

Evaluation and Benchmarking



CS 288: Advanced Natural Language Processing

Tasks and Metrics



- What are some basic types of tasks in NLP?
- How do we design a function that tells us whether a model can “do” a task or not?
 - Evaluation metrics

Tasks (in General)



Most tasks can be thought of as a mapping from some input X to some output Y , where one or both of these have to do with language

Task	Input (X)	Output (Y)
Text classification	Text	Label from a fixed class
Automatic speech recognition	Audio signal	Text
Dependency parsing	Text	Dependency tree
Code generation	Text	Executable code
Question answering	Document and question (both text)	Answer (text)
Translation	Text (in source language)	Text (in target language)
Open-ended NLG	Optional prompt (text)	Text
Referring expression generation	Image and target object	Referring expression (text)
Dialogue	Conversation history (text)	Next utterance (text)

Classification

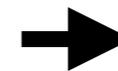
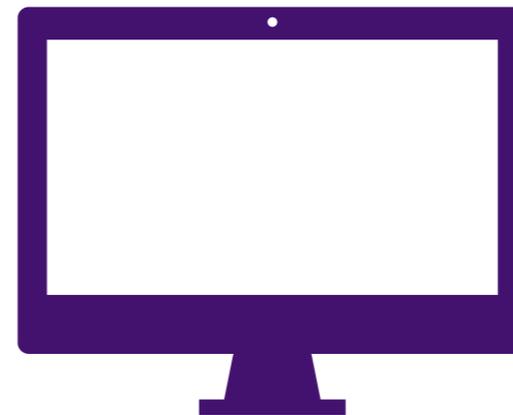
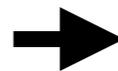
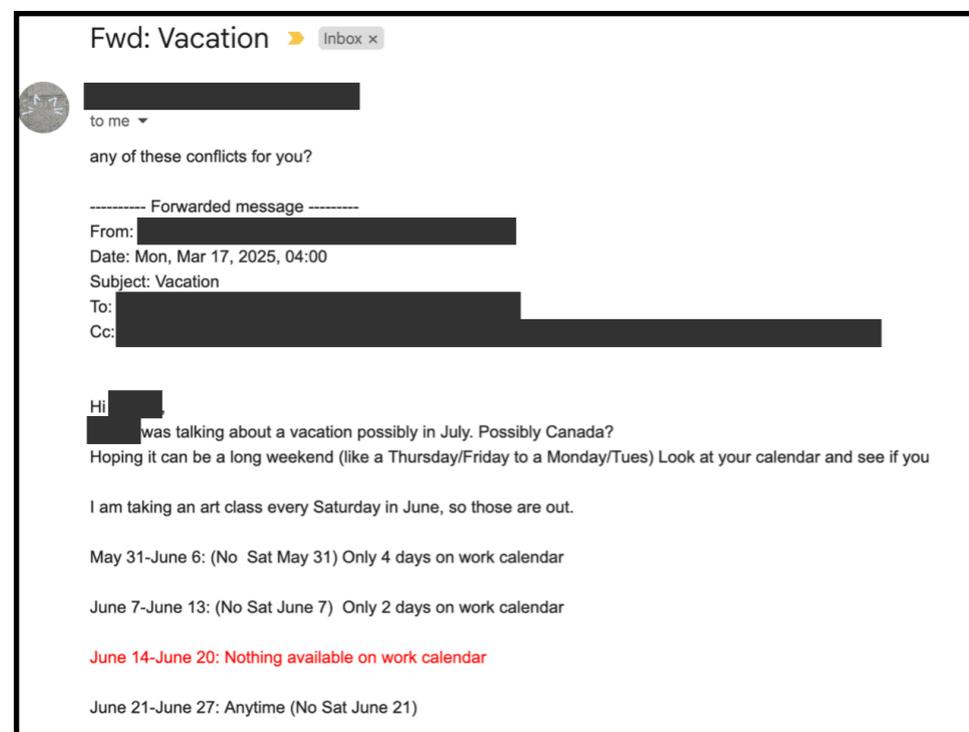


- **Input:** text data
- **Output:** label from a closed set

Binary Classification



- **Input:** text data
- **Output:** label from a closed set
- **Spam detection**

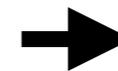
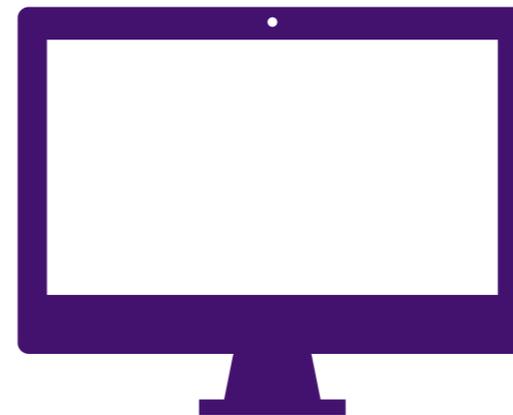
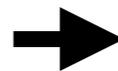
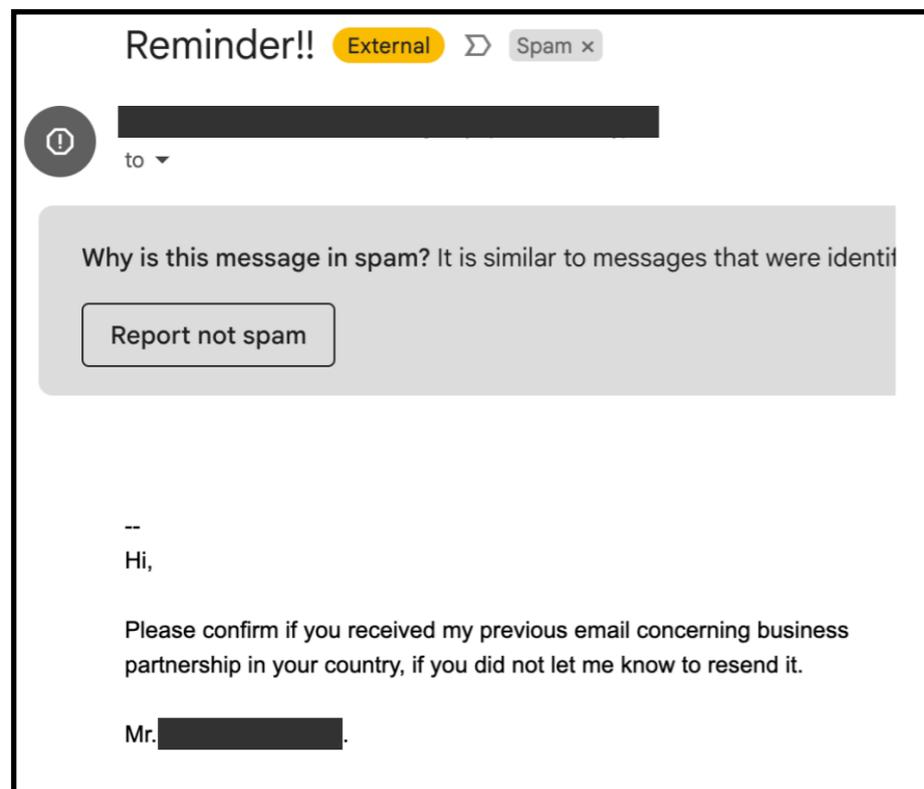


Not Spam

Binary Classification



- **Input:** text data
- **Output:** label from a closed set
- **Spam detection**



Spam

Multiclass Classification



- **Input:** text data
- **Output:** label from a closed set
- **Part of speech tagging**

Battle-tested industrial managers here always buck

JJ JJ NNS RB RB VB

up nervous newcomers with the tale of the first of

RP JJ NNS IN DT NN IN DT JJ IN

their countrymen to visit Mexico, a boatload of

PP NNS TO VB NNP DT NN IN

samurai warriors blown ashore 375 years ago.

NNS NNS VB RB CD NNS RB

Evaluation



Input (31 words)

Battle-tested industrial ...
Battle-tested industrial ...
... industrial managers here ...
... managers here always ...
... here always buck up ...
...
... blown ashore 375 years ago .

Correct Label★

JJ

JJ

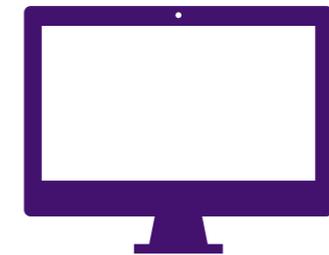
NNS

RB

RB

...

RB



VBD

JJ

NNS

RB

RB

...

RB

Automatic Speech Recognition



Task: Convert a speech *utterance* into a text *transcript*

- ASR performance is measured using error rates
- Sentence error rate (exact match) can be too penalizing (1 or 0)
- Word Error Rate (WER) captures average number (%) of wrong words in the transcript
- For now, let's assume words are separated by spaces
 - For languages that are not space delimited, Character Error Rate (CER) can be used

Word Error Rate (WER)



Possible Errors : Substitutions (S), Deletions (D), Insertions (I)

$$\frac{S + D + I}{N}$$

- *Reference* : Take me to UC campus (# words N=5)
- *ASR Transcript* : Take me to **you** **see** campus
 - 1 substitution 1 insertion 0 deletions
 - $WER = 2/5 * 100 = 40 \%$
- WER can be greater than 100% (eg. Too many insertions)
- S + D + I needs to be computed using Edit (Levenshtein) distance

Levenshtein/Edit distance



Dynamic Programming based edit matrix computation $d [N, M]$

Transcript or Hypothesis (i)

	0.	1. Take	2. me	3. to	4. you	5. see	6. campus
0.							
1. Take							
2. me							
3. to							
4. UC							
5. campus							

Reference (j)

Substitution # Deletion

Insertion $d[i,j]$

Calculate the least cost alignment/edit path allowing insertion, deletion and substitution of words

$$d [i, j] = \min (\begin{matrix} d [i-1, j] + 1, & \# \text{ Insertion} \\ d [i, j -1] + 1, & \# \text{ Deletion} \\ d [i -1, j -1] + \text{local_substitution} (i, j) & \# \text{ Substitution} \end{matrix})$$

Structured Prediction



- **Input:** text data
- **Output:** structured combination of labels from a closed set
- **Syntactic** (constituency) parsing

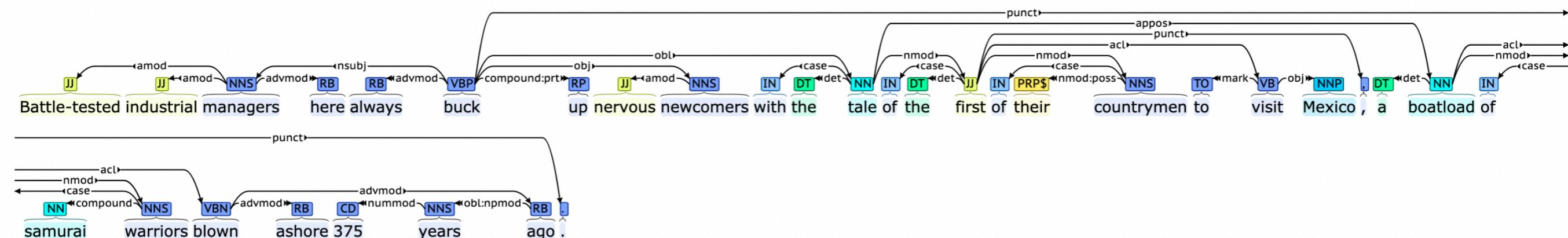
```
( (S
  (NP Battle-tested industrial managers
    here)
  always
  (VP buck
    up
    (NP nervous newcomers)
    (PP with
      (NP the tale
        (PP of
          (NP (NP the
            (ADJP first
              (PP of
                (NP their countrymen)))
            (S (NP *)
              to
              (VP visit
                (NP Mexico))))
          ,
          (NP (NP a boatload
            (PP of
              (NP (NP warriors)
                (VP-1 blown
                  ashore
                    (ADVP (NP 375 years)
                      ago))))))
            (VP-1 *pseudo-attach*)))))))))
  .)
```

Penn Treebank, Marcus et al. 1993

Structured Prediction



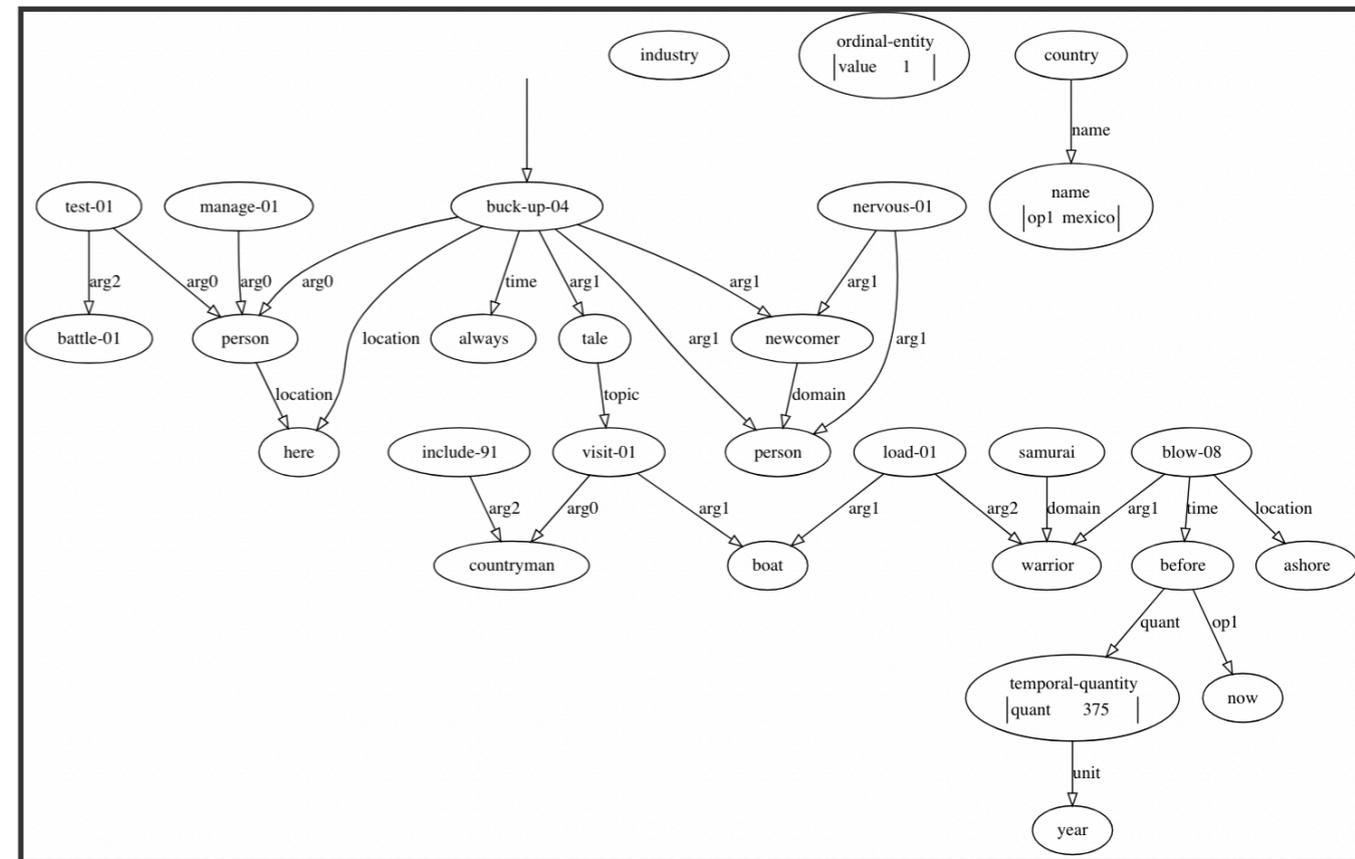
- **Input:** text data
- **Output:** structured combination of labels from a closed set
- **Syntactic** (dependency) parsing



Structured Prediction



- **Input:** text data
- **Output:** structured combination of labels from a closed set
- **Semantic parsing** (abstract meaning representation)



Structured Prediction



- **Input:** text data
- **Output:** structured combination of labels from a closed set
- **Semantic parsing** (text-to-SQL)

Task-specific eval metrics:

- exact match accuracy
- execution accuracy



airline	#
AA	123
Delta	456
...	...
JetBlue	404

?
=

airline	#
AA	123
Delta	456
...	...
United	789

show me flights from seattle to boston next monday

```
(SELECT DISTINCT flight.flight_id FROM flight WHERE (flight.from_airport IN (SELECT airport.service.airport_code FROM airport.service WHERE airport.service.city_code IN (SELECT city.city_code FROM city WHERE city.city_name = 'SEATTLE')))) AND (flight.to_airport IN (SELECT airport.service.airport_code FROM airport.service WHERE airport.service.city_code IN (SELECT city.city_code FROM city WHERE city.city_name = 'BOSTON')))) AND (flight.flight_days IN (SELECT days.days_code FROM days WHERE days.day_name IN (SELECT date_day.day_name FROM date_day WHERE date_day.year = 1993 AND date_day.month_number = 2 AND date_day.day_number = 8))));
```

Structured Prediction



- **Input:** text data
- **Output:** structured combination of labels from a closed set
- **Semantic parsing** (code generation)

Task-specific eval metrics:

- exact match accuracy
- test case pass rate

```
def incr_list(l: list):  
    """Return list with elements incremented by 1.  
    >>> incr_list([1, 2, 3])  
    [2, 3, 4]  
    >>> incr_list([5, 3, 5, 2, 3, 3, 9, 0, 123])  
    [6, 4, 6, 3, 4, 4, 10, 1, 124]  
    """  
    return [i + 1 for i in l]
```

```
def solution(lst):  
    """Given a non-empty list of integers, return the sum of all of the odd elements  
    that are in even positions.  
  
    Examples  
    solution([5, 8, 7, 1]) ==>12  
    solution([3, 3, 3, 3, 3]) ==>9  
    solution([30, 13, 24, 321]) ==>0  
    """  
    return sum(lst[i] for i in range(0, len(lst)) if i % 2 == 0 and lst[i] % 2 == 1)
```

```
def encode_cyclic(s: str):  
    """  
    returns encoded string by cycling groups of three characters.  
    """  
    # split string to groups. Each of length 3.  
    groups = [s[(3 * i):min((3 * i + 3), len(s))] for i in range((len(s) + 2) // 3)]  
    # cycle elements in each group. Unless group has fewer elements than 3.  
    groups = [(group[1:] + group[0]) if len(group) == 3 else group for group in groups]  
    return "".join(groups)  
  
def decode_cyclic(s: str):  
    """  
    takes as input string encoded with encode_cyclic function. Returns decoded string.  
    """  
    # split string to groups. Each of length 3.  
    groups = [s[(3 * i):min((3 * i + 3), len(s))] for i in range((len(s) + 2) // 3)]  
    # cycle elements in each group.  
    groups = [(group[-1] + group[:-1]) if len(group) == 3 else group for group in groups]  
    return "".join(groups)
```

HumanEval, Chen et al. 2021

Text Comprehension



- **Input:** text data
- **Output:** short piece of text (*extractive* QA: span in input text)

Task-specific eval metrics:
- span selection accuracy

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under **gravity**. The main forms of precipitation include drizzle, rain, sleet, snow, **graupel** and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals **within a cloud**. Short, intense periods of rain in scattered locations are called “showers”.

What causes precipitation to fall?

gravity

What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?

graupel

Where do water droplets collide with ice crystals to form precipitation?

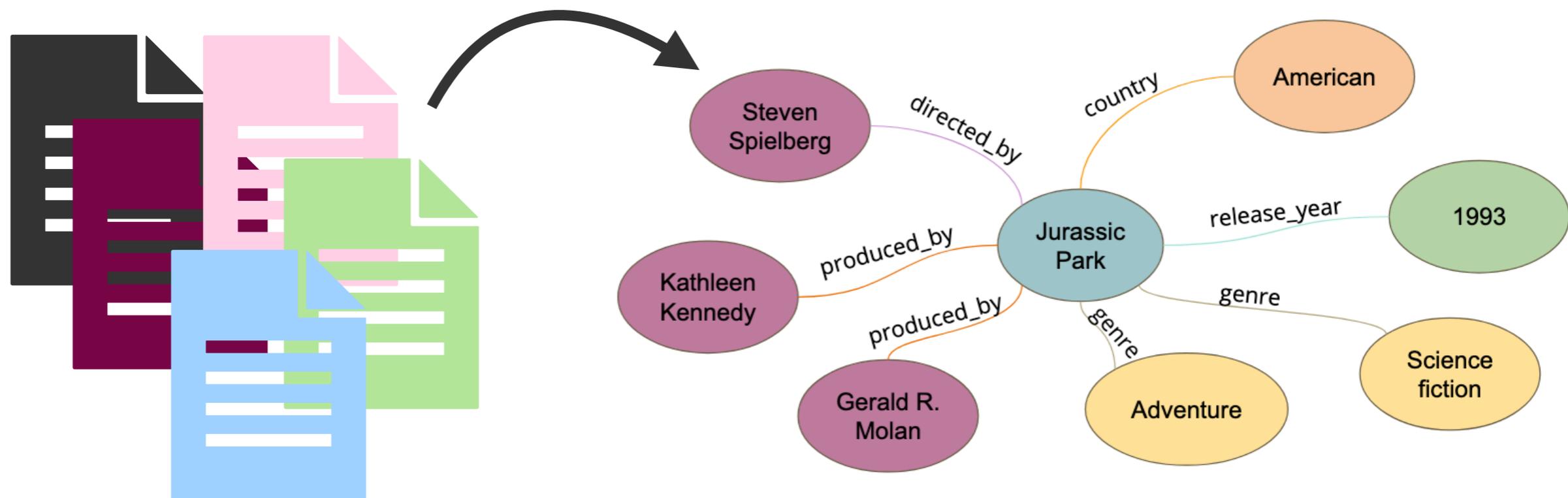
within a cloud

Rajpurkar et al. 2016

Information Extraction



- **Input:** lots of text data
- **Output:** structured representation of information



Task-specific eval metrics:

- precision of extracted facts
- recall of known facts

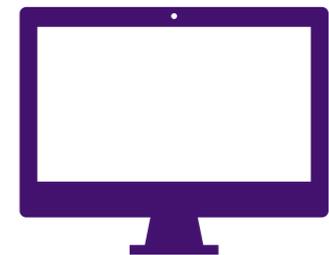
Question Answering



- **Input:** none
- **Output:** short piece of text
- Factual and commonsense

Task-specific eval metrics:
- multiple-choice accuracy

Options



0.2%

★ (b) whirlpool bath

0.1% ✗

(c) cup

0.3%

(d) puddle

0.3%

If someone wants to submerge themselves in water, what should they use?

Question Answering



- **Input:** none
- **Output:** short piece of text
- Factual and commonsense

Task-specific eval metrics:

- multiple-choice accuracy
- string similarity?

**most likely
answer**

If someone wants to submerge themselves in water, what should they use?



bathtub ✓
≈ whirlpool bath

Reference-Based Text Generation



- **Input:** text data
- **Output:** same text, but in a different language
- **Machine translation**

The bottle floated into the cave



La botella entró a la cueva flotando

Reference-Based Evaluation: BLEU



- Reference y
The most natural form of language use is dialogue.
- System outputs / candidates \hat{y}
 - \hat{y}_1 *The most common form of language use is conversation.*
 - \hat{y}_2 *The most common form of language is speech.*

Reference-Based Evaluation: BLEU



- Reference y
The most natural form of language use is dialogue.
- System outputs / candidates \hat{y}
 \hat{y}_1 *The most common form of language use is conversation.*
 \hat{y}_2 *The most common form of language is speech.*
- $G_n(x)$ is the set of n -grams in sequence x

Reference-Based Evaluation: BLEU



- Reference y

The most natural form of language use is dialogue.
unigram

- System outputs / candidates \hat{y}

\hat{y}_1 *The most common form of language use is conversation.*

\hat{y}_2 *The most common form of language is speech.*

- $G_n(x)$ is the set of n -grams in sequence x

$G_1(y) = \{the, most, natural, form, of, language, use, is, dialogue, .\}$

Reference-Based Evaluation: BLEU



- Reference y

The most natural form of language use is dialogue.

bigram

- System outputs / candidates \hat{y}

\hat{y}_1 *The most common form of language use is conversation.*

\hat{y}_2 *The most common form of language is speech.*

- $G_n(x)$ is the set of n -grams in sequence x

$G_1(y) = \{the, most, natural, form, of, language, use, is, dialogue, .\}$

$G_2(y) = \{the\ most, most\ natural, natural\ form, form\ of, \dots\}$

Reference-Based Evaluation: BLEU



- Reference y
The most natural form of language use is dialogue.
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 \hat{y}_1 *The most common form of language use is conversation.*
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 $G_1(y) = \{the, most, natural, form, of, language, use, is, dialogue, .\}$
 $G_2(y) = \{the\ most, most\ natural, natural\ form, form\ of, \dots\}$
- $C(s, x)$ is the number of occurrences of n -gram s in x
 $C(the, y) = 1$ $C(most, y) = 1$ $C(natural\ form, y) = 1$

Reference-Based Evaluation: BLEU



***n*-gram precision**

How many of the *n*-grams actually occur in the reference?

$$P_n(\hat{y}, y) = \frac{\sum_{s \in G_n(\hat{y})} \min(C(s, \hat{y}), C(s, y))}{\sum_{s \in G_n(\hat{y})} C(s, \hat{y})}$$

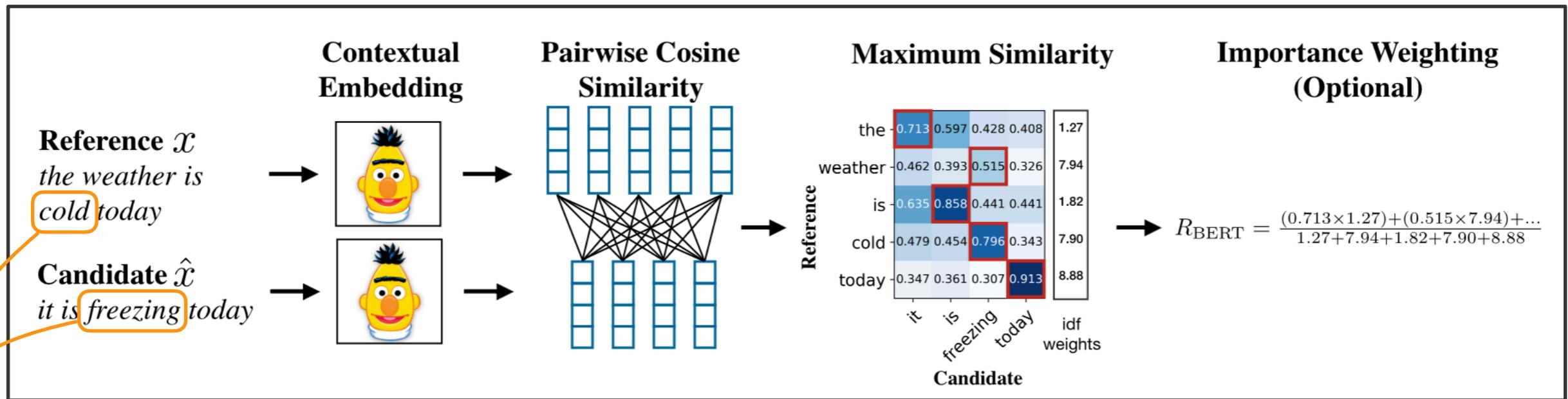
Brevity penalty

$$\text{BP}(\hat{y}, y) = \begin{cases} 1 & |\hat{y}| \geq |y| \\ e^{(1 - (|y|/|\hat{y}|))} & |\hat{y}| < |y| \end{cases}$$

$$\text{BLEU} = \text{BP}(\hat{y}, y) \exp \left(\sum_{n=1}^N \frac{1}{N} \ln P_n(\hat{y}, y) \right)$$

In practice: Average *n*-gram precision, for up to $N = 4$

Reference-Based Evaluation: Representation Similarity



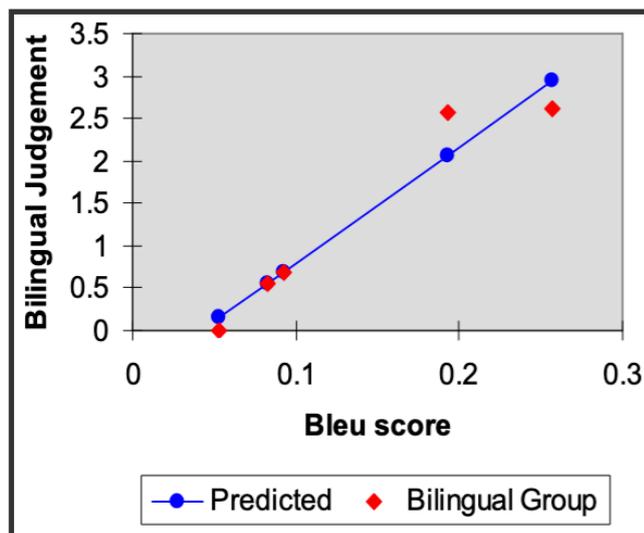
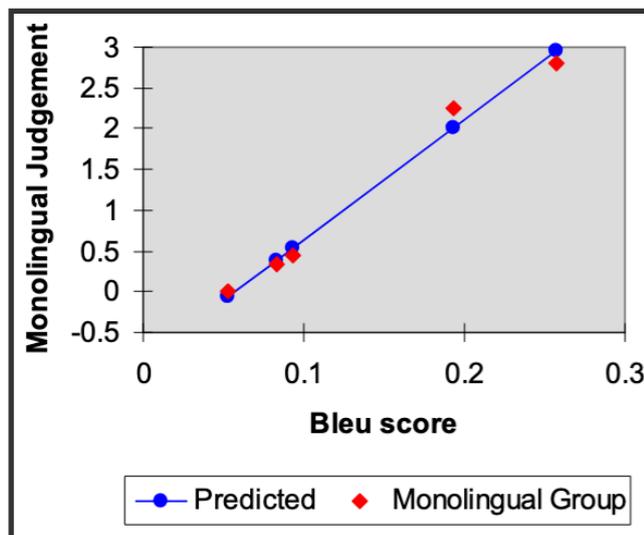
No n -gram overlap,
but should still get
some credit!

BERTScore, Zhang et al. 2020

Correlation with Human Judgment



Does our automatic metric reflect human judgments?



Papineni et al. 2002

Metric	en↔cs (5/5)	en↔de (16/16)	en↔et (14/14)	en↔fi (9/12)	en↔ru (8/9)	en↔tr (5/8)	en↔zh (14/14)
BLEU	.970/.995	.971/.981	.986/.975	.973/.962	.979/.983	.657/.826	.978/.947
ITER	.975/.915	.990/.984	.975/.981	.996/.973	.937/.975	.861/.865	.980/ -
RUSE	.981/ -	.997/ -	.990/ -	.991/ -	.988/ -	.853/ -	.981/ -
YiSi-1	.950/.987	.992/.985	.979/.979	.973/.940	.991/.992	.958/.976	.951/.963
P_{BERT}	.980/.994	.998/.988	.990/.981	.995/.957	.982/.990	.791/.935	.981/.954
R_{BERT}	.998/.997	.997/.990	.986/.980	.997/.980	.995/.989	.054/.879	.990/.976
F_{BERT}	.990/.997	.999/.989	.990/.982	.998/.972	.990/.990	.499/.908	.988/.967
$F_{\text{BERT}}(\text{idf})$.985/.995	.999/.990	.992/.981	.992/.972	.991/.991	.826/.941	.989/.973

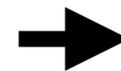
Zhang et al. 2020

Reference-Free Text Generation



- **Input:** maybe a natural language prompt, but nothing very complex
- **Output:** long piece of text

PREMISE: After years of being content with only a small inheritance, Sarah's life is turned upside down when she discovers she is actually a millionaire. She must learn to navigate her new life of luxury while also dealing with the guilt she feels over her new-found fortune.



GENERATED STORY:

Sarah Jensen never knew she had inherited a fortune until her mother died. In fact, she had never met her father ...[15 words]...
The only thing Sarah did know was that he had died long ago and that her mother had been left a sizeable inheritance. ...[23 words]...
Sarah's mother never spent any of the money ... all that mattered to her was how much it would mean to her daughter when she inherited it ...[81 words]...
Sarah learned that she was a millionaire. ...[417 words]...
She would never have had a chance like this - an opportunity to be financially independent, to live on her own ...[544 words]...
Now that she was rich, things were going to be different for her. She could afford a hotel suite and a lavish meal if she wanted it. ...[450 words]...
The words "Forgive me, father, for I have sinned" came unbidden into her mind as she reached out for her drink and took a large sip straight from the glass. ...[383 words]...
But the guilt was weighing on her now. ...[346 words]...

Human Evaluation



- Pairwise preference comparisons between outputs
 - Overall preference
 - Across different axes
- Identification of specific error types
- Humanlikeness

Human Evaluation



Pairwise Preference

Error Analysis

Humanlikeness

Questions:

- 1) Which story do you prefer / find more interesting overall?
 - Story A
 - Story B
 - Both are about equally good
 - Neither is good
- 2) Which story has a more coherent overarching plot?
 - Story A
 - Story B
 - Both are about equally good
 - Neither is good
- 3) Which story's plot is closer to the premise?
 - Story A
 - Story B
 - Both are about equally good
 - Neither is good
- 4) Indicate which of the following problems are present in Story A (possibly none, possibly more than one).
 - Jarring change(s) in narration or style
 - Factual inconsistencies/oddities
 - Very confusing or hard to understand
 - Often ungrammatical or disfluent
 - Highly repetitive
 - None of the above
- 5) Indicate which of the following problems are present in Story B (possibly none, possibly more than one).
 - Jarring change(s) in narration or style
 - Factual inconsistencies/oddities
 - Very confusing or hard to understand
 - Often ungrammatical or disfluent
 - Highly repetitive
 - None of the above
- 6) Do you think Story A was written by a human?
 - Yes
 - No
- 7) Do you think Story B was written by a human?
 - Yes
 - No

1. **Interesting.** Interesting to the reader.
2. **Coherent.** Plot-coherent.
3. **Relevant.** Faithful to the initial premise.
4. **Humanlike.** Judged to be human-written.

We additionally track how often generated stories suffer from any of the following writing issues:

1. *Narration.* Jarring change(s) in narration and/or style.
2. *Inconsistent.* Factually inconsistent or containing very odd details.
3. *Confusing.* Confusing or difficult to follow.
4. *Repetitive.* Highly repetitive.
5. *Disfluent.* Frequent grammatical errors.

Method	Interesting ↑	Coherent ↑	Relevant ↑	Humanlike ↑	Misc. Problems ↓
ROLLING	45.0	45.7	44.0	74.0	1.20
RE ³	54.3	60.0	64.0	83.3	1.07
ROLLING-FT	52.7	48.7	49.3	74.7	1.48
RE ³	53.7	60.0	65.3	80.0	1.35

LLM-as-a-Judge



- Human evaluation is expensive
- Maybe we can just prompt LLMs to judge for us?
- **Open question!**

Communicative Success



- Language is all about **getting things done in the world**
 - Directing a listener's attention to something
 - Instructing or suggesting a listener to do something
 - Acquiring information that someone else has
 - Teaching something to someone else
 - ...
- How well do our systems take action via language?

Evaluating NLG through Communicative Success



- Example task: reference game
- Input: image and target object



Evaluating NLG through Communicative Success



- Example task: reference game
- Input: image and target object
- Output: referring expression



Evaluating NLG through Communicative Success



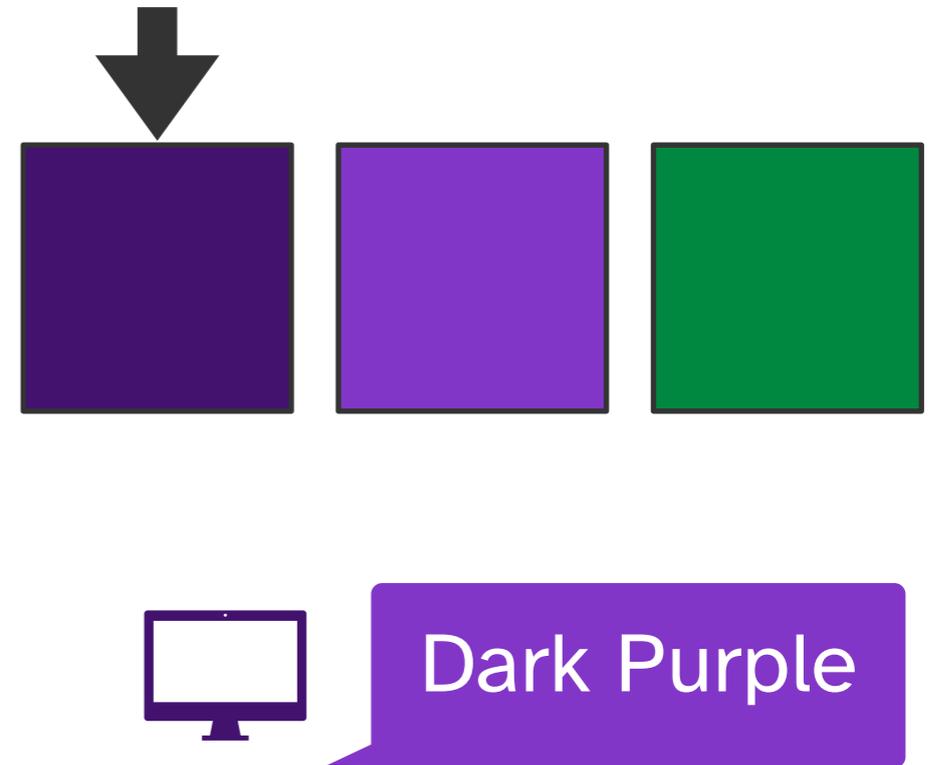
- Example task: reference game
- Input: image and target object
- Output: referring expression
- Communicative success is achieved if the listener, who has access to the image, can successfully identify the target



Evaluating NLG through Communicative Success



- Example task: reference game
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Evaluating NLG through Communicative Success



- Example task: reference game
- Input: image and target object
- Output: referring expression
- Communicative success is achieved if the listener, who has access to the image, can successfully identify the target

really easy to evaluate!



Dark Purple



Dialogue and Interactive Systems



- Language is all about **interaction**:
 - How do the utterances we produce influence the world around us?
 - How do other language users change their language use in response to yours?
- **Dynamic properties of interaction**
 - Formation of common ground
 - Alignment
- We need to study models in multi-turn interaction!

Dialogue and Interactive Systems



But evaluating interaction is hard:



What's a good place to get gluten free pastries in Berkeley?



For dedicated gluten-free pastries in Berkeley, your absolute best bet is **Mariposa Baking Company.**

A gluten-free pastry lover in Berkeley!
You're in luck because Berkeley is a haven for GF enthusiasts! Here are some top recommendations for gluten-free pastries in Berkeley:

1. Bette's Oceanview Diner (1807 4th St, Berkeley) — This beloved diner has

...

Dialogue and Interactive Systems



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What's a good place to get gluten free pastries in Berkeley?



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That's too far from me. Do you have a recommendation near downtown Berkeley?

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Are any of these open on Sundays?

Dialogue and Interactive Systems



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...

because user behavior changes depending on system behavior!

Slot-Filling Dialogue Systems



- In well-defined tasks, we can define **slots** that need to be filled before providing information to the user
- However, this reduces the expressivity of dialogue:
 - “I was hoping you could **recommend** something”
 - “Are there any churches **or** museums on the east side?”
 - “I would like the **latest** train leaving that will arrive by 9:15 please.”

A: Hello! This is Concierge Service. I can help you find attractions, hotels, restaurants in Cambridge.

U: I'm looking for a restaurant.

[Domain=Restaurant]

A: What cuisine would you like?

U: I would like Italian food.

[Domain=Restaurant, Food=Italian]

A: Would you like a cheap, moderate or expensive Italian restaurant?

U: Actually, never mind, let's do Chinese.

[Domain=Restaurant, Food=Chinese]

A: Would you like a cheap, moderate or expensive Chinese restaurant?

User Simulators



- Use another model (or a set of rules) to “simulate” a human user
 - Allows scaling up experiments, including to more complex domains
 - Allows stability across system evaluations
- But doesn't reflect the real-world complexity of actual use case, e.g., user adaptation to systems over time
- **Open question!**

Evaluation via Benchmarking



- Given a model, we want to know whether it can “do” the task (i.e., its performance on a task metric)
- We typically evaluate this by measuring how well it can generalize to new instances of the task
- What is “new”?
 - Generally speaking: anything we didn’t have access to when implementing our model
- How can we estimate performance on new task instances?
 - Simulate it using held-out data just for evaluation!
- Our current question: how do we design benchmarks that reliably tell us whether a model can “do” a task?

Why do we need benchmarks?



- Estimating how well our models will work on real-world data
- Shared understanding of model performance with standardized evaluations
- Building trust within a community in proving how well a new model does
- Driving progress towards specific tasks and capabilities

Evaluation Data



Before pretrained models, nearly all datasets came with splits, assumed to be IID:

Training data
For updating model parameters directly

Validation data
For deciding when to stop training

Development data
For performing ablations, choosing hyperparameters, etc.

Test data
For estimating performance on the “real” task

Evaluation Data



Before pretrained models, nearly all datasets came with splits, assumed to be IID:

Training data
For updating model parameters directly

Validation data
For deciding when to stop training

Development data
For performing ablations, choosing hyperparameters, etc.

Public test data

Private test data

Evaluation Data



Now, with pretrained LMs, we typically focus on benchmark design (i.e. collecting useful test datasets)

Training data
(we don't know what's in here!)

Test data
For estimating
performance on the
“real” task

Single-Task Benchmarks



A man inspects the uniform of a figure in some East Asian country.	contradiction C C C C C	The man is sleeping
An older and younger man smiling.	neutral N N E N N	Two men are smiling and laughing at the cats playing on the floor.
A black race car starts up in front of a crowd of people.	contradiction C C C C C	A man is driving down a lonely road.
A soccer game with multiple males playing.	entailment E E E E E	Some men are playing a sport.
A smiling costumed woman is holding an umbrella.	neutral N N E C N	A happy woman in a fairy costume holds an umbrella.

SNLI, Bowman et al. 2015

... [_{Arg0} the company] to ... offer [_{Arg1} a 15% to 20% stake] [_{Arg2} to the public] (wsj_0345)¹

... [_{Arg0} Sotheby's] ... offered [_{Arg2} the Dorrance heirs] [_{Arg1} a money-back guarantee] (wsj_1928)

... [_{Arg1} an amendment] offered [_{Arg0} by Rep. Peter DeFazio] ... (wsj_0107)

... [_{Arg2} Subcontractors] will be offered [_{Arg1} a settlement] ... (wsj_0187)

PropBank, Palmer et al. 2005

Third-quarter sales in Europe were exceptionally strong, boosted by promotional programs and new products – although weaker foreign currencies reduced the company's earnings.

Michelle lives in a hotel room, and although she drives a canary-colored Porsche, she hasn't time to clean or repair it.

Most oil companies, when they set exploration and production budgets for this year, forecast revenue of \$15 for each barrel of crude produced.

The Penn Discourse Treebank, Prasad et al. 2008

What is the capital of the state with the largest population?
answer(C, (capital(S,C), largest(P, (state(S), population(S,P))))).

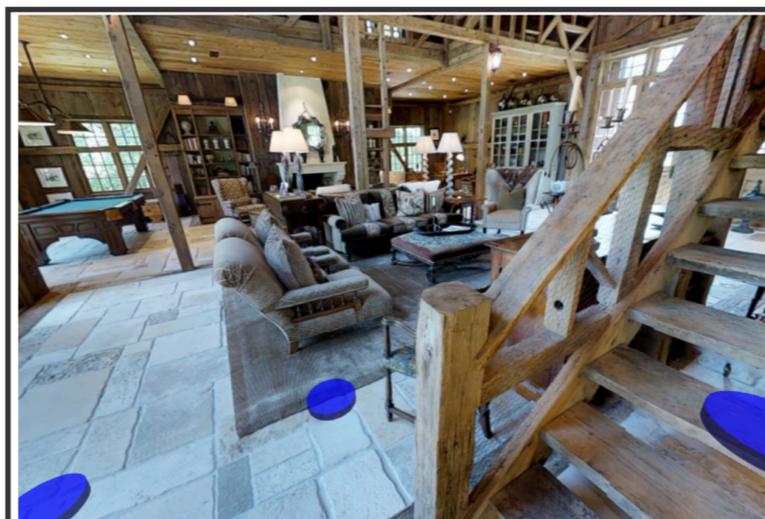
What are the major cities in Kansas?
answer(C, (major(C), city(C), loc(C,S), equal(S, stateid(kansas))))).

GeoQuery, Zelle and Mooney 1996

Battle-tested/NNP*/JJ industrial/JJ managers/NNS here/RB always/RB buck/VB*/VBP up/IN*/RP nervous/JJ newcomers/NNS with/IN the/DT tale/NN of/IN the/DT first/JJ of/IN their/PP\$ countrymen/NNS to/TO visit/VB Mexico/NNP ,/, a/DT boatload/NN of/IN samurai/NNS*/FW warriors/NNS blown/VBN ashore/RB 375/CD years/NNS ago/RB ./.

"/" From/IN the/DT beginning/NN ,/, it/PRP took/VBD a/DT man/NN with/IN extraordinary/JJ qualities/NNS to/TO succeed/VB in/IN Mexico/NNP ,/, "/" says/VBZ Kimihide/NNP Takimura/NNP ,/, president/NN of/IN Mitsui/NNS*/NNP group/NN 's/POS Kensetsu/NNP Engineering/NNP Inc./NNP unit/NN ./.

The Penn Treebank, Marcus et al. 1993



Instruction: Head upstairs and walk past the piano through an archway directly in front. Turn right when the hallway ends at pictures and table. Wait by the moose antlers hanging on the wall.

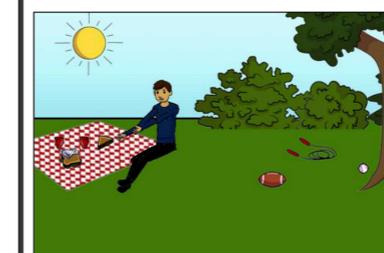
Room-to-Room, Anderson et al. 2018



What color are her eyes?
What is the mustache made of?



How many slices of pizza are there?
Is this a vegetarian pizza?



Is this person expecting company?
What is just under the tree?



Does it appear to be rainy?
Does this person have 20/20 vision?

VQA, Agrawal et al. 2015

Single-Task Benchmarks



		Classification
A man inspects the uniform of a figure in some East Asian country.	contradiction C C C C C	The man is sleeping
An older and younger man smiling.	neutral N N E N N	Two men are smiling and laughing at the cats playing on the floor.
A black race car starts up in front of a crowd of people.	contradiction C C C C C	A man is driving down a lonely road.
A soccer game with multiple males playing.	entailment E E E E E	Some men are playing a sport.
A smiling costumed woman is holding an umbrella.	neutral N N E C N	A happy woman in a fairy costume holds an umbrella.

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... [_{Arg0} the company] to ... off [_{Arg0} (wsj_0345)]¹

... [_{Arg0} Sotheby's] ... offered [_{Arg2} the Dorrance heirs] [_{Arg1} a money-back guarantee] (wsj_1928)

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Michelle lives in a hotel room, and although she drives a canary-colored Porsche, she hasn't time to clean or repair it.

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answer(C, (capital(S,C), largest(P, (state(S), population(S,P))))).

What are the major cities in Kansas?
answer(C, (major(equal(S, stateid(k

Structured Prediction

GeoQuery, Zelle and Mooney 1996

.../JJ industrial/JJ managers/NNS here/RB
.../VBP up/IN*/RP nervous/JJ newcomers/NNS with/IN
.../DT first/JJ of/IN their/PP\$ countrymen/NNS to/TO
visit/VB Mexico/NNP ,/, a/DT boatload/NN of/IN samurai/NNS*/FW
warriors/NNS blown/VBN ashore/RB 375/CD years/NNS ago/RB ./.
"/" From/IN the/DT beginning/NN ,/, it/PRP took/VBD a/DT man/NN
with/IN extraordinary/JJ qualities/NNS to/TO succeed/VB in/IN Mexico/NNP ,/,
"/" says/VBZ Kimihide/NNP Takimura/NNP ,/, president/NN of/IN
Mitsui/NNS*/NNP group/NN 's/POS Kensetsu/NNP Engineering/NNP Inc./NNP
unit/NN ./.

Tagging

The Penn Treebank, Marcus et al. 1993



Sequence Generation

Instruction: Head upstairs and walk past the piano through an archway directly in front. Turn right when the hallway ends at pictures and table. Wait by the moose antlers hanging on the wall.

Room-to-Room, Anderson et al. 2018



Question Answering

What color are her eyes?
What is the mustache made of?

How many slices of pizza are there?
Is this a vegetarian pizza?

Is this person expecting company?
What is just under the tree?

Does it appear to be rainy?
Does this person have 20/20 vision?

VQA, Agrawal et al. 2015

Marcus et al. 1993, CL, "Building a large annotated corpus of English"; Zelle and Mooney 1996, AAAI, "Learning to parse database queries using inductive logic programming"; Palmer et al. 2005, CL, "The Proposition Bank"; Prasad et al. 2008, LREC, "The Penn Discourse TreeBank 2.0"; Bowman et al. 2015, EMNLP, "A large annotated corpus for learning natural language inference"; Agrawal et al. 2015, ICCV, "VQA"; Anderson et al. 2018, CVPR, "Vision-and-language navigation"

How to Build a Benchmark



1. How do we source data to annotate?
2. How do we acquire annotations?
3. How do we verify our annotations are correct?

Tasks Requiring Expertise



- Case study: semantic role labeling (PropBank)

... [_{Arg0} the company] to ... *offer* [_{Arg1} a 15% to 20% stake] [_{Arg2} to the public] (wsj_0345)¹

... [_{Arg0} Sotheby's] ... *offered* [_{Arg2} the Dorrance heirs] [_{Arg1} a money-back guarantee] (wsj_1928)

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... [_{Arg1} an amendment] *offered* [_{Arg0} by Rep. Peter DeFazio] ... (wsj_0107)

... [_{Arg2} Subcontractors] will be *offered* [_{Arg1} a settlement] ... (wsj_0187)

1. Collect some source data to annotate
2. Develop an annotation scheme
3. Train annotators
4. Annotate the data! (May take a couple of years)

Acquiring Source Data



Where do you get lots of text before the Internet was widely used?

- Scanned documents
- Transcribed voice messages
- Multilingual data?
- Early Internet: Wikipedia, blogs, reviews

... [_{Arg0} the company] to ... offer [_{Arg1} a 15% to 20% stake] [_{Arg2} to the public] (wsj_0345)¹

... [_{Arg0} Sotheby's] ... offered [_{Arg2} the Dorrance heirs] [_{Arg1} a money-back guarantee] (wsj_1928)

... [_{Arg1} an amendment] offered [_{Arg0} by Rep. Peter DeFazio] ... (wsj_0107)

... [_{Arg2} S ...]

Table 4 Marcus et al. 1992
Penn Treebank (as of 11/92).

Description	Tagged for Part-of-Speech (Tokens)	Skeletal Parsing (Tokens)
Dept. of Energy abstracts	231,404	231,404
Dow Jones Newswire stories	3,065,776	1,061,166
Dept. of Agriculture bulletins	78,555	78,555
Library of America texts	105,652	105,652
MUC-3 messages	111,828	111,828
IBM Manual sentences	89,121	89,121
WBUR radio transcripts	11,589	11,589
ATIS sentences	19,832	19,832
Brown Corpus, retagged	1,172,041	1,172,041
Total:	4,885,798	2,881,188

Icon in Figure 5 Nivre et al. 2016

Icon in Figure 5	Genre
	bible
	blog
	fiction
	grammar examples
	legal text
	medical text
	news
	non-fiction
	reviews
	spoken
	social (other user-generated content)
	web
	wikipedia

Table 5: Genres present in the UD treebanks.

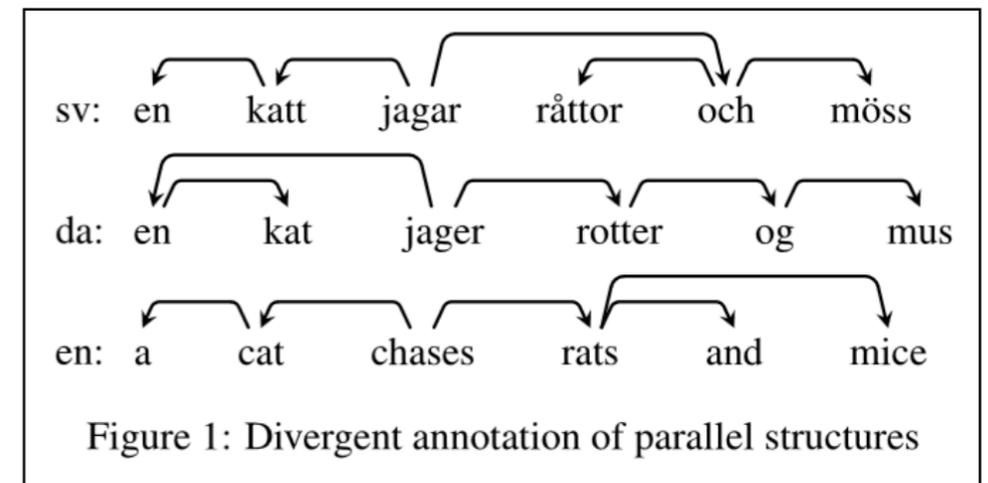
https://en.wikipedia.org/wiki/Brown_Corpus

Developing an Annotation Scheme



- Desiderata
 - Simplicity
 - Consistency
 - Leaving room for ambiguity
 - Generalizability, to domains and across languages (this is hard!)
- User-friendly interface for annotation

... [_{Arg0} the company] to ... offer [_{Arg1} a 15% to 20% stake] [_{Arg2} to the public] (wsj_0345)¹
... [_{Arg0} Sotheby's] ... offered [_{Arg2} the Dorrance heirs] [_{Arg1} a money-back guarantee] (wsj_1928)
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Dependency annotation
without standardization
(Nivre et al. 2016)

Annotation Process



... [_{Arg0} the company] to ... offer [_{Arg1} a 15% to 20% stake] [_{Arg2} to the public] (wsj_0345)¹
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... [_{Arg2} Subcontractors] will be offered [_{Arg1} a settlement] ... (wsj_0187)

- Train annotators with guidelines
- Need to be able to manage annotator disagreements and confusions
- Can bootstrap annotation with smaller, less-performant models

The annotators themselves were drawn from a variety of backgrounds, from undergraduates to holders of doctorates, including linguists, computer scientists, and others. Undergraduates have the advantage of being inexpensive but tend to work for only a few months each, so they require frequent training. Linguists make the best overall judgments although several of our nonlinguist annotators also had excellent skills. The learning curve for the annotation task tended to be very steep, with most annotators becoming comfortable with the process within three days of work. This

**PropBank (Palmer et al. 2005)
has a 66-page annotation
guidelines document**

Alternative to Experts: Crowdsourcing



- How to reduce annotation cost and time? If you don't need experts, use cheaper labor
- Very popular option: crowdsourcing platforms (MTurk, Prolific...)
- Basic pipeline
 - Design and pilot task (critical step!)
 - Recruit crowdworkers, e.g., via a qualification task
 - Incentive design
 - Deploying task and managing workers
- It's not trivial to do crowdsourcing well!
 - Well = getting high quality data = **respecting workers as people**
 - Lots of HCI work on crowdsourcing ecosystems and tools workers use

Find the Answer to this Question

We believe that the answer to the question

What is Mark Twain's real name?

is contained in the below article.

Please scan the article and copy the **complete sentence** that best answers the question and paste it in the first box below. Please also identify the **answer itself** in the answer sentence and copy it in the second box below. Please copy and paste only! Do not fill the boxes by typing!

Occasionally, it might happen that you need to copy two consecutive sentences. In the *unlikely* event that the article does not contain the answer, please enter "NA" (without the quotes).

This is the article:

Twain's Account of Hanging Found

VIRGINIA CITY, Nev. (AP) -- The folklore of the Old West is often a mishmash of myth and reality, so an archivist knew he was onto something when he discovered a newspaper account of one of the state's first public hangings.

"I can see that stiff straight corpse hanging there yet," wrote the reporter, "with its black pillow-cased head turned rigidly to one side, and the purple streaks creeping through the hands and driving the fleshy hue of life before them. Ugh!"

The reporter? Samuel Langhorne Clemens, better known as Mark Twain.

...

Please COPY AND PAST the COMPLETE ANSWER SENTENCE from the article here:

Please COPY AND PASTE (do not type) the ANSWER (usually one or a few words) from the answer sentence here:

Finished with this HIT?

Submit HIT

Let someone else do it?

Return HIT

Kaisser and Lowe 2008

Question Answering Benchmarks: Two Case Studies



- Task: question answering (QA)
 - Input: natural language question (optional: passage)
 - Output: answer to the question
 - Evaluation metric: whether a the model's answer is equivalent to the gold-standard answer
- How to collect a benchmark like this?
 - Ask people to ask questions
 - Observe questions people ask

Crowdsourcing QA: SQuAD



In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under **gravity**. The main forms of precipitation include drizzle, rain, sleet, snow, **graupel** and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals **within a cloud**. Short, intense periods of rain in scattered locations are called "showers".

What causes precipitation to fall?

gravity

What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?

graupel

Where do water droplets collide with ice crystals to form precipitation?

within a cloud

Figure 1: Question-answer pairs for a sample passage in the SQuAD dataset. Each of the answers is a segment of text from the passage.

Paragraph 1 of 43

Spend around 4 minutes on the following paragraph to ask 5 questions! If you can't ask 5 questions, ask 4 or 3 (worse), but do your best to ask 5. Select the answer from the paragraph by clicking on 'Select Answer', and then highlight the smallest segment of the paragraph that answers the question.

Oxygen is a chemical element with symbol O and atomic number 8. It is a member of the chalcogen group on the periodic table and is a highly reactive nonmetal and oxidizing agent that readily forms compounds (notably oxides) with most elements. By mass, oxygen is the third-most abundant element in the universe, after hydrogen and helium. At standard temperature and pressure, two atoms of the element bind to form dioxygen, a colorless and odorless diatomic gas with the formula O₂.

2. Diatomic oxygen gas constitutes 20.8% of the Earth's atmosphere. However, monitoring of atmospheric oxygen levels show a global downward trend, because of fossil-fuel burning. Oxygen is the most abundant element by mass in the Earth's crust as part of oxide compounds such as silicon dioxide, making up almost half of the crust's mass.

When asking questions, **avoid using** the same words/phrases as in the paragraph. Also, you are encouraged to pose **hard questions**.

Ask a question here. Try using your own words

Select Answer

Ask a question here. Try using your own words

Select Answer

Figure 2: The crowd-facing web interface used to collect the dataset encourages crowdworkers to use their own words while asking questions.

Crowdsourcing QA: SQuAD



Step 1. Curate passages from Wikipedia

- popular articles
- remove images/figures/tables and short paragraphs
- split into train/dev/test articles
- keep around individual paragraphs

Step 2. Ask people to write questions about passages

- provide examples of good/bad questions on a sample passage
- provide guidance about how they should ask questions

Step 3. Question authors select answer spans in the passage

Paragraph 1 of 43

Spend around 4 minutes on the following paragraph to ask 5 questions! If you can't ask 5 questions, ask 4 or 3 (worse), but do your best to ask 5. Select the answer from the paragraph by clicking on 'Select Answer', and then highlight the smallest segment of the paragraph that answers the question.

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Crowdsourcing QA: SQuAD



- For articles in the dev/test sets, collect 2 additional answers for each question:
 - To ensure high-quality test labels
 - To compute agreement among annotators
- Problems with SQuAD?
 - All questions are answerable wrt. the paragraph provided
 - All answers are immediately available directly in the passage (more evaluating “reading comprehension” than general QA)
 - Limited domain

Paragraph 1 of 43

Spend around 4 minutes on the following paragraph to ask 5 questions! If you can't ask 5 questions, ask 4 or 3 (worse), but do your best to ask 5. Select the answer from the paragraph by clicking on 'Select Answer', and then highlight the smallest segment of the paragraph that answers the question.

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Select Answer

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Select Answer

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Crowdsourcing QA: Natural Questions



Step 1. Curate real questions from the Google search engine, paired with Wikipedia articles

- queries of 8 words or more issued to the Google search engine by multiple users in a short period of time
- queries where a Wikipedia page appears in the top 5 search results

Step 2. Get annotations of “long” and (optional) “short” answers to the questions

- long answers: spans of the Wikipedia article
- short answers: entity mentioned in the long answer that directly answers the question

Step 3. Get “experts” to evaluate whether the answers are correct to each of the questions

Example 1

Question: what color was john wilkes booth’s hair

Wikipedia Page: John_Wilkes_Booth

Long answer: Some critics called Booth “the handsomest man in America” and a “natural genius”, and noted his having an “astounding memory”; others were mixed in their estimation of his acting. He stood 5 feet 8 inches (1.73 m) tall, had jet-black hair, and was lean and athletic. Noted Civil War reporter George Alfred Townsend described him as a “muscular, perfect man” with “curling hair, like a Corinthian capital”.

Short answer: jet-black

Example 2

Question: can you make and receive calls in airplane mode

Wikipedia Page: Airplane_mode

Long answer: Airplane mode, aeroplane mode, flight mode, offline mode, or standalone mode is a setting available on many smartphones, portable computers, and other electronic devices that, when activated, suspends radio-frequency signal transmission by the device, thereby disabling Bluetooth, telephony, and Wi-Fi. GPS may or may not be disabled, because it does not involve transmitting radio waves.

Short answer: BOOLEAN:NO

Example 3

Question: why does queen elizabeth sign her name elizabeth r

Wikipedia Page: Royal_sign-manual

Long answer: The royal sign-manual usually consists of the sovereign’s regnal name (without number, if otherwise used), followed by the letter R for Rex (King) or Regina (Queen). Thus, the sign-manual of both Elizabeth I and Elizabeth II read Elizabeth R. When the British monarch was also Emperor or Empress of India, the sign manual ended with R I, for Rex Imperator or Regina Imperatrix (King-Emperor/Queen-Empress).

Short answer: NULL

NaturalQuestions vs. SQuAD?

Figure 1: Example annotations from the corpus.

Single-Task NLP



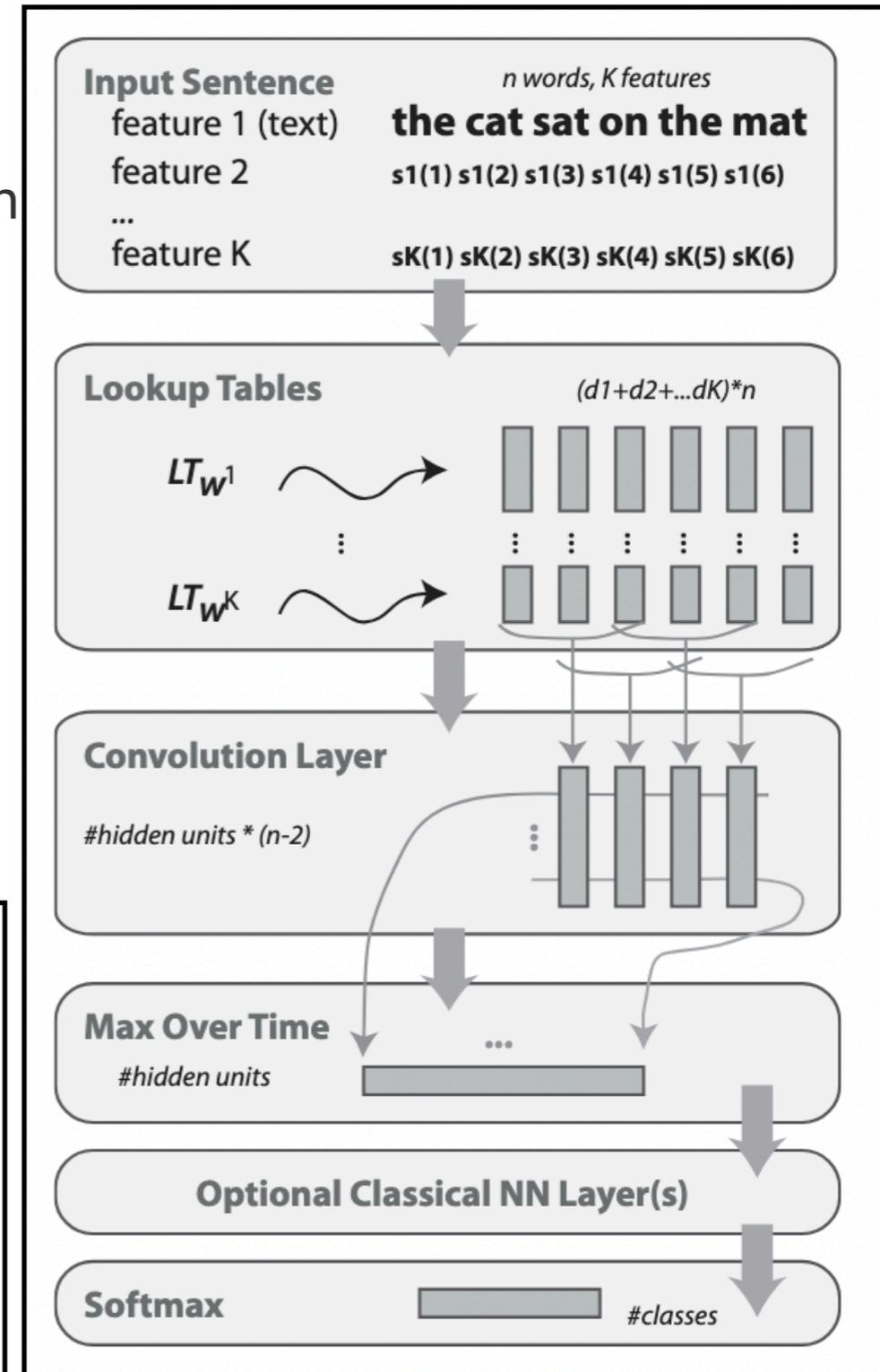
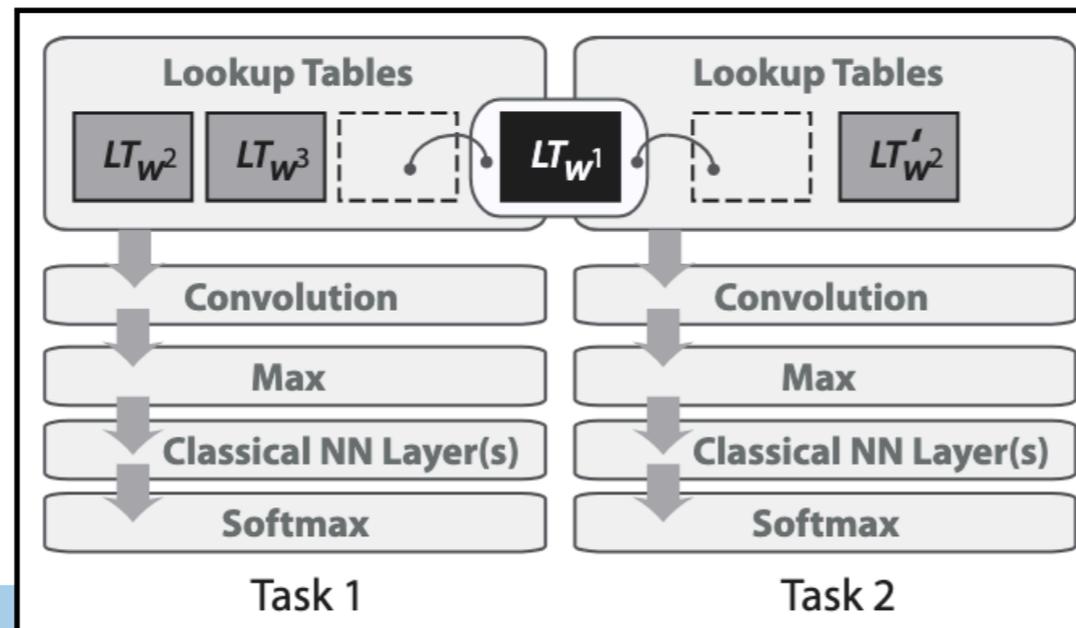
- NLP working assumptions pre-2018
 - We first need to understand the atomic units (which ones?), then we can study how they are composed to give rise to meaning
 - These compositional processes need to be modeled explicitly
 - If we want to do something beyond language modeling, we need to train a specialized model
 - Eventually, we can combine everything into an end-to-end dialogue system...
- There were some efforts to train natively multitask language models...

The Dream of Multitask NLP



- Map words to embeddings, including positional embeddings
- Convolution-based context processing for variable length sequences
- Multi-layer prediction for classification task
- End-to-end training via backpropagation on different NLP tasks (SRL, POS tagging, etc.)
- Leverage unlabeled data with a language modeling objective
- Why didn't we get GPT in 2008?

A General Deep Architecture for NLP (2008)



The Dream of Multitask NLP



Cal is in _____, California
knowledge → information extraction

I put _____ fork down on the table
syntax → POS tagging

The woman walked across the street, checking for traffic over _____ shoulder

coreference

coreference resolution

I went to the ocean to see the fish, turtles, seals, and _____

lexical semantics

word embeddings

Overall, the value I got from the two hours watching it was the sum total of the popcorn and the drink.

reasoning

question answering

The movie was _____

sentiment

sentiment classification

I'm thinking about a sequence that goes 1, 2, 3, 5, 8, 13, 21, _____

Realizing the Dream



- **What happened to our pre-2018 assumptions?**
- What we learn from language modeling looks a lot like what need for traditional NLP tasks!
- Self-supervised approaches showed we might not need to independently learn word and sentence representations
- (In fact, we can recover a lot of the structural features we were explicitly modeling before from these representations!)

Probing

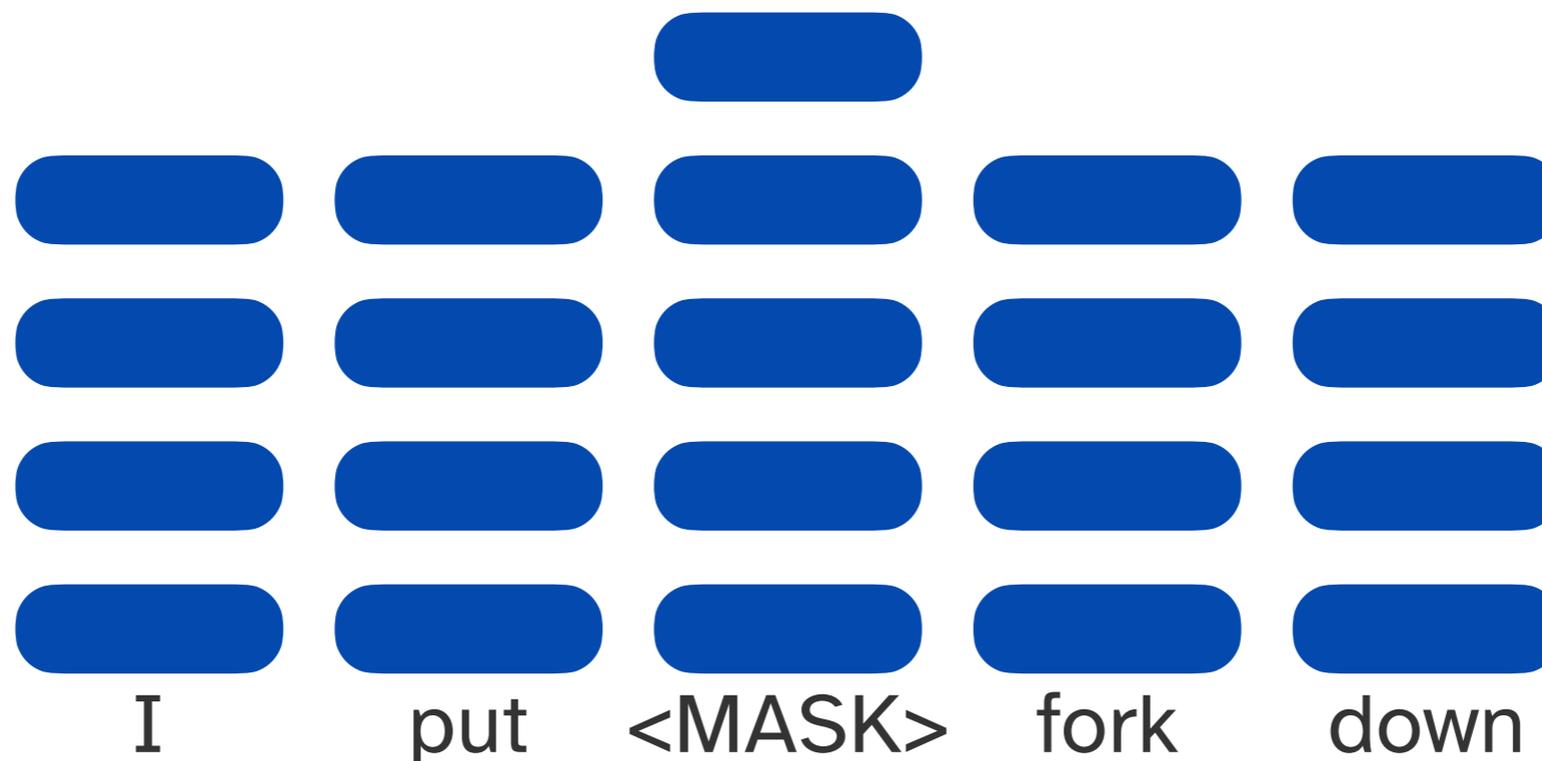


- Main research question:
 - We've trained an end-to-end language model that isn't a combination of a bunch of NLP tasks
 - But were these tasks still useful for the model to learn?
- How do we know what the model has “learned”, besides what we test it on?
- Method: probing

Probing



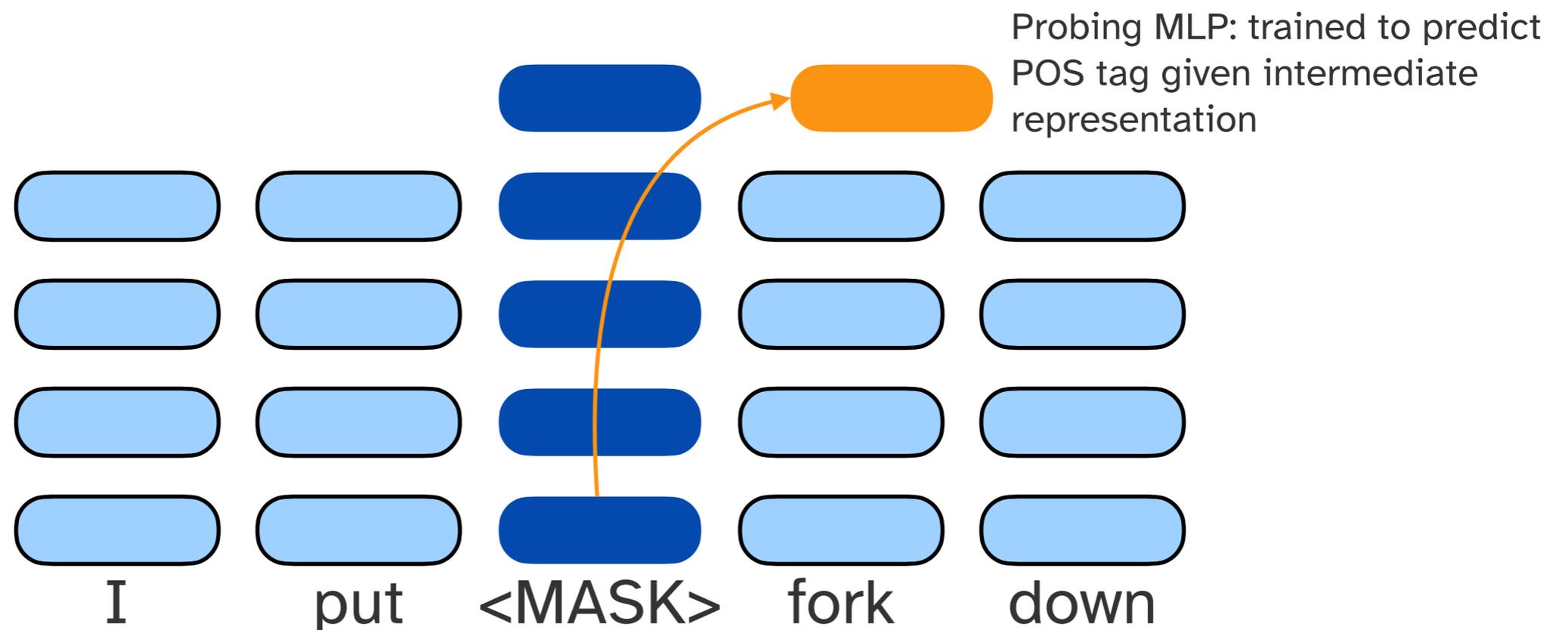
- As we run inference on a model to predict the next word, we compute intermediate vector representations (e.g., values at different transformer layers)
- Do these intermediate values contain the information relevant to an NLP task?



Probing



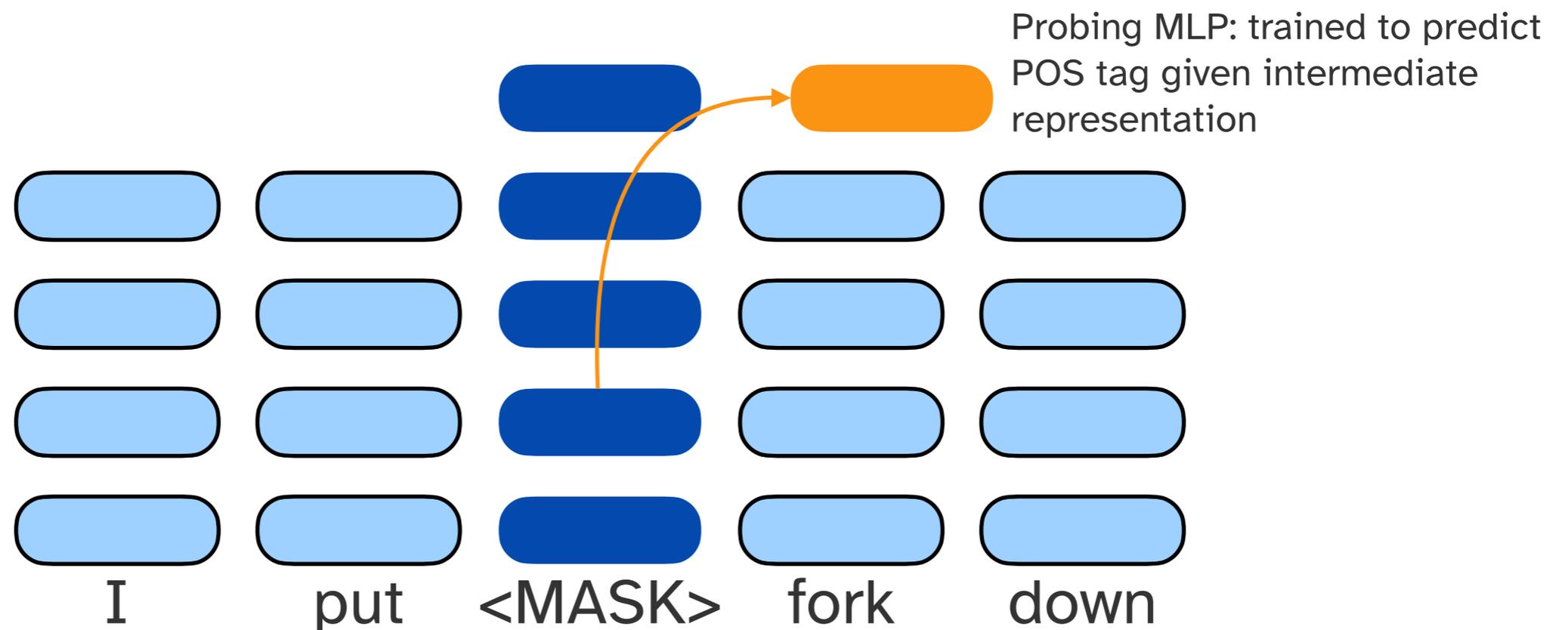
- As we run inference on a model to predict the next word, we compute intermediate vector representations (e.g., values at different transformer layers)
- Do these intermediate values contain the information relevant to an NLP task?



Probing



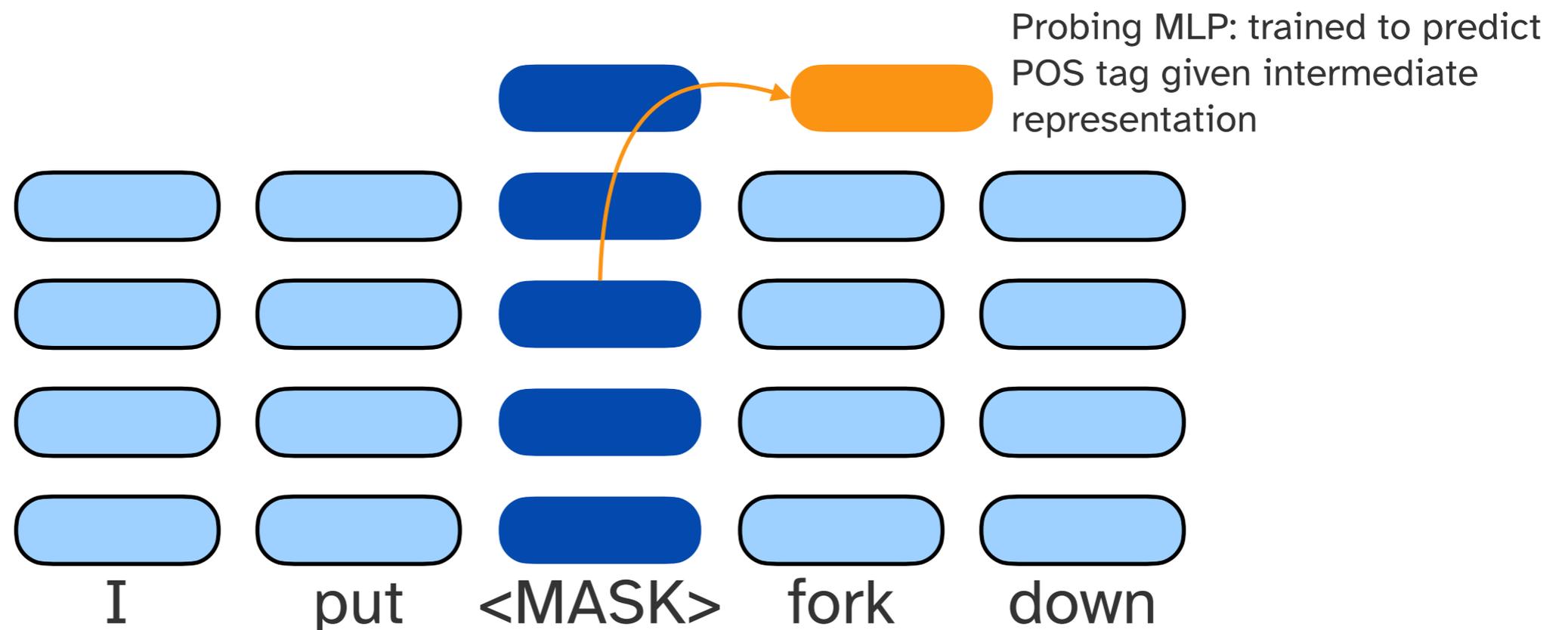
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Probing



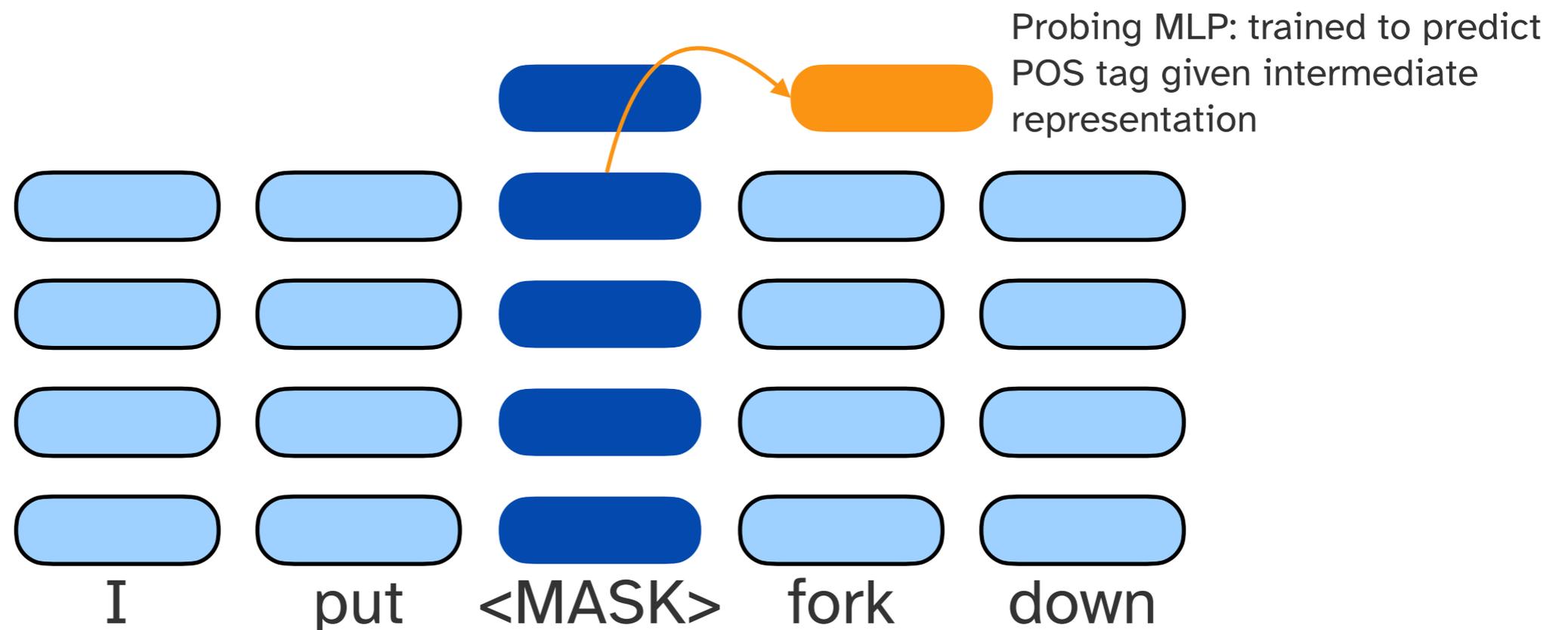
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Probing



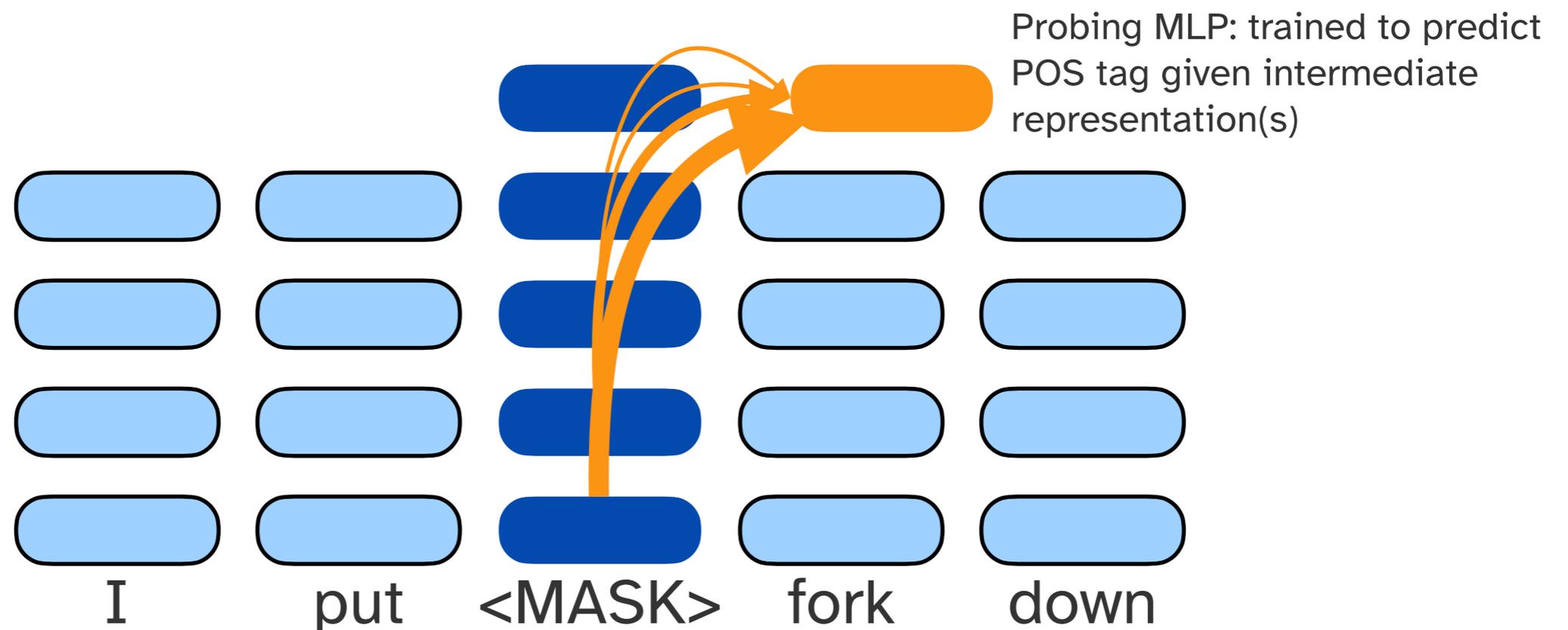
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Probing



- As we run inference on a model to predict the next word, we compute intermediate vector representations (e.g., values at different transformer layers)
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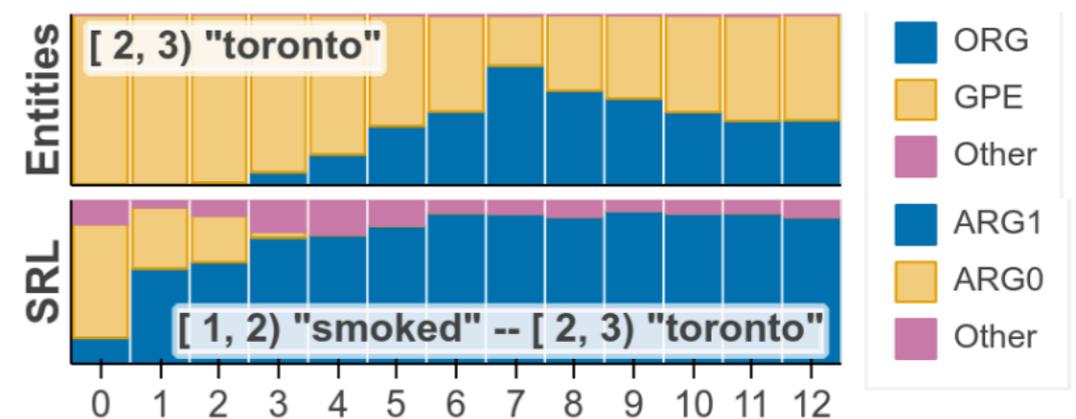


Probing

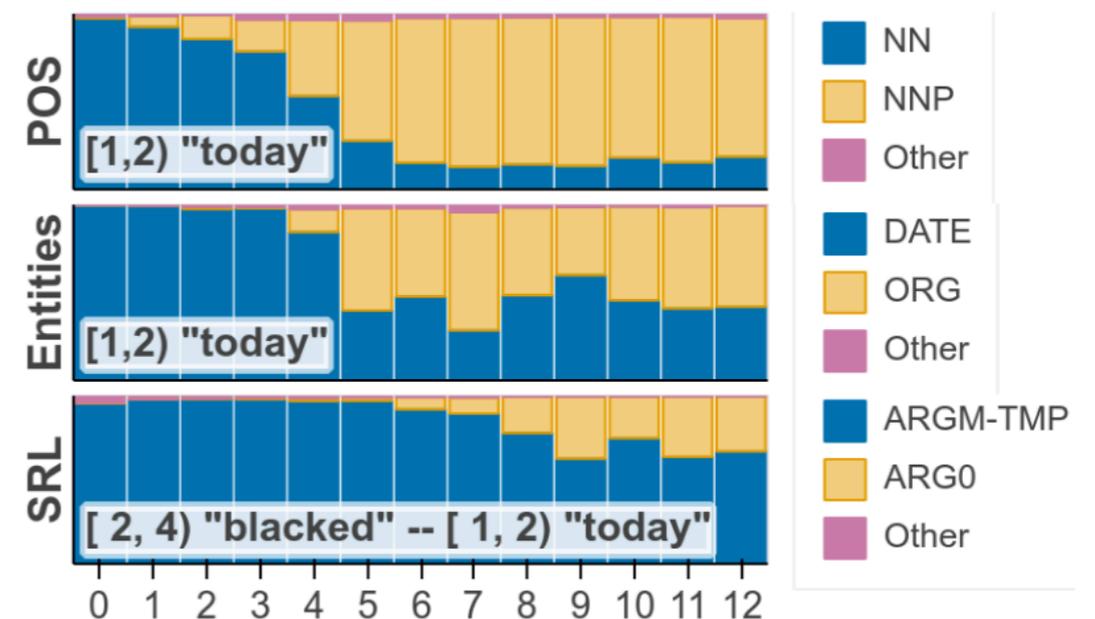


- “BERT rediscovers the classical NLP pipeline” (2019)
- Intermediate representations of BERT at different layers contain sufficient information to perform well on NLP tasks, without any task-specific training!

(a) he smoked **toronto** in the playoffs with six hits, seven walks and eight stolen bases ...



(b) china **today** blacked out a cnn interview that was ...

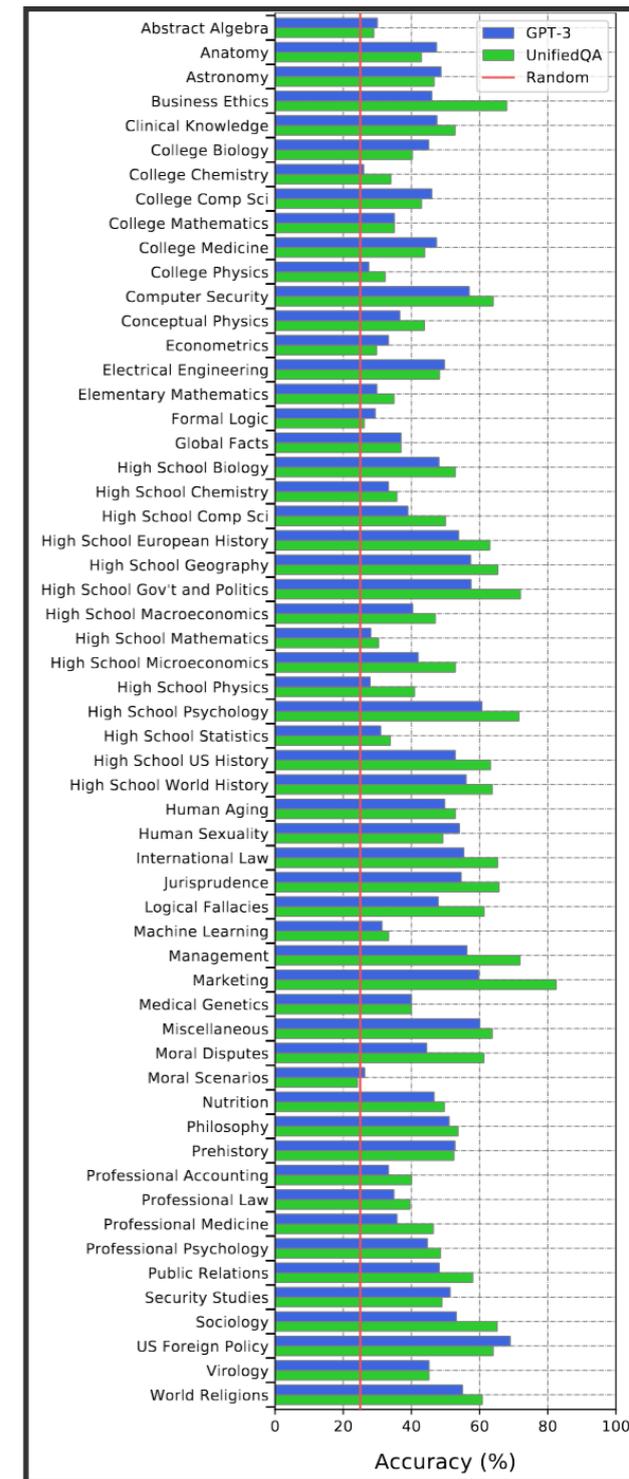


Multi-Task Benchmarks



Corpus	Train	Test	Task	Metrics	Domain
Single-Sentence Tasks					
CoLA	8.5k	1k	acceptability	Matthews corr.	misc.
SST-2	67k	1.8k	sentiment	acc.	movie reviews
Similarity and Paraphrase Tasks					
MRPC	3.7k	1.7k	paraphrase	acc./F1	news
STS-B	7k	1.4k	sentence similarity	Pearson/Spearman corr.	misc.
QQP	364k	391k	paraphrase	acc./F1	social QA questions
Inference Tasks					
MNLI	393k	20k	NLI	matched acc./mismatched acc.	misc.
QNLI	105k	5.4k	QA/NLI	acc.	Wikipedia
RTE	2.5k	3k	NLI	acc.	news, Wikipedia
WNLI	634	146	coreference/NLI	acc.	fiction books

GLUE, Wang et al. 2019

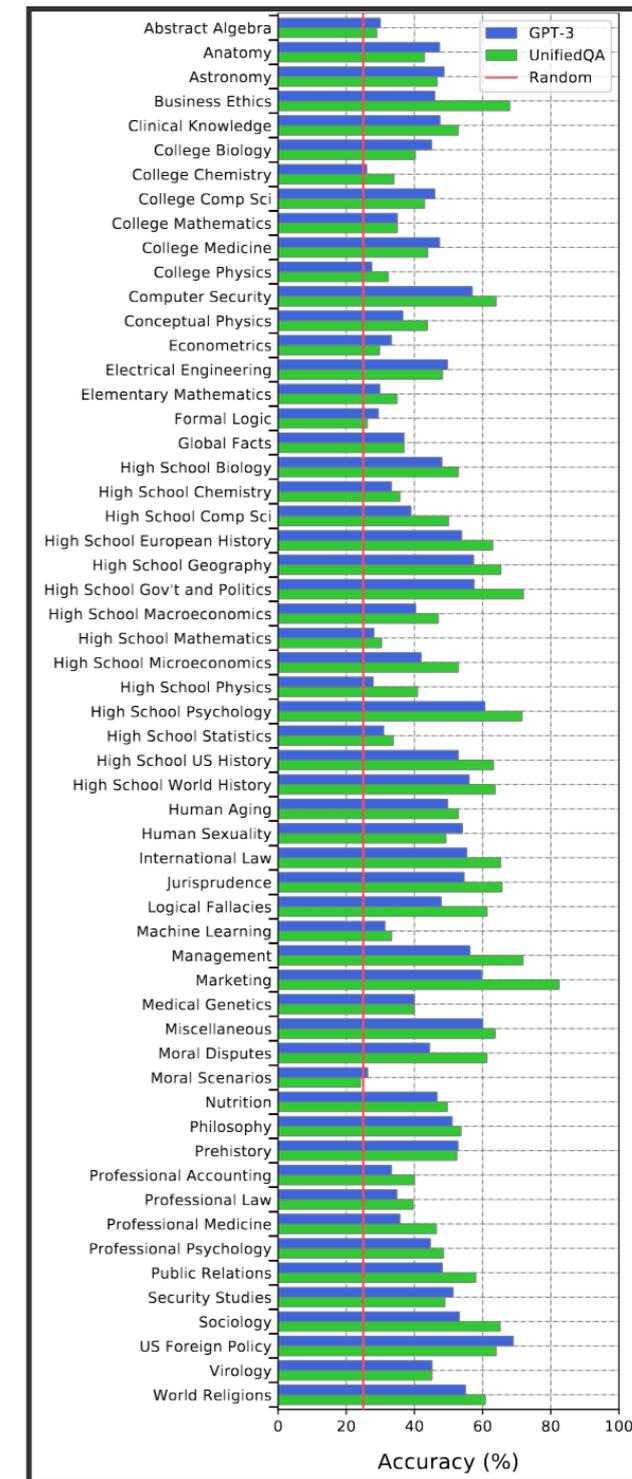


MMLU, Hendrycks et al. 2021

Multi-Task Case Study: MMLU



- Goal: questions across 57 different subject areas, at least 100 questions per subject area
- Sourcing questions:
 - Manually collected from freely available online sources
 - Practice questions for tests like GRE; questions in textbooks
 - Sorted into difficulty levels (“elementary”, “high school”, “college”, “professional”)
- Split data into few-shot development set, validation set, and test set
- Measure human performance across different groups: MTurk workers (34.5% accuracy) and real-world experts (performance at the 95th percentile of real test takers, 89.8%)

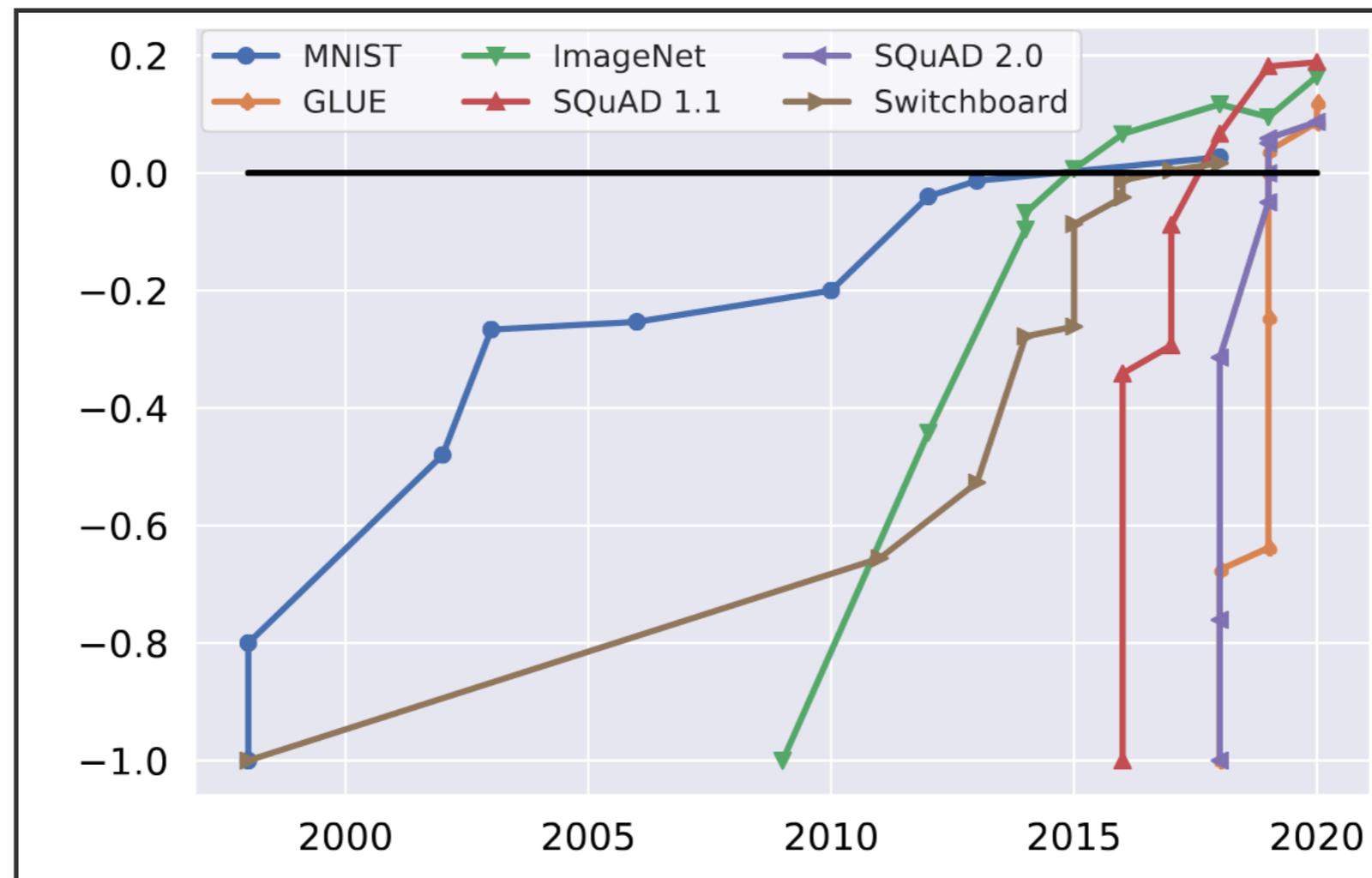


MMLU, Hendrycks et al. 2021

Capability-Pushing Benchmarks



Benchmarks are getting saturated quickly!



Kiela et al. 2021

Capability-Pushing Benchmarks



Capability-focused evaluation: choose a complex task and curate examples of it

Organic Chemistry

Methylcyclopentadiene (which exists as a fluxional mixture of isomers) was allowed to react with methyl isoamyl ketone and a catalytic amount of pyrrolidine. A bright yellow, cross-conjugated polyalkenyl hydrocarbon product formed (as a mixture of isomers), with water as a side product. These products are derivatives of fulvene. This product was then allowed to react with ethyl acrylate in a 1:1 ratio. Upon completion of the reaction, the bright yellow color had disappeared. How many chemically distinct isomers make up the final product (not counting stereoisomers)?

- A) 2
- B) 16
- C) 8
- D) 4

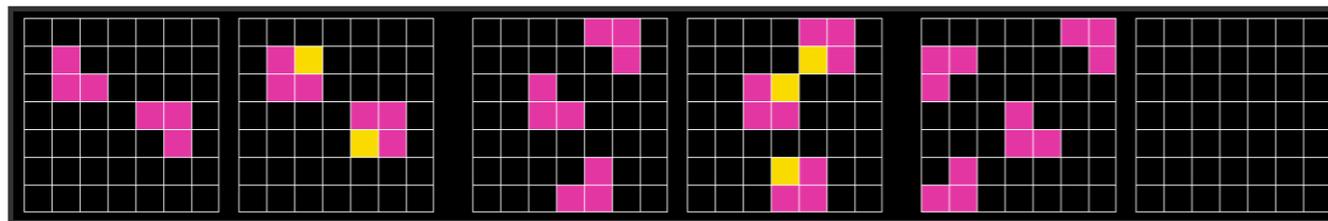
GPQA, Rein et al. 2024



BabyLM Challenge

Sample-efficient pretraining on a developmentally plausible corpus

BabyLM, Warstadt et al. 2023



ARC-AGI-1, Chollet 2019

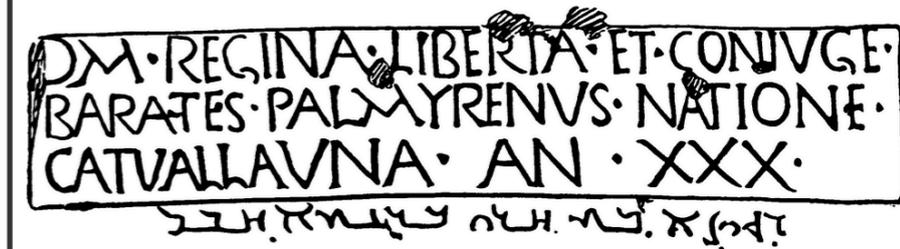
Konwinski Prize

\$1M for the AI that can close 90% of new GitHub issues

Andy Konwinski

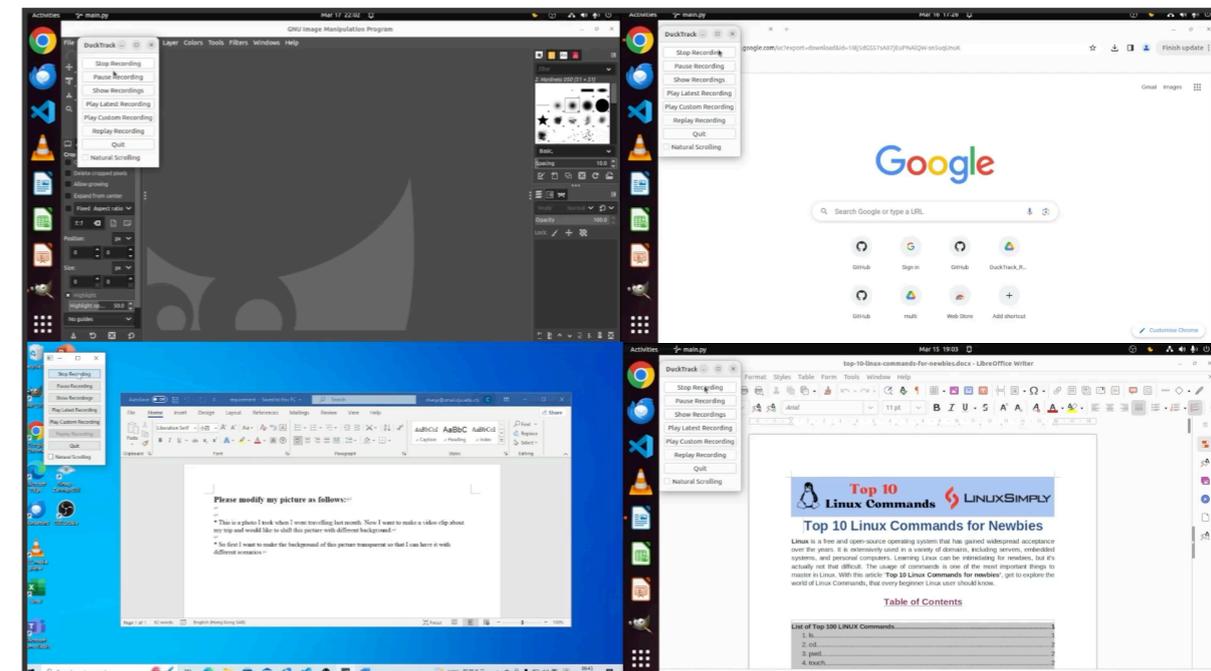
Classics

Question:



Here is a representation of a Roman inscription, originally found on a tombstone. Provide a translation for the Palmyrene script. A transliteration of the text is provided: RGYN° BT HRY BR °T° HBL

HLE, Phan et al. 2025



OSWorld, Xie et al. 2024

Case Study: GPQA



Question writing (by question writer)



Question and choices

Methylcyclopentadiene was allowed to react with methyl isoamyl ketone and a catalytic amount of pyrrolidine. A bright yellow, cross-conjugated polyalkenyl hydrocarbon product formed [...] How many chemically distinct isomers make up the final product (not counting stereoisomers)?

(a) 2 (b) 16 (c) 8 (d) 4

Correct answer (b)

Explanation Methylcyclopentadiene exists as an interconverting mixture of 3 isomers [...] if there are 4 dienes, and 4 different directions of approach the dienophile can take to each of them, there are $4 \times 4 = 16$ possible products.

Expert validation #2 (by expert validator #2)

Part 1: answer Q (correct answer & explanations not shown)

My answer is (b). Here's the explanation: [...]



Part 2: provide feedback (correct answer & explanations shown)

Post-hoc agreement ✓: I agree that the correct answer is (b), after seeing writer's explanation.

Feedback / revision: It's difficult and takes a long time [...] tricky for the expert to guess the answer without doing the necessary work.



Non-expert validation

(by non-expert validators who are experts in other domains; at least 15 min, avg ~37 min, allowing Google)



Non-expert #1	(c)	✗
Non-expert #2	(b)	✓
Non-expert #3	(a)	✗

Expert validation #1 (by expert validator #1)

Part 1: answer Q (correct answer & explanations not shown)

My answer is (a). Here's my explanation: [...]



Part 2: provide feedback on the following dimensions (correct answer & explanations shown to the validator)

- Post-hoc agreement: Is the answer uncontroversial?
- Did you understand Q fully, now that you see the explanations?
- Is your background sufficient to answer correctly?
- Detailed feedback
- Q difficulty
- Q & answer choice revisions

Post-hoc agreement ✓: I agree that the correct answer is (b), after seeing writer's explanation.

Feedback / revision: [...] I got confused with the sentence 'not counting isomers'. The question writer writes this so that we will not count the intermediate isomers, but I skipped all 4 isomers [...] it is my personal mistake.



Question revision (by question writer)



Revised question and choices

Methylcyclopentadiene (which exists as a fluxional mixture of isomers) was allowed to react with methyl isoamyl ketone and a catalytic amount of pyrrolidine. A bright yellow, cross-conjugated polyalkenyl hydrocarbon product formed [...] How many chemically distinct isomers make up the final product (not counting stereoisomers)?

(a) 2 (b) 16 (c) 8 (d) 4

Correct answer & explanation [Same as before]

Include this Q in the **DIAMOND** set because

- (1) 2 out of 2 expert validators agree*
- (2) ≤ 1 out of 3 non-expert validators answers correctly

Saturated (achieved expert performance) very quickly.

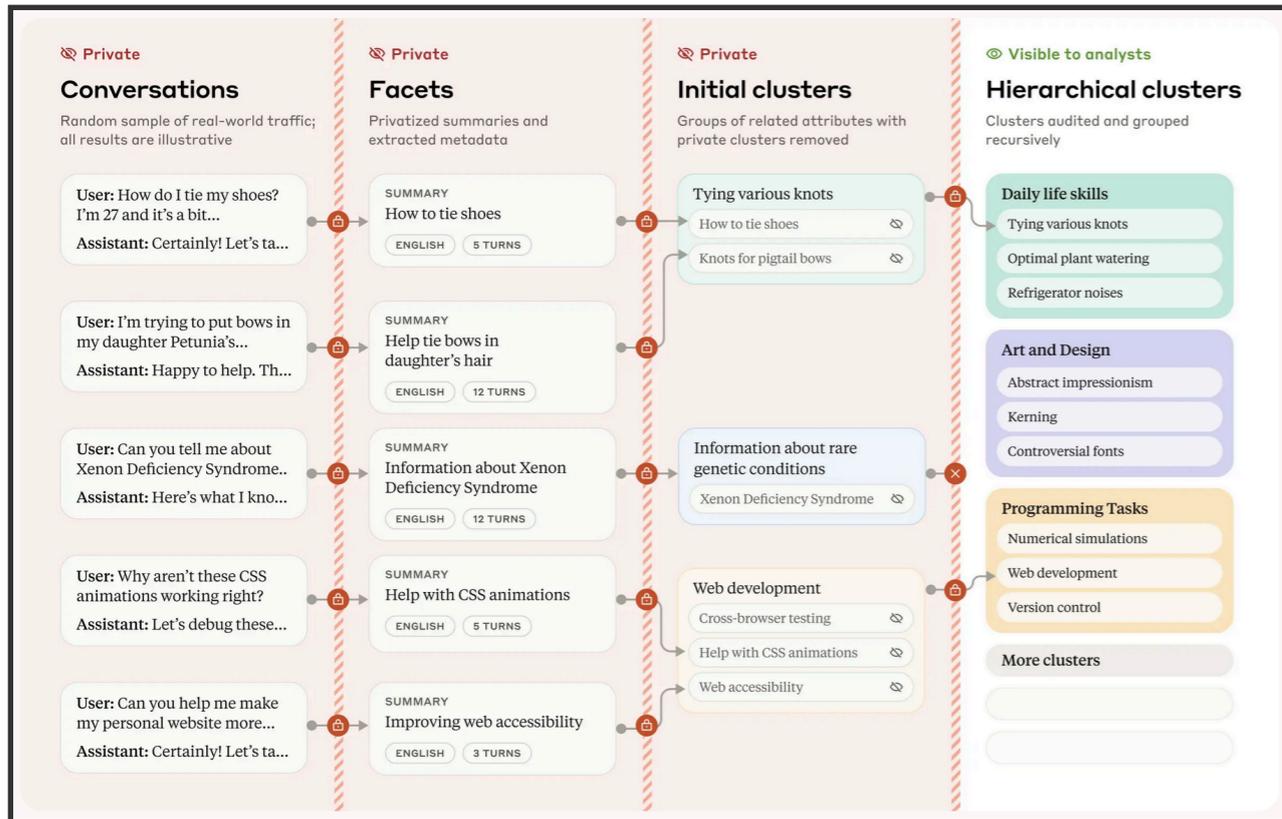
Why?

Use of Language Technologies

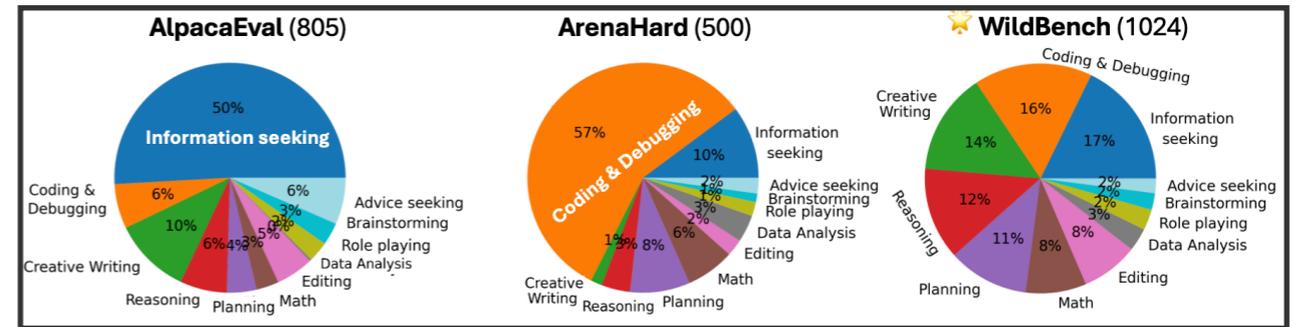
“In the Wild”



What are people *actually* using LMs for, and how well do they do?



Clio, Tamkin et al. 2024



WildChat (Zhao et al. 2024), WildBench (Lin et al. 2024)

LMarena / Chatbot Arena, Chiang et al. 2024

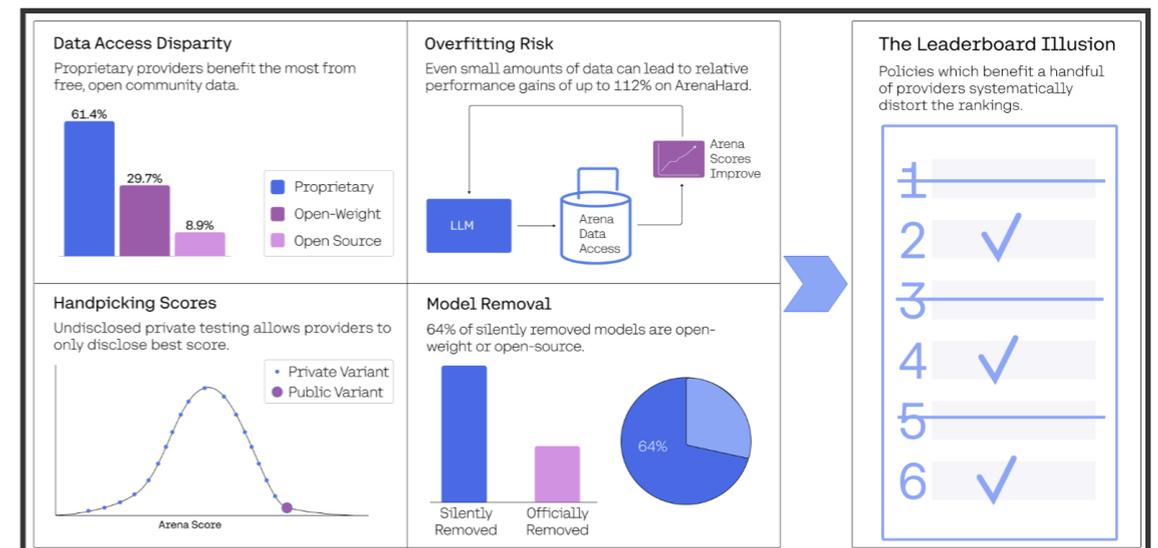
Model	Overall	Hard Prompts	Coding	Math	Creative Writing	Instruction Following	Longer Query	Multi-Turn
gemi-2.5-pro-prev...	1	1	1	1	1	1	1	1
gemi-2.5-pro-prev...	2	2	2	1	1	1	1	1
o3-2025-04-16	2	2	2	1	3	3	6	4
chatgpt-4o-latest-2...	4	4	2	6	2	3	1	1
gpt-4.5-preview-202...	4	4	2	4	3	3	2	1

LMarena / Chatbot Arena, Chiang et al. 2024

OpenRouter

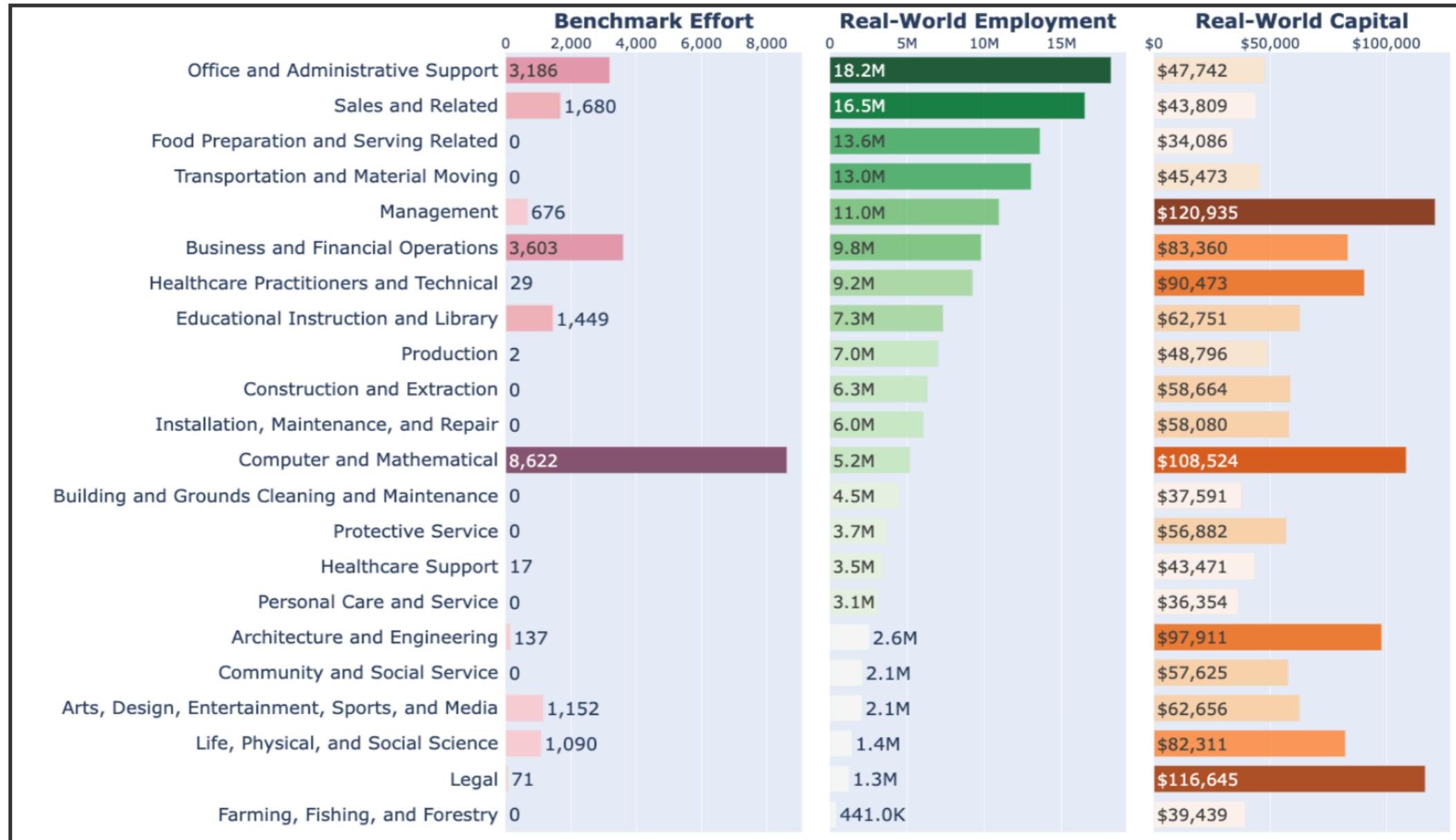
Rank	Model	Token Usage	Change
1.	Google: Gemini 2.0 Flash	267B tokens	↑ 12%
2.	Anthropic: Claude Sonnet 4	196B tokens	↓ 5%
3.	OpenAI: GPT-4o-mini	188B tokens	↓ 58%
4.	Google: Gemini 2.5 Flash Preview 05-20	163B tokens	↑ 61%
5.	Anthropic: Claude 3.7 Sonnet	137B tokens	↑ 1%

OpenRouter



Singh et al. 2025

Use of Language Technologies “In the Wild”

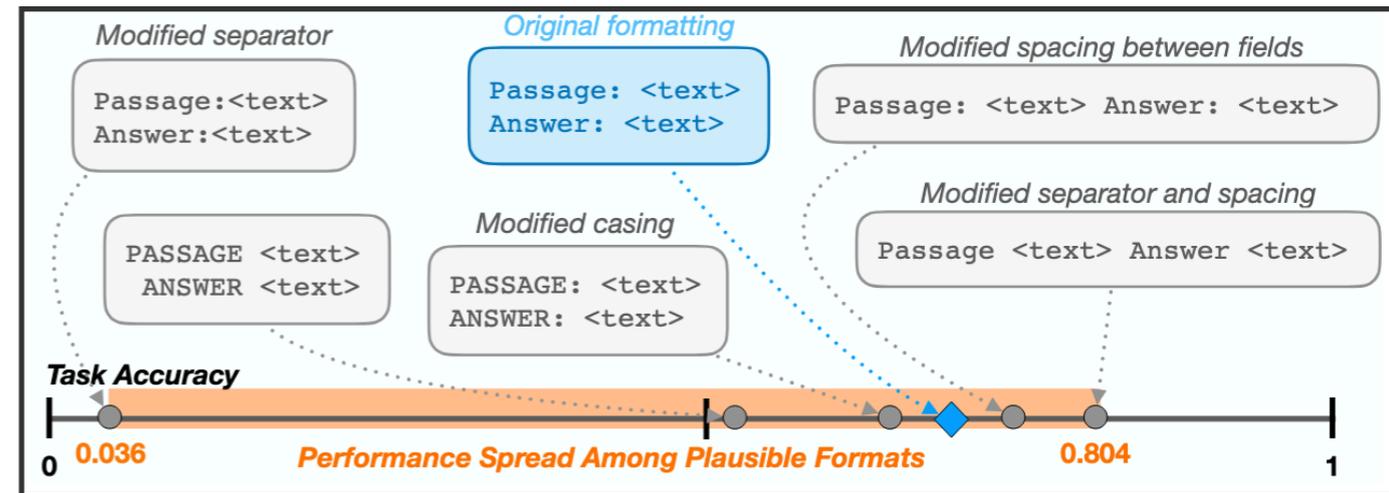


Wang et al. 2026

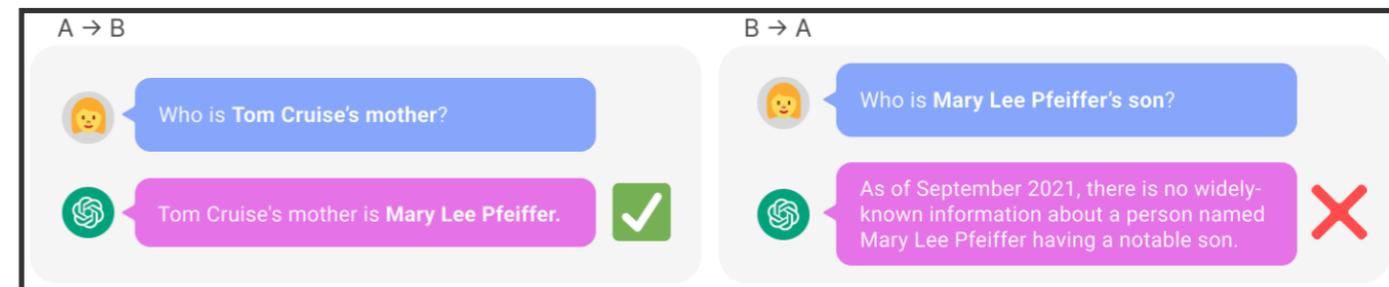
Distributional Model Evaluation



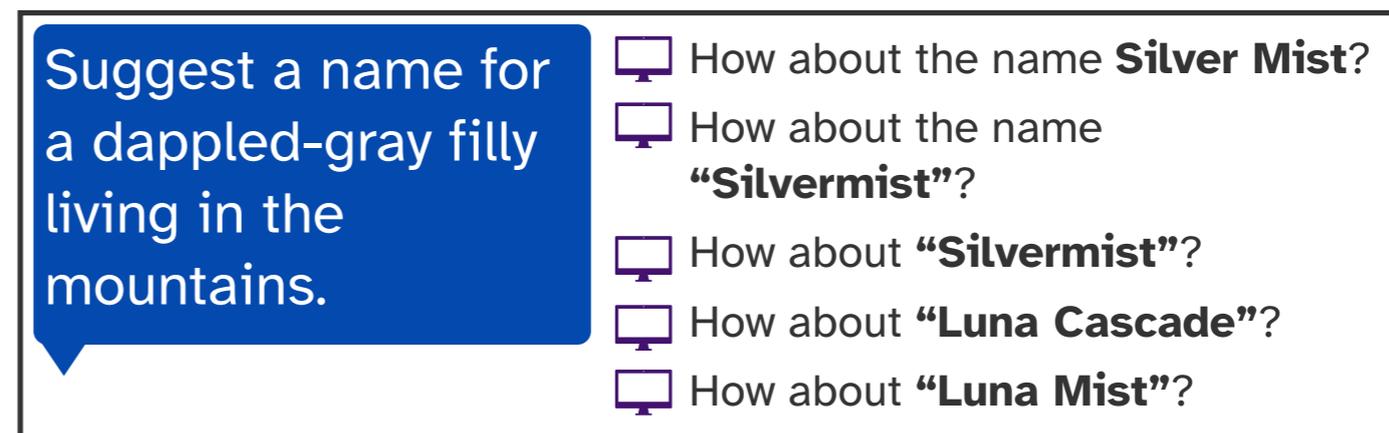
- What are the properties of the outputs models produce in general?
- **Consistency:** when evaluating models on the same task (or variations of it) multiple times, how consistent is its behavior?
- **Diversity:** do the outputs models generate have the same distributional properties as human language?



Sclar et al. 2024



Berglund et al. 2024



Zhang et al. 2025

Pitfall: Dataset Contamination



Before pretrained models, nearly all datasets came with splits, assumed to be IID:

Training data
For updating model parameters directly

Validation data
For deciding when to stop training

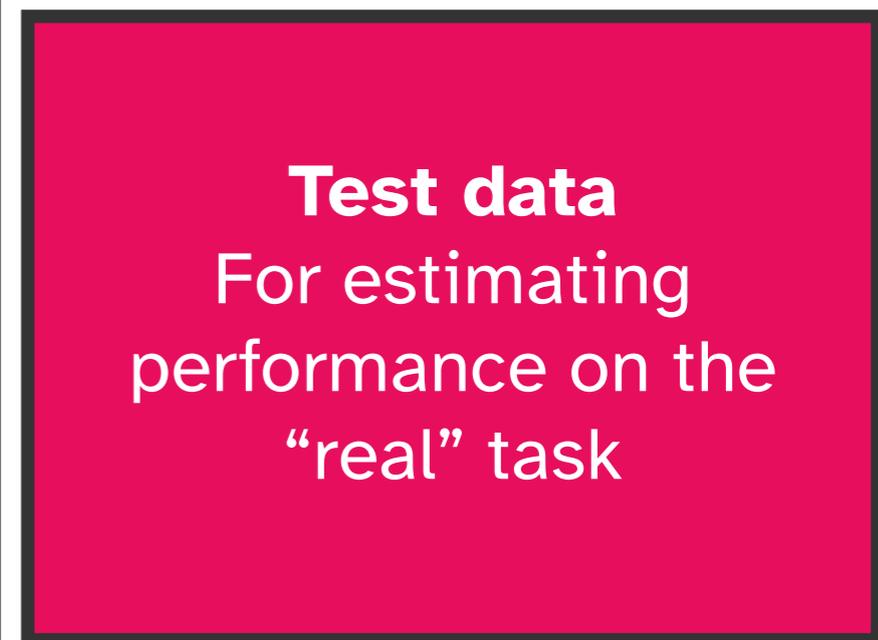
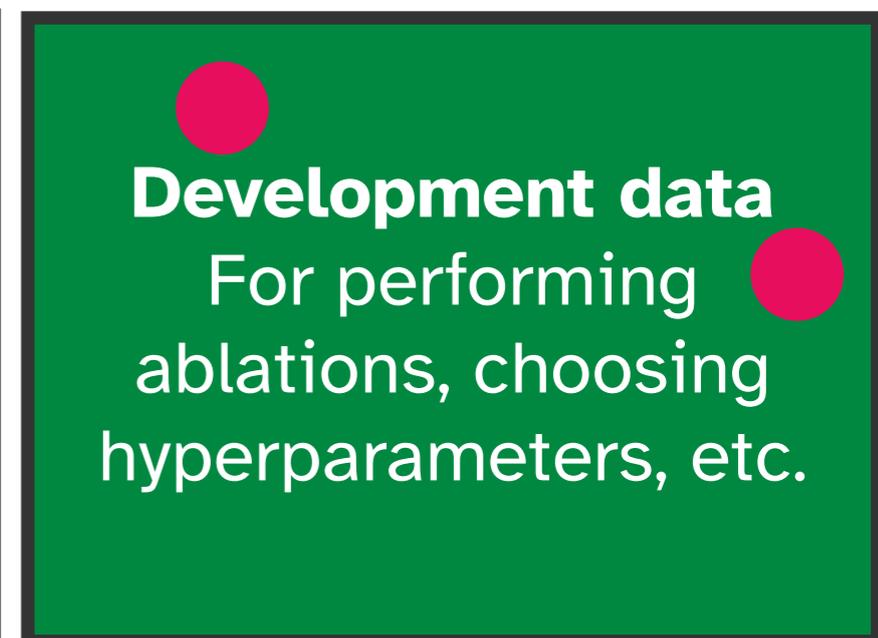
Development data
For performing ablations, choosing hyperparameters, etc.

Test data
For estimating performance on the “real” task

Pitfall: Dataset Contamination



Dataset contamination occurs when actual test data is used in any of the previous splits (no longer IID). **Why is this bad?**



Pitfall: Dataset Contamination



After pre-training for multi-task models, it becomes especially problematic

Training data
Models might memorize test data that happens to be in their pretraining dataset!

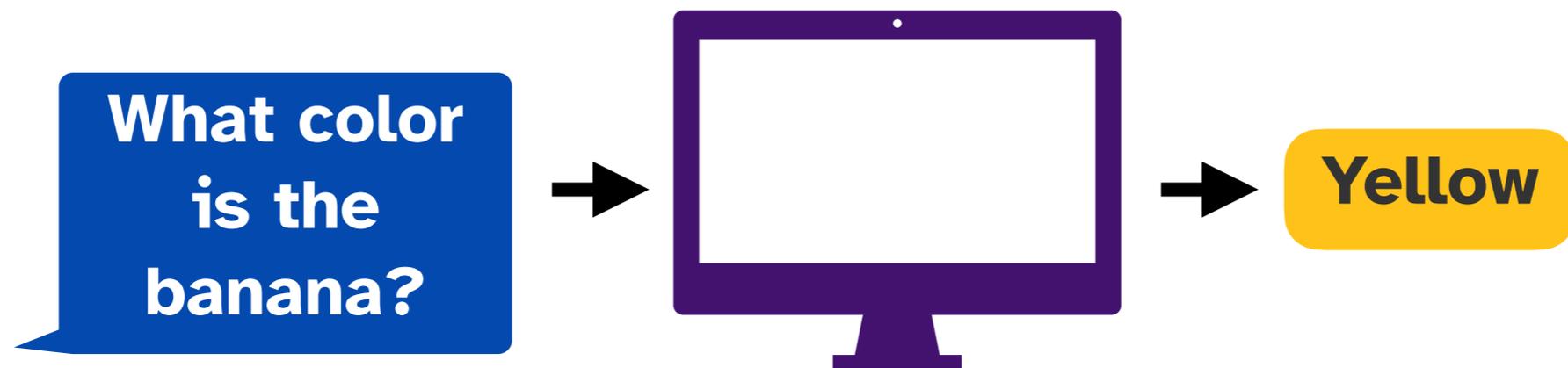
Development tasks
For performing ablations, choosing hyperparameters, etc.

Test tasks
For estimating performance on the “real” task

Pitfall: Spurious Correlations



Does the benchmark actually evaluate what we want it to?



Correct 80% of the
time without looking
at an image!

- Learned a spurious correlation that gives the model high accuracy: bananas are yellow
- Doesn't actually test visual understanding

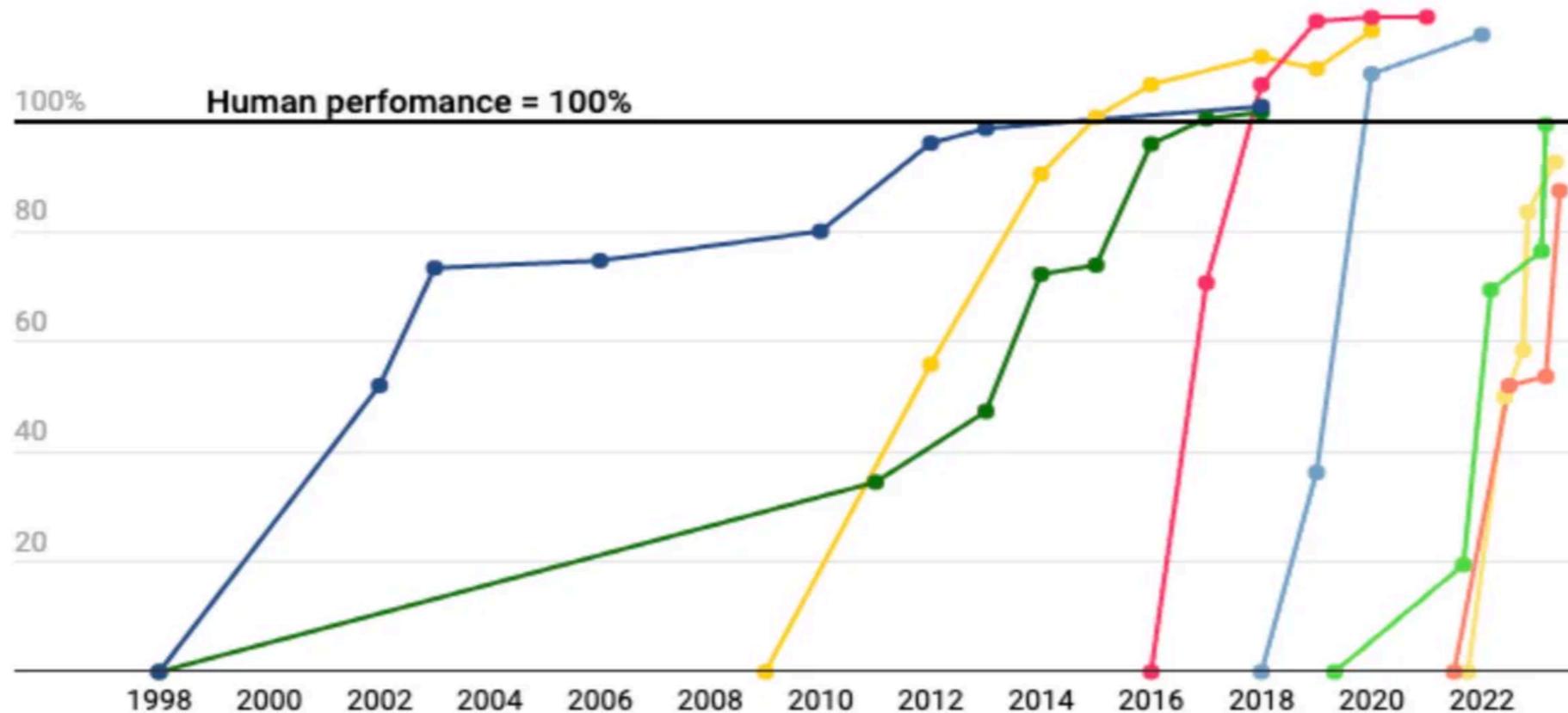
Pitfall: Defining “Human Performance”



AI has surpassed humans at a number of tasks and the rate at which humans are being surpassed at new tasks is increasing

State-of-the-art AI performance on benchmarks, relative to human performance

- Handwriting recognition ● Speech recognition ● Image recognition ● Reading comprehension
- Language understanding ● Common sense completion ● Grade school math ● Code generation



For each benchmark, the maximally performing baseline reported in the benchmark paper is taken as the “starting point”, which is set at 0%. Human performance number is set at 100%. Handwriting recognition = MNIST, Language understanding = GLUE, Image recognition = ImageNet, Reading comprehension = SQuAD 1.1, Reading comprehension = SQuAD 2.0, Speech recognition = Switchboard, Grade school math = GSK8k, Common sense completion = HellaSwag, Code generation = HumanEval.

Chart: Will Henshall for TIME • Source: [ContextualAI](#)

TIME

Pitfall: Defining “Human Performance”



Who is the human in “human performance”?

- Are they incentivized to perform well?
- Do they have the required expertise?

Organic Chemistry

Methylcyclopentadiene (which exists as a fluxional mixture of isomers) was allowed to react with methyl isoamyl ketone and a catalytic amount of pyrrolidine. A bright yellow, cross-conjugated polyalkenyl hydrocarbon product formed (as a mixture of isomers), with water as a side product. These products are derivatives of fulvene. This product was then allowed to react with ethyl acrylate in a 1:1 ratio. Upon completion of the reaction, the bright yellow color had disappeared. How many chemically distinct isomers make up the final product (not counting stereoisomers)?

- A) 2
- B) 16
- C) 8
- D) 4

GPQA, Rein et al. 2024

1. Write a question, including possible multiple choice answers and an explanation of the answer
2. Get expert #1 to validate by having them answer the question and suggest revisions
3. Revise the question given feedback
4. Get expert #2 to validate again
5. Get 3x non-expert (experts in other domains) to attempt to answer the question by allowing Google searches

Keep questions where both experts agree, and at most 1 non-experts can answer the question correctly with Google

Pitfall: Defining “Human Performance”

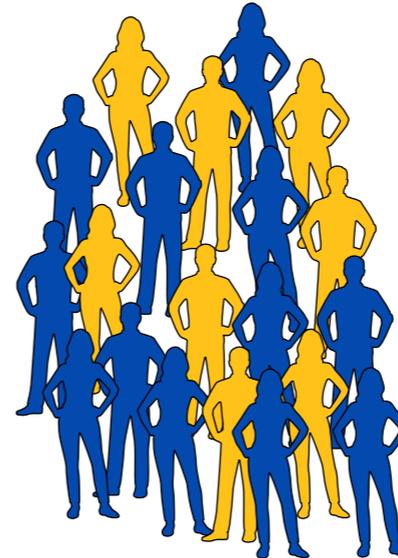


Is the task actually evaluable?

- Is there an objectively correct label?

What color should we make our Berkeley t-shirts?

- Do annotators disagree? If so, how are we processing their disagreements?

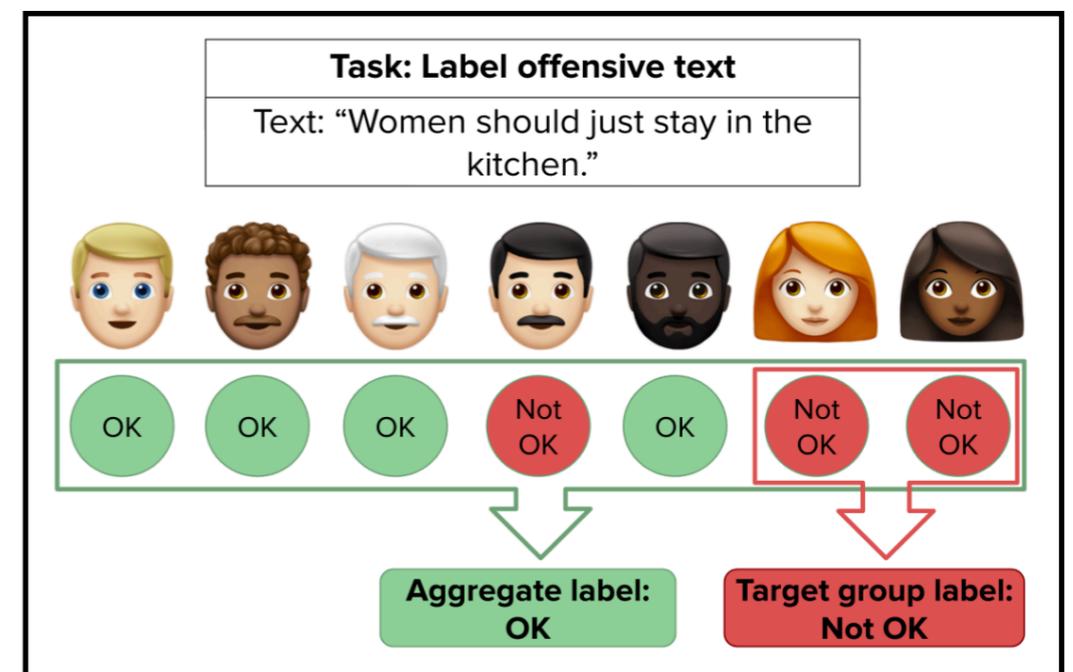


20 annotators

“Gold” label:

Blue

Human performance:
 $12/20 = 60\%$



Fleisig et al. 2023

Pitfall: Defining “Human Performance”



Do they match human performance in dimensions other than average single-instance performance?

- Consistency?
- Explainability?
- Generalizability?

Pitfall: The Long-Tail Paradox



- Which of the following words is most rare?
myriad, solipsist, anachronistic, apricate
- Can you think of a rarer word than these? (Check in the [Google Books Ngram Viewer](#))
- LLMs can look really impressive when we are trying to challenge them with tricks, but maybe this is because we're bad at coming up with long-tail (rare) challenging tasks out of the blue!
- Can seem even more impressive when the task is unverifiable, and any model response could satisfy you!

“People... are easily fooled into reading structure into chaos, reading meaning into nonsense... how much different is interpreting non sequitur as whimsical conversation? ... a test based on fooling people is confoundingly simple to pass”

—Stuart Shieber, “Lessons from a restricted Turing test”

Zooming Out: The Role of Language Technologies



- What is their **intended** use?
 - Keeping users engaged?
 - Interacting with users as little as possible?
 - What kinds of users?
- How does this influence their design?
 - Their interface
 - The underlying model
 - The assumptions they are making

Zooming Out: The Role of Language Technologies



- How are they **actually** used?
 - Where do they fail?
 - How do users adapt to failures?
- What other considerations should we make in deployment?
 - Resource utilization and efficiency
 - Fairness, ethics, and social impact

Capabilities vs. Affordances



Being able to ask and answer questions like the following is becoming increasingly influential in the field of AI and LLMs:

“(How well) can LLMs do X?”

What drives our choices in X?