Berkeley NLP

Supervising AI to Do Things I Can't

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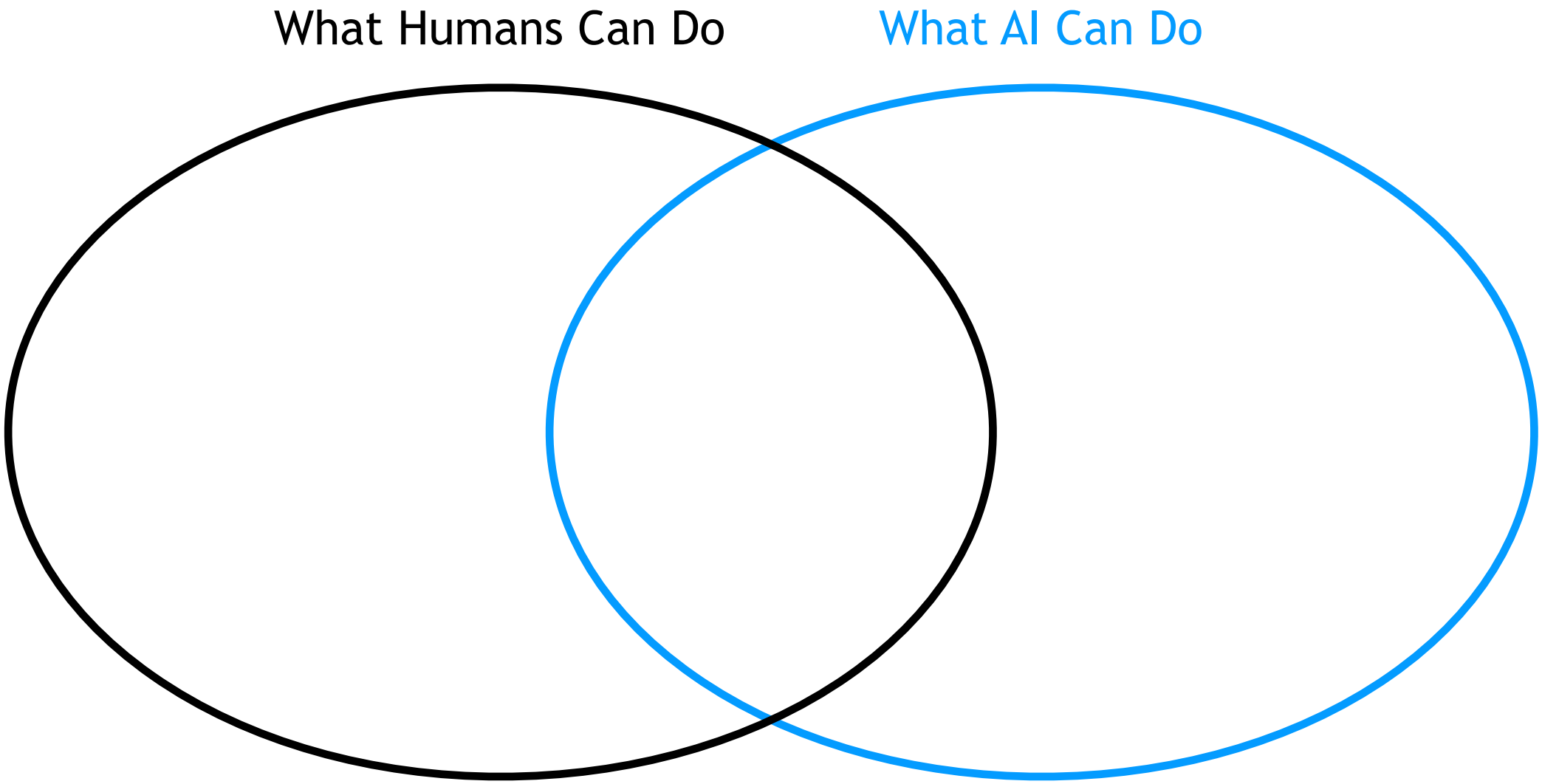
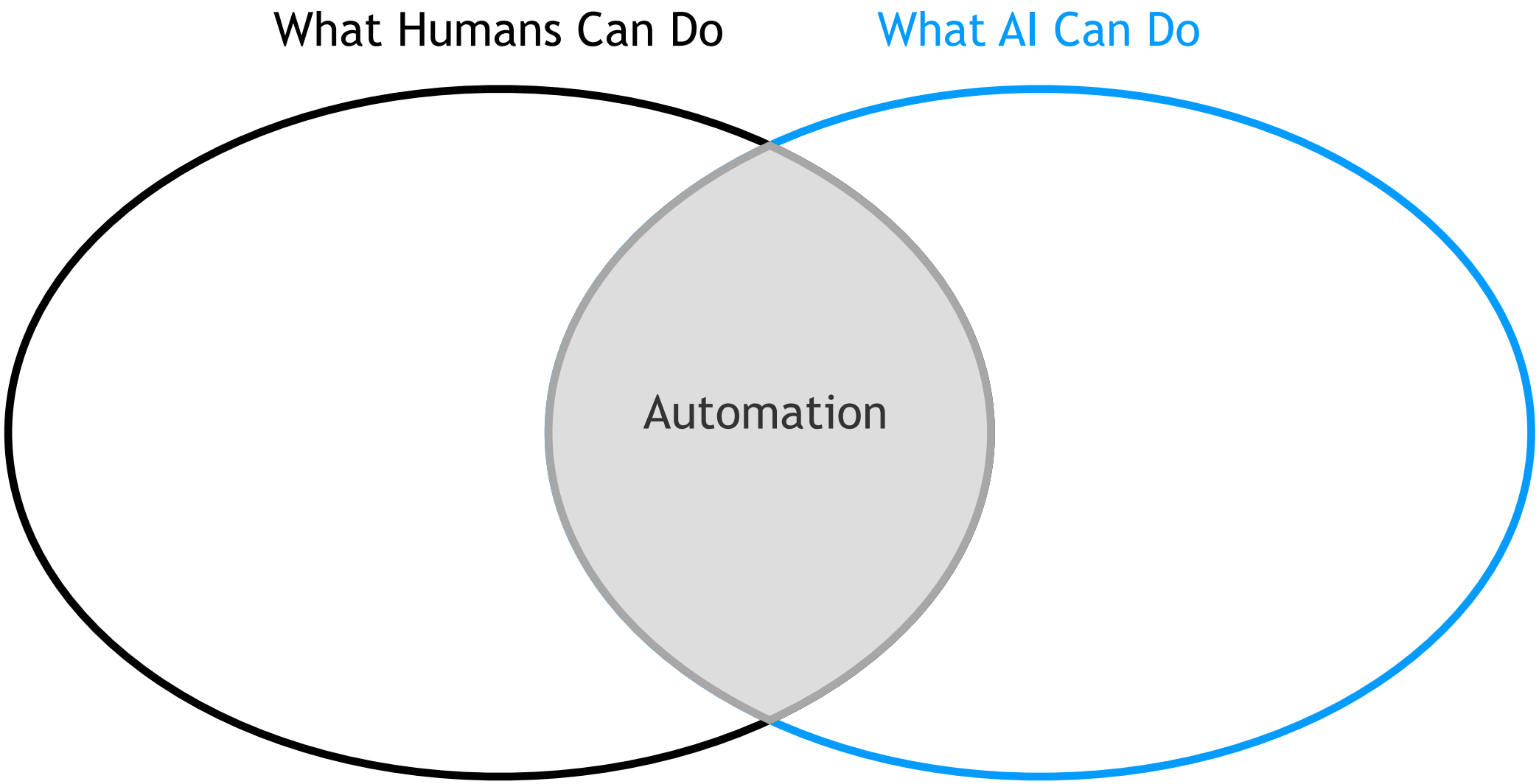
Automation vs. Augmentation



Automation vs. Augmentation



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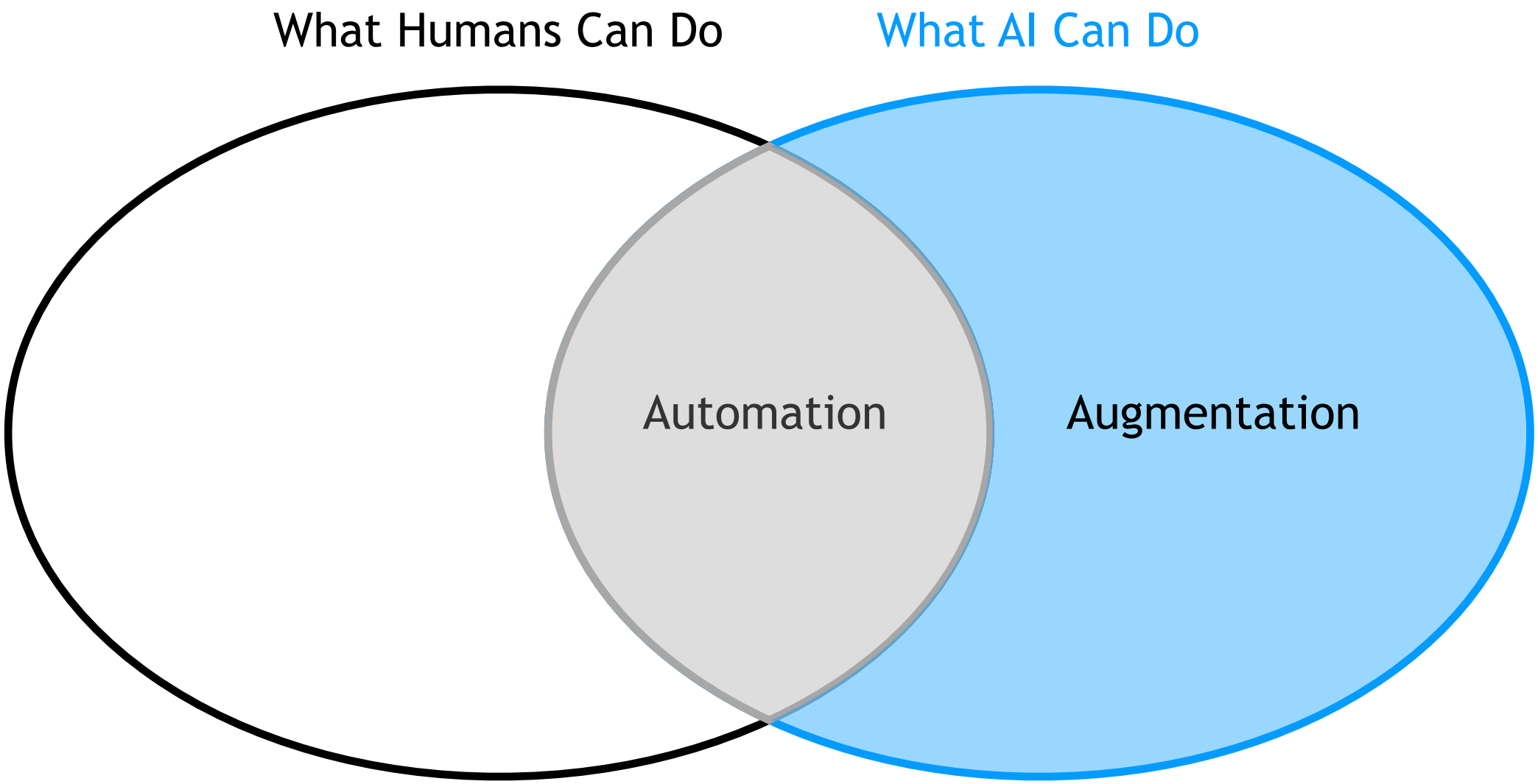


Today's Talk

How to supervise AI even when we struggle to determine the ground truth?

Example Tasks

Find the first name of students who have both cat and dog pets.

```
SELECT fname FROM Student WHERE
StuID IN (SELECT T1.stuid FROM
student AS T1 JOIN has_pet ……
```

Corpus 1

- Pieck rescued Gabi from the dungeon and transformed into a Titan afterwards.
- All four of my maternal and fraternal grandparents are professors, and that's why I'm determined to become a prof as well.
- My mom took me to the hospital, and the nurse said that she has never seen this symptom before.
- I was really fortunate to be advised Prof. McKeown and Prof. Hirschberg at Columbia on NLP research, and Prof. Andoni on Theoretical computer science.
- Historia was born as the illegitimate and unrecognized daughter of Rod Reiss. Her mother, Alma, was a servant in his household.
- I called her to explain what happened to her aunt.
- It's quite ironical that such a centralized government fail to locate the suspects who gravely injured those girls earlier this month.

Corpus 2

- She carried a total of eight torpedoes. Her deck was reinforced to enable her to lay a minefield.
- My mom and I were best friends and we used to hunt together.
- Lucy and Peter co-authored a paper on machine learning but got a really bad review.
- Adding to Historia's isolation, the other children outside the estate would throw rocks at her, and she was not allowed to leave.
- Bentham defined as the "fundamental axiom" of his philosophy the principle that "it is the greatest happiness of the greatest number that is the measure of right and wrong."
- Large language models advanced the state of the art by quite a lot but there are still rooms for improvements.
- After 10 years of lockdown due to the pandemics, I finally saw my grandfather — I thought I might never see him again.

"*Corpus 1 mentions more female entities*"

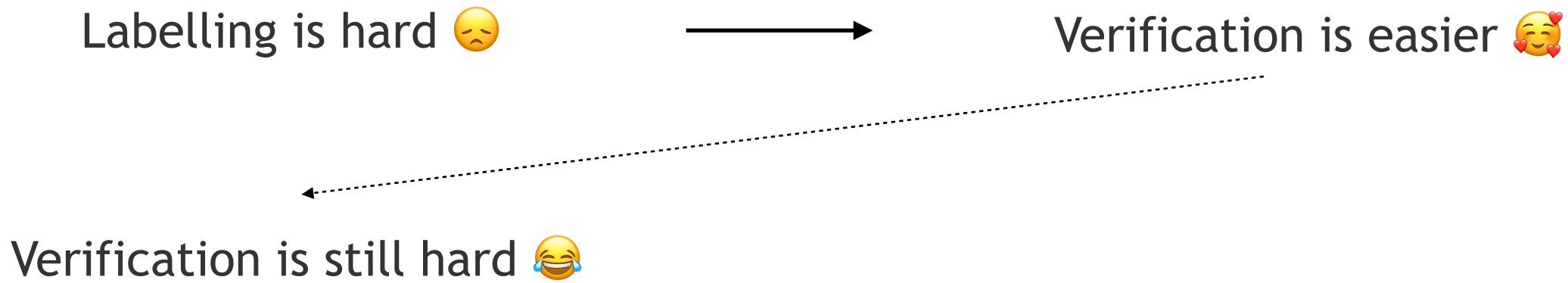
Label —> Verify —> Reduce

Labelling is hard 😞

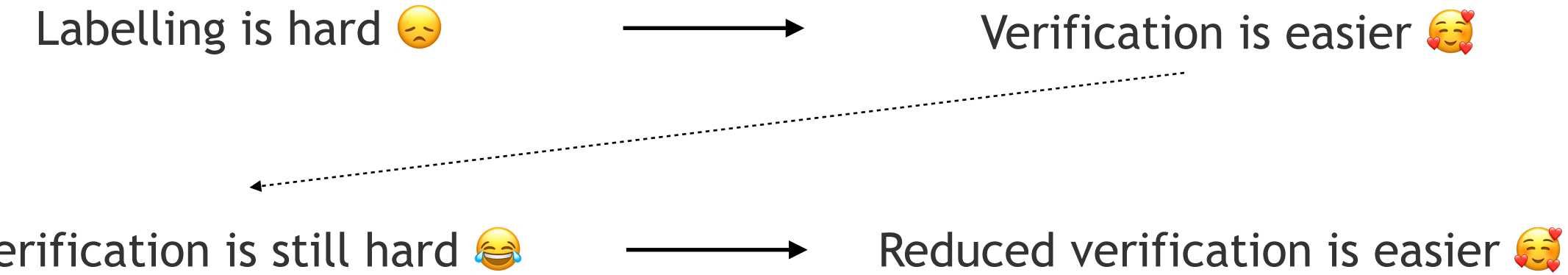
Label —> Verify —> Reduce

Labelling is hard 😞 ⟶ Verification is easier 🥰

Label —> Verify —> Reduce



Label —> Verify —> Reduce



Task I: Enabling Non-Experts to Indirectly Label Complex Programs

Semantic Parsing

Natural Language *How old is the youngest person from department A?*

SQL Program

```
SELECT MIN(Age) from People
  WHERE Department = 'A'
```

Semantic Parsing

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Expensive!!

How do non-experts label these programs to train a model?

Label Full Output —> Verify

Natural Language *How old is the youngest person from department A?*

	Probabilities	SQL
Candidates	7/10	`SELECT MAX(Name) from People`
	1/10	`SELECT MAX(Age) from People`
		……
	1/80	`SELECT MIN(Age) from People WHERE Department = 'A'`

Label Full Output —> Verify

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How do non-experts verify which candidate is correct?

Hard to Verify

Find the first name of students who have both cat and dog pets.

Candidate 1

```
SELECT fname FROM Student WHERE StuID IN
  (SELECT T1.stuid FROM student AS T1 JOIN has_pet AS T2 ON T1.stuid = T2.stuid
   JOIN pets AS T3 ON T3.petid = T2.petid
   WHERE T3.pettype = 'cat' INTERSECT
     SELECT T1.stuid FROM student AS T1 JOIN has_pet AS T2 ON T1.stuid = T2.stuid
     JOIN pets AS T3 ON T3.petid = T2.petid WHERE T3.pettype = ‘dog')
```

Candidate 2

```
SELECT t1.fname FROM student AS t1 JOIN has_pet AS t2 ON t1.stuid = t2.stuid
JOIN pets AS t3 ON t3.petid = t2.petid WHERE t3.pettype = 'cat' INTERSECT
  SELECT t1.fname FROM student AS t1 JOIN has_pet AS t2 ON t1.stuid = t2.stuid
  JOIN pets AS t3 ON t3.petid = t2.petid WHERE t3.pettype = 'dog'
```

Reduction: Verify with Input-Output

How old is the youngest person from department A?

```
SELECT MAX(Name) from People

SELECT MAX(Age) from People

SELECT MIN(Age) from People
    WHERE Department = 'A'
```

Reduction: Verify with Input-Output

How old is the youngest person from department A?

NAME	Age	Department
Alice	26	A
Bob	23	A
Cathy	28	B

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SELECT MAX(Name) from People

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Reduction: Verify with Input-Output

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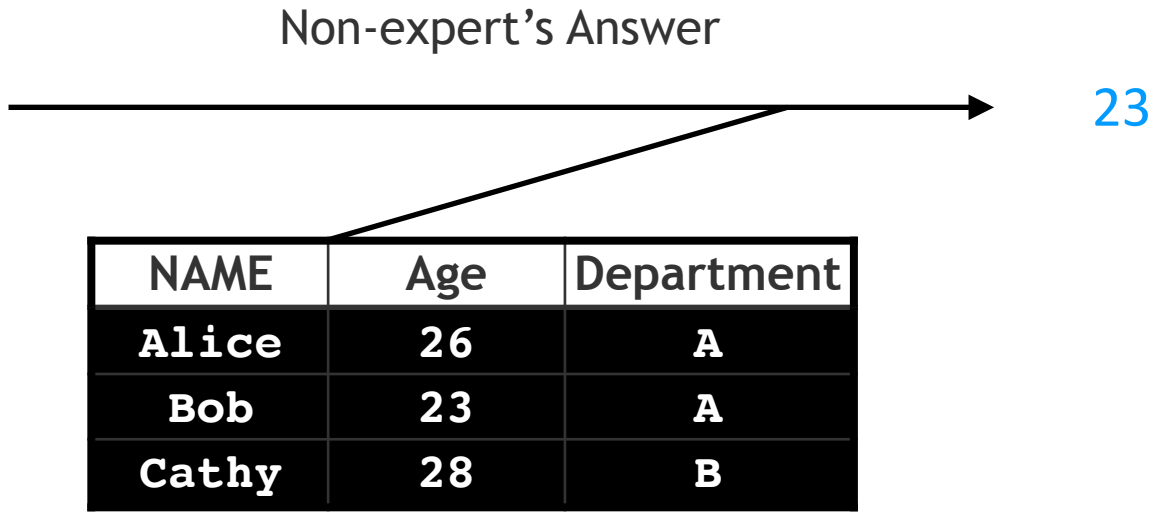


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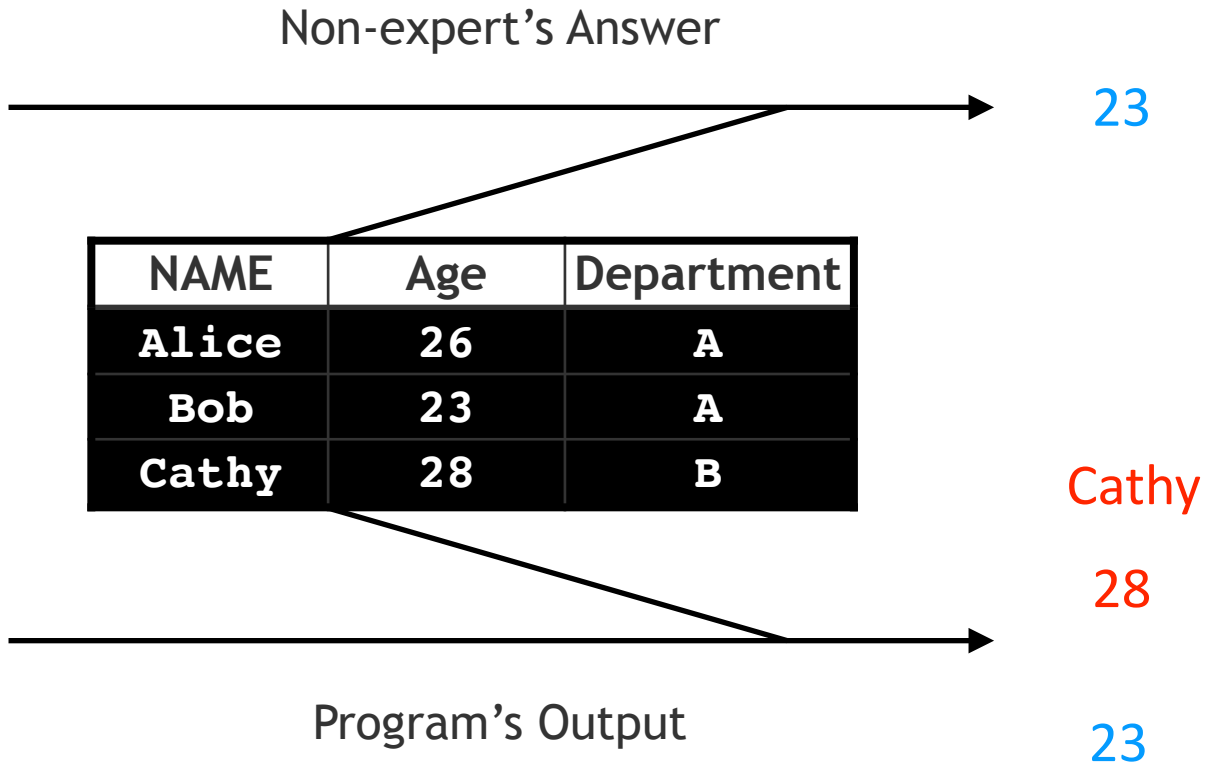

Reduction: Verify with Input-Output

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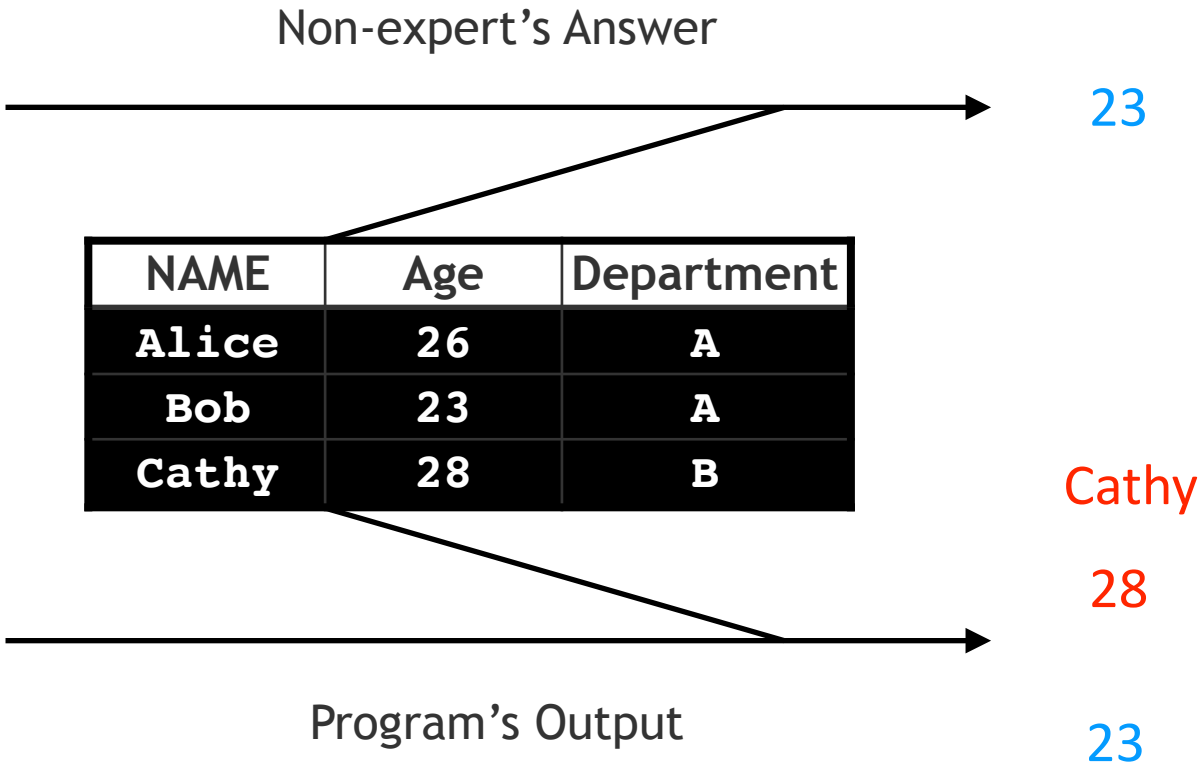
```



Where does this database come from?

How old is the youngest person from department A?

```
SELECT MAX(Name) from People
```

```
SELECT MAX(Age) from People
```

```
SELECT MIN(Age) from People
   WHERE Department = 'A'
```

Non-expert's Answer

23

NAME	Age	Department
Alice	26	A
Bob	23	A
Cathy	28	B

Cathy

28

Program's Output

23

Making Verification Simpler

Making Verification Simpler

- Choose the database wisely

Making Verification Simpler

- Choose the database wisely
  - is small enough to comprehend

Making Verification Simpler

- Choose the database wisely
  - is small enough to comprehend
  - make different programs return different values

Making Verification Simpler

How old is the youngest person from department A?

NAME	Age	Department
Collin	26	A
Bob	23	A
Cathy	28	B
David	19	A
Eric	11	A
Jacob	12	A
Alice	34	A
Dan	98	A
Alice	12	C
Kevin	38	B
Kevin	20	A

[In total 1000 rows, rest omitted]

→ Annotators' Answer ?????

Making Verification Simpler

How old is the youngest person from department A?

The **database input** must be **simple to comprehend**

NAME	Age	Department
Collin	26	A
Bob	23	A
Cathy	28	B
David	19	A
Eric	11	A
Jacob	12	A
Alice	34	A
Dan	98	A
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[In total 1000 rows, rest omitted]

→ Annotators' Answer ?????

Making Verification Simpler

Size (

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Collin	26	A
Bob	23	A
Cathy	28	B
David	19	A
Eric	11	A
Jacob	12	A
Alice	34	A
Dan	98	A
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Kevin	20	A

) = 1000

[In total 1000 rows, rest omitted]

Making Verification Effective

How old is the youngest person from department A?

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Collin	26	A
Bob	23	A

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SELECT MIN(Age) from People
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```
SELECT MIN(Age) from People
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Making Verification Effective

How old is the youngest person from department A?

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→ Annotators' Answer **23**

```
SELECT MIN(Age) from People
```
→ **23**

```
SELECT MIN(Age) from People
   WHERE Department = 'A'
```
→ **23**

Making Verification Effective

How old is the youngest person from department A?

NAME	Age	Department
Collin	26	A
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→ Annotators' Answer **23**

Not Informative!

```
SELECT MIN(Age) from People
```
→ **23**

```
SELECT MIN(Age) from People
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```
→ **23**

Expected Information Gain

Probabilities	SQL		
1/3	`SELECT MIN(Age) from People`	→	**23**
1/3	`SELECT MIN(Age) from People WHERE Department = 'A'`	→	**23**
1/3	`SELECT MAX(Age) from People WHERE Department = 'A'`	→	**26**

NAME	Age	Department
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Expected Information Gain

Probabilities	SQL	
1/3	`SELECT MIN(Age) from People`	→ 23
1/3	`SELECT MIN(Age) from People WHERE Department = 'A'`	→ 23
1/3	`SELECT MAX(Age) from People WHERE Department = 'A'`	→ 26

Answer Entropy: -2/3 * log(2/3) - 1/3 * log(1/3) = 0.92

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Expected Information Gain

Probabilities	SQL		
1/3	`SELECT MIN(Age) from People`	→	23
1/3	`SELECT MIN(Age) from People WHERE Department = 'A'`	→	23
1/3	`SELECT MAX(Age) from People WHERE Department = 'A'`	→	26

Answer Entropy: -2/3 * log(2/3) - 1/3 * log(1/3) = 0.92

InfoGain (

NAME	Age	Department
Collin	26	A
Bob	23	A

) = 0.92 bit

Technical Details in Our Paper

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- Search i with small Size(i) and large InfoGain(i)

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- Search i with small Size(i) and large InfoGain(i)
  - fuzzing; then drop rows greedily.

Technical Details in Our Paper

- Search i with small Size(i) and large InfoGain(i)
  - fuzzing; then drop rows greedily.
- Multi-round interaction

Human Study Setup

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- 11 students: non-CS; zero SQL experience

Human Study Setup

- 11 students: non-CS; zero SQL experience
- Answer on average 4 databases with 9 rows per question

Dataset and Baselines

Natural Language

How old is the youngest person from department A?

Expert Annotations

```
SELECT MIN(Age) from People
WHERE Department = 'A'
```

Dataset and Baselines

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How old is the youngest person from department A?

Codex

Probabilities

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`Codex Top-1`

Test suite
(Zhong et al. 2020)

Dataset and Baselines

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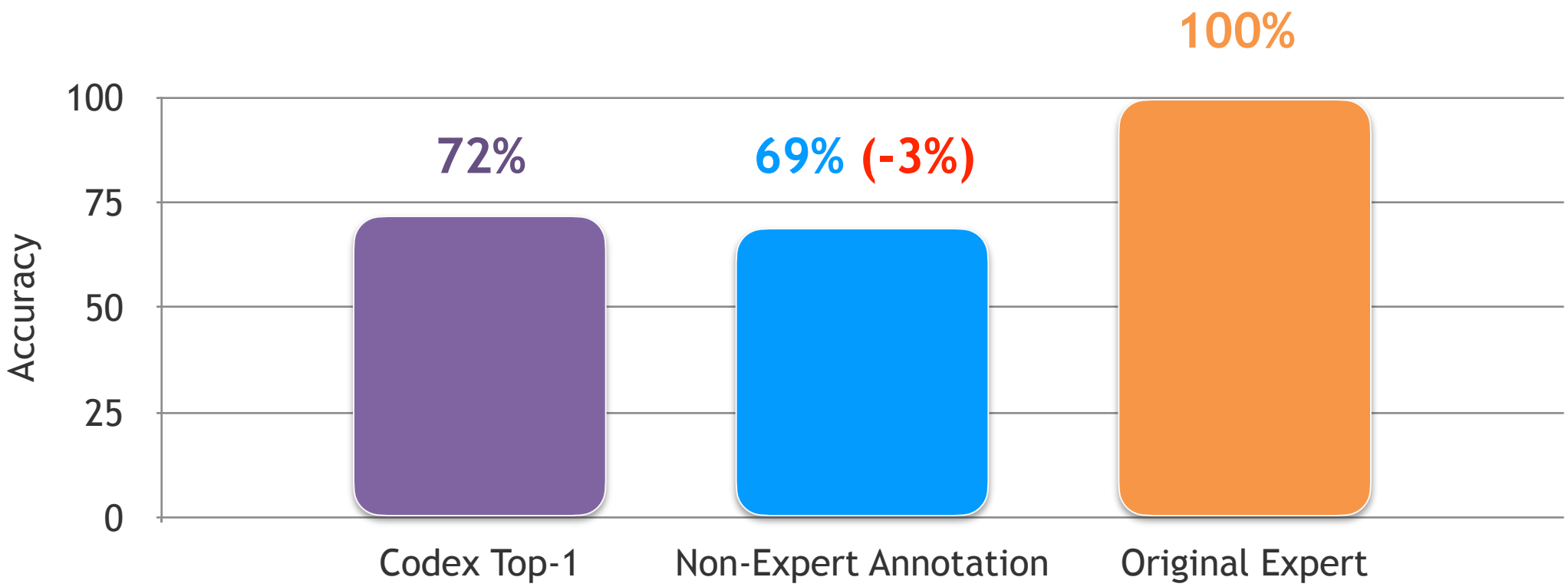
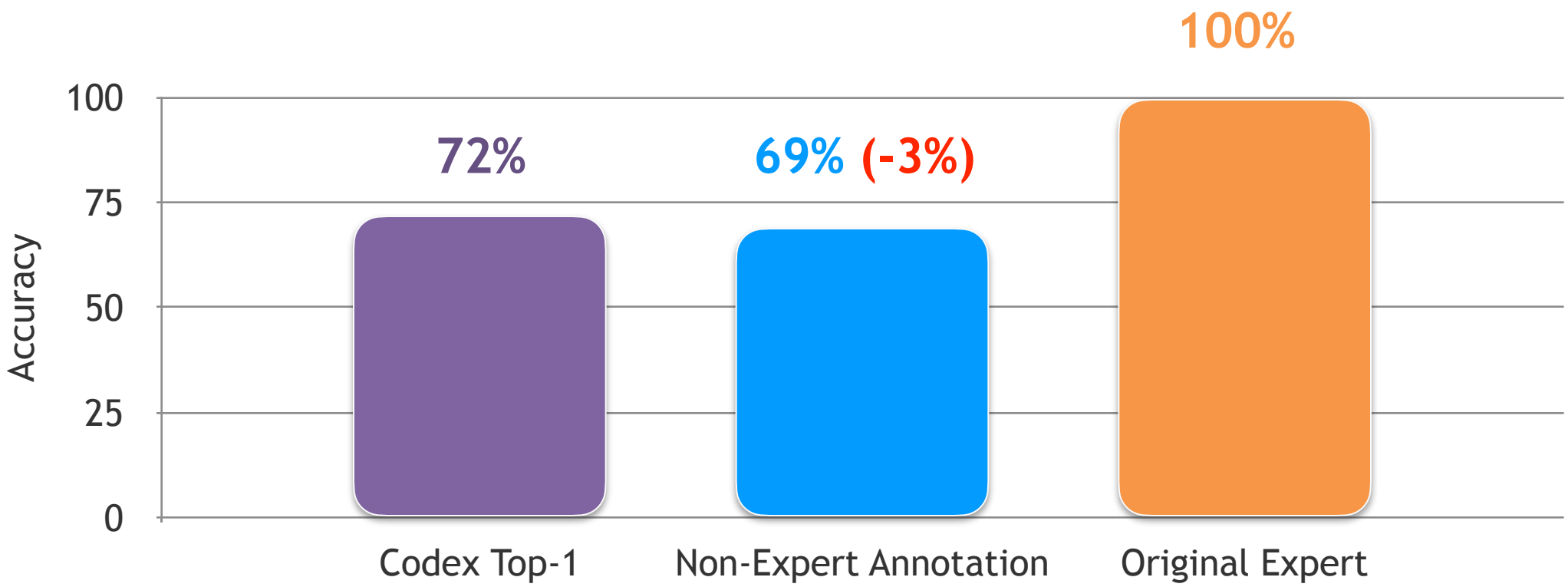
Codex Top-1

Our Annotation

Using Original Labels as the Ground Truth



Using Original Labels as the Ground Truth



Complex SQL Programs Revisit

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```

An expert wrote this

```
SELECT t1.fname FROM student AS t1 JOIN has_pet AS t2 ON t1.stuid = t2.stuid
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```

An Effective Database Simplifies Verification

Find the first name of students who have both cat and dog pets.

Ownership (merged)

StuId	First Name	Last Name	PetType	PetId
Student_A	Alex	Pan	Cat	Pet_1
Student_B	Alex	Wei	Dog	Pet_2

Re-annotation

Re-annotation

- Authors use the new framework to re-label

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- Stick to the original label if ambiguous

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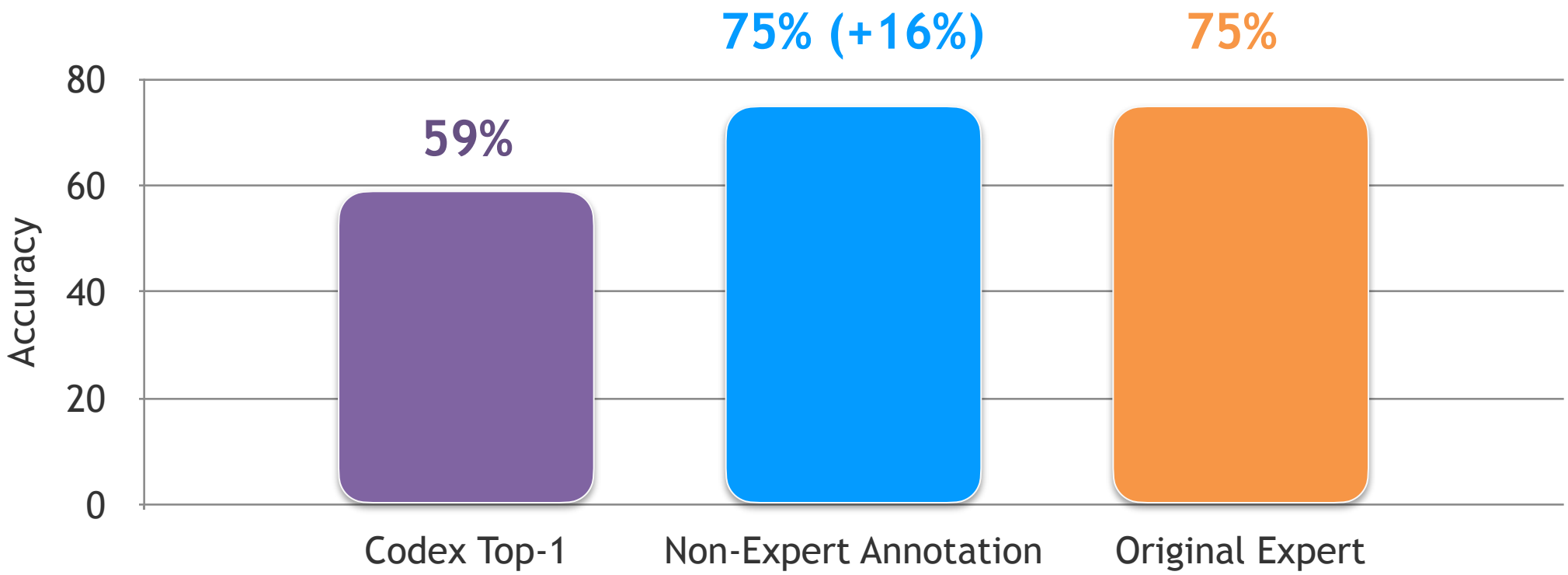
Re-annotation

- Authors use the new framework to re-label
- Stick to the original label if ambiguous
- Fix only the uncontroversially worse labels
- Supported by the SPIDER 1st author

After Re-annotation with Our System …



Recap

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- Labeling programs —> verifying programs

Recap

- Labeling programs —> verifying programs
- Verifying programs —> reducing to input-outputs

Recap

- Labeling programs —> verifying programs
- Verifying programs —> reducing to input-outputs
- Making verification simple and effective by choosing databases wisely

Application II: Describing Differences between Text Distributions (ICML 2022)

Difference between Distributions

D_1

- Ma mère m’a emmené à l’hôpital.
- J'ai 10 $. Je dépense 3 $ sur un livre.
- Le gouvernement n'a pas réussi à localiser les suspects.

D_2

- My mom and I were best friends.
- Lucy and Peter co-authored a paper.
- Yesterday, I called her to explain why I did horribly on the test.

Difference between Distributions

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s = “D_1 contains more French sentences compared to D_2”

Difference between Distributions

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s = "D_1 contains more French sentences compared to D_2"

s = "D_1 contains more accent mark compared to D_2"

Tell the Difference!

D_1

- Pieck rescued Gabi from the dungeon and transformed into a Titan afterwards.
- All four of my maternal and fraternal grandparents are professors, and that's why I'm determined to become a prof as well.
- My mom took me to the hospital, and the nurse said that she has never seen this symptom before.
- I was really fortunate to be advised Prof. McKeown and Prof. Hirschberg at Columbia on NLP research, and Prof. Andoni on Theoretical computer science.
- Historia was born as the illegitimate and unrecognized daughter of Rod Reiss. Her mother, Alma, was a servant in his household.
- I called her to explain what happened to her aunt.

D_2

- She carried a total of eight torpedoes. Her deck was reinforced to enable her to lay a minefield.
- My mom and I were best friends and we used to hunt together.
- Lucy and Peter co-authored a paper on machine learning but got a really bad review.
- Adding to Historia's isolation, the other children outside the estate would throw rocks at her, and she was not allowed to leave.
- Bentham defined as the "fundamental axiom" of his philosophy the principle that "it is the greatest happiness of the greatest number that is the measure of right and wrong."
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Example Insights

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- The test distribution involves more formal writing than the training distribution.
  D_1 s D_2

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- Public opinions from this year are more optimistic about the pandemic than last year.
  D_1 s D_2

Example Insights

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  D_1 s D_2
- A text cluster contains more sports-related articles than other clusters.
  D_1 s D_2
- Public opinions from this year are more optimistic about the pandemic than last year.
  D_1 s D_2
- Find dataset shortcuts
- Summarize author styles
- …

The Two Challenges …

- Hard to label —> easier to verify
- Hard to verify —> reduce to something simpler

Label Full Output —> Verify

Group A: The author proposed a novel and impactful task. Accept!
Group A: Strong accept.
Group A: The method is simple but effective.
Group A: [Other random samples from D_1]

Group B: Thanks for the author, but this paper should be rejected.
Group B: Is this a high school tech report?
Group B: Total waste of time reading this submission.
Group B: [Other random samples from D_2]

Compared to sentences from group B, each sentence from group A

GPT-3

- Is more positive
- Is offensive in tone
- [Other descriptions]

The Two Challenges …

- Hard to label —> easier to verify
- Hard to verify —> reduce to something simpler

Reduction: Verify on Individual Samples

A good description helps humans tell ***individual samples*** from D_1 and D_2 apart.

Reduction: Verify on Individual Samples

s = "Samples from D_1 are more positive than those from D_2"

Reduction: Verify on Individual Samples

s = "Samples from D_1 are more positive than those from D_2"

$x_a \sim D_a$ "This paper proposes an impactful task."

$x_b \sim D_b$ "The approach of this paper is too trivial."

Reduction: Verify on Individual Samples

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Human Classifies

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Human Classifies

I think x_a is from D_1 and x_b is from D_2

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Human Classifies

I think x_a is from D_1 and x_b is from D_2

Loss(s): Repeat 100 times and calculate human classification error rate.

Learning a Natural Language Hypothesis

Learning a Natural Language Hypothesis

- Classical: find the most discriminative linear weight to separate input vectors.

Learning a Natural Language Hypothesis

- Classical: find the most discriminative linear weight to separate input vectors.
- Ours : find the most discriminative natural language string to separate input text.

Reduction: Verify on Individual Samples

s = "Samples from D_1 are more positive than those from D_2"

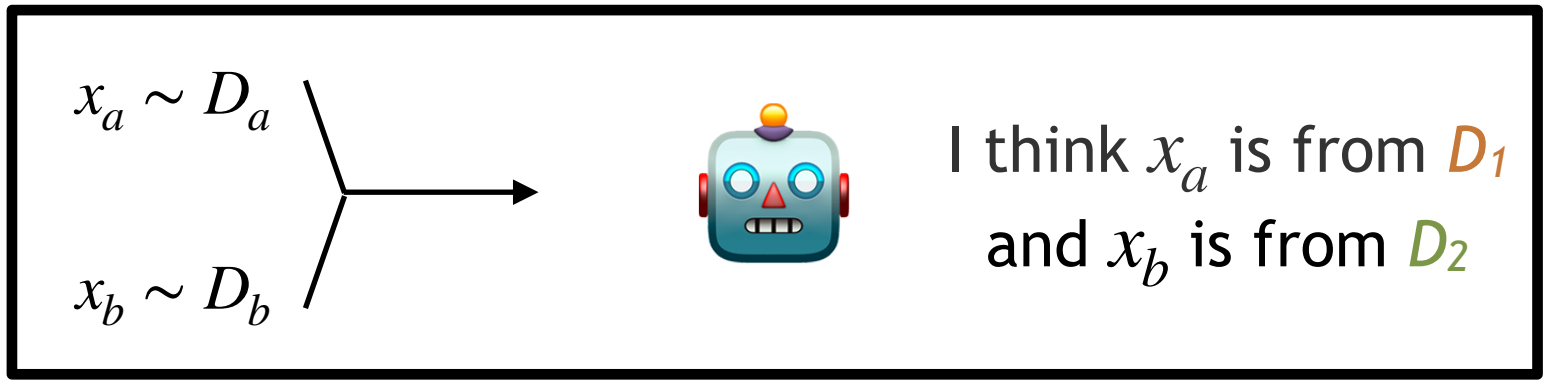
Loss(*s*): Calculate a human's error rate.

~$10 to evaluate a single description.

Making Verification Cheaper

s = "Samples from D_1 are more positive than those from D_2"

Loss(*s*): Calculate a model's error rate.



Much cheaper to calculate the error rate of a model

Method Overview

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- Create fine-tuning data for GPT-3 (see our paper)

Benchmark

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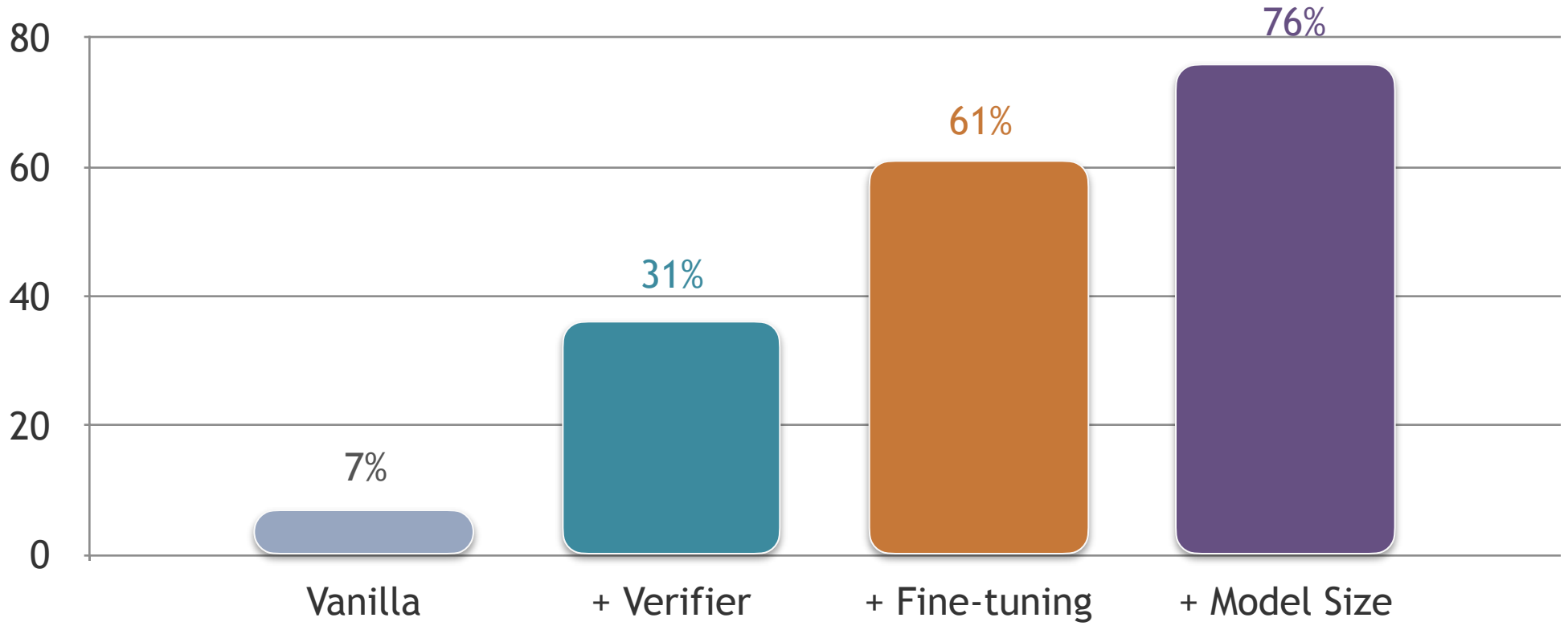

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To gather subjective sentences, we collected 5000 movie review snippets from www.rottentomatoes.com . To obtain (mostly) objective data, we took 5,000 sentences from plot summaries available from ww.imdb.com

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  D_1 D_2
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- Fine-tuned RoBERTa predicts spam whenever it sees a hyperlink!!!

Recap

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- Labeling descriptions —> verifying descriptions

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- Verifying on the entire distribution —> reducing to individual samples
- Making verification cheaper by simulating human verification

Future Work & Discussion

What can AI do?

What can AI do?

what one human can do

What can AI do?

what one human can verify

What can AI do?

what a large group of humans can verify with the help of AI and other tools

Augmentative AI: Opportunities

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- Search
  - Creativity
  - Effective strategies

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- Long input
  - Summarization
  - Generation

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  - What if humans can’t indirectly verify?
- Verification is going to be harder

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- Automation : I spent $2K on **AMT** to label **20,000** datapoints. **I can tell that the labels are correct** by scrutinizing some annotations.

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- Augmentation: I spent $2K on **experts** to label **54** datapoints. The labels look reasonable, but I am **uncertain whether they are correct**.

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  - Rule out incapable systems with high confidence labels
  - Collaborate with capable systems to improve low confidence labels

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- Label —> Verify —> Reduce
- Vastly under-explored research with opportunities & challenges.

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- Statistical Models of How Models Behave
  - Approximating How Single Head Attention Learns
  - Are Larger Pretrained Language Models Uniformly Better? Comparing Performance at the Instance Level

Thanks!