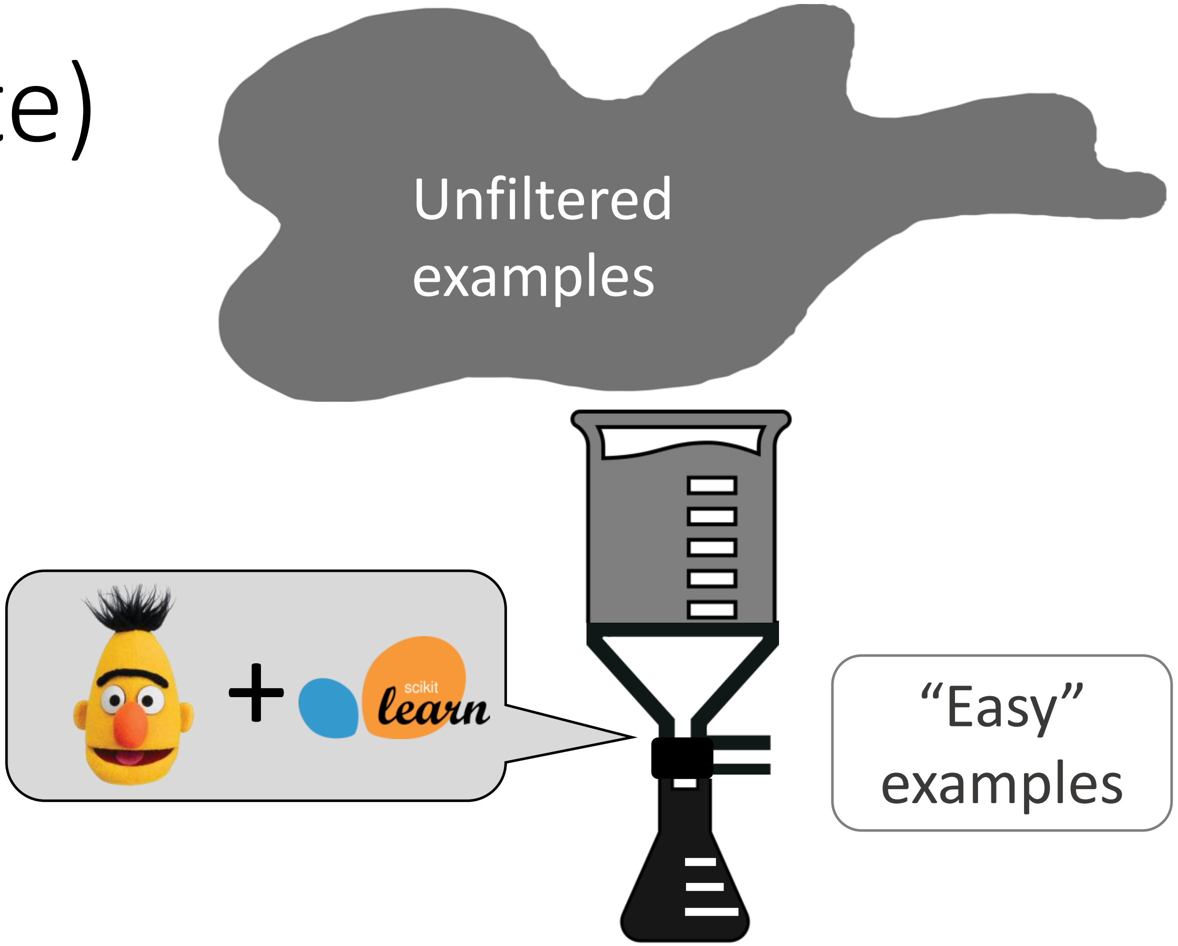

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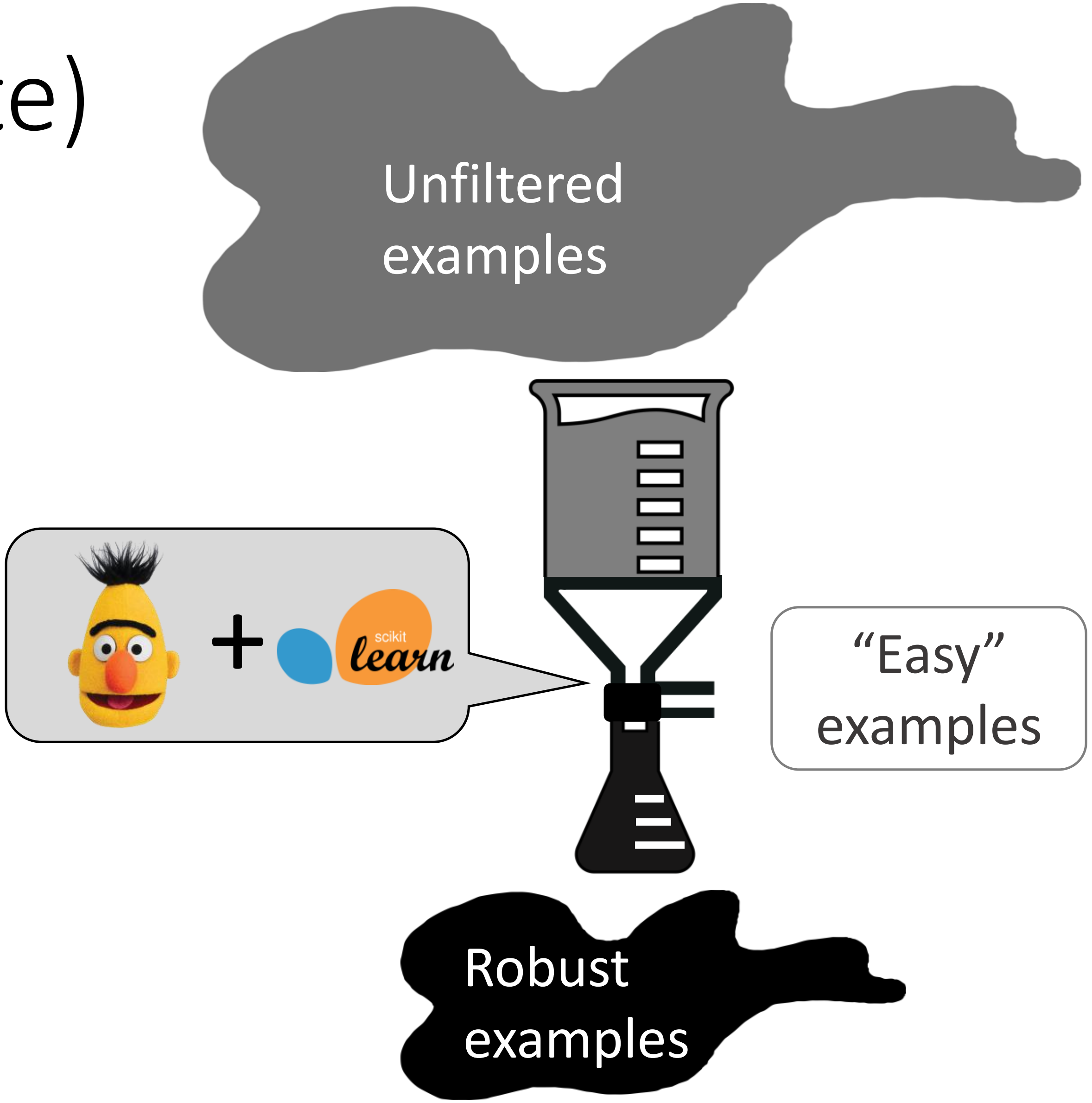

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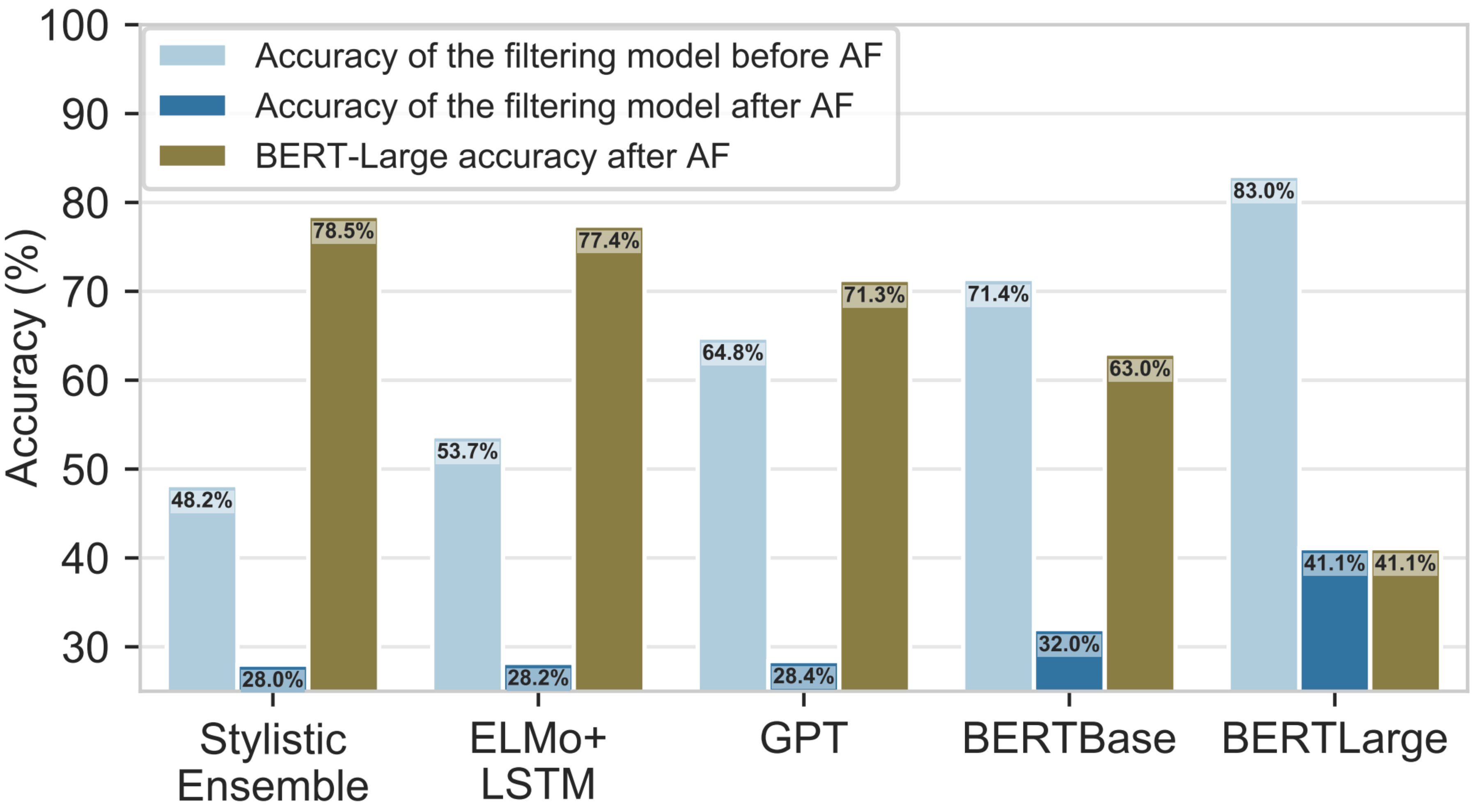
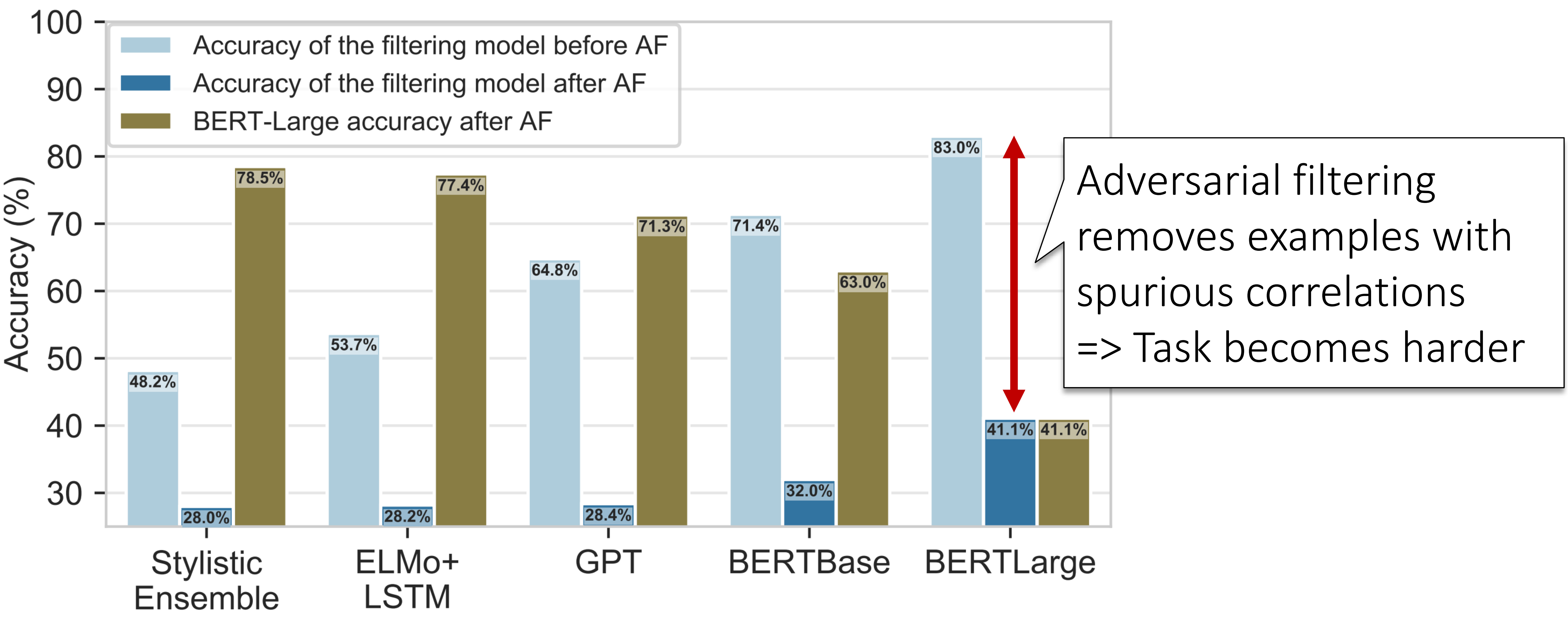


Performance of models on the WikiHow portion of HellaSwag (Zellers et al., 2019) with different AF settings and different training models



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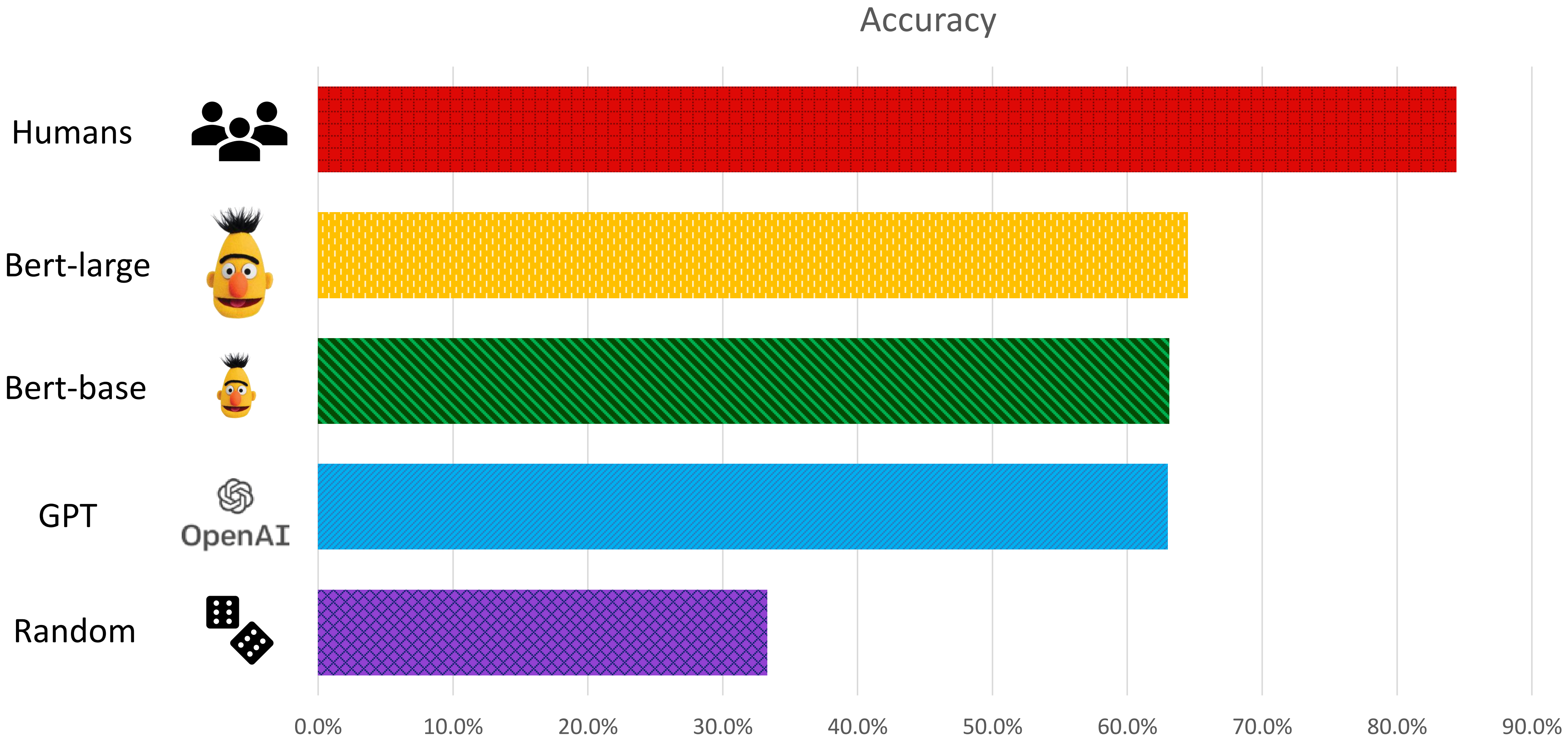
Model performance on SOCIAL IQA



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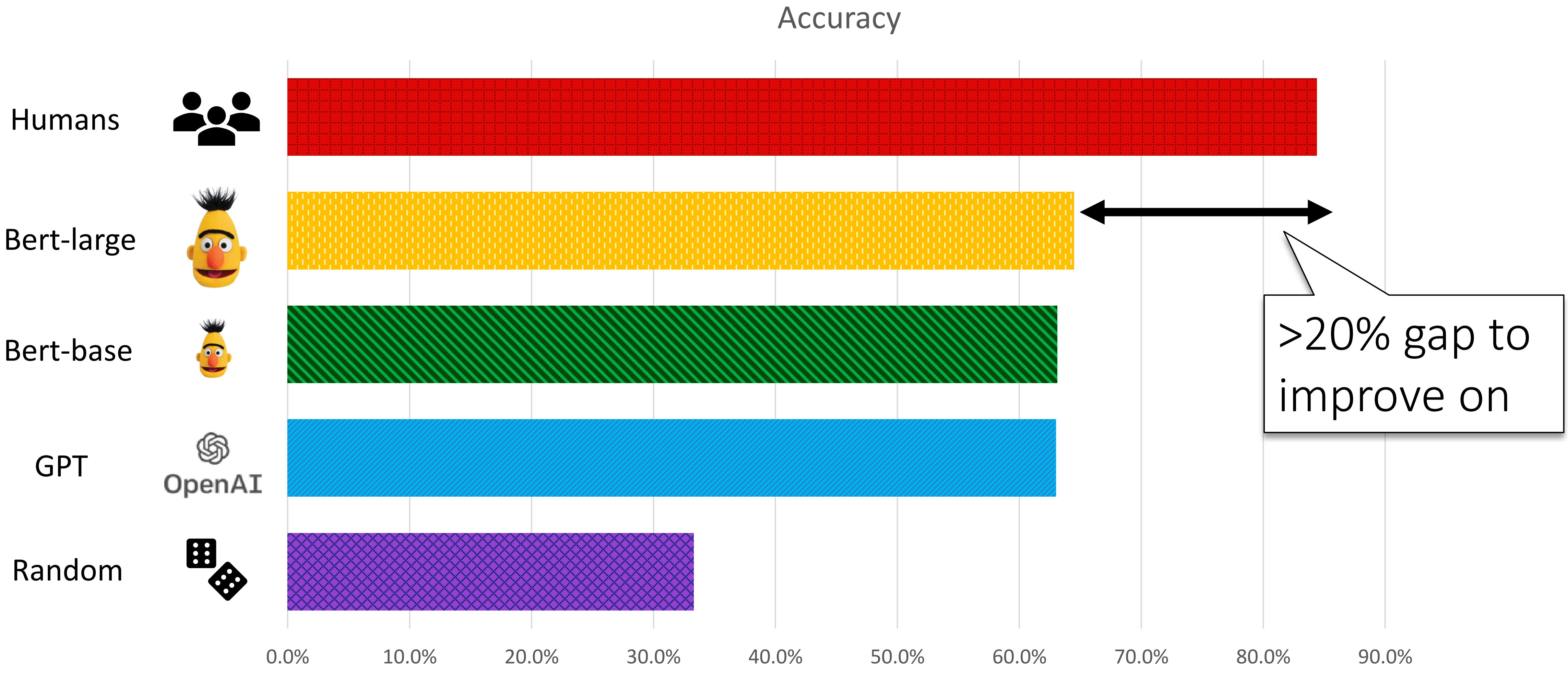

Challenging SOCIAL IQA examples for BERT-large

Although Aubrey was older and stronger, they lost to Alex in arm wrestling.

How would Alex feel as a result?

 ashamed — how **Aubrey** would feel, not Alex

✓ boastful

they need to practice more

Need more robust, person-centric reasoning

Remy gave Skylar, the concierge, her account so that she could check into the hotel.

What will Remy want to do next?

lose her credit card

 arrive at a hotel — what Remy did **before**

✓ get the key from Skylar

Need better notion of causes vs. effects

Commonsense benchmarks

Social commonsense

- Naïve Psychology
- ROC story
- Social IQa
- WSC
- COPA
- VCR
- WinoGrande

Physical commonsense

- Physical IQa
- HellaSwag
- SWAG
- JHU Ordinal Commonsense

Abductive NLI

CommonsenseQA

Temporal commonsense

- MCTaco

Commonsense reading comprehension

- ReCORD
- CosmosQA
- MultiRC