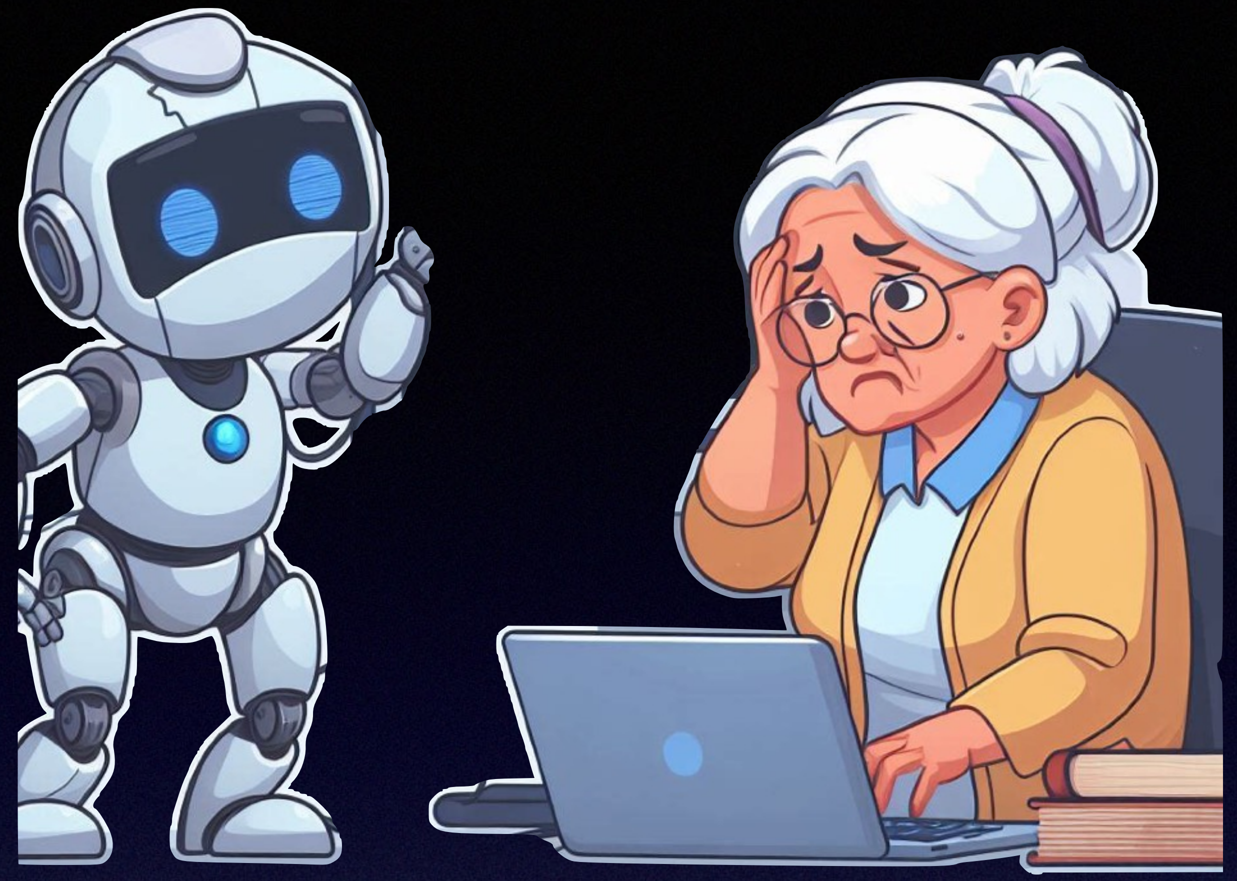
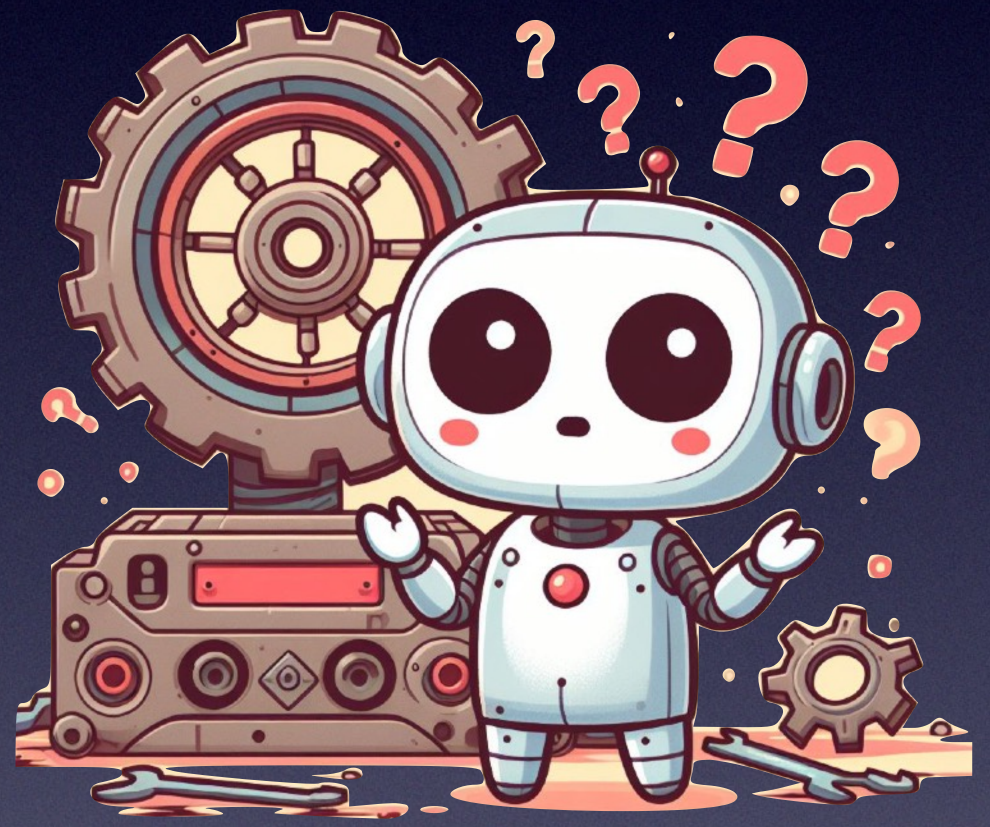


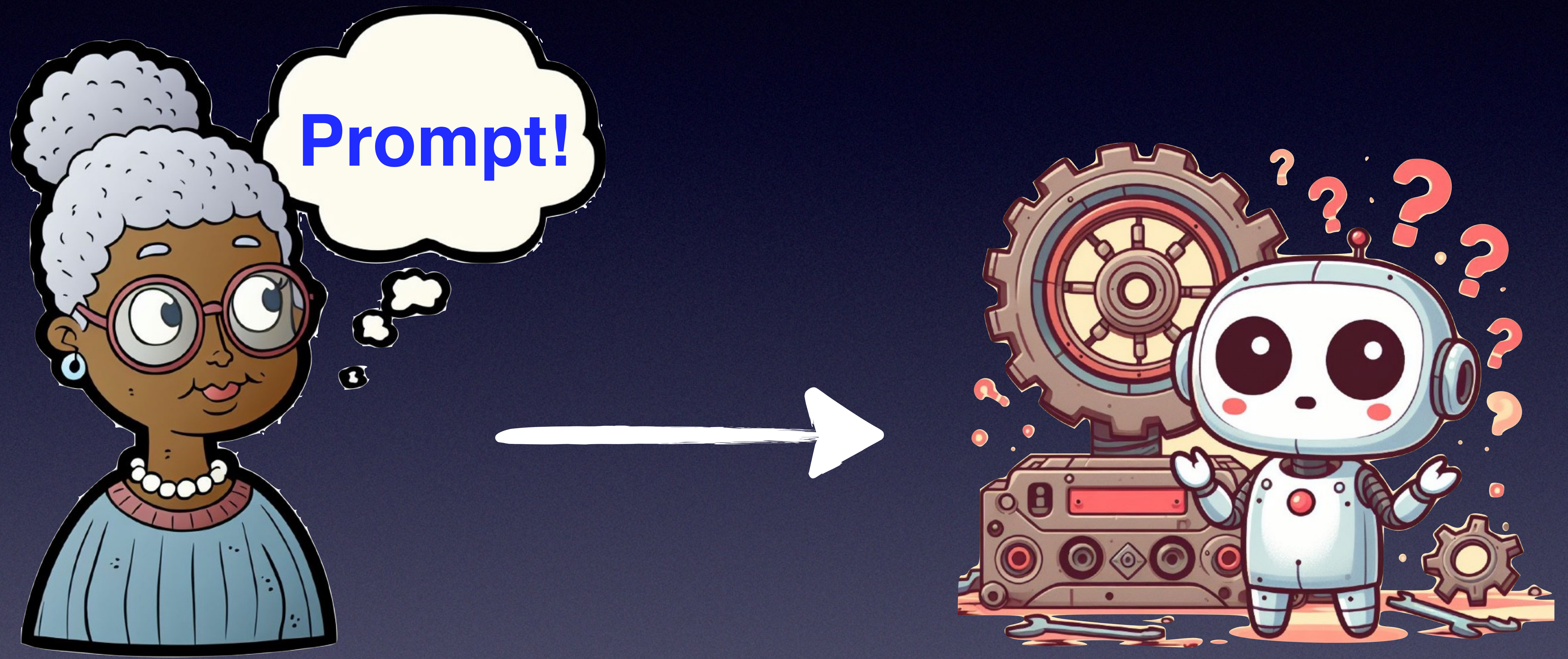
Last Mile Headaches
(Using LLMs for Code)

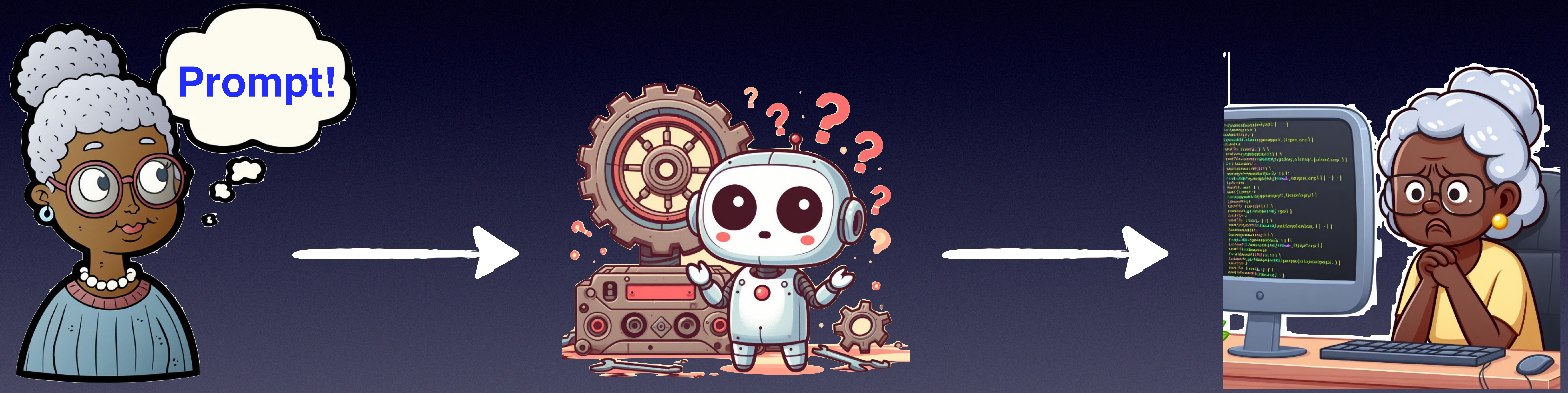
(With) **Claudio Spiess, David Gros**, Toufique Ahmed
Yuvraj Virk, Somesh Jha, Amin Alipour, Michael Pradel, Prem Devanbu

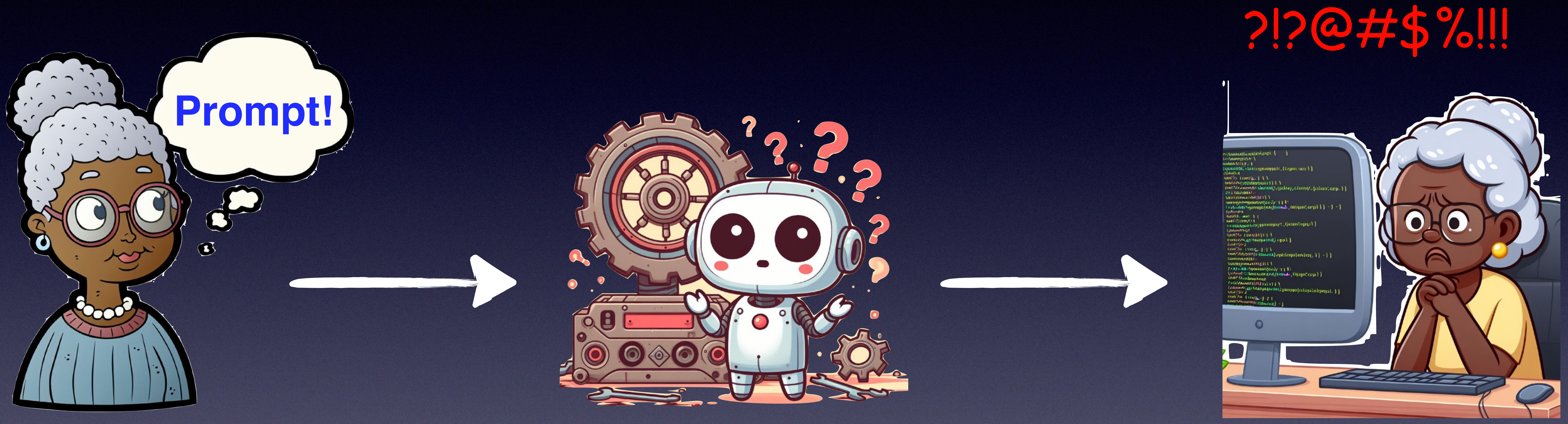
UC Davis *(ICSE 2025, to appear)*

Unterstützt von / Supported by
Alexander von Humboldt Stiftung / Foundation

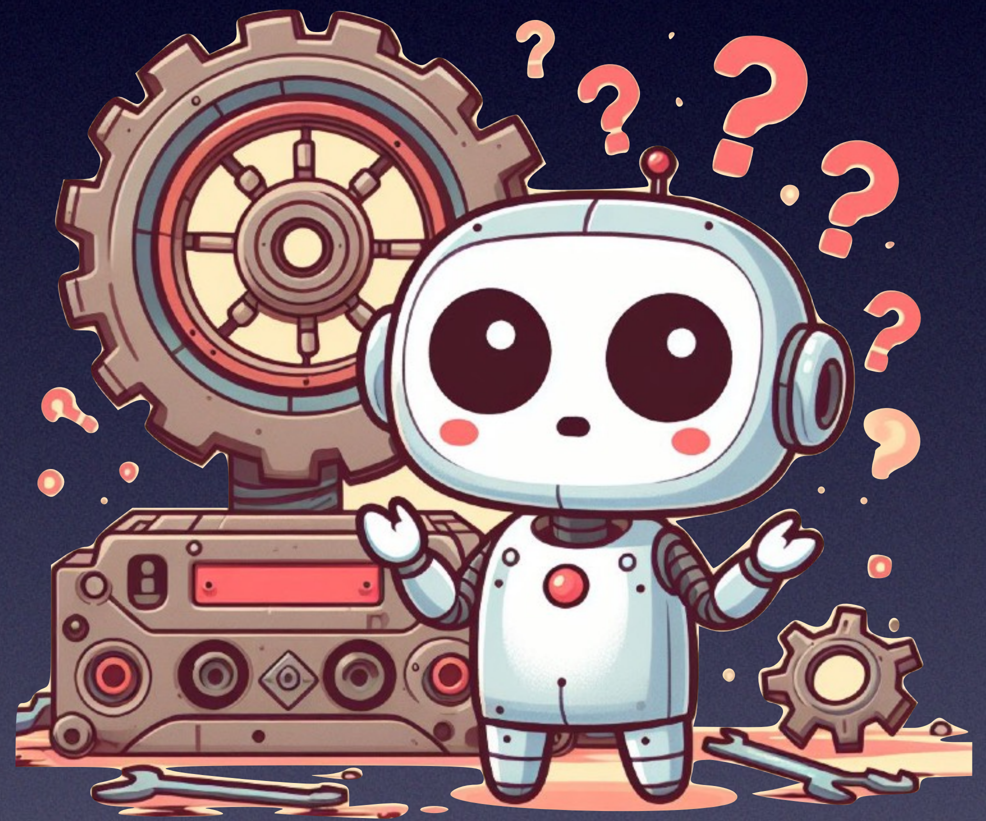



Prompt!


Prompt!

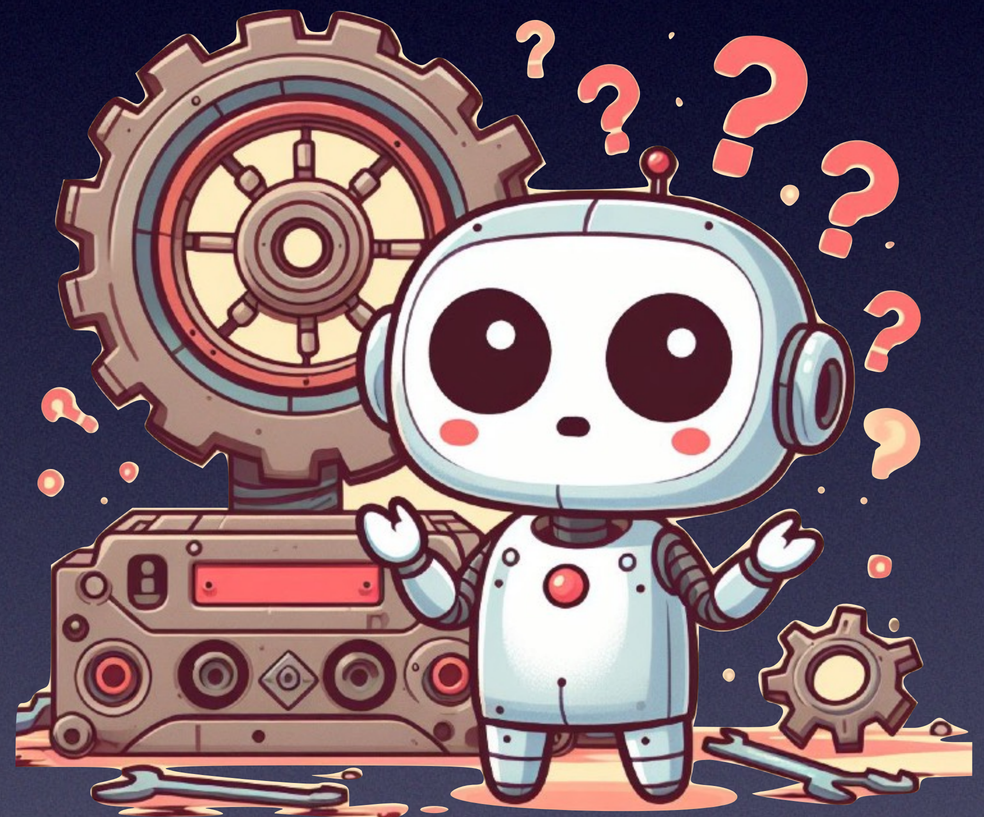

Prompt!
?!?@#$%!!!

First
Mile



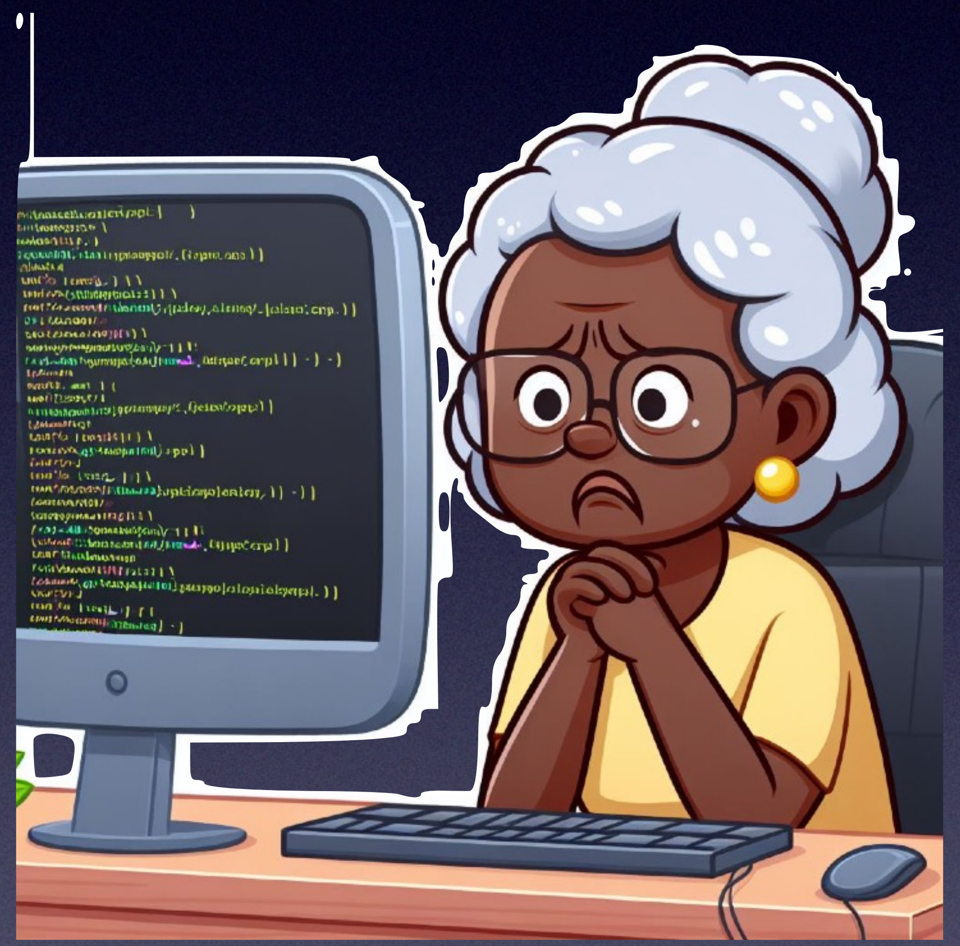
?!?@#$%!!!

First Mile

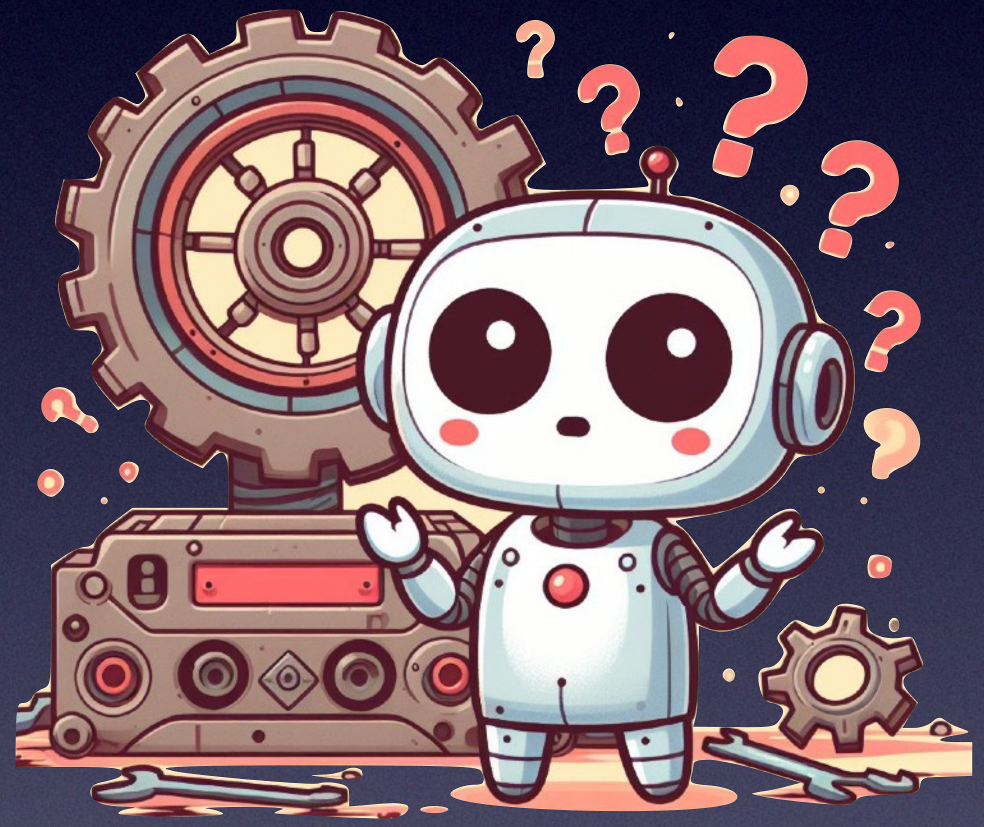


“Last” Mile

?!?@#$%!!!



First
Mile



“Last”
Mile

?!?@#$%!!!

.. and the rest of
the way?

.. and the rest of
the way?

.. and the rest of
the way?

Maintenance costs are heavy!

.. and the rest of
the way?

Maintenance costs are heavy!

..and we don’t know what they are…

GOOGLE / TECH / ARTIFICIAL INTELLIGENCE

More than a quarter of new code at Google is generated by AI / AI is hugely important to Google's products, and it sounds like the company relies on it internally, too.

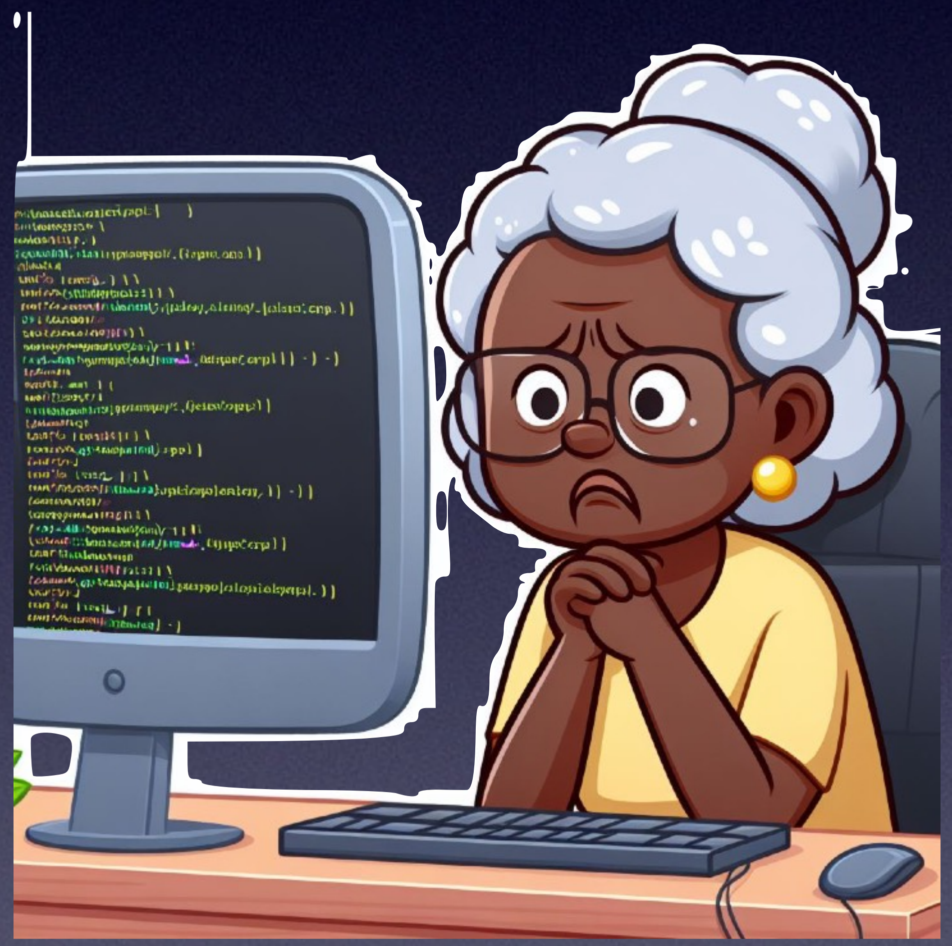
By Jay Peters, a news editor who writes about technology, video games, and virtual worlds. He's submitted several accepted emoji proposals to the Unicode Consortium.

Oct 29, 2024, 5:05 PM EDT

Last Mile can be problematic

(L2R Completion: CodeGen2-16B, Codex, GPT-3.5)

?!?@#$%!!!



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?!?@#$%!!!

- Code Completion (DyPyBench)

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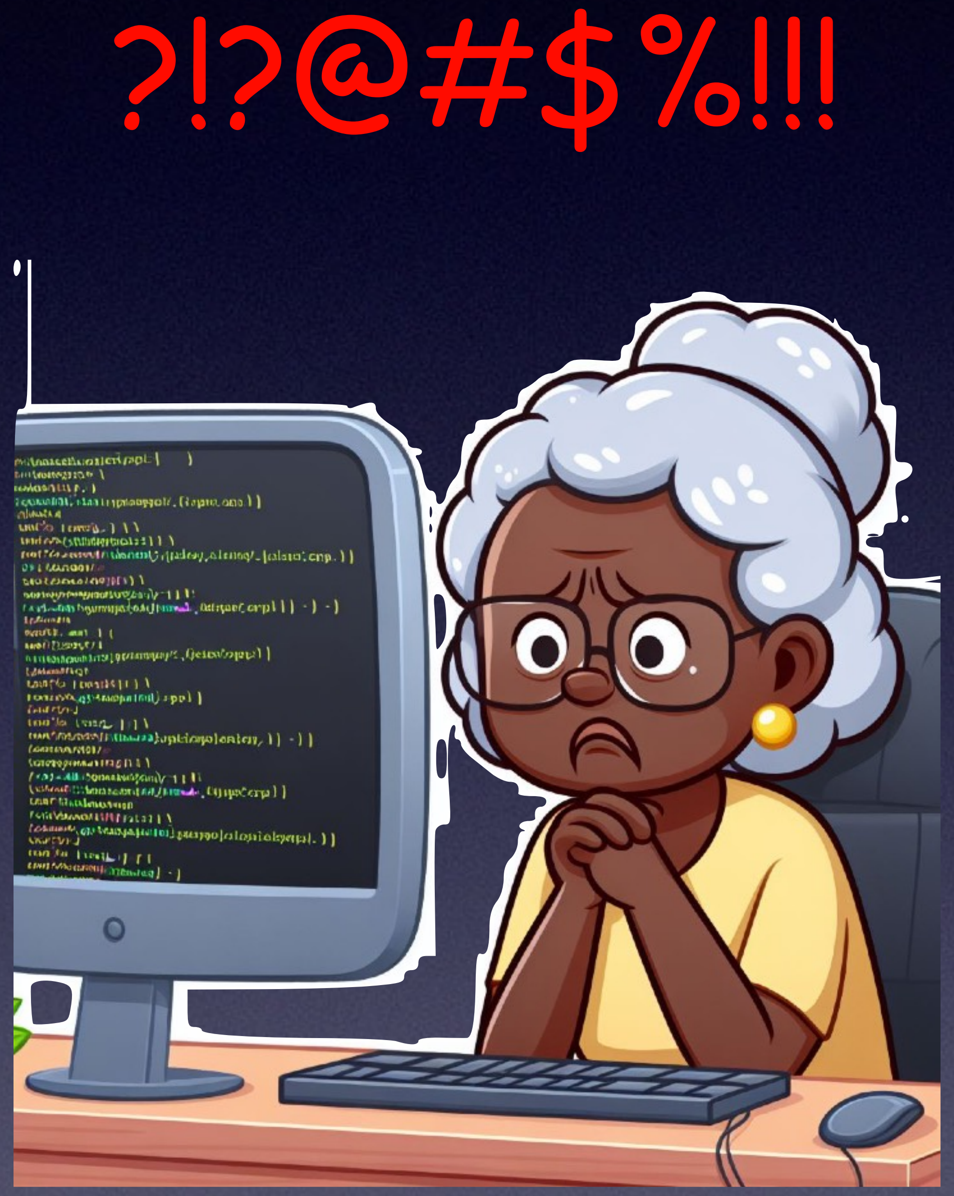

- Code Completion (DyPyBench)
  - ✓ *Correctness around 30%*

Last Mile can be problematic

(L2R Completion: CodeGen2-16B, Codex, GPT-3.5)

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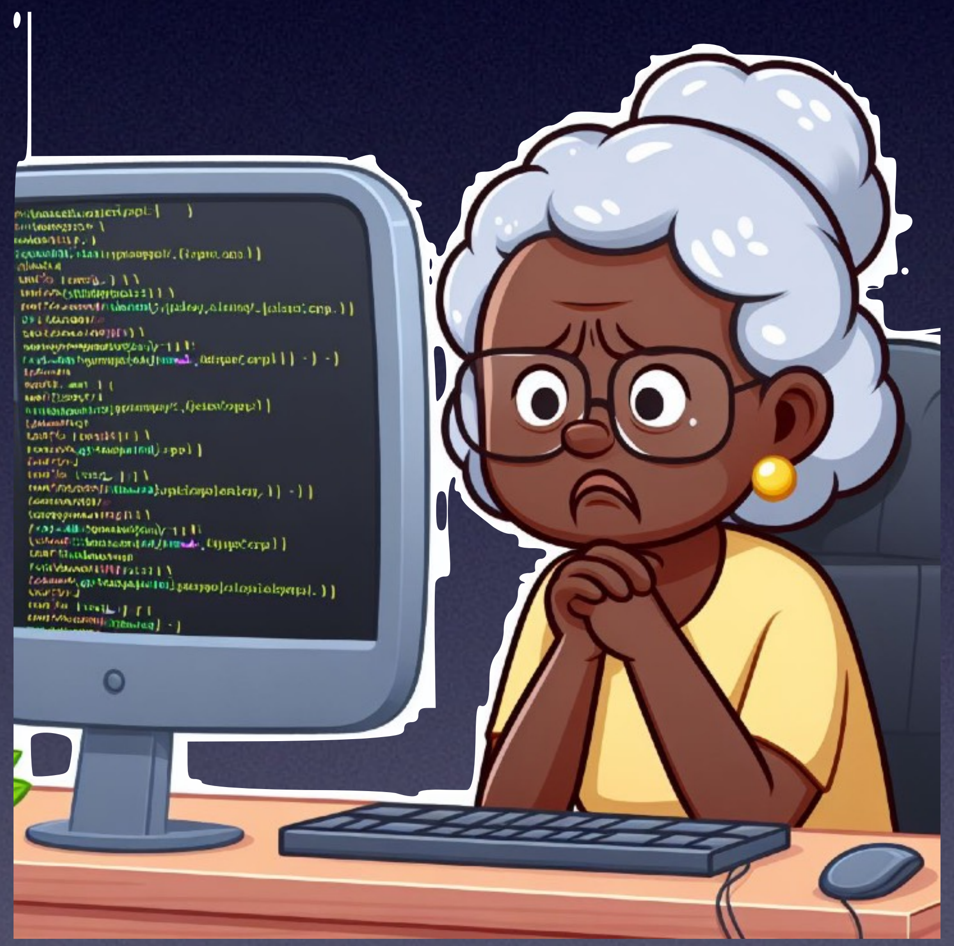

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- Buggy/Fixed Code (SStubs4J)

Last Mile can be problematic

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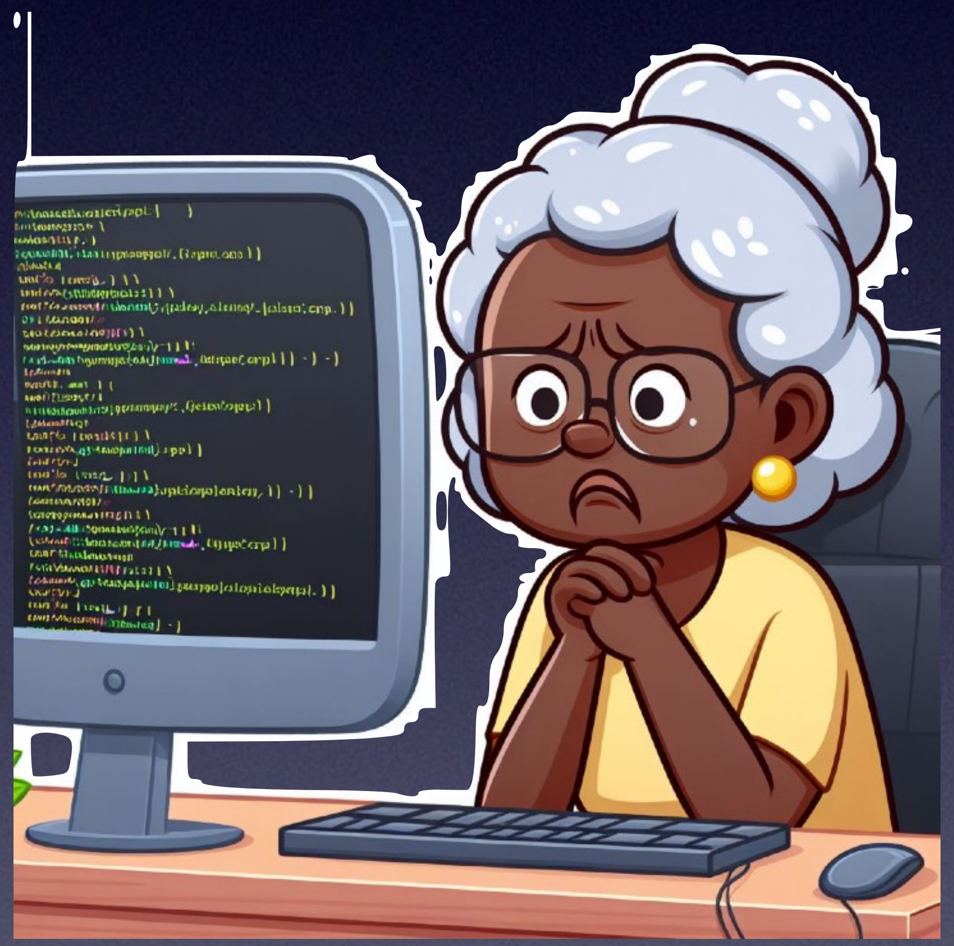
?!?@#$%!!!



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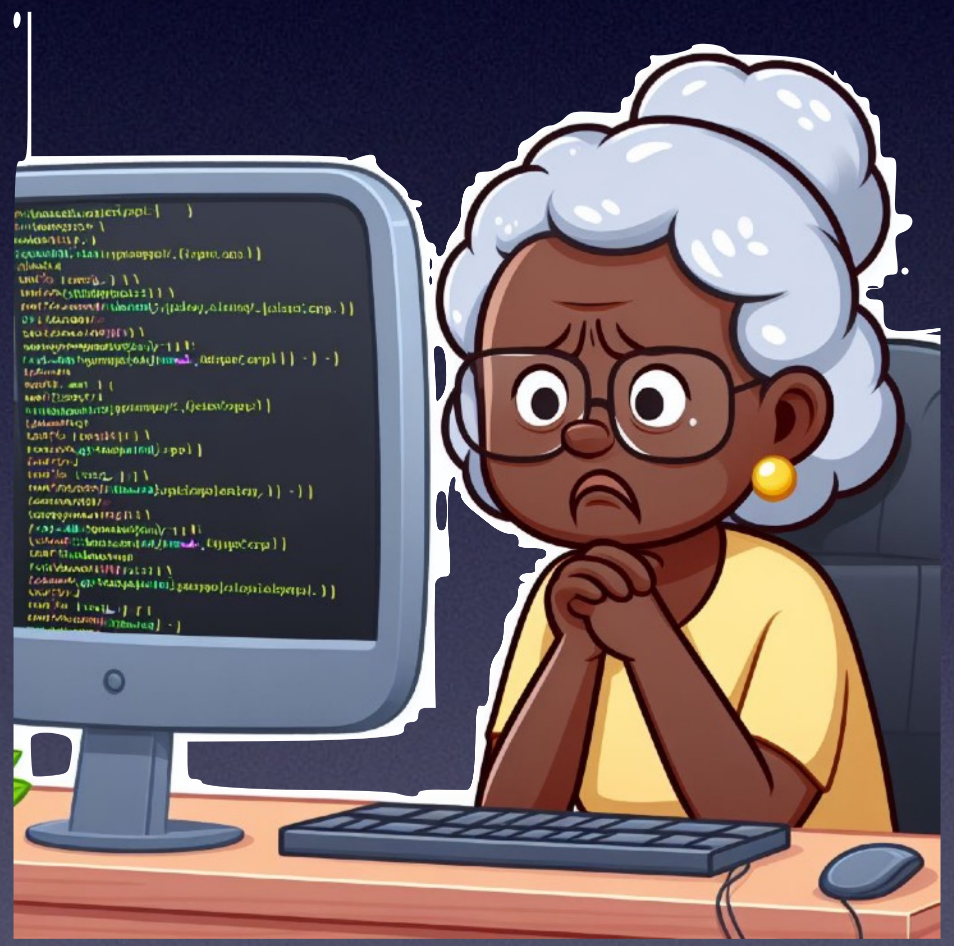
?!?@#$%!!!



- Code Completion (DyPyBench)
  - ✓ *Correctness around 30%*
- Buggy/Fixed Code (SStubs4J)
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Yes, *L2R* is a difficult setting

(FIM, SAFIM easier)

Another Evaluation: Simple Stupid bugs
(Sutton & Karampatsis, 2020)

- Single-statement bug fixes from project version history ~ 17K examples after cleaning.
- Collected from about 1000 projects
- Median fix-time, about 4 days..but sometimes much longer.
- Widely used dataset, entire conference track devoted to it *(MSR 2021)*

*All samples in dataset used
were fixed before
LLM training data was gathered.*

Methodology

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RQ: Does Codex repeat human mistakes?

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1. Find the SStuB introduction in version history.

2. Use the prefix to the SStuB as prompt, and..

3. Ask LLM to prompt.

4. Classify resulting completion:

Bug? Patch? Other?

Example

```
            g2d.setColor(tabFillColor);
            g2d.fill(shaper.reset().doRect(boundsX, topY + shape.path.deltaY(1),
                    boundsWidth, paintBorder.top).getShape());

            //If the top of the border is a non-paint border, then the border is painted.
            if (
      Bug           paintBorder.top >= 1
                    paintBorder.top > 1      Fix
            ) {
                g2d.setColor(borderColor);
                final int topLine = topY + shape.path.deltaY(paintBorder.top - 1);
                g2d.draw(shaper.reset().doRect(boundsX, topLine, boundsWidth - 1,
                        1).getShape());
            }
        }
    }
```

Example

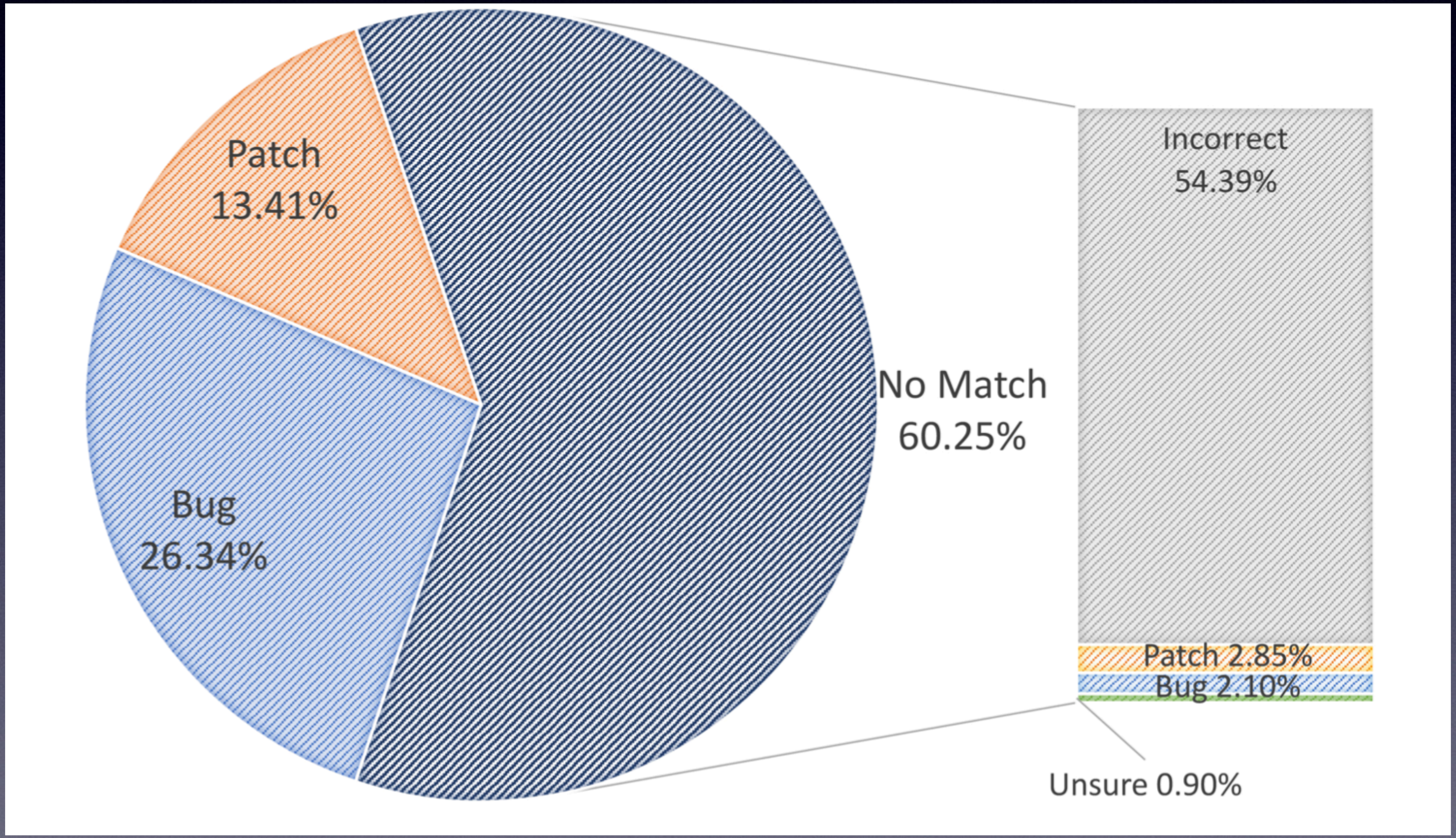
```
//If the top of the border is a non-paint border, then t
if (
    paintBorder.top >= 1
    paintBorder.top > 1
) {
    g2d.setColor(borderColor);
```

Bug

Fix

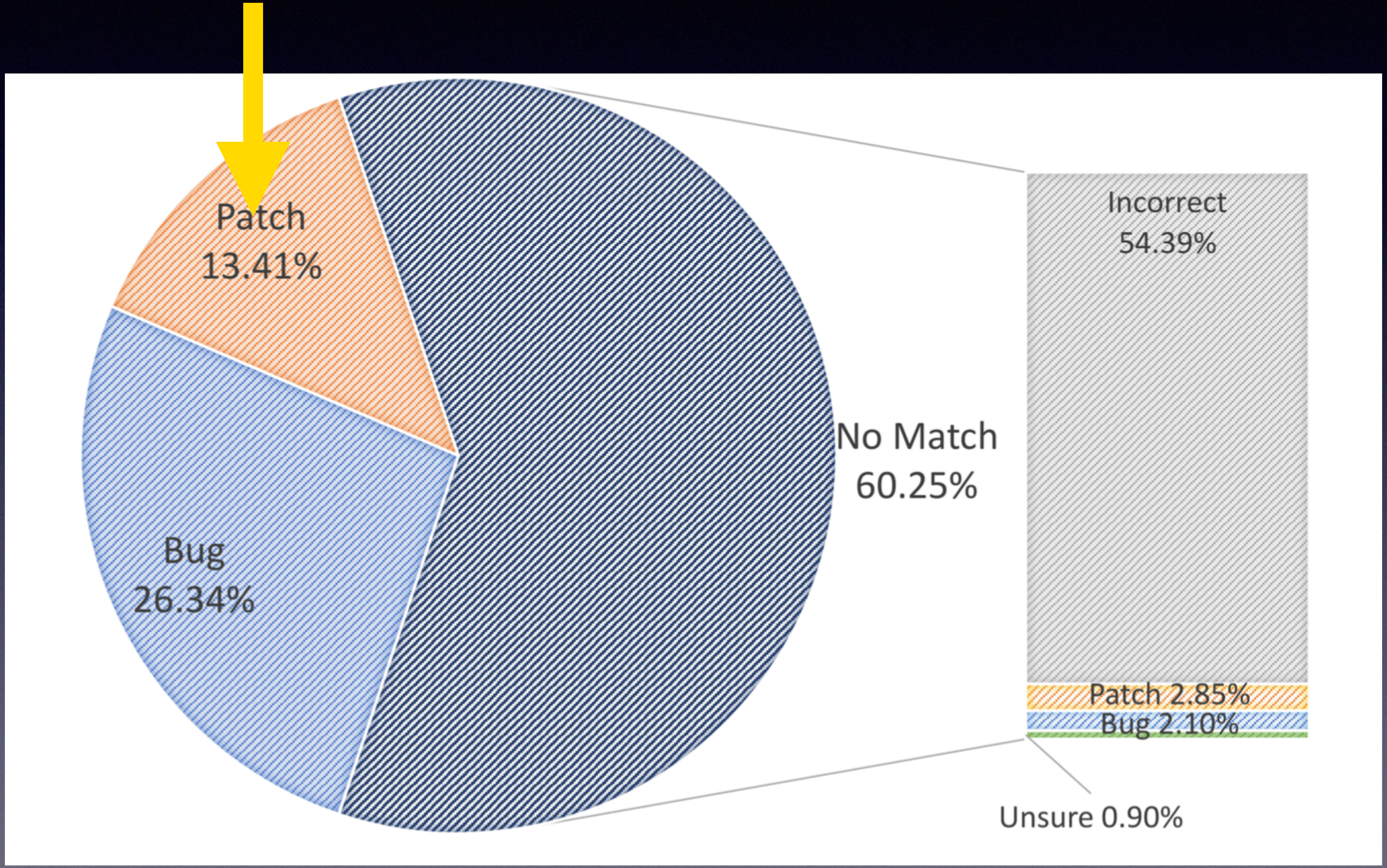
Result

Result


Patch
13.41%
Bug
26.34%
No Match
60.25%
Incorrect
54.39%
Patch 2.85%
Bug 2.10%
Unsure 0.90%

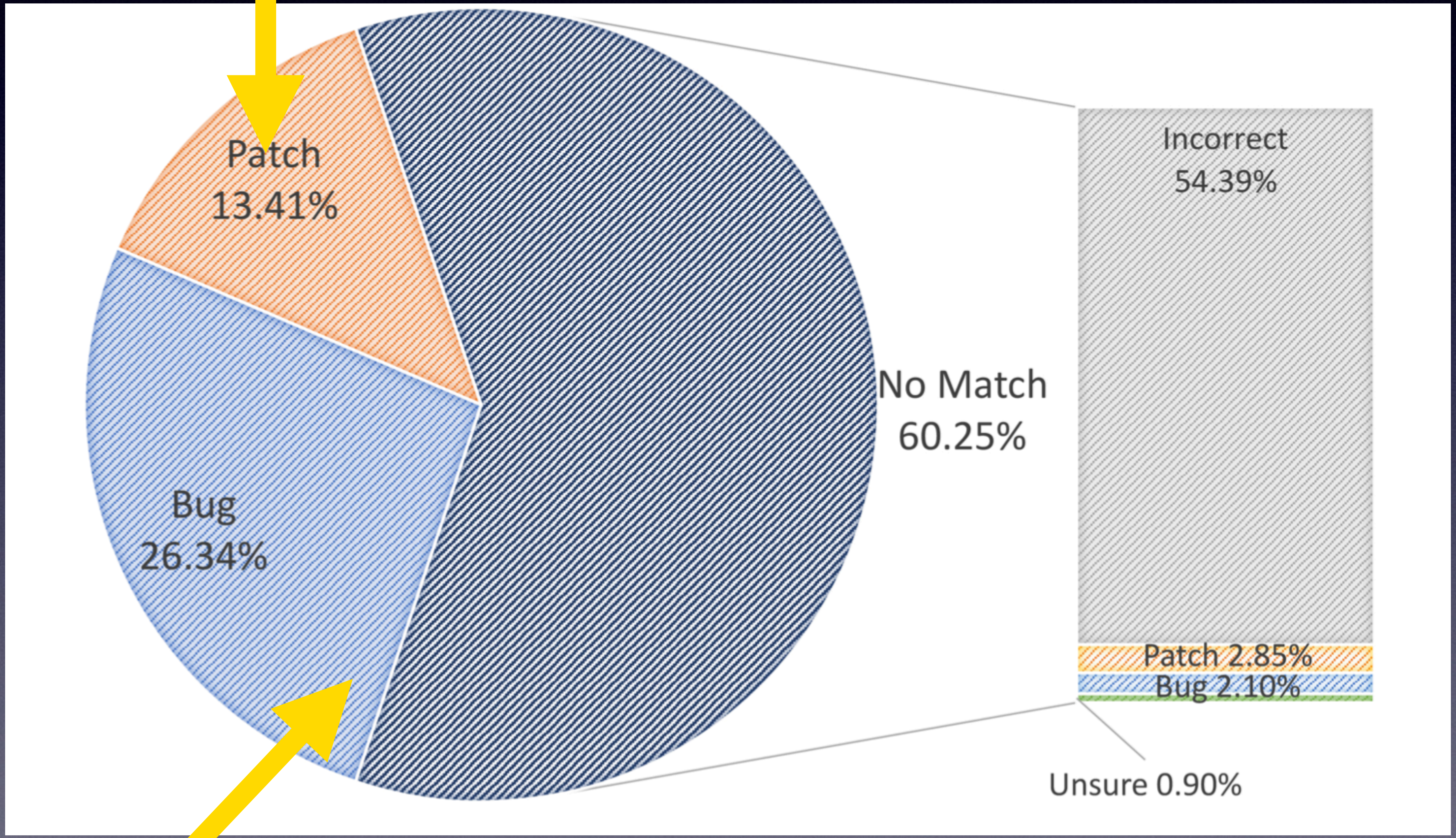
Result

Codex produces fixed code



Result

Codex produces fixed code

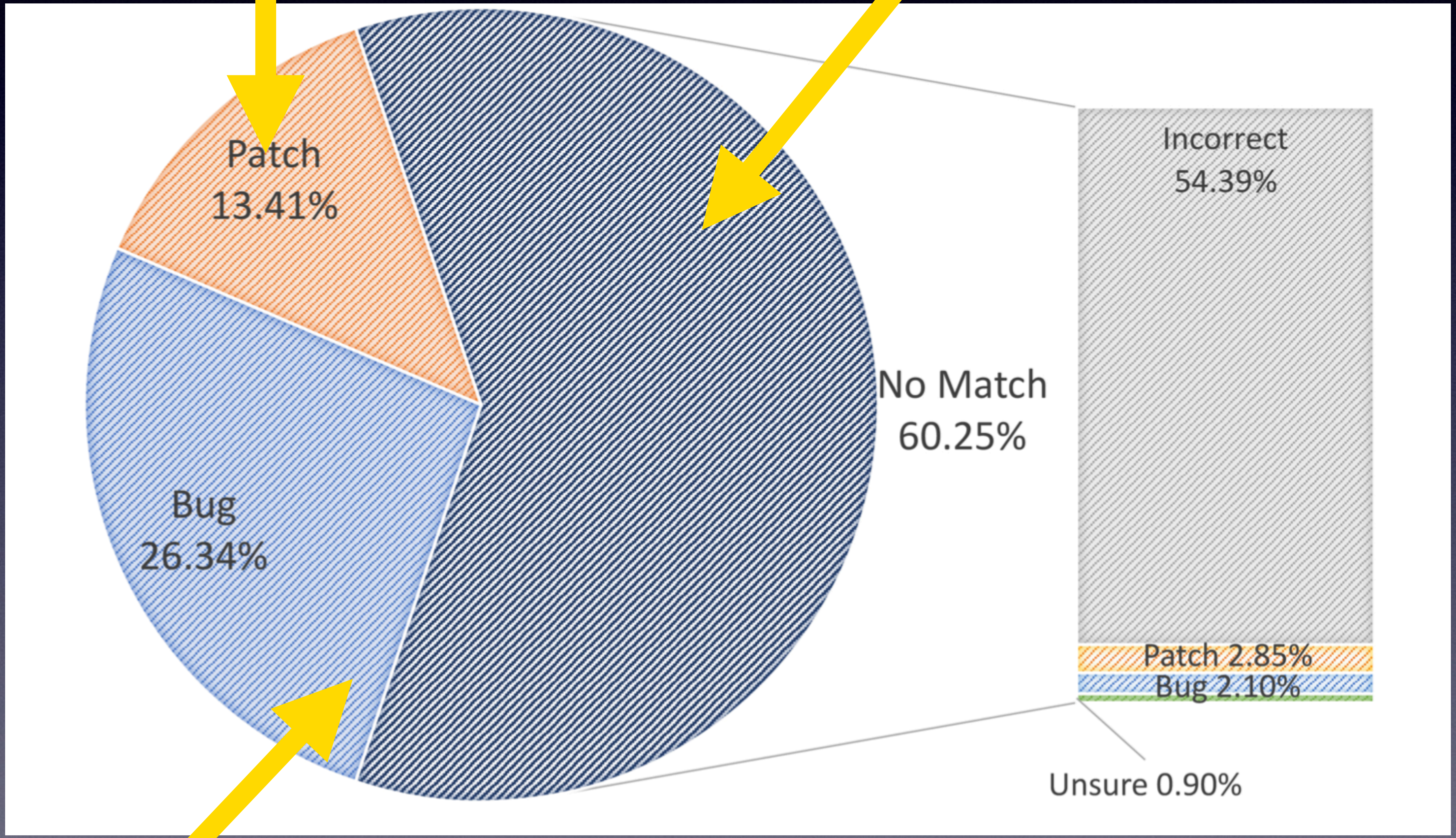


Codex produces buggy code TWICE as often

Result

Codex produces fixed code

Something else



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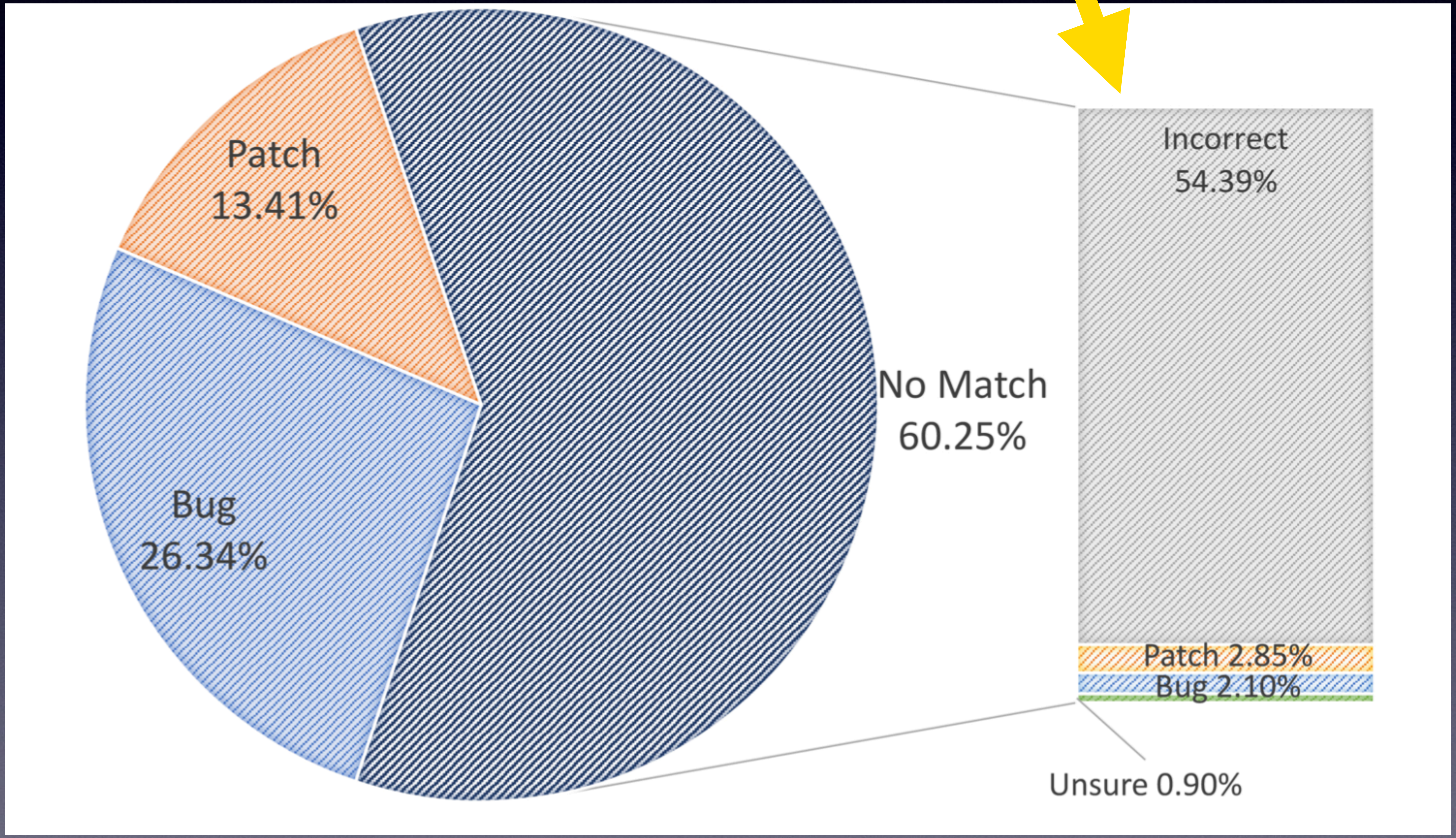
Result

Manual Review,
401 samples

Result

Manual Review,
401 samples



How “sticky” are Codex-generated bugs?

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“Sticky” $\Longrightarrow$ Takes Longer to Fix. 🤔🤔

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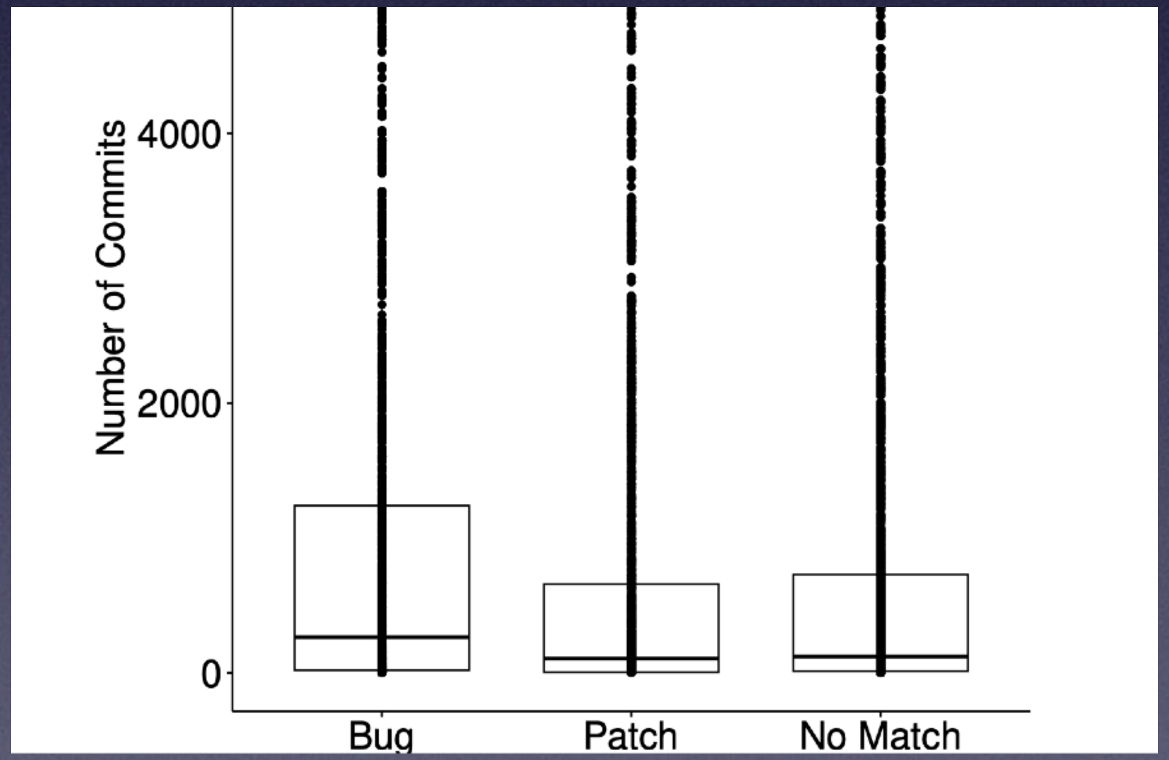

How “sticky” are Codex-generated bugs?

“Sticky” $\implies$ Takes Longer to Fix. 🤔🤔

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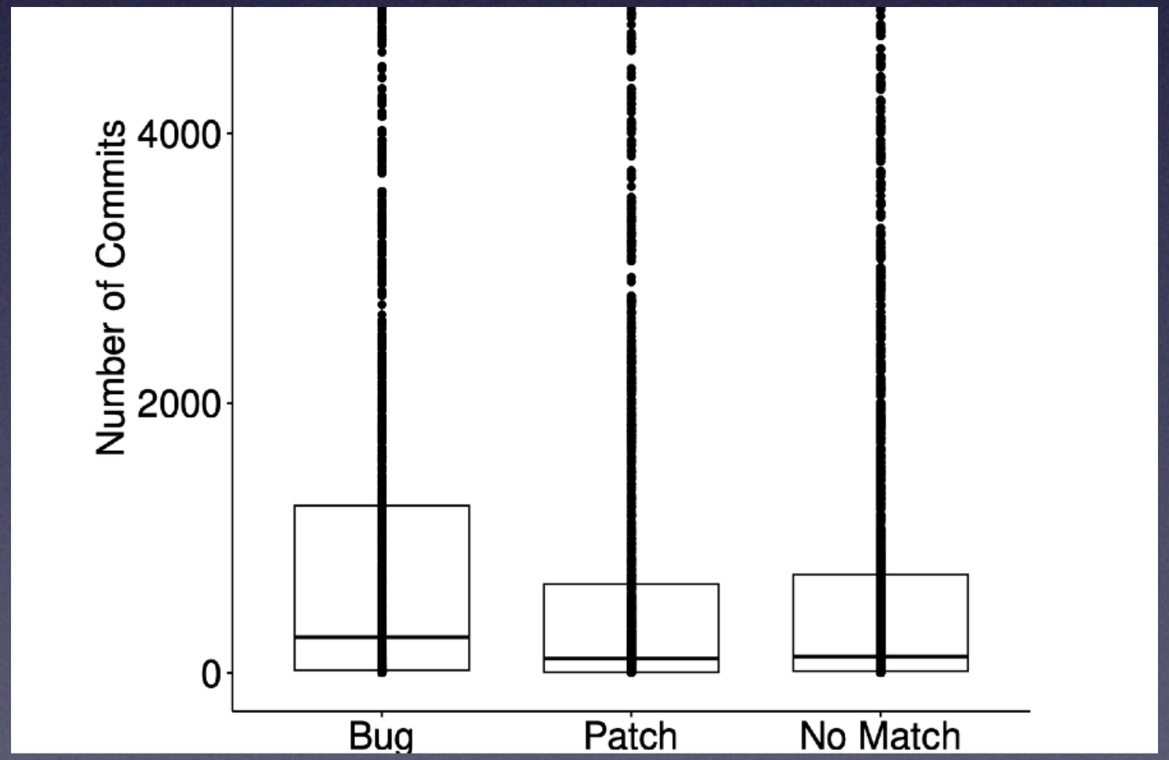

More “Natural” Bugs $\implies$ Longer to Fix ???

Overall Theme

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- LLMs: Codex, GPT-x, etc are now widely used to generate code and related artifacts.

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- Is this code any good? 🤨

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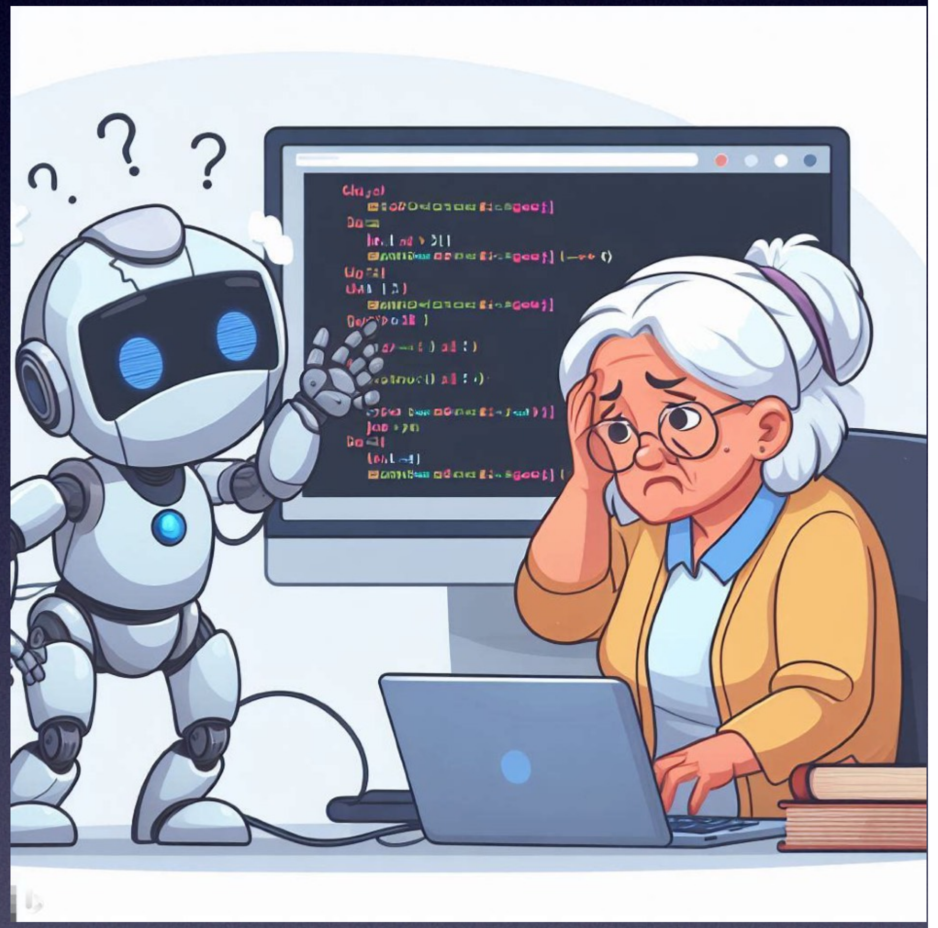
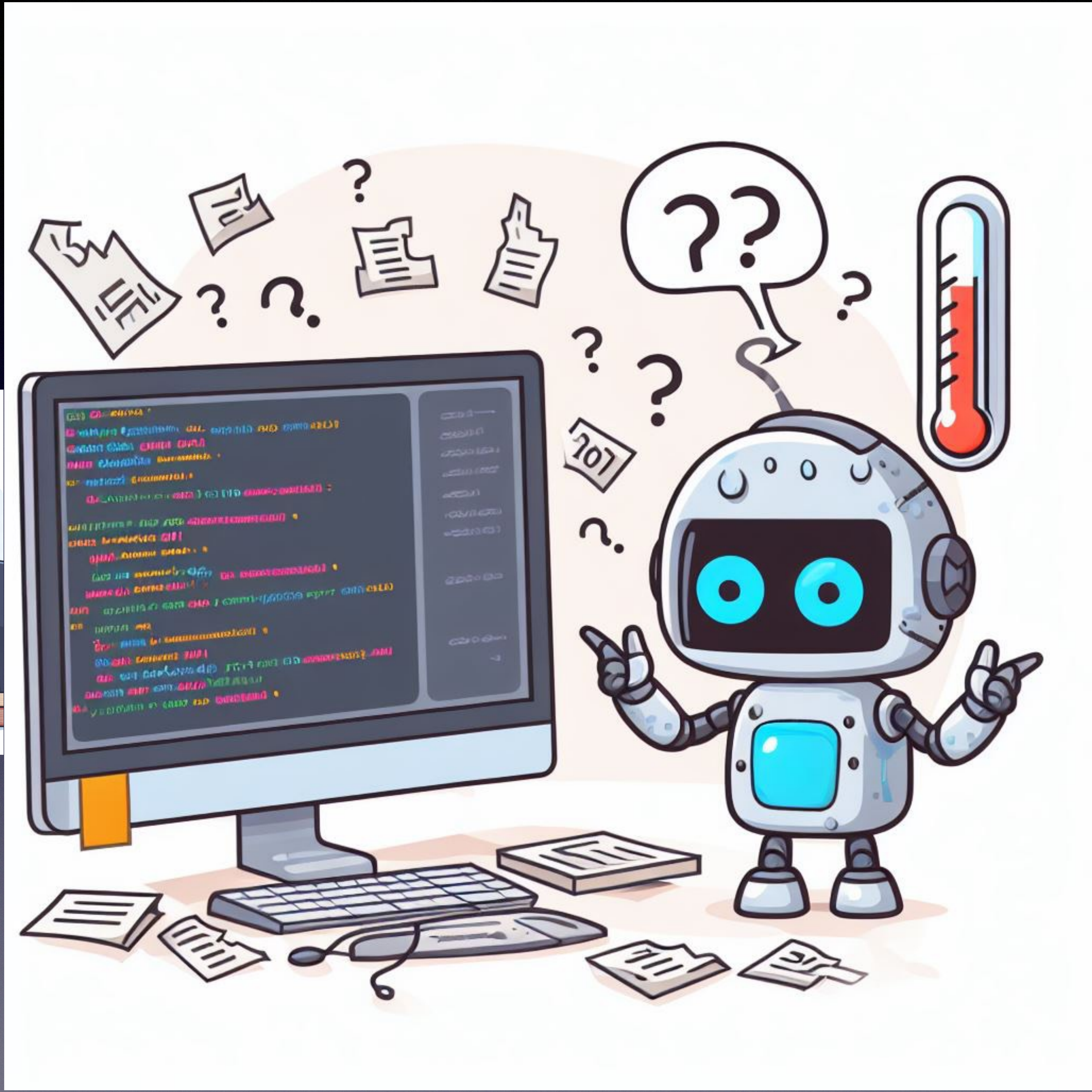
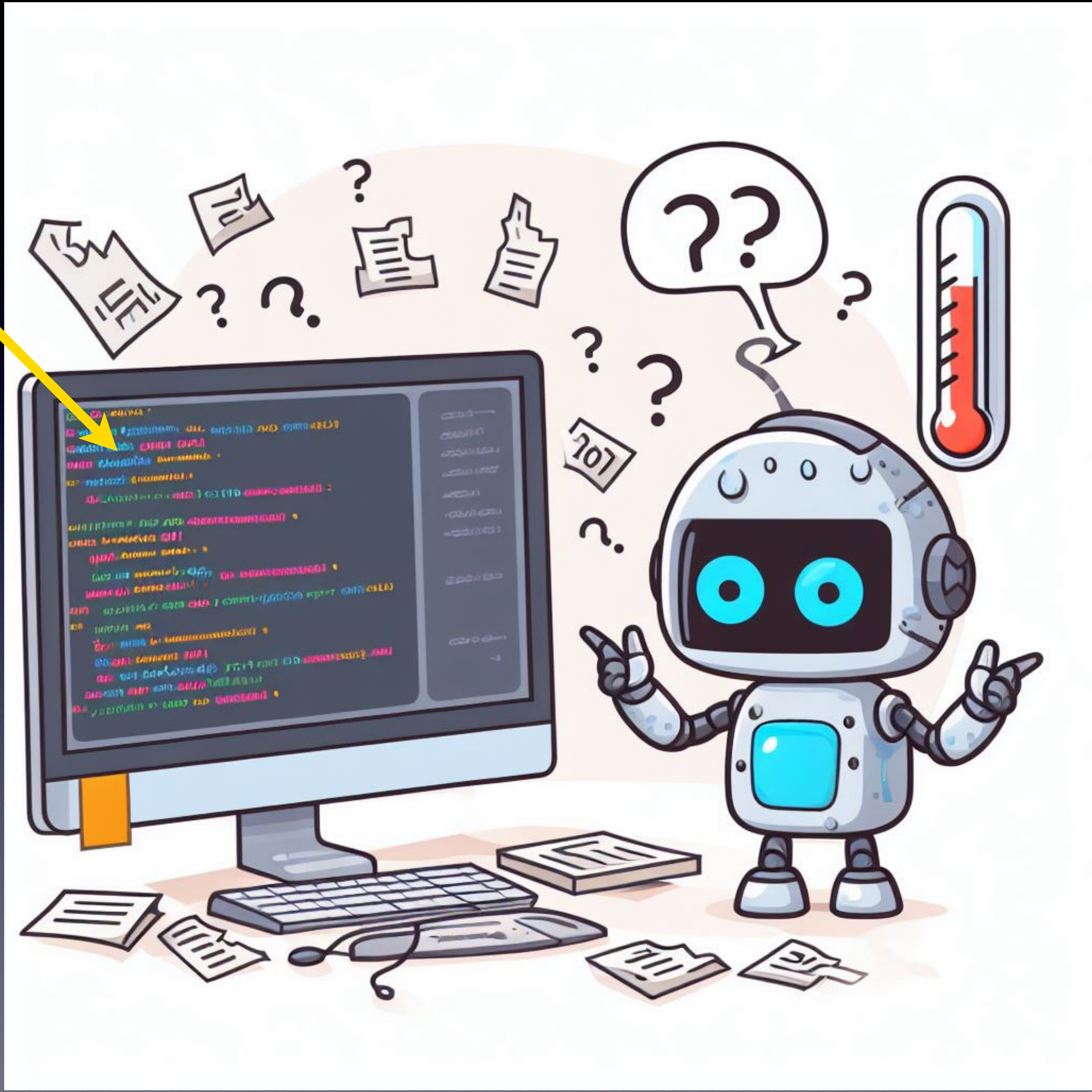
- LLMs: Codex, GPT-x, etc are now widely used to generate code and related artifacts.
- Is this code any good? 🤨
- If it's not always good what happens? 😱





Potentially *Incorrect* Text



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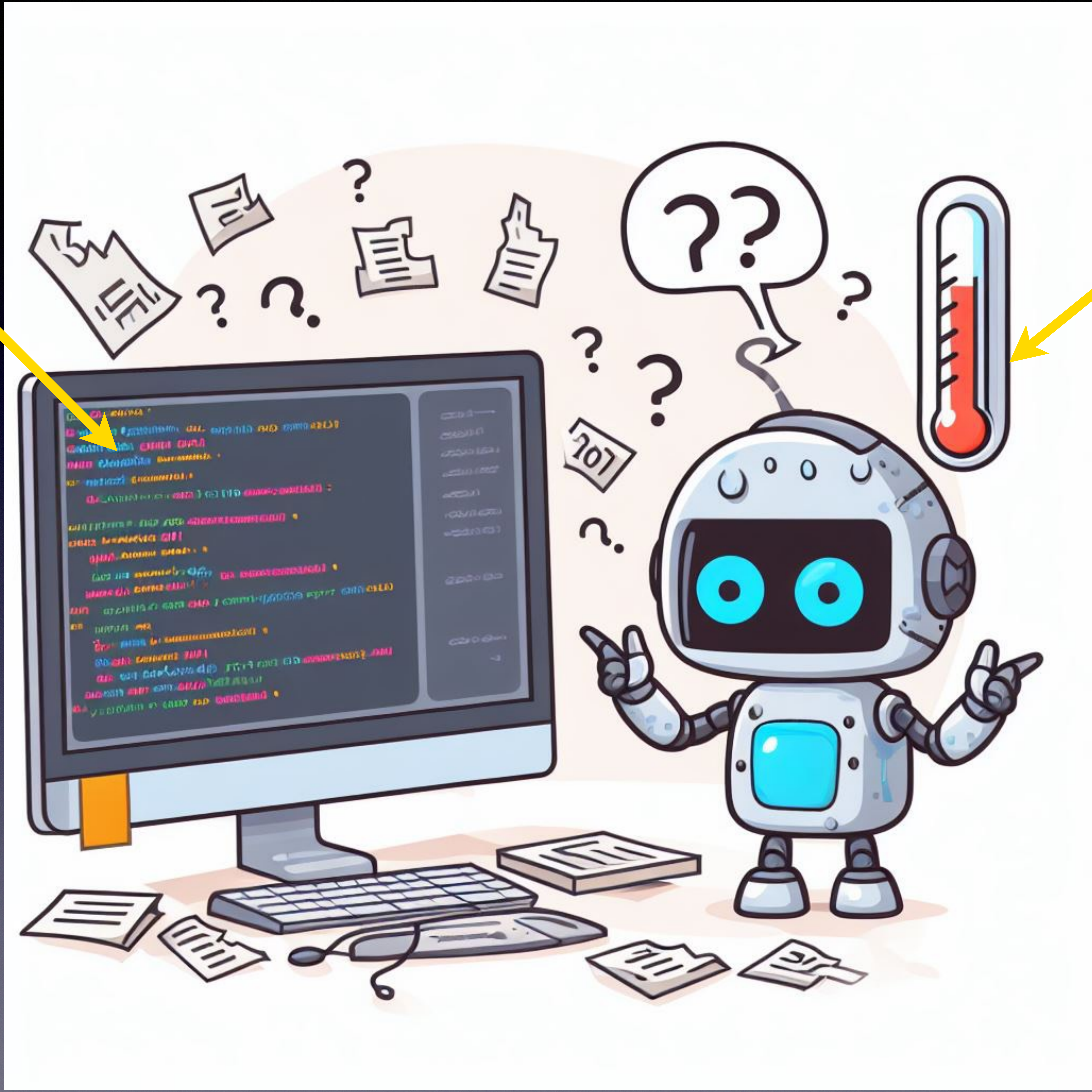
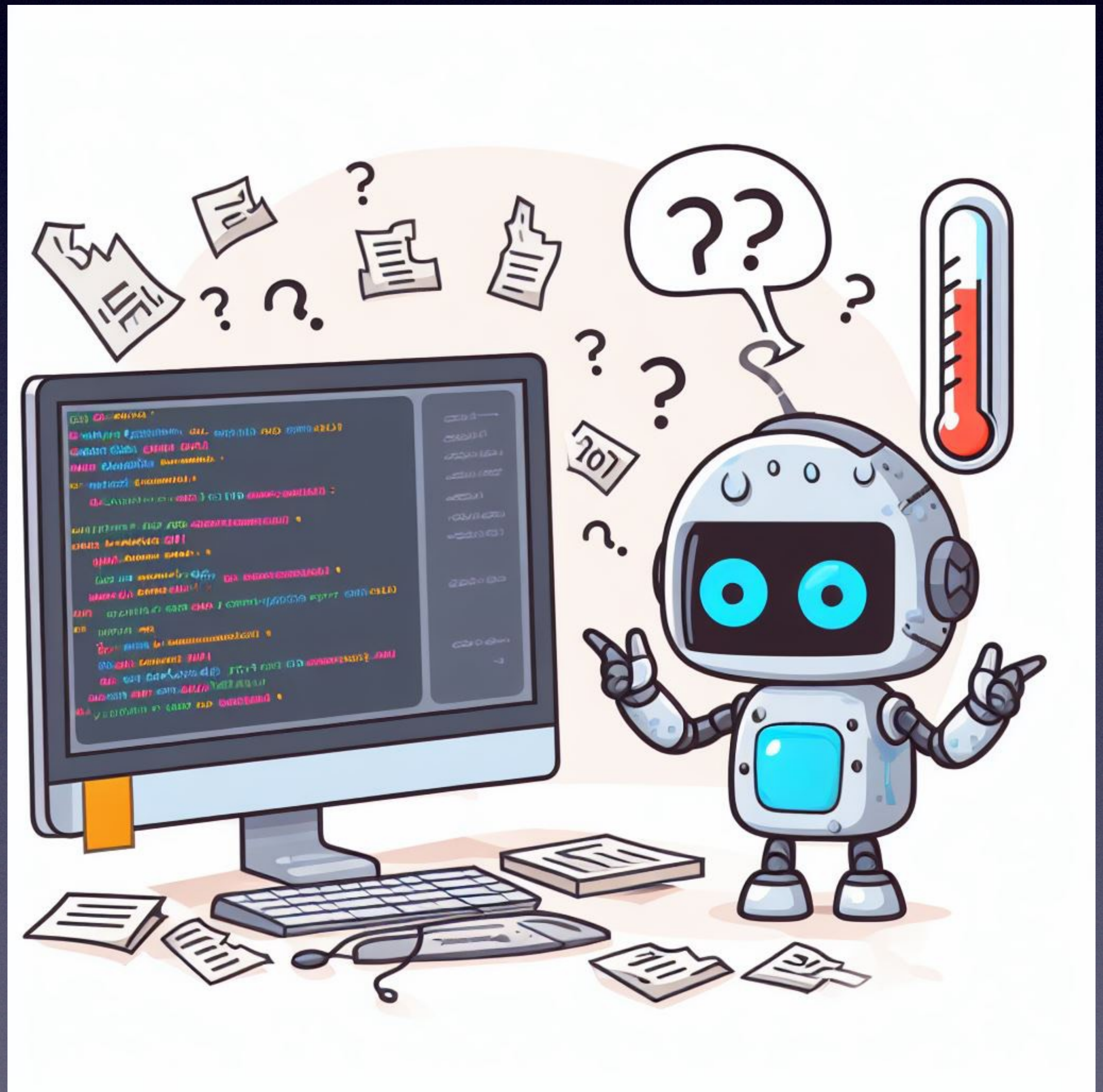
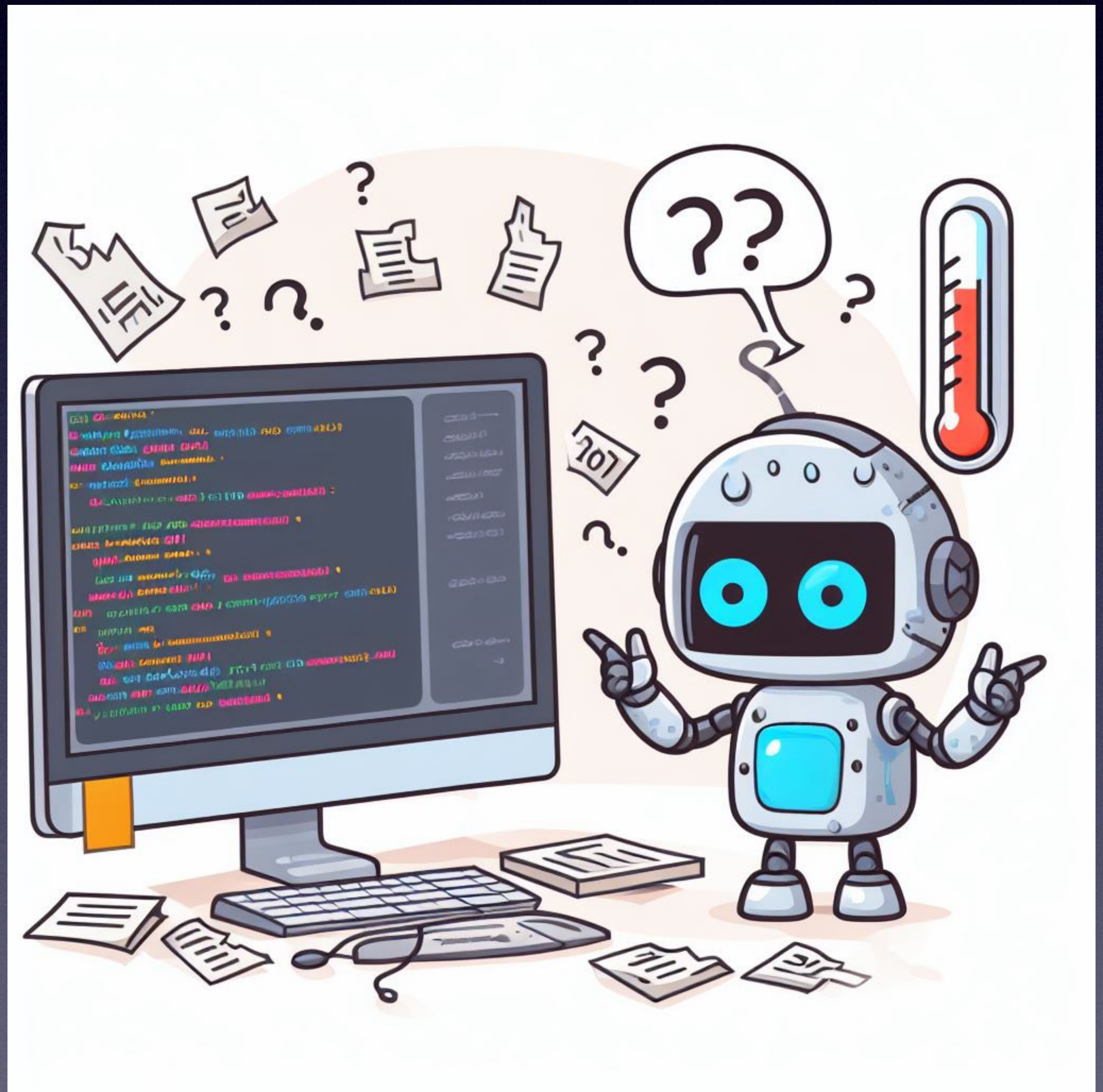


Indication Of *Confidence* In *Correctness*

Rational Decision Making



Rational Decision Making



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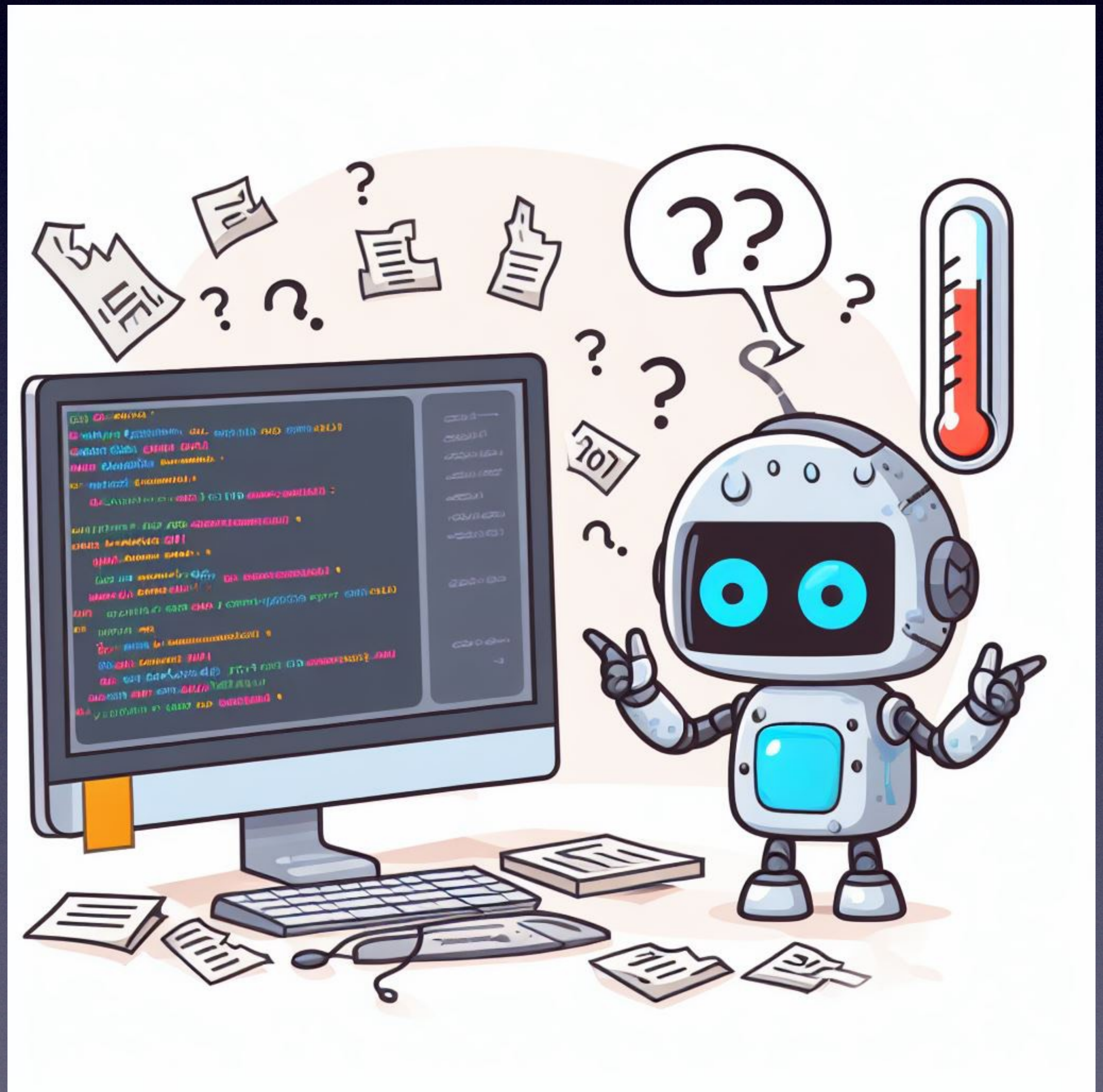
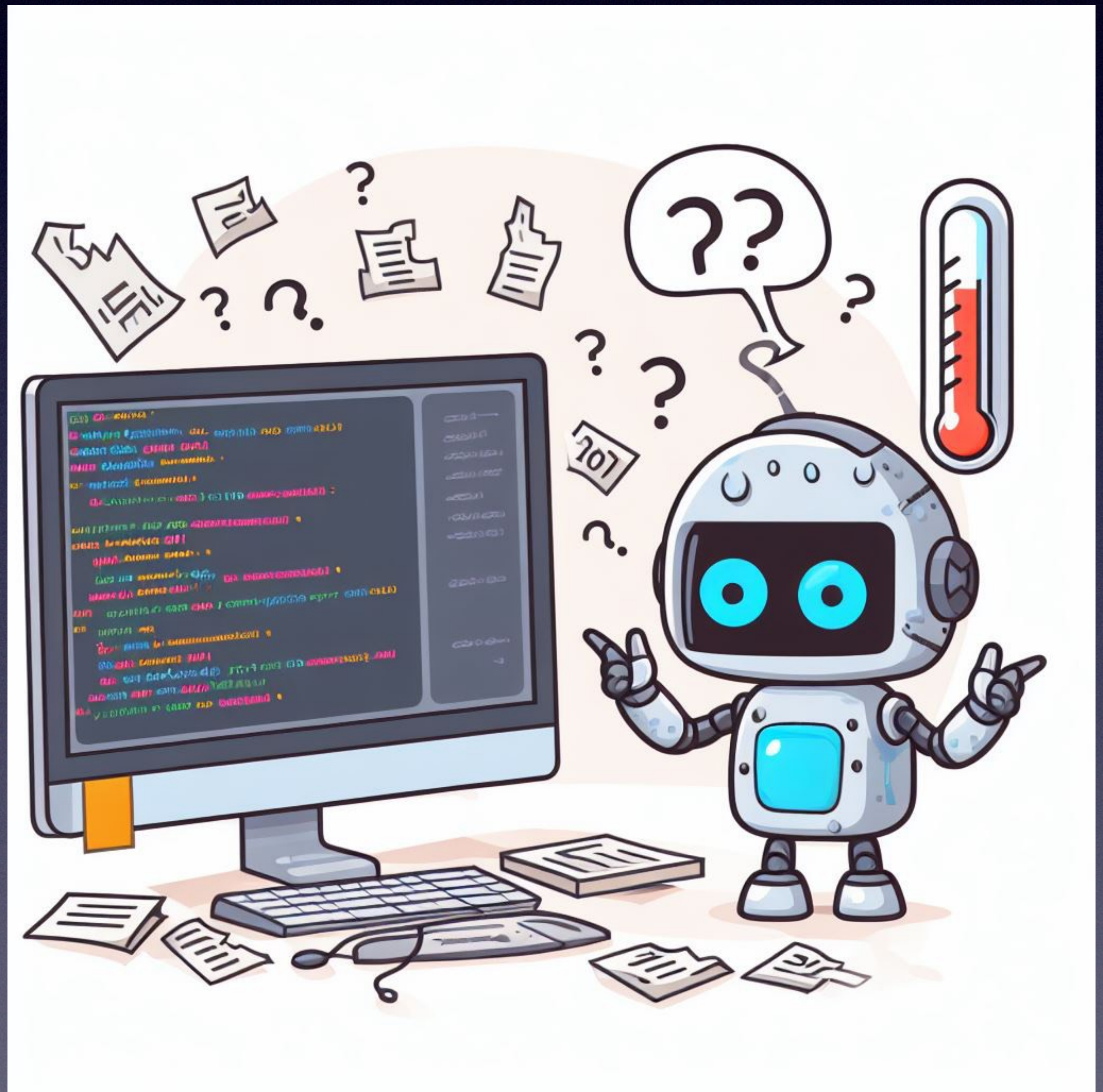


I'll ***discard***
if Confidence
is low

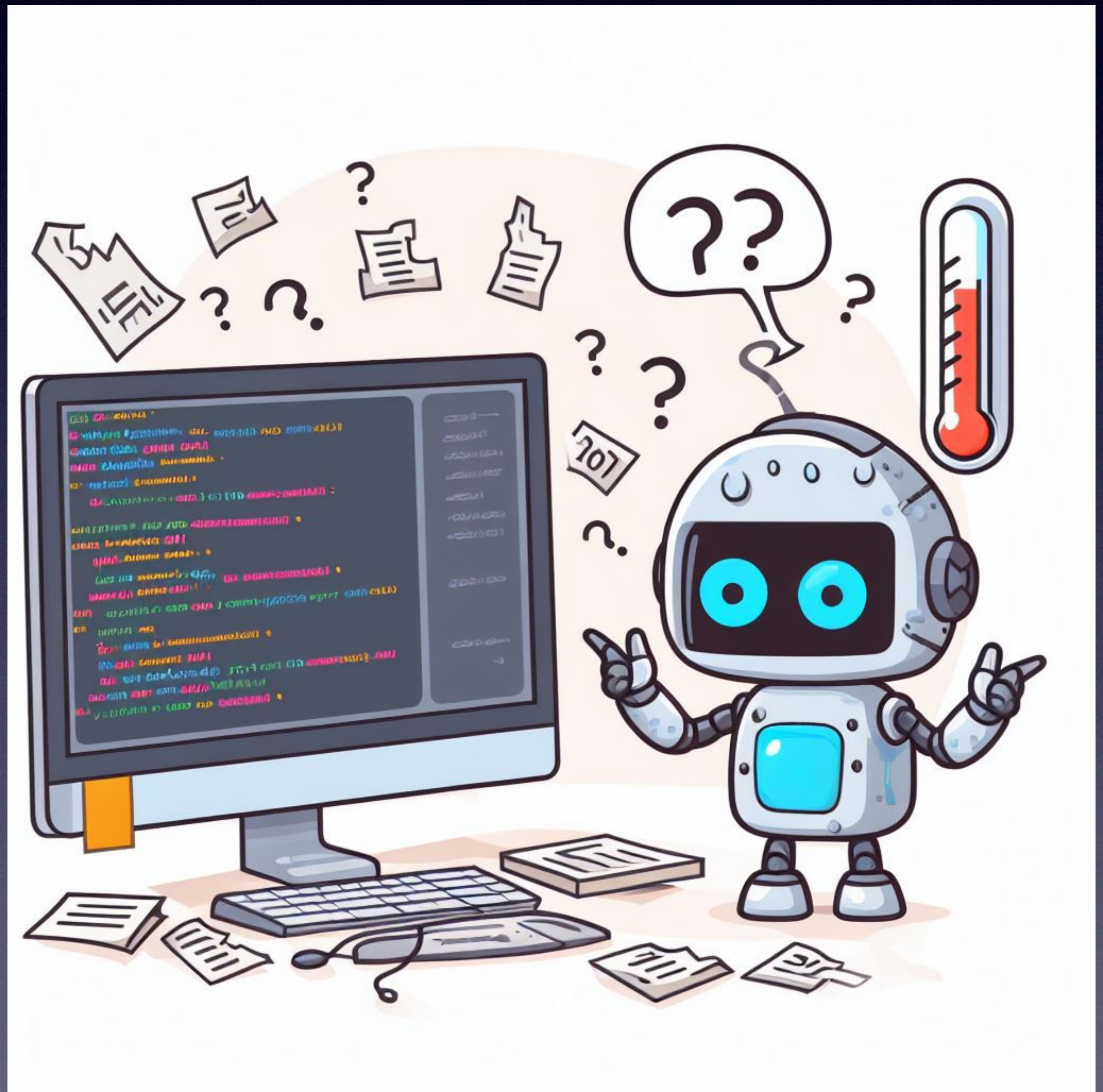
Rational Decision Making



I'll ***use Directly***
if Confidence
Is high

I'll ***discard***
if Confidence
is low

Rational Decision Making

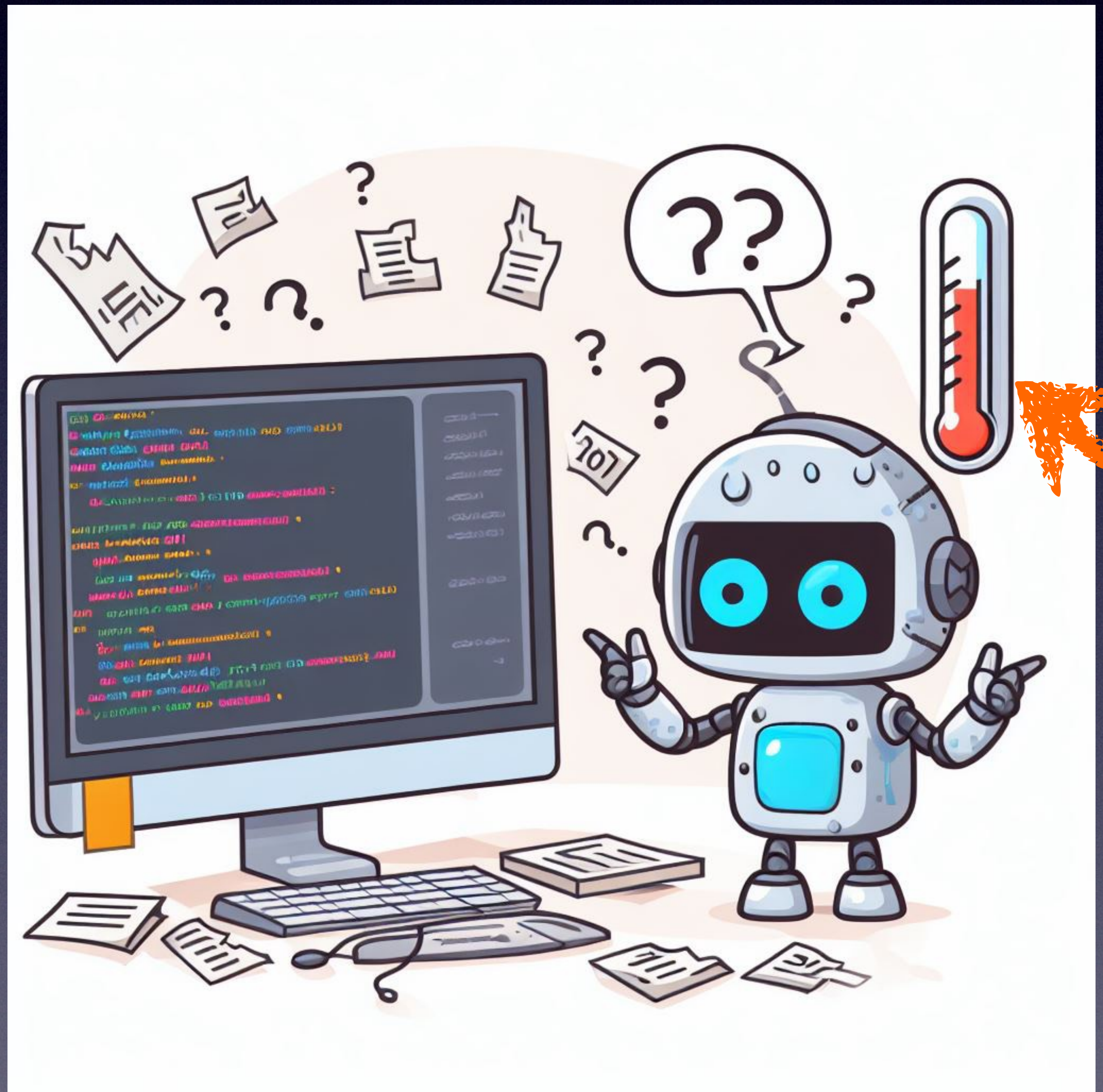


Rational Decision Making

I'll ***review &edit***
if Confidence
is medium

I'll ***use***
Directly
if Confidence
Is high

I'll ***discard***
if Confidence
is low



..but for this to work, we need well-calibrated Confidence!!

Rational Decions, *in Expectation*

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- Whenever output is generated at high-confidence, it should be empirically ***correct*** most often. *Otherwise…*

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Rational Decions, *in Expectation*

- Whenever output is generated at high-confidence, it should be empirically ***correct*** most often. *Otherwise…*
- Whenever output is generated at low-confidence, it should be empircally ***wrong*** most often. *Otherwise…*
- Whenever output is generated at medium-confidence, it should be empirically ***right*** *and* ***wrong*** about the same. *Otherwise…*

Calibration of Predictive Models

Rain Prediction Model

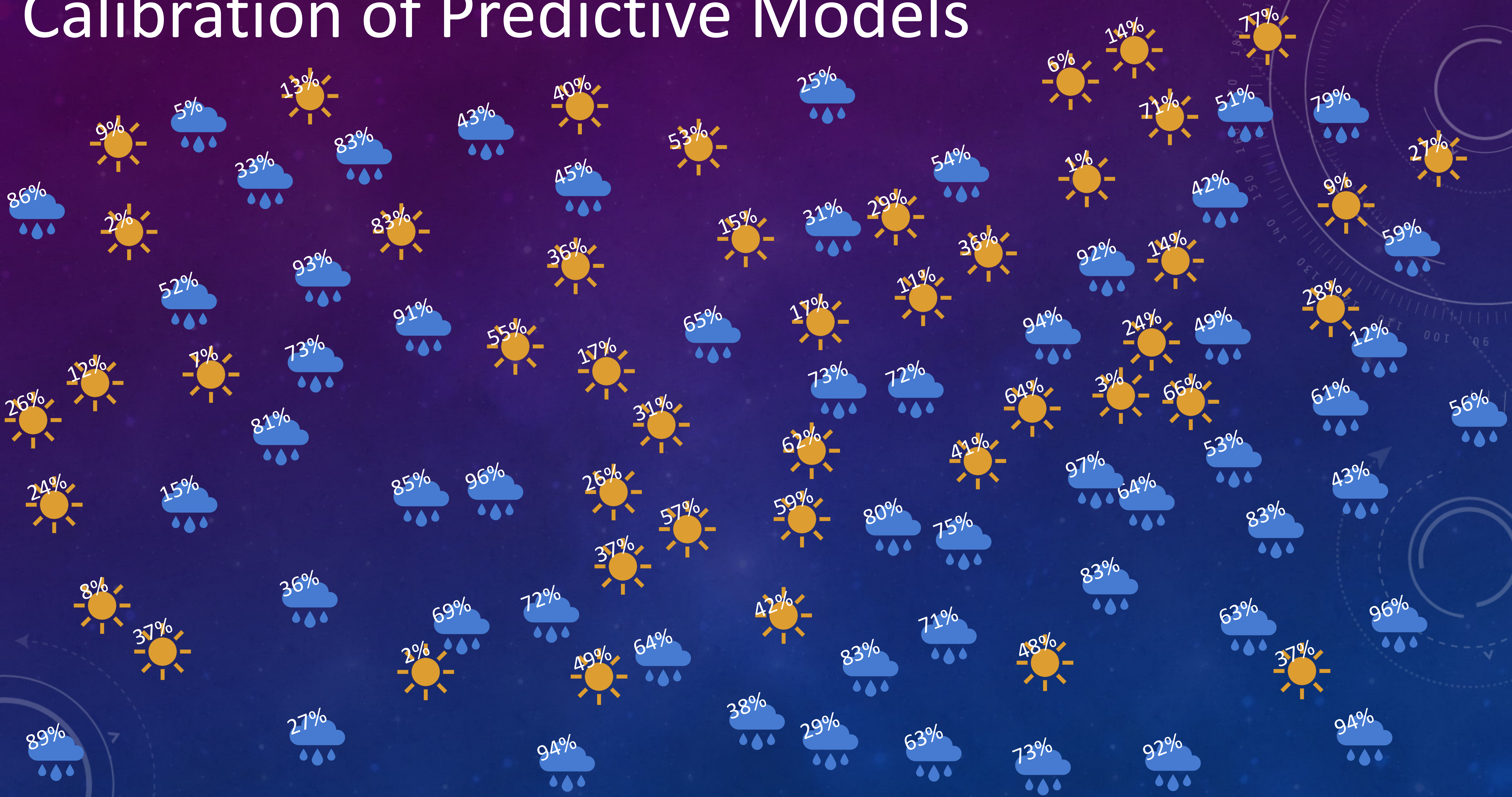
54%

Calibration of Predictive Models

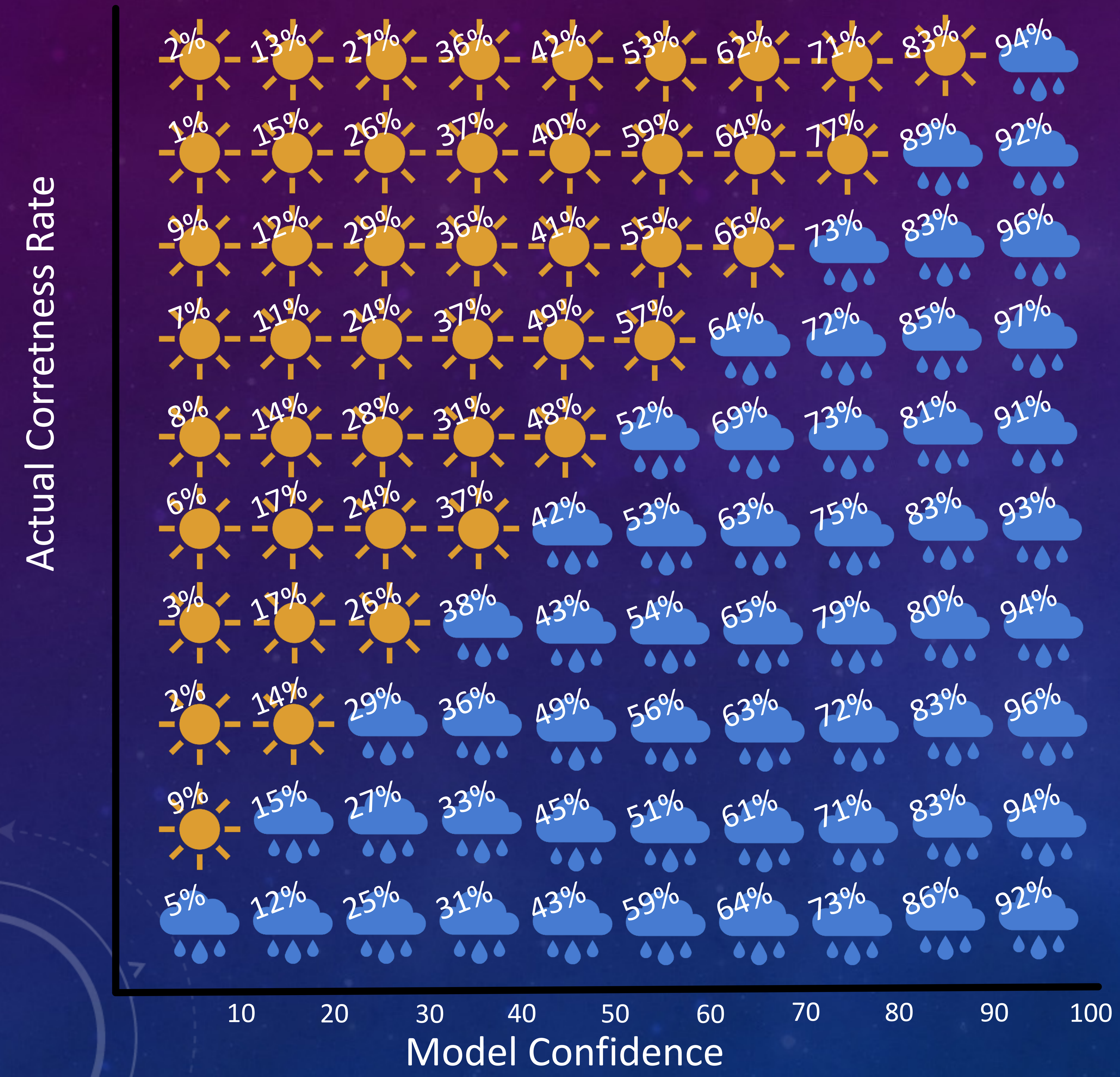
36%

54%

Calibration of Predictive Models



Calibration of Predictive Models



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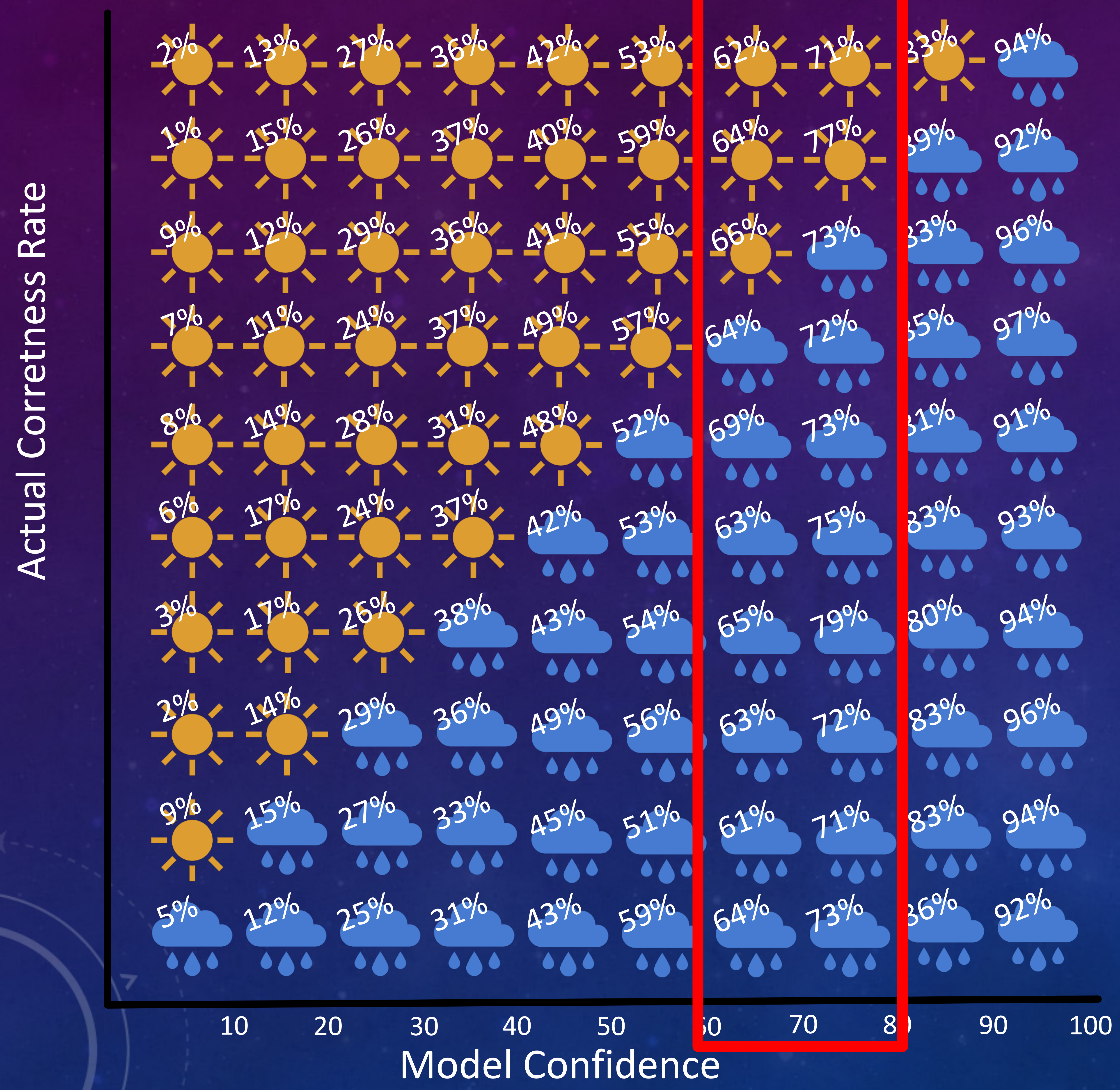

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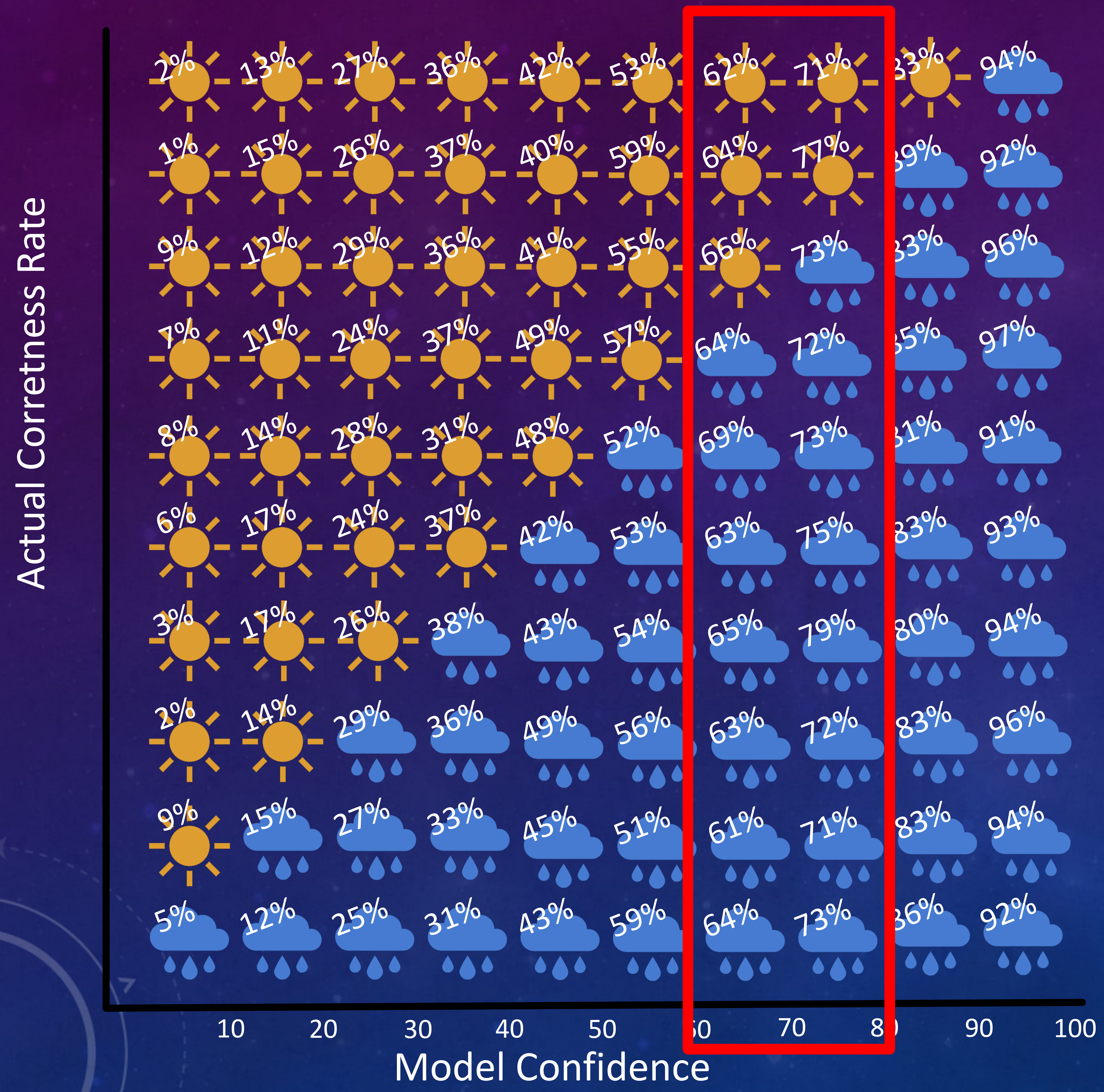

=> Rational Decision Making!

Correctness? Confidence?

Correctness?

Confidence?

- Exact match with Provided Correct Code

Correctness?

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- Exact match with Provided Correct Code
- Correctness modulo testing. (Which tests?)

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Confidence?

- ***“Intrinsic probabilities”*** from the model *(average and cumulative)*

Correctness?	Confidence?

Correctness?

- Exact match with Provided Correct Code
- Correctness modulo testing. (Which tests?)

Confidence?

- ***“Intrinsic probabilities”*** from the model *(average and cumulative)*
- … Other measures later

“Intrinsic Probabilities”

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- LLMs generate text one token at a time, each according to a probability space for choices.

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```
print ( “ hello
```

“Intrinsic Probabilities”

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print (“ hello

!
world
\
“
the

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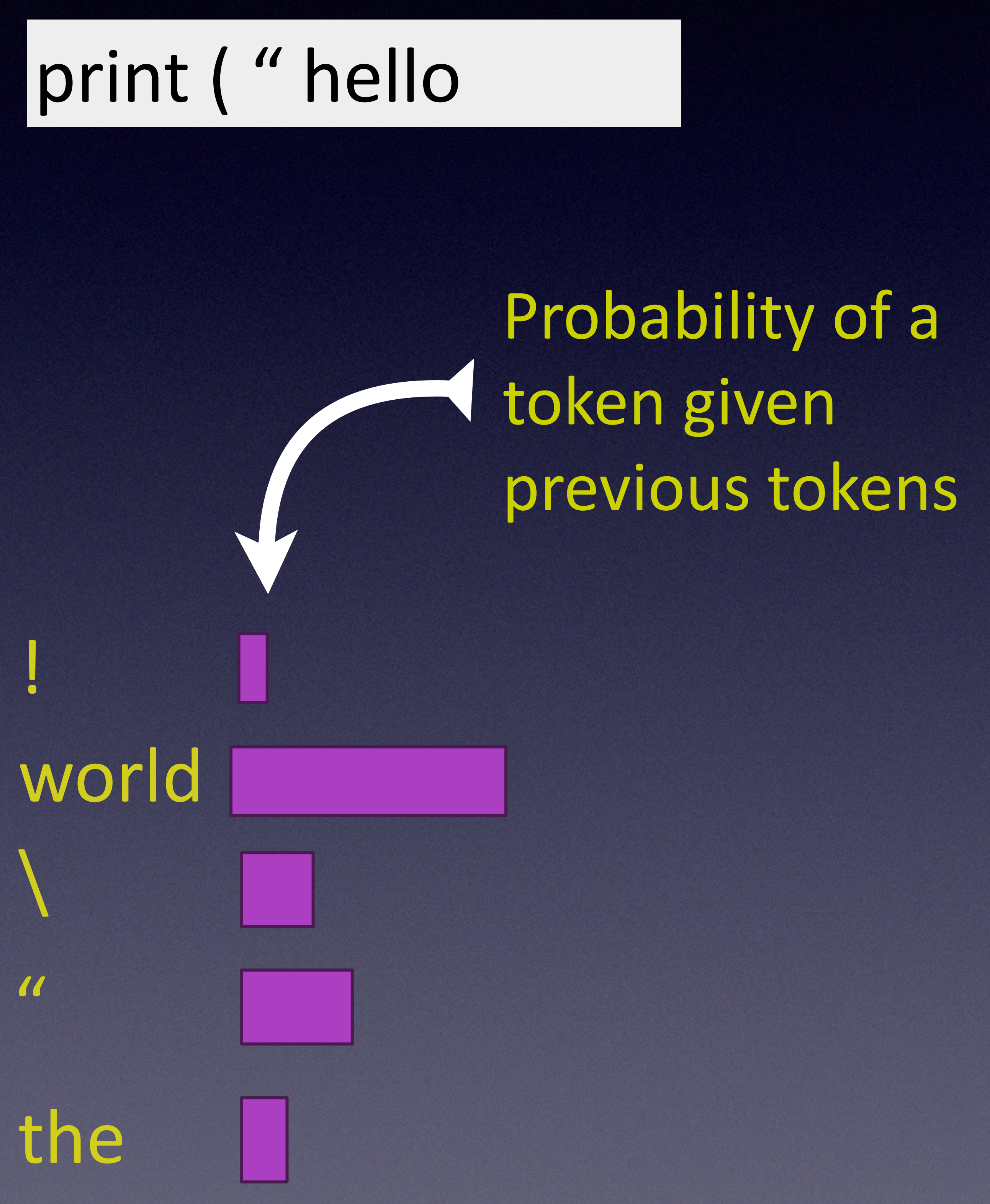
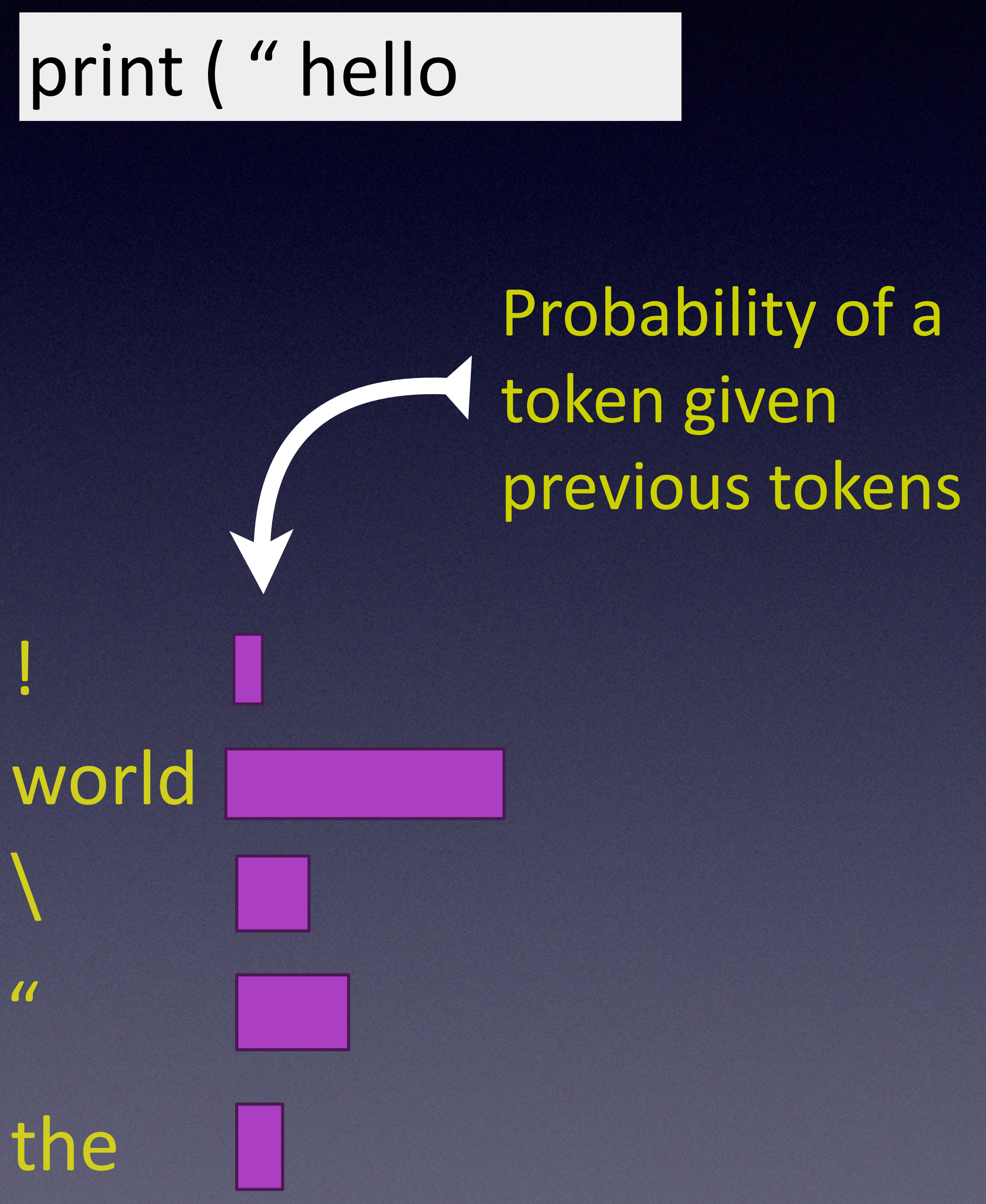


“Intrinsic Probabilities”

- LLMs generate text one token at a time, each according to a probability space for choices.
- “Intrinsic” confidence measure for us, is just this probability.



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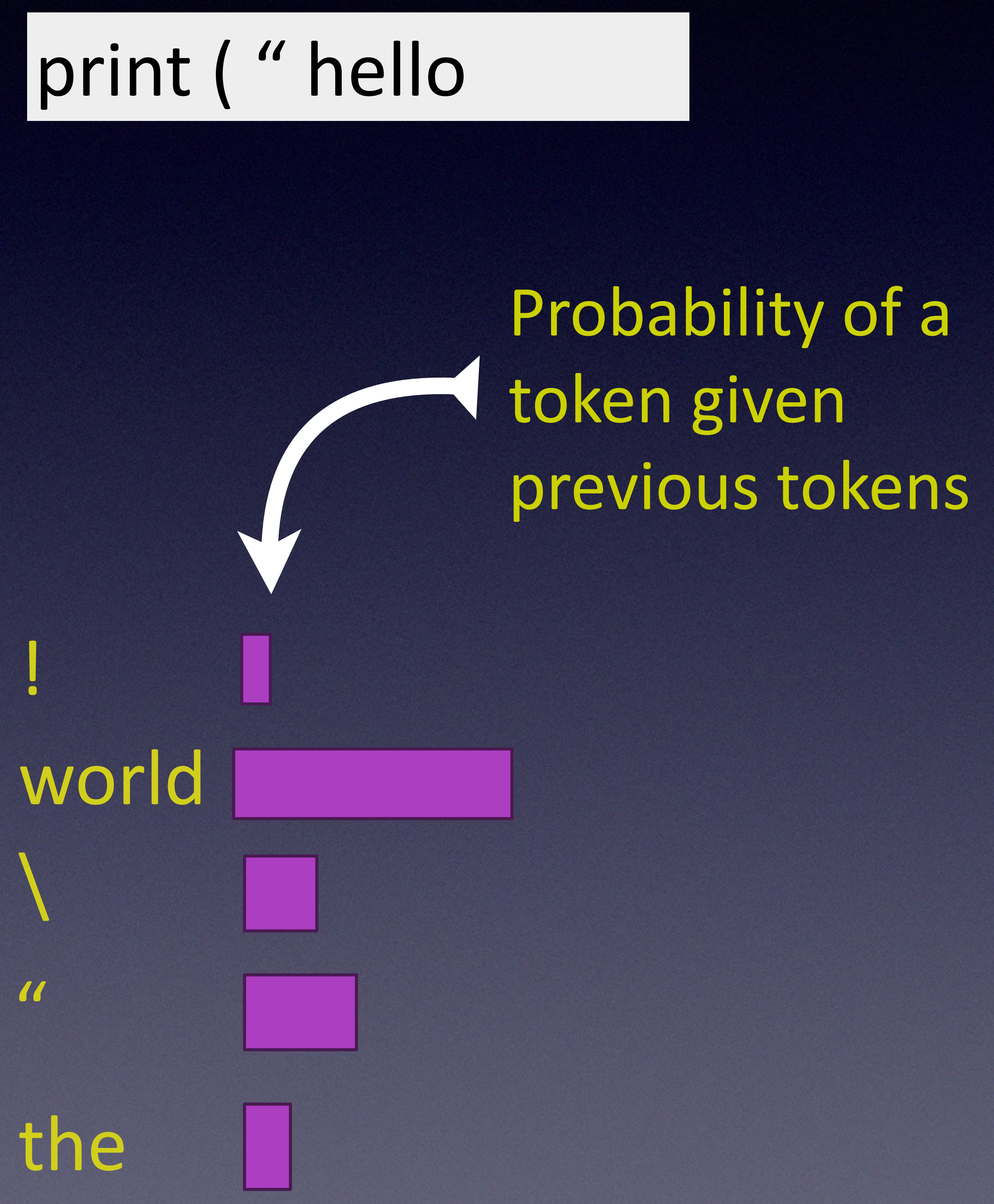

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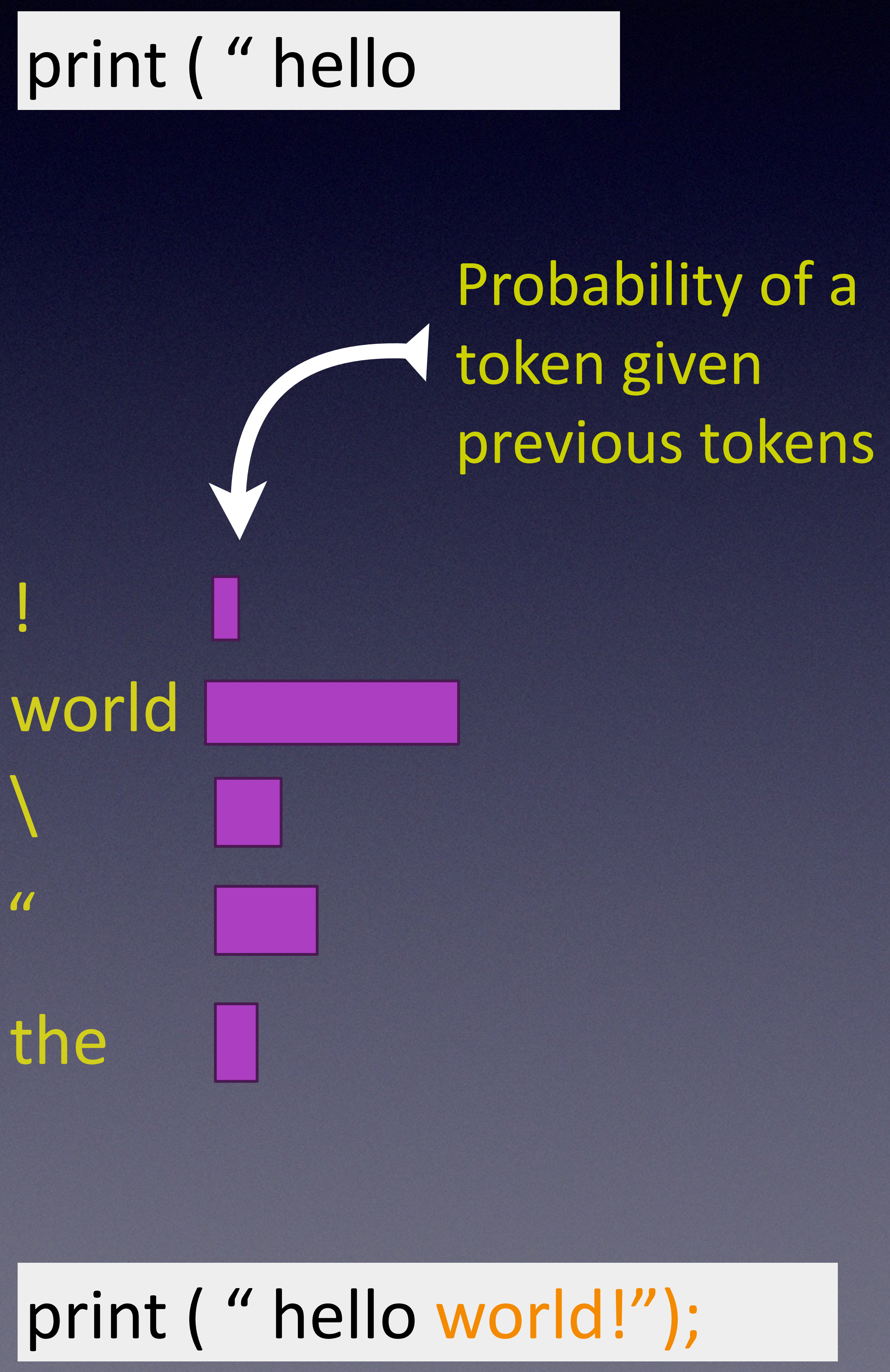

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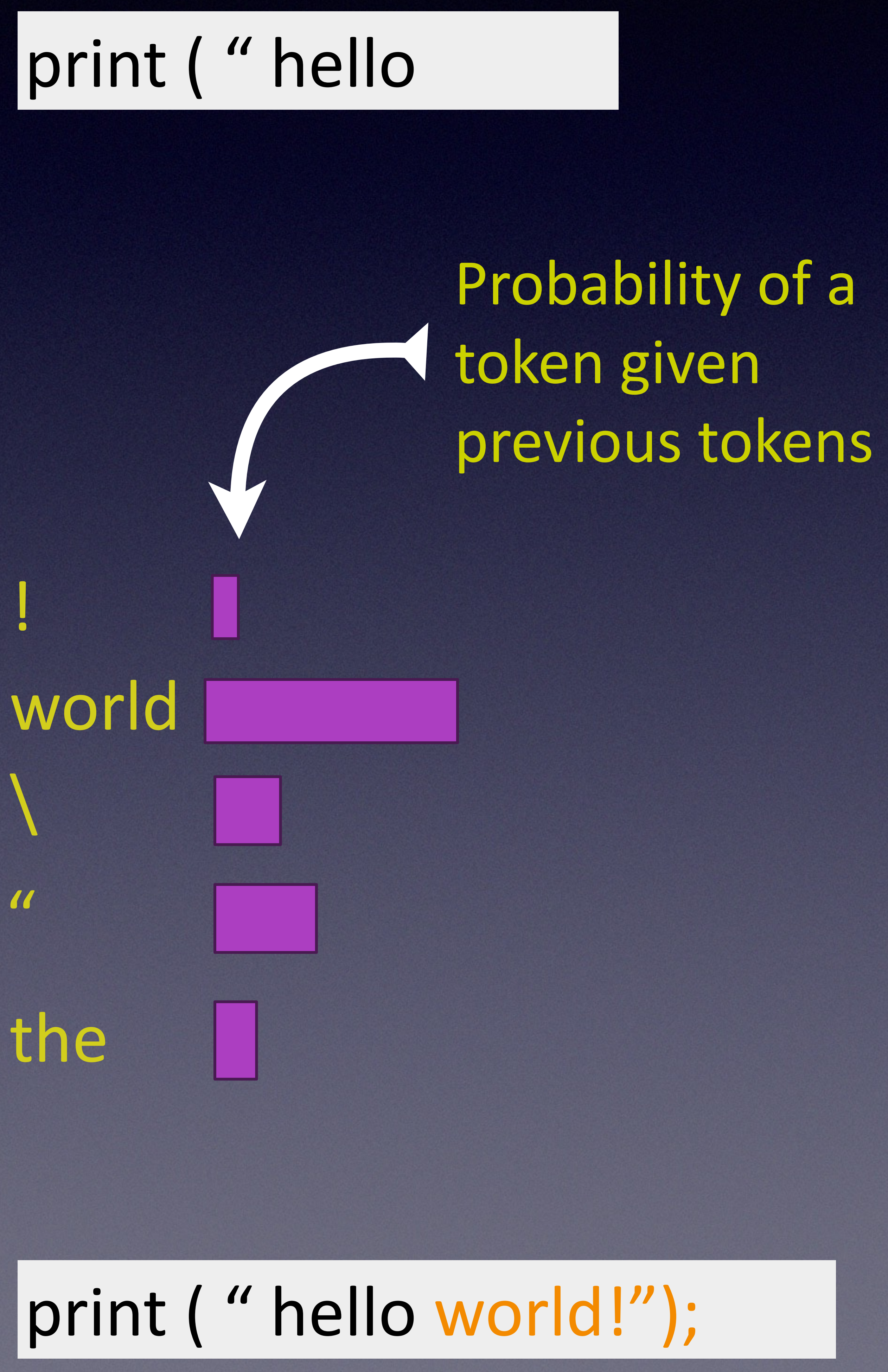
- Take per-token log-probs, and summarize (*Avg & Product*)



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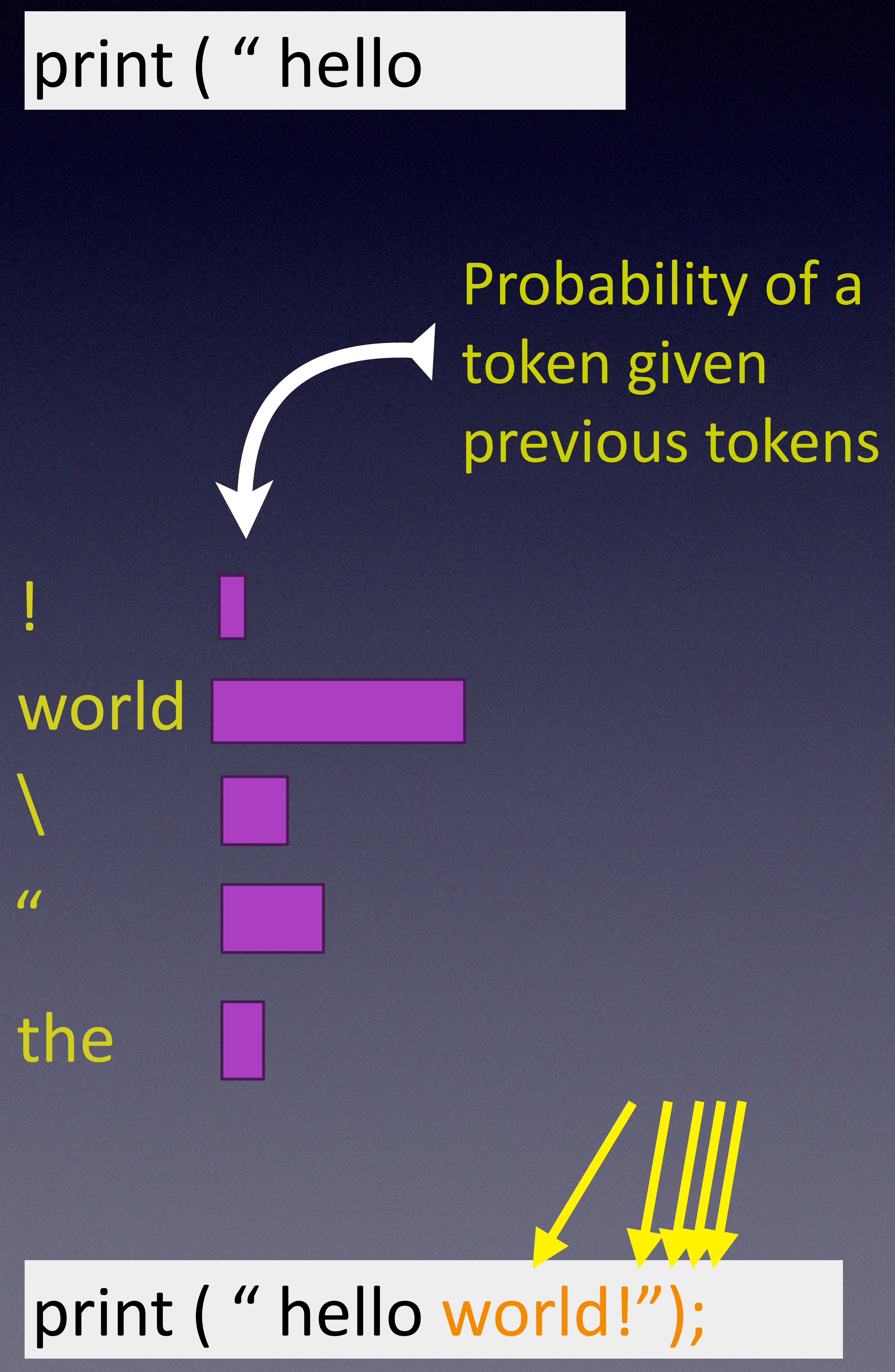

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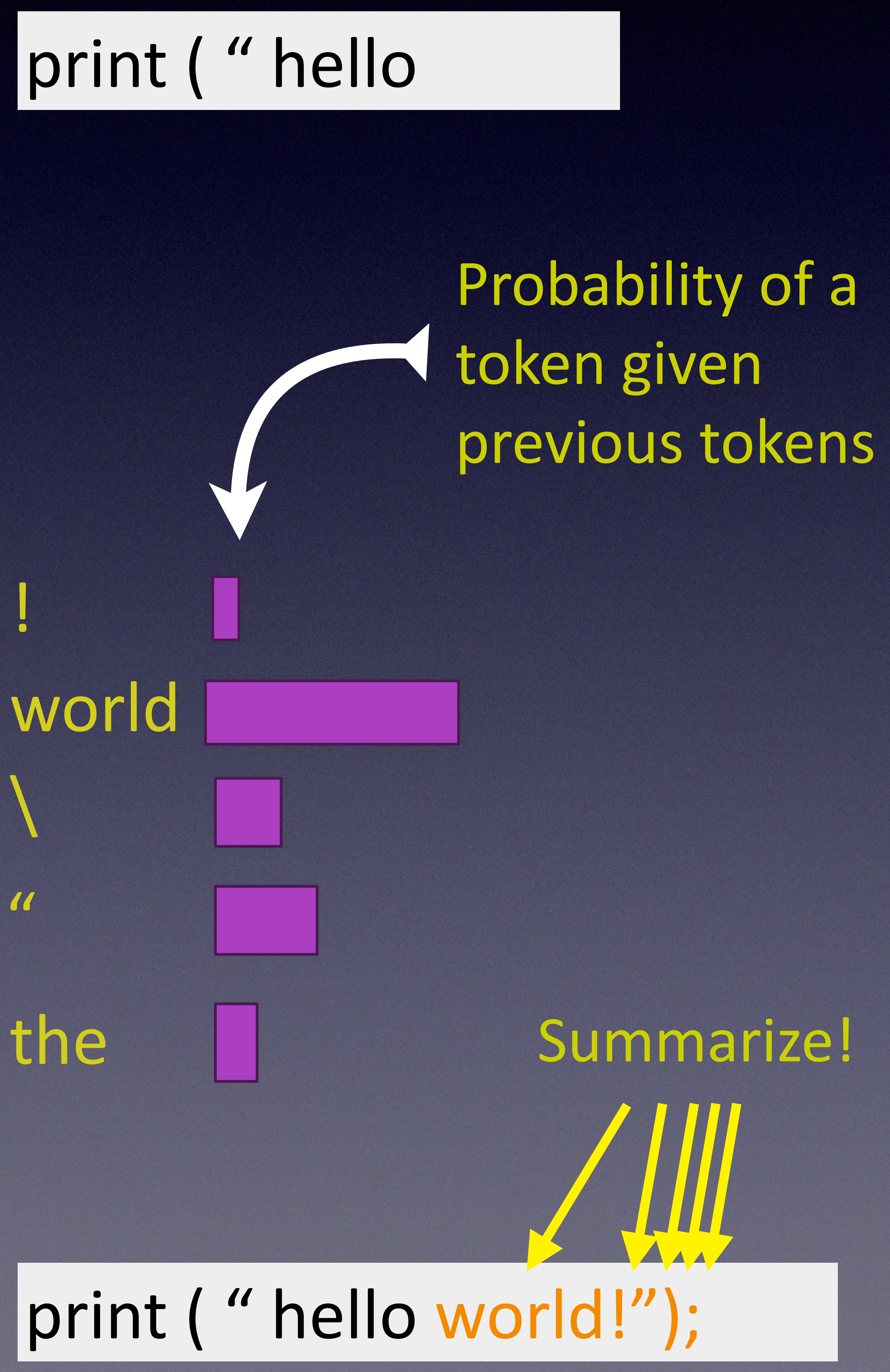
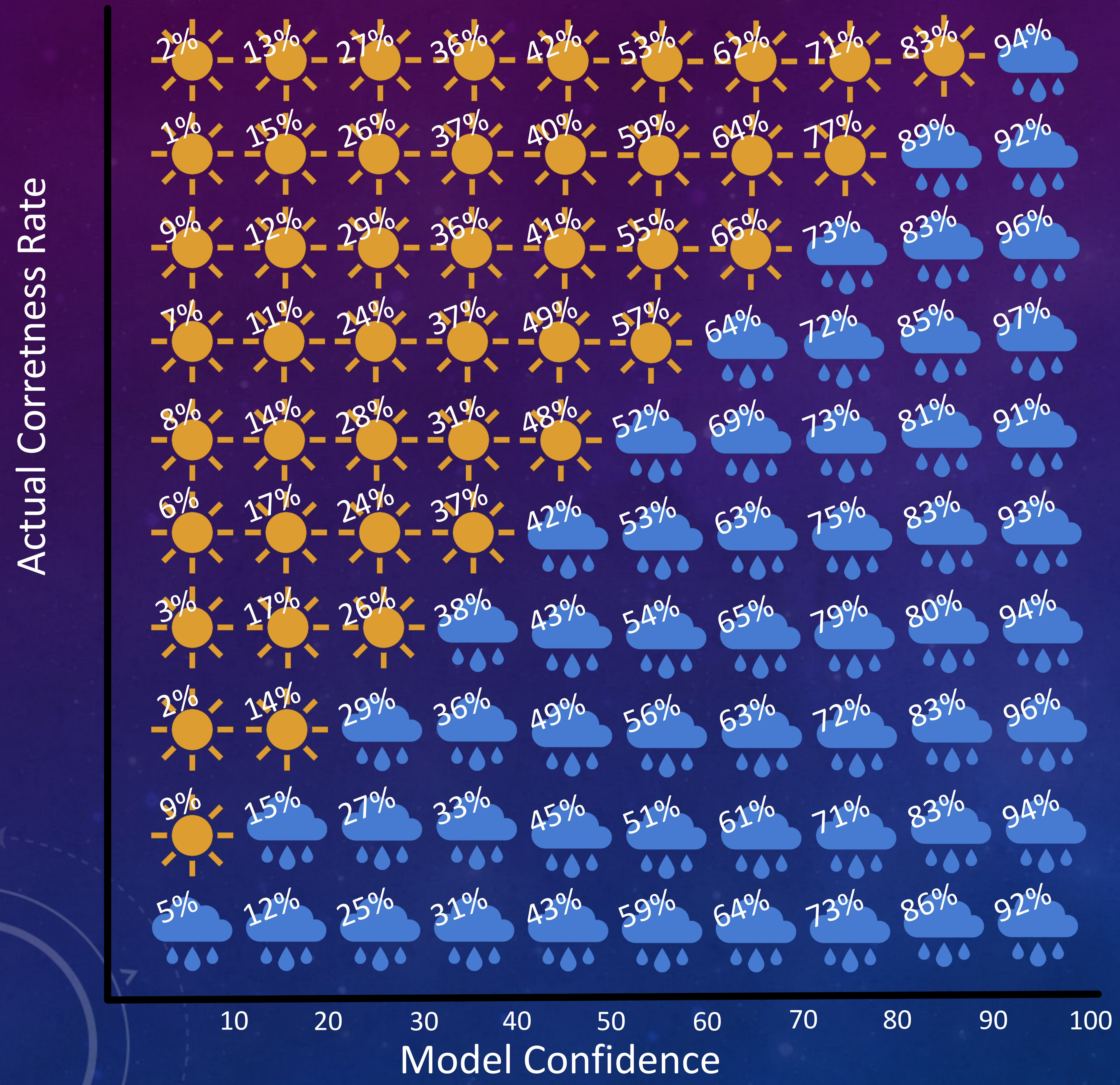


Calibration of Predictive Models



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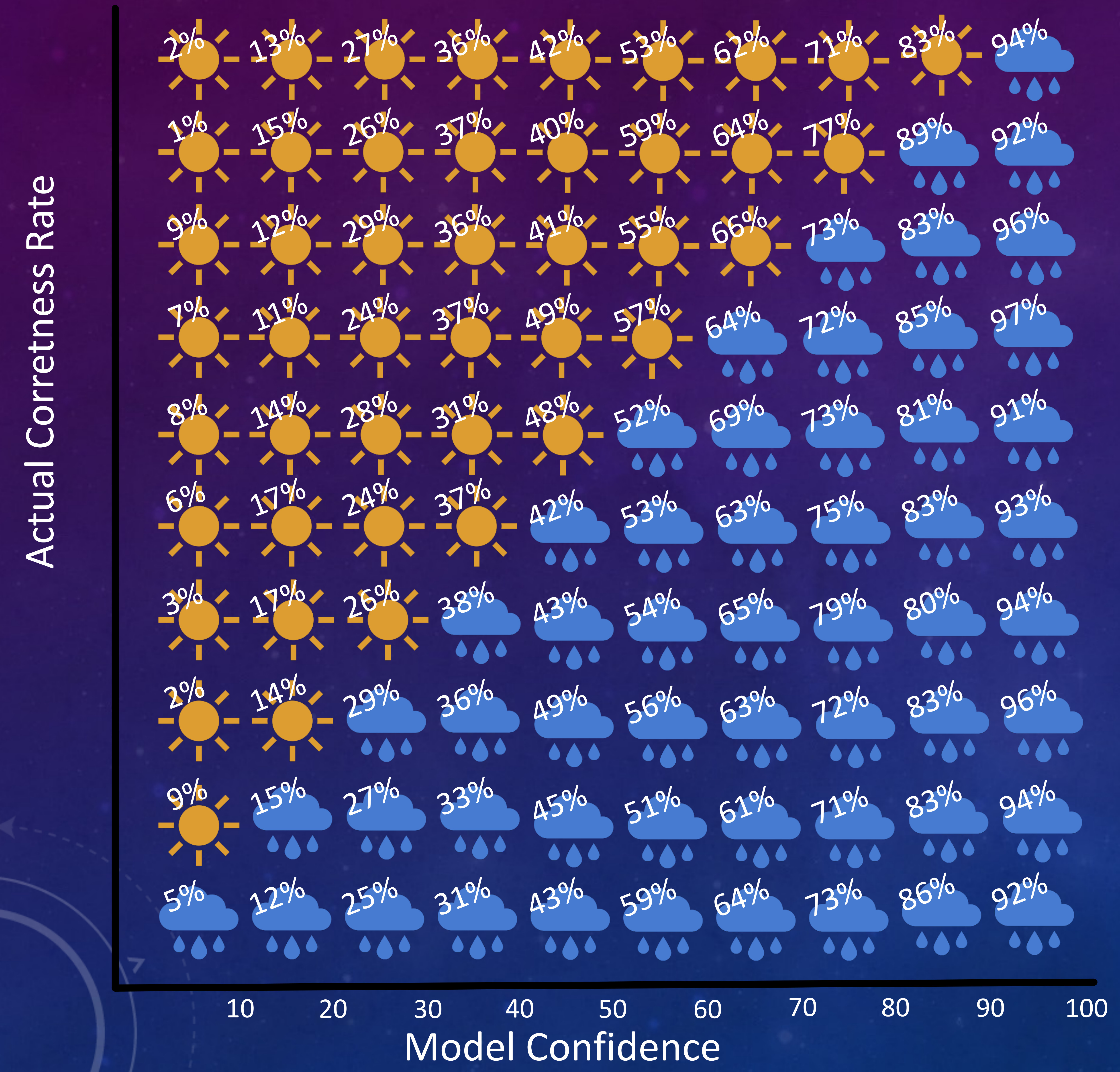
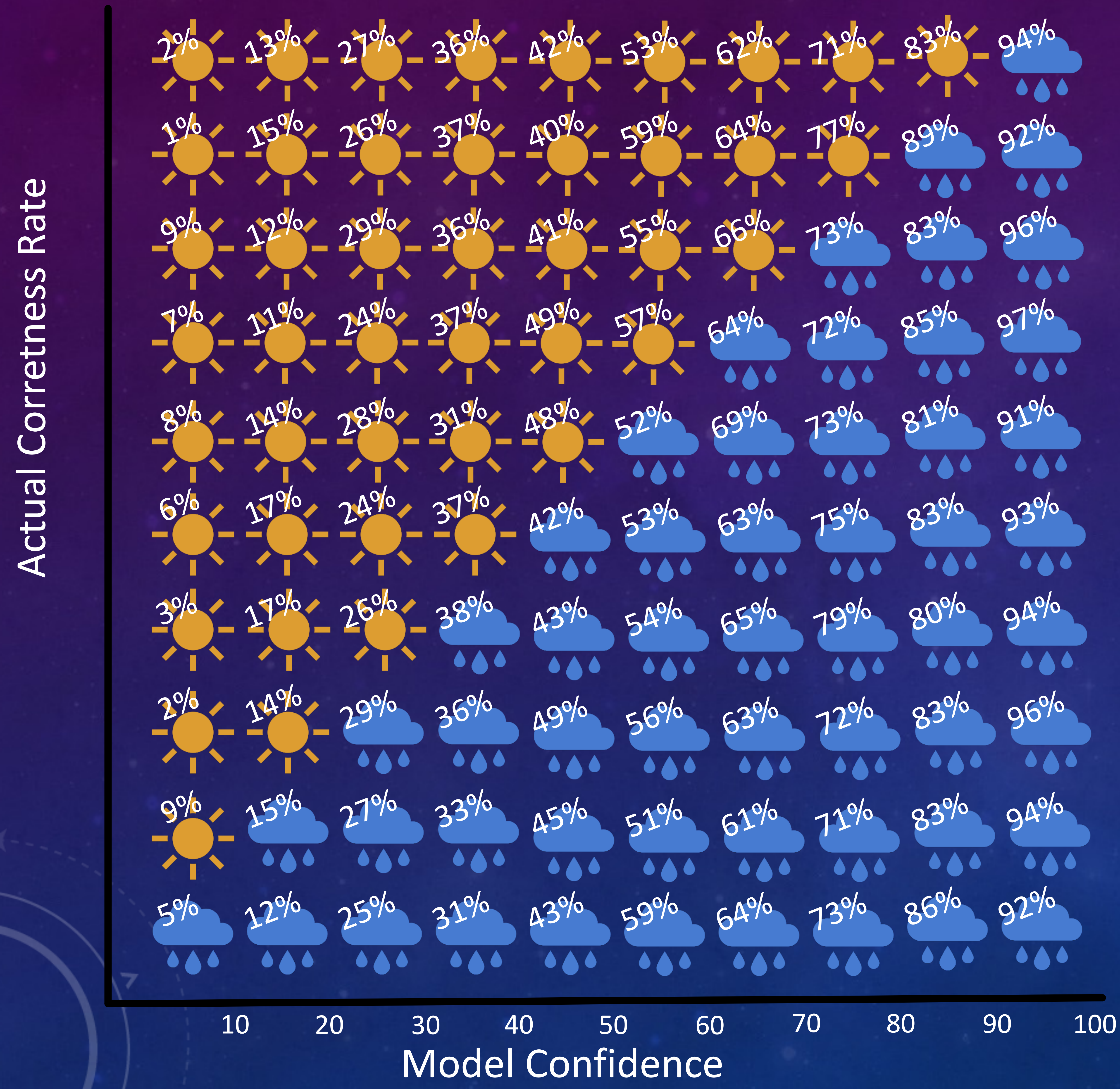


- Formalize this?

Calibration of Predictive Models



- Formalize this?
- Measuring how close we are to this ideal?

Calibration is a "constraint" On a Conditional Probability.

p(|) =

Calibration is a “constraint” On a Conditional Probability.

p(| model predicts with “π” confidence) =

Calibration is a “constraint” On a Conditional Probability.

p(model’s prediction is correct | model predicts with “π” confidence) =

Calibration is a "constraint" On a Conditional Probability.

$p(\text{model's prediction is correct} \mid \text{model predicts with "}\pi\text{" confidence}) = \pi$

Calibration is a "constraint"
On a Conditional Probability.

p(model's prediction is correct | model predicts with "π" confidence) = π

$$p(y = \hat{y} \,|\, P_{\mathscr{M}}(x, \hat{y}) = \pi) = \pi$$

Calibration is a "constraint" On a Conditional Probability.

p(model's prediction is correct | model predicts with "π" confidence) = π

$$p(y = \hat{y} \mid P_{\mathbb{M}}(x, \hat{y}) = \pi) = \pi$$

y correct output for x

$\hat{y}$ model output for x

$P_{\mathbb{M}}(x, \hat{y})$ model confidence for input x output ŷ

Reliability Diagram:

Confidence vs. Correctness

p(|) =

Reliability Diagram:

Confidence vs. Correctness

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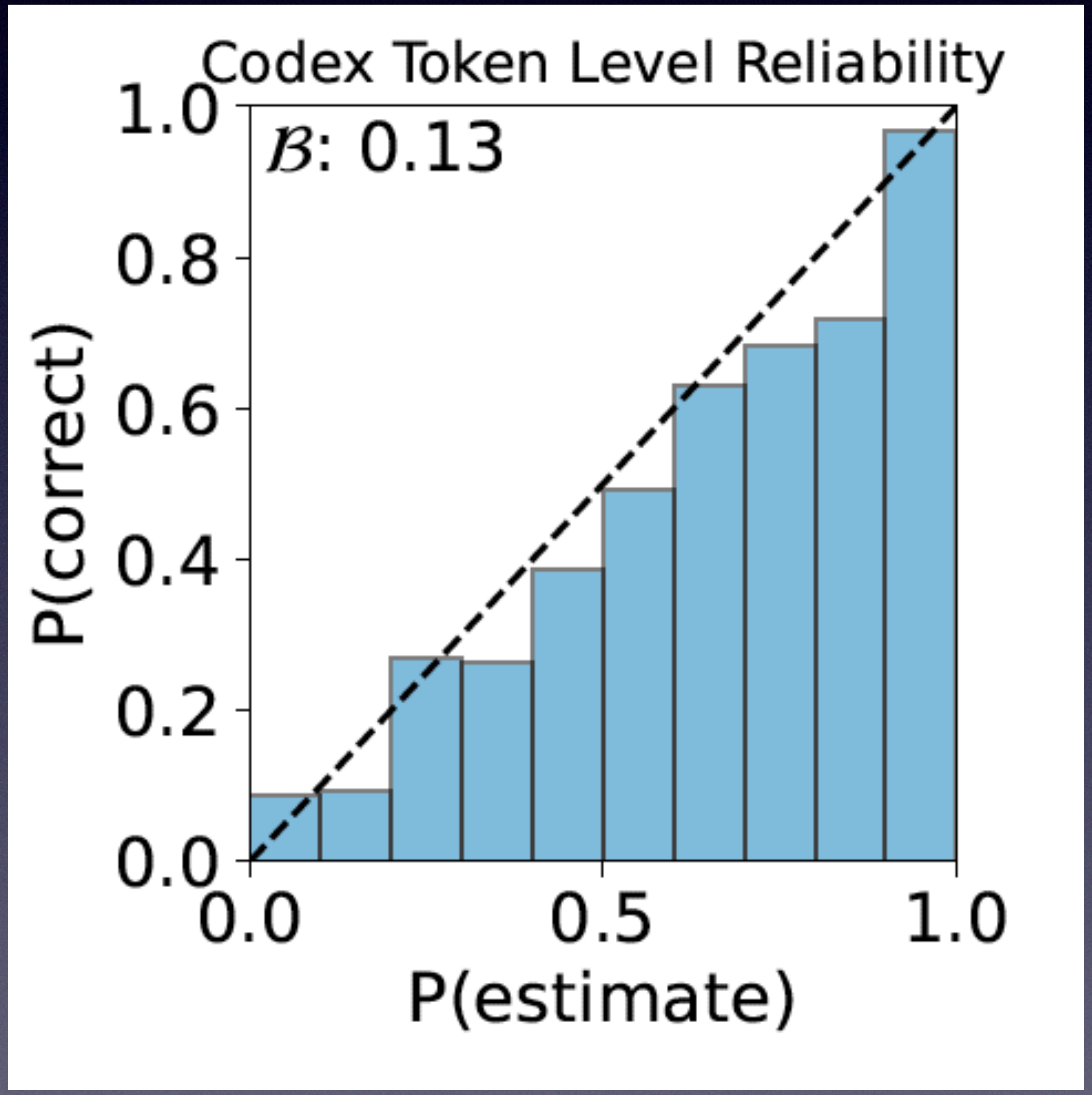
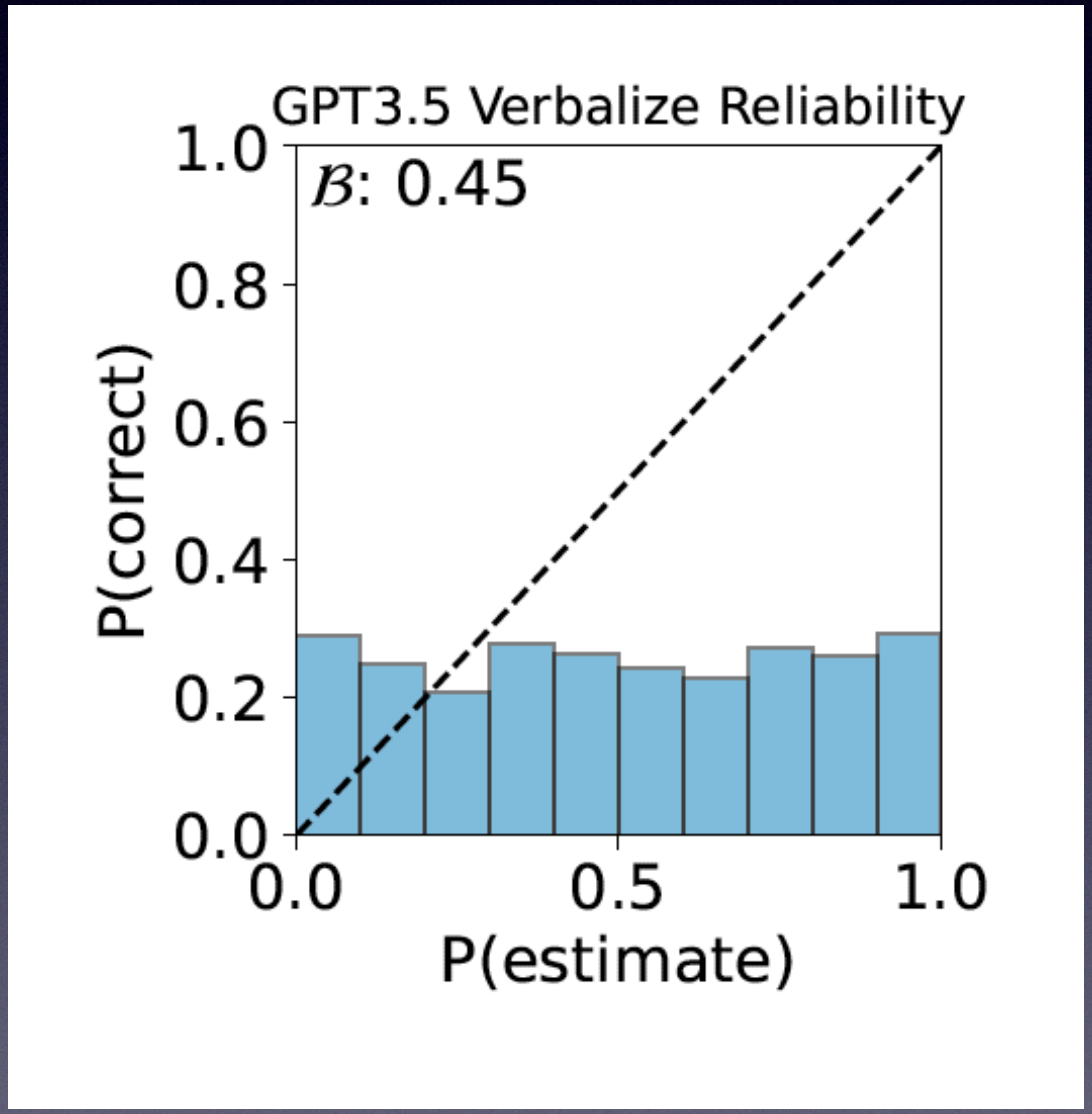
Reliability Diagram:

Confidence vs. Correctness





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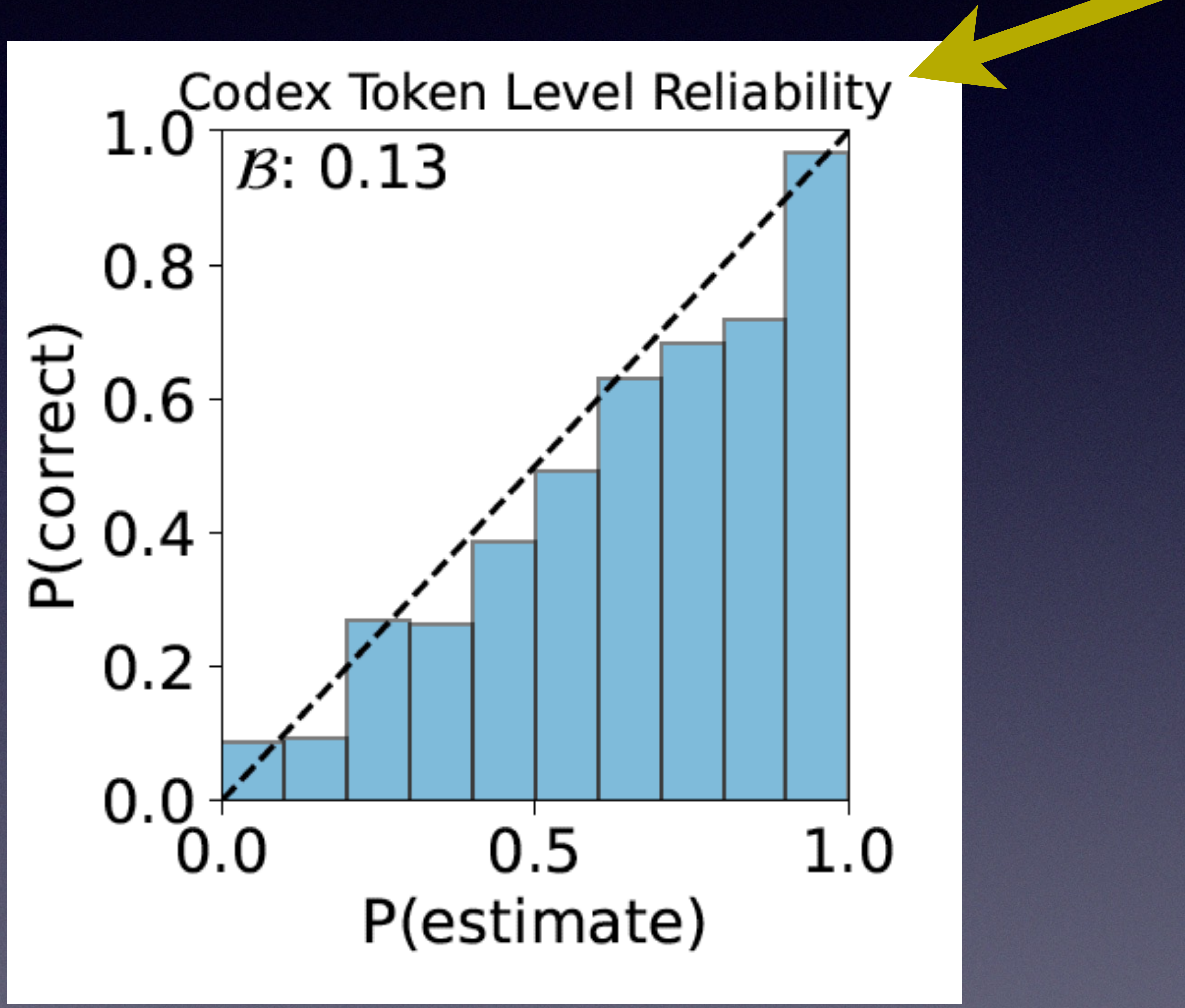

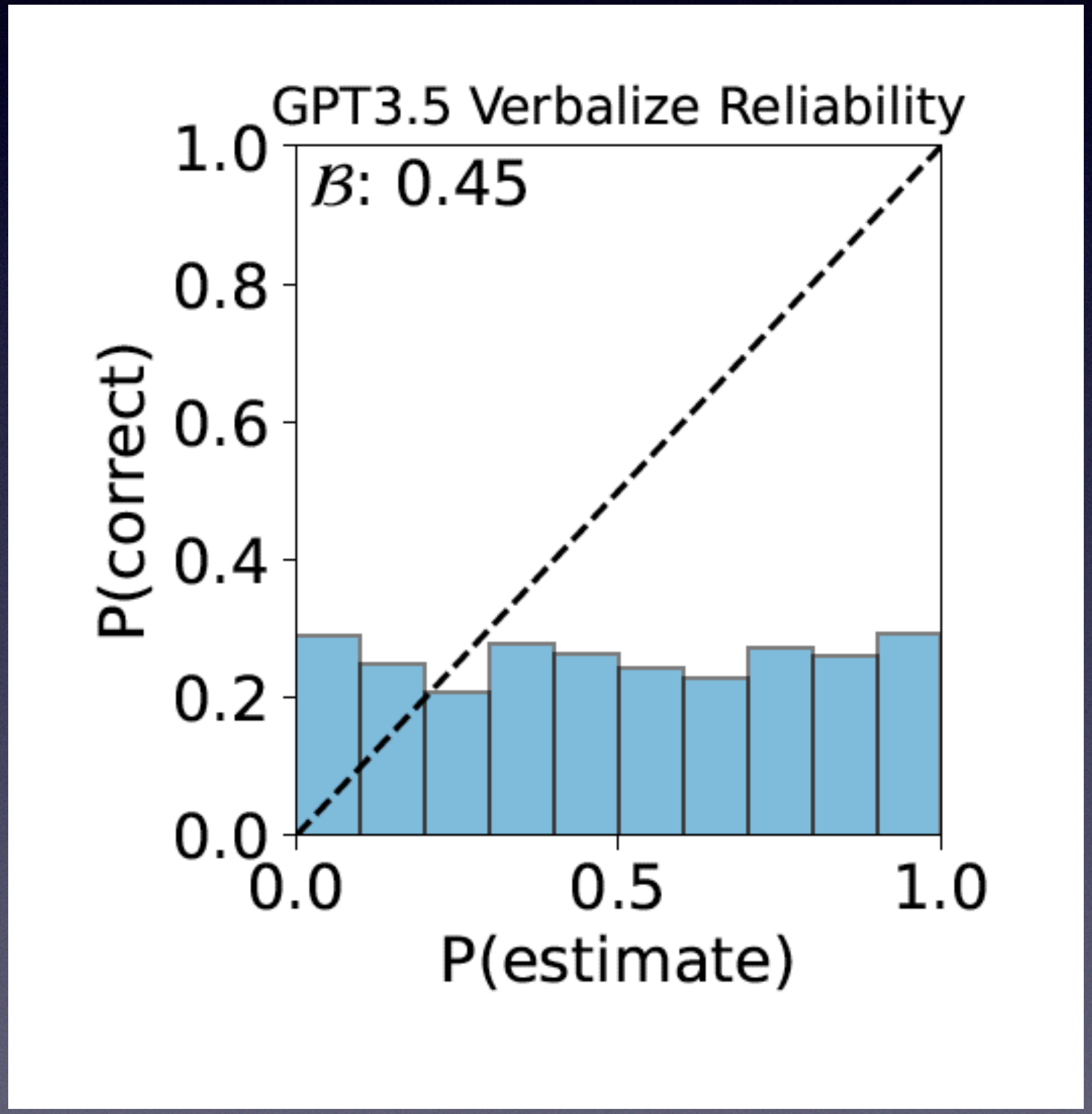

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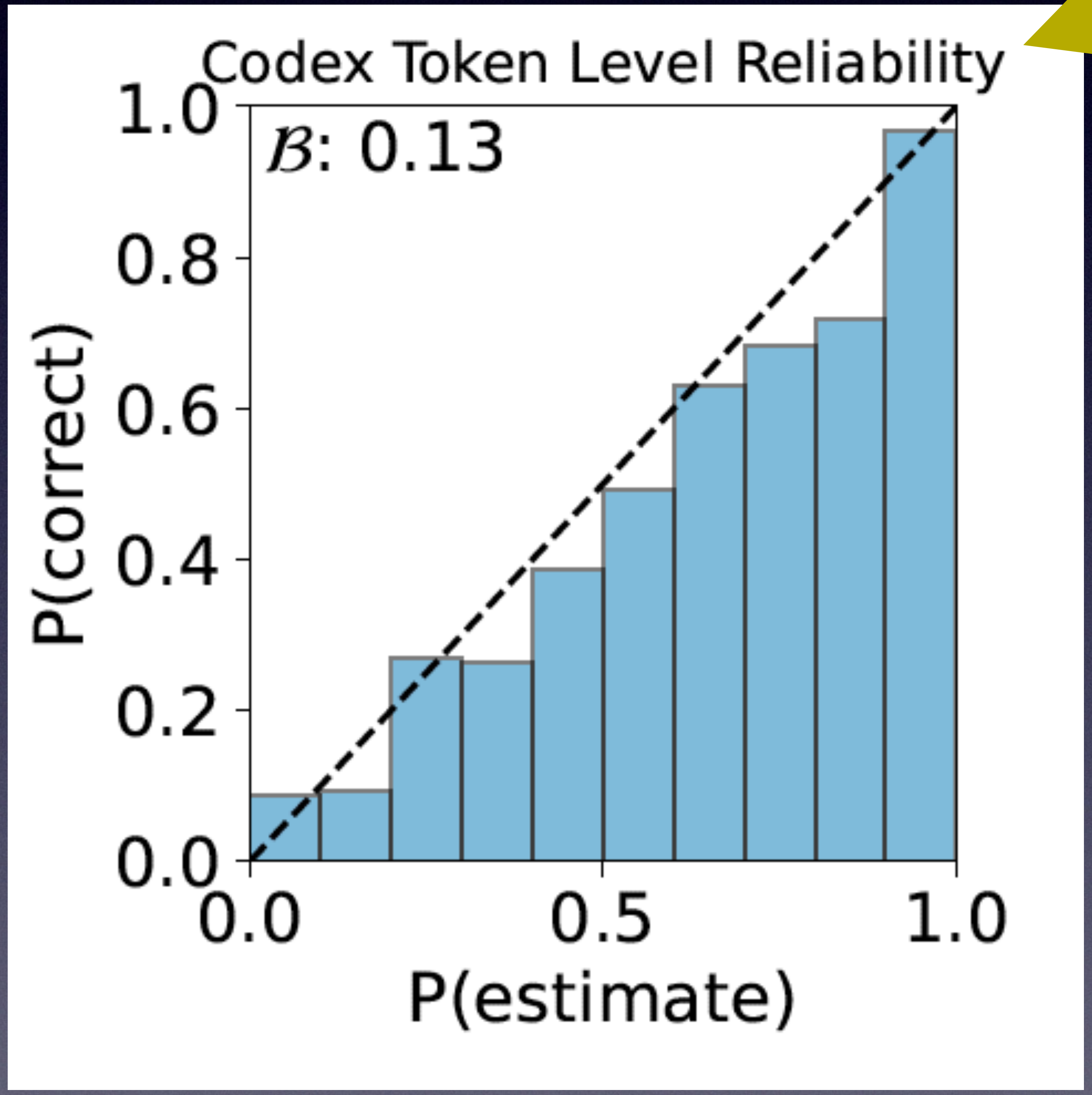

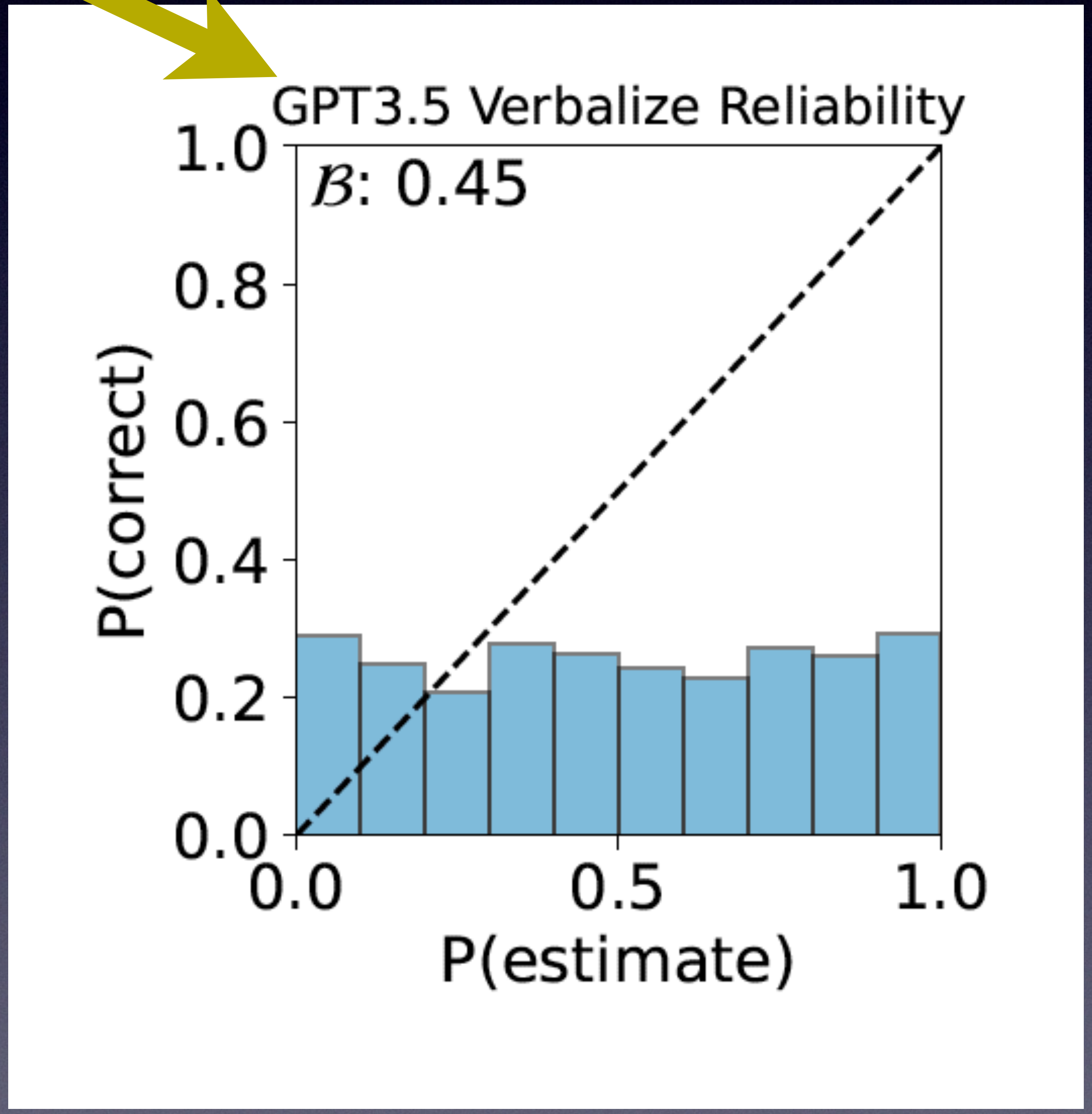

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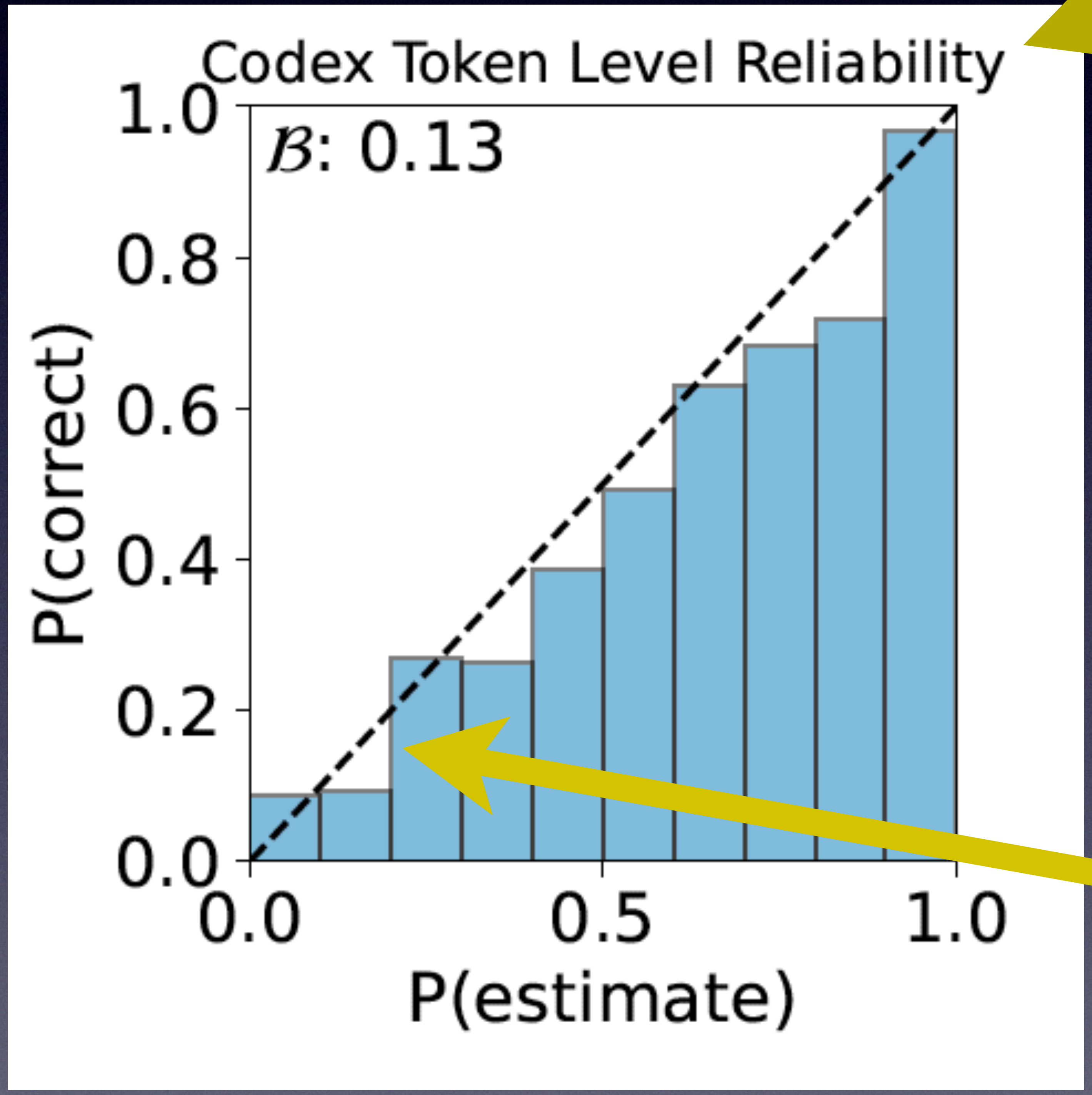
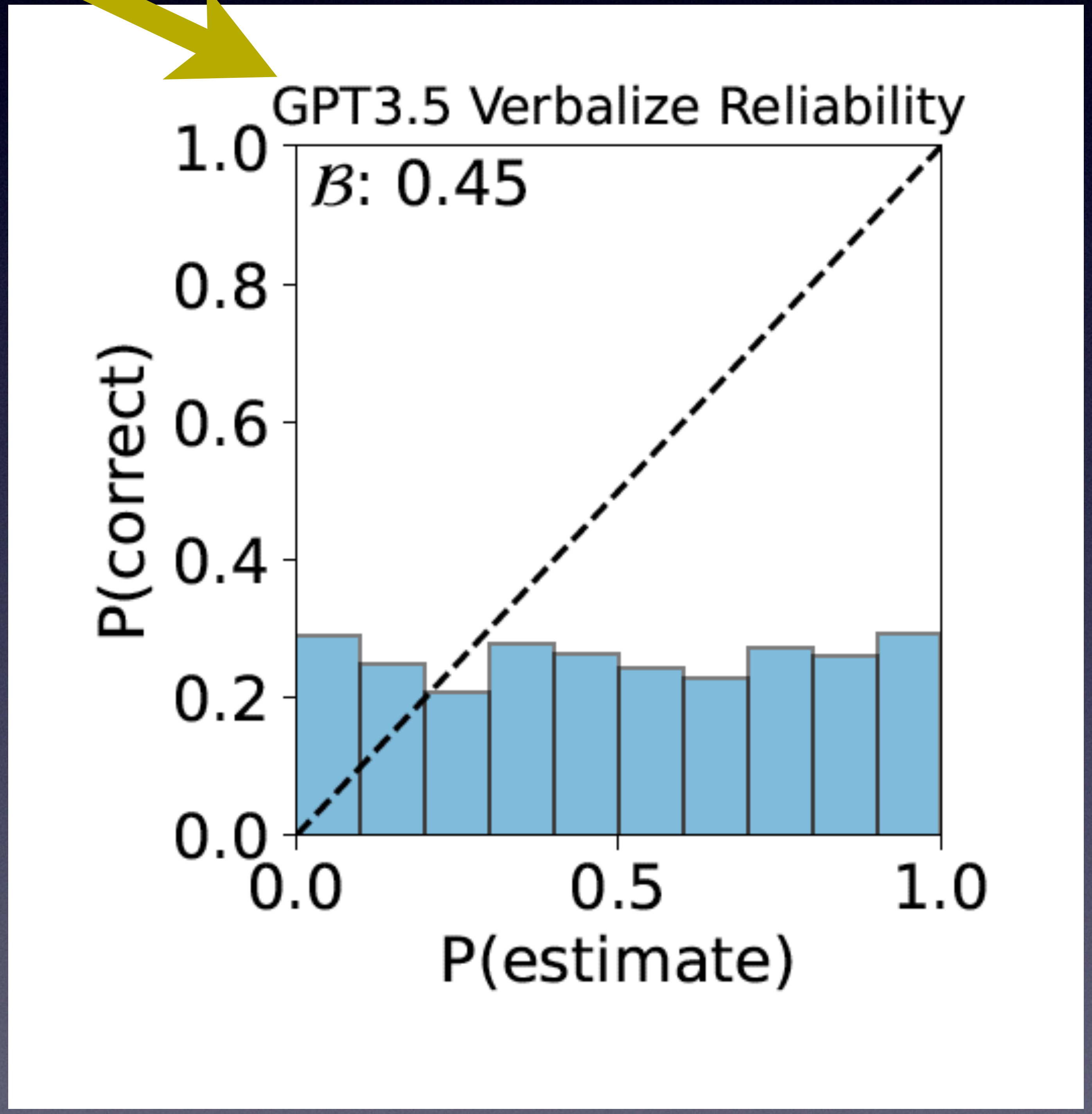


All Predictions
With confidence
Between 0.2 and 0.3



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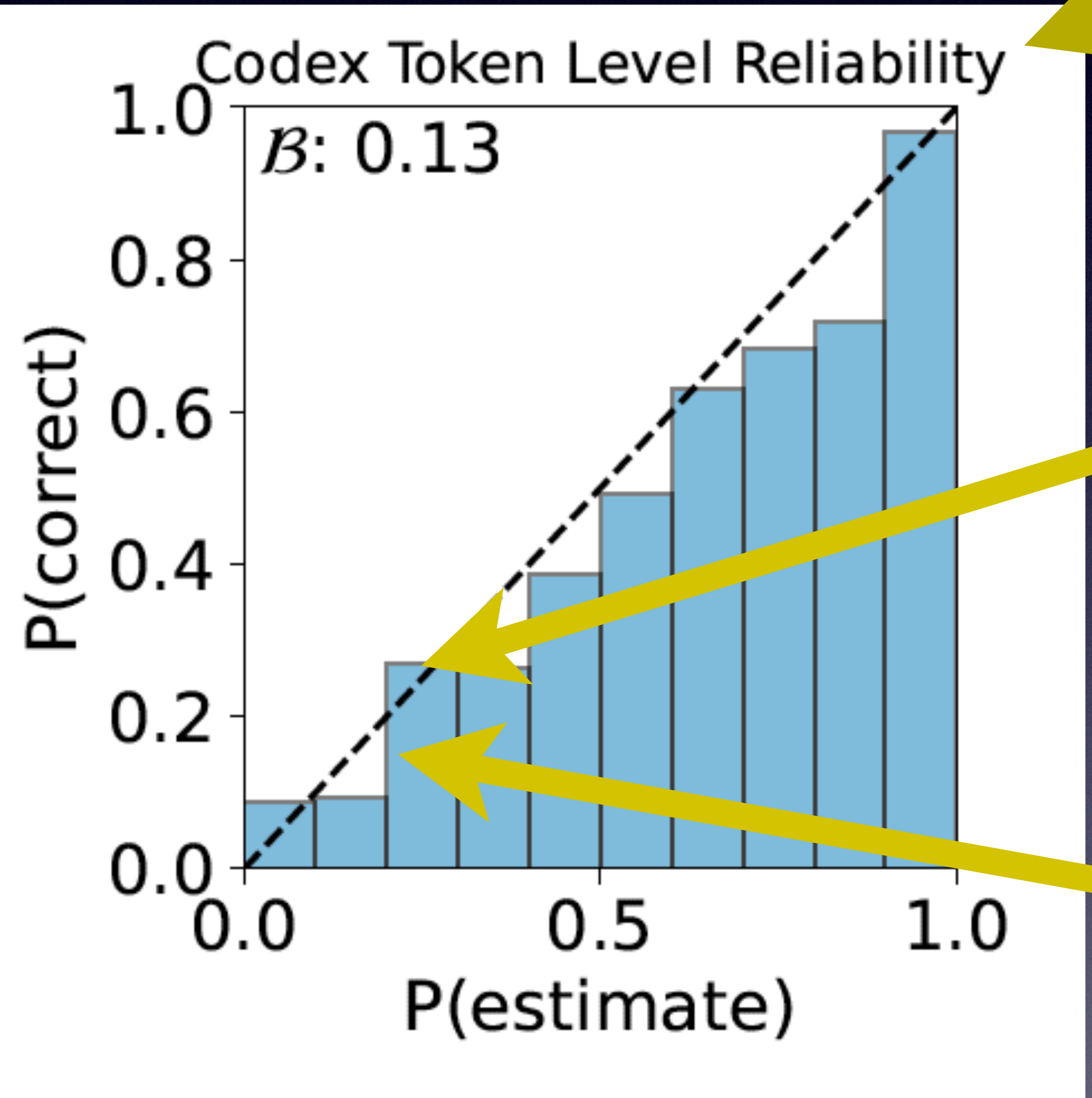
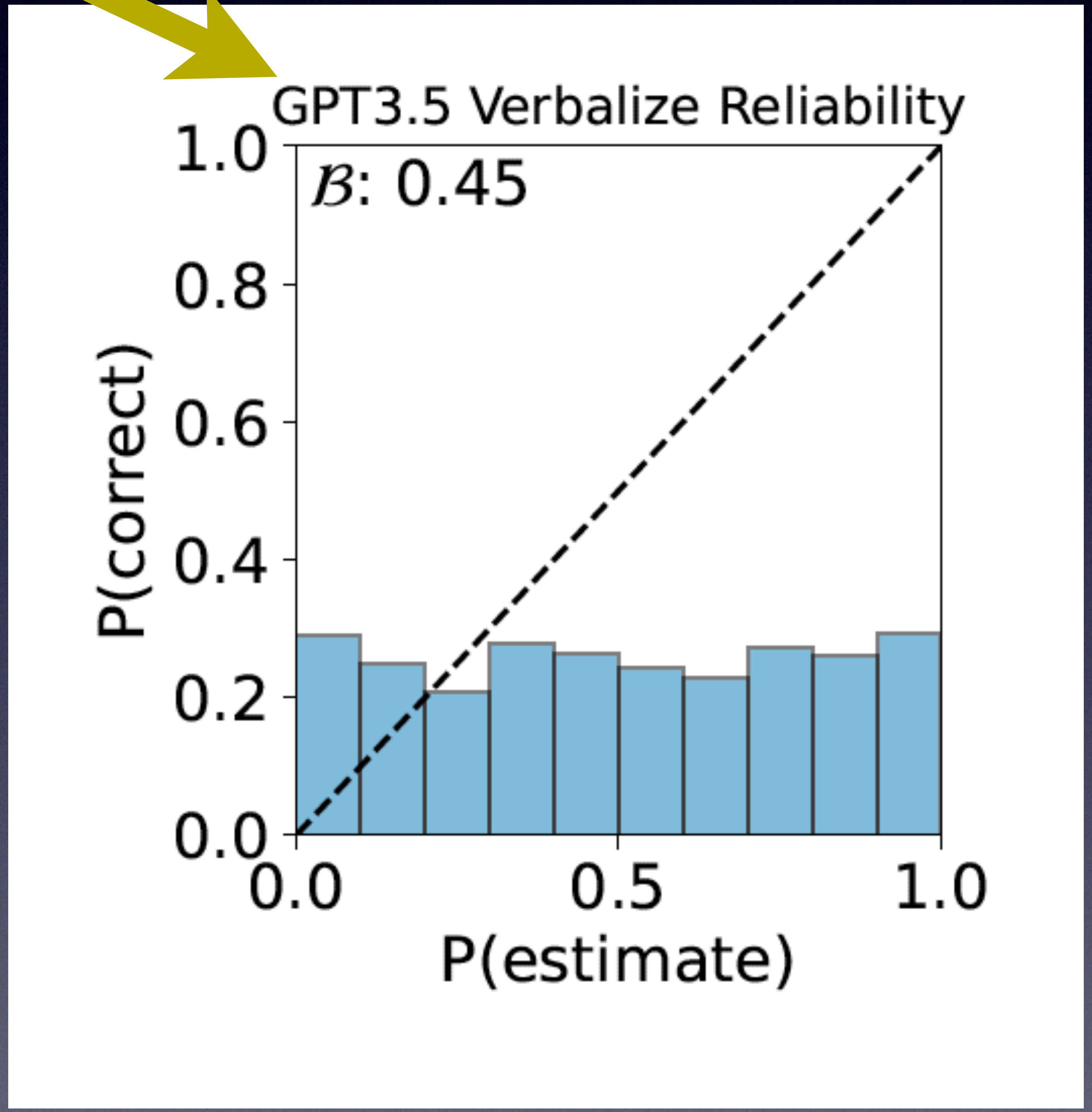


Predictions in this Range are about 30% Correct (good!)

All Predictions With confidence Between 0.2 and 0.3



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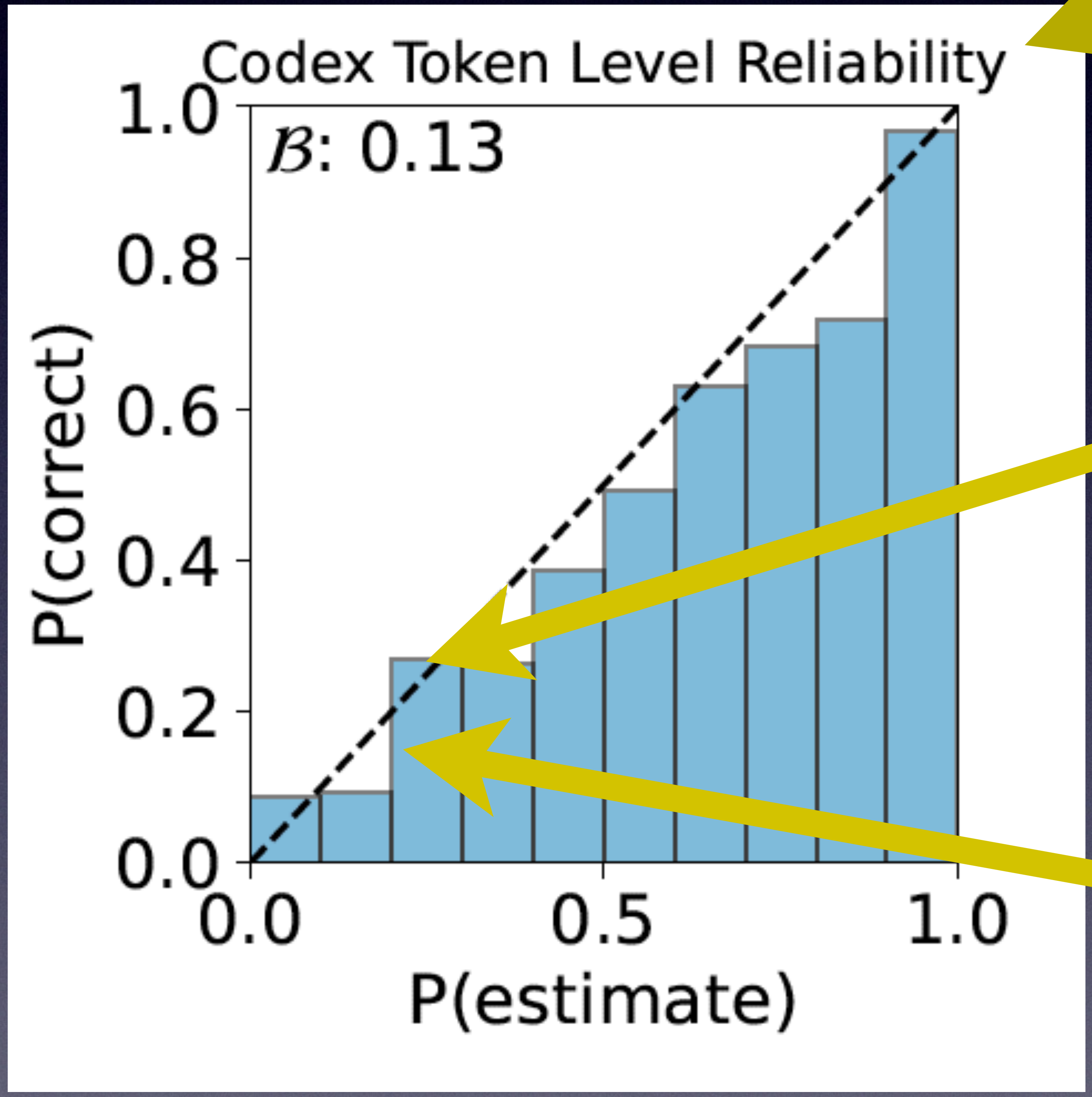

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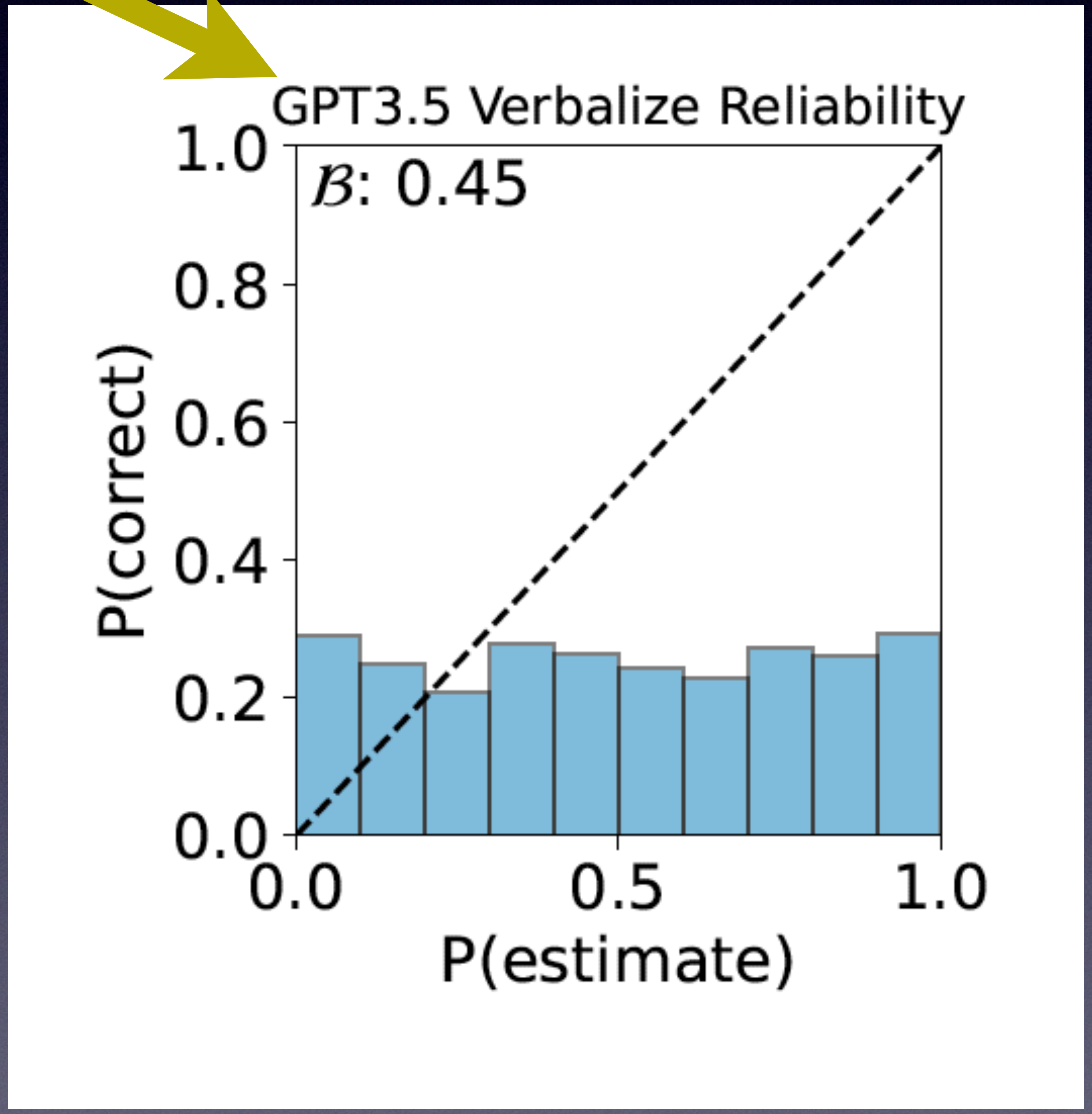

Under Confident

Over Confident

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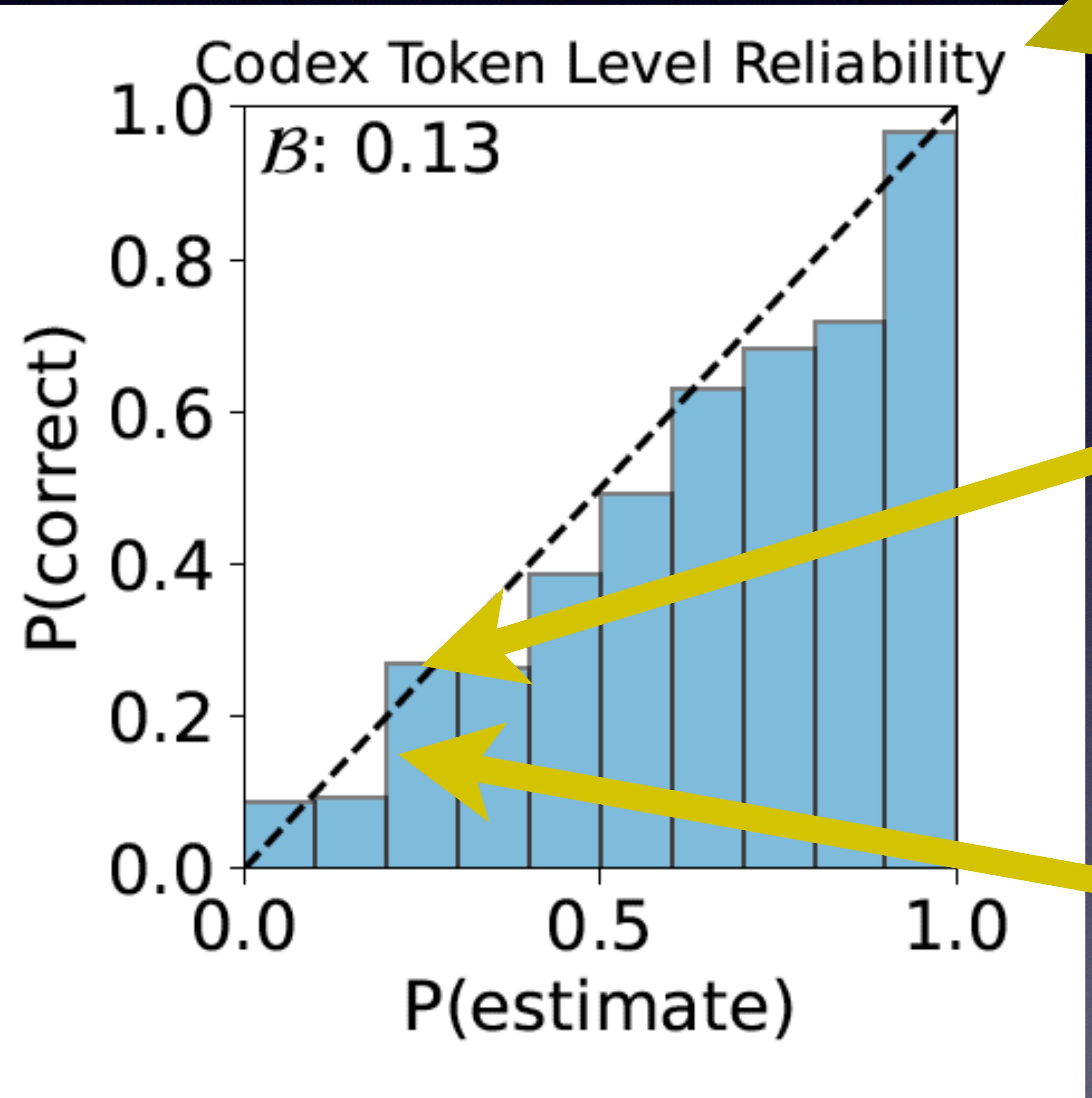
Reliability Diagram:

Confidence vs. Correctness



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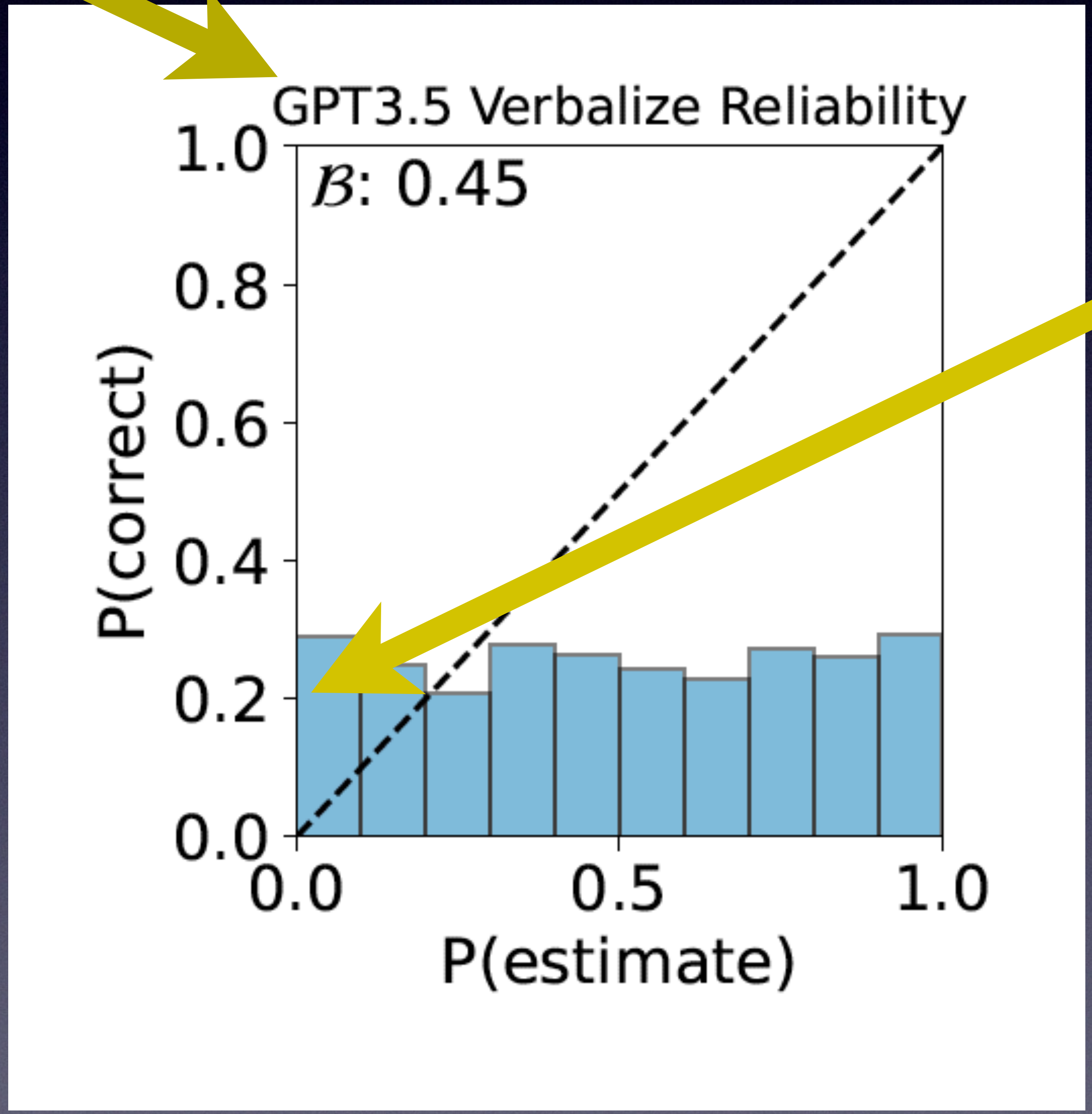

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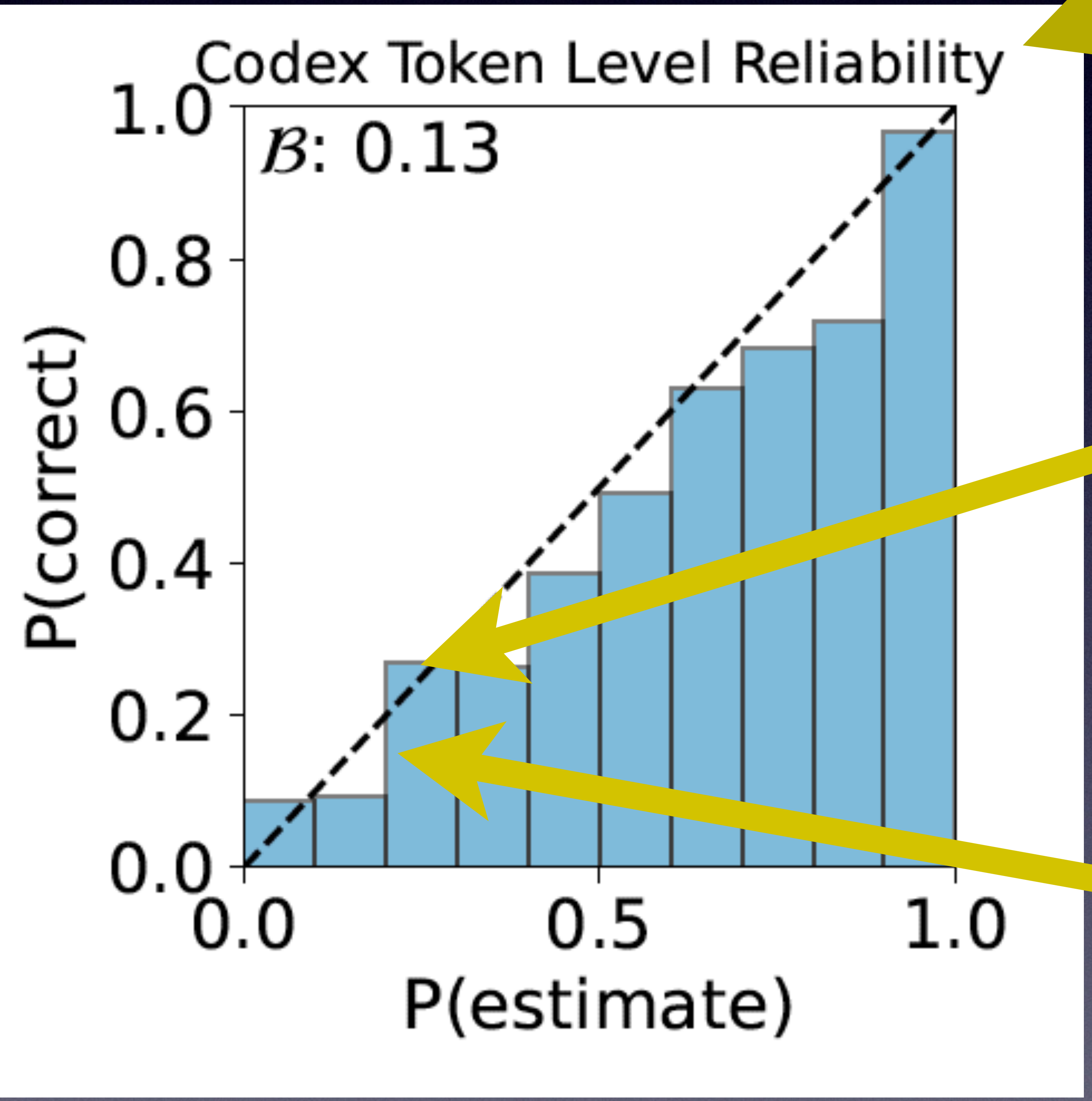

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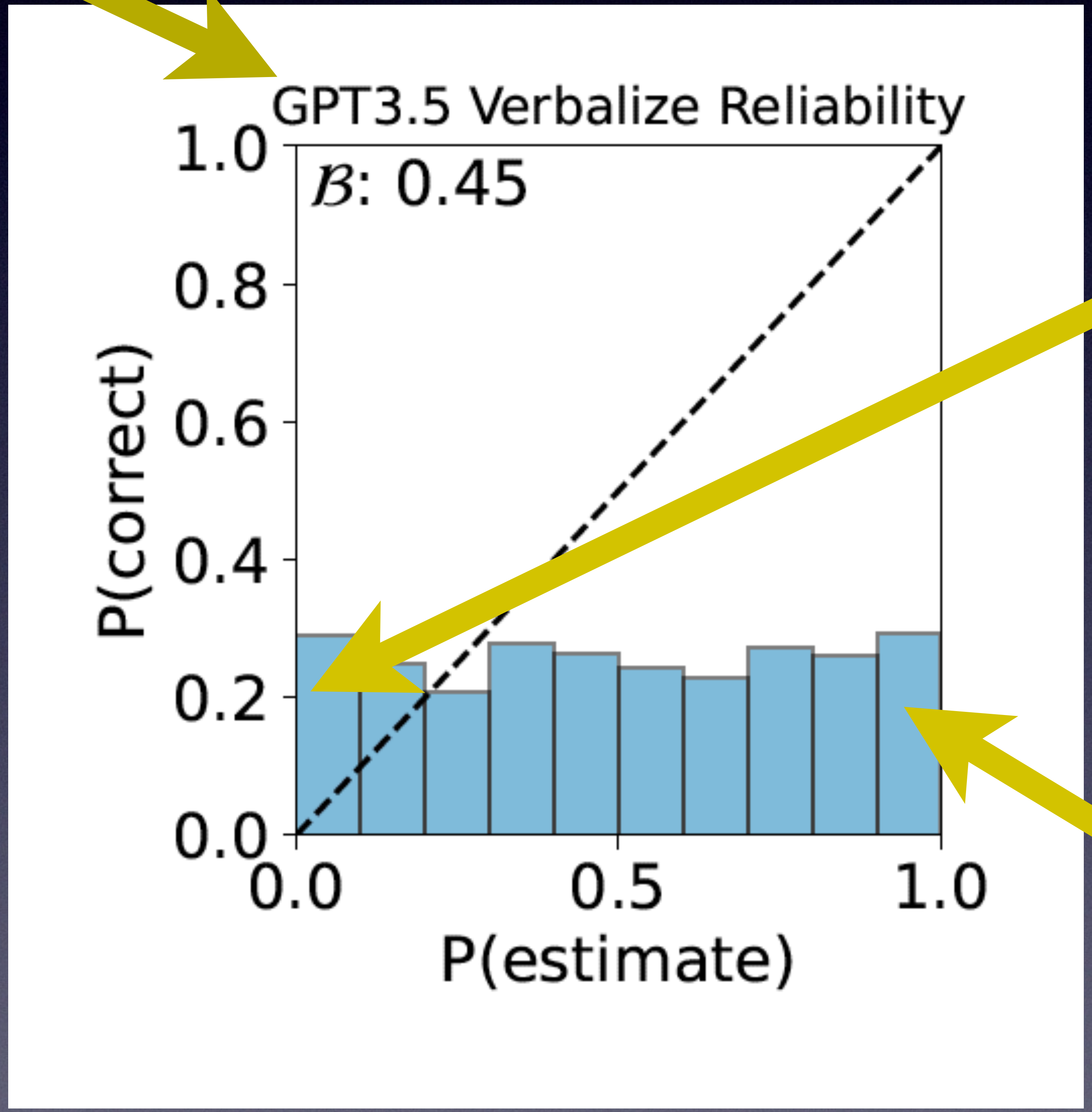

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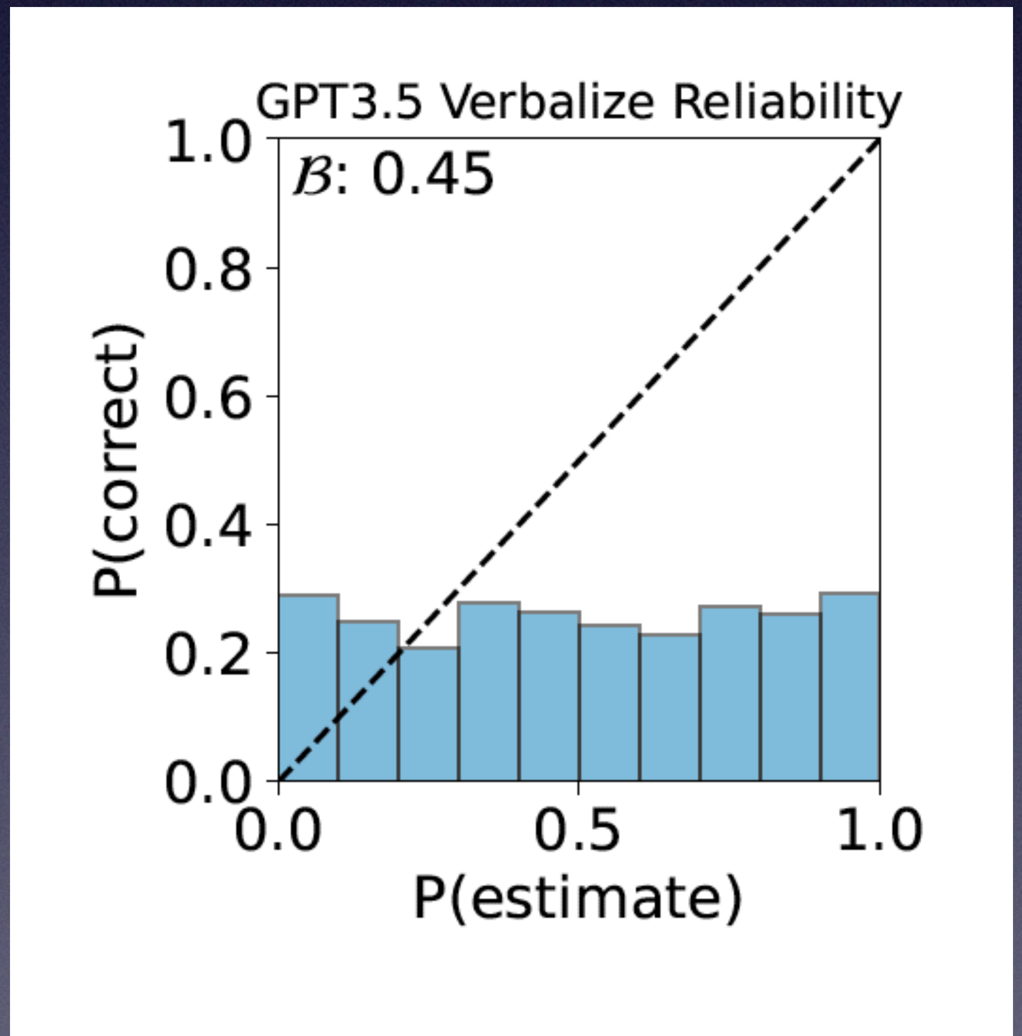
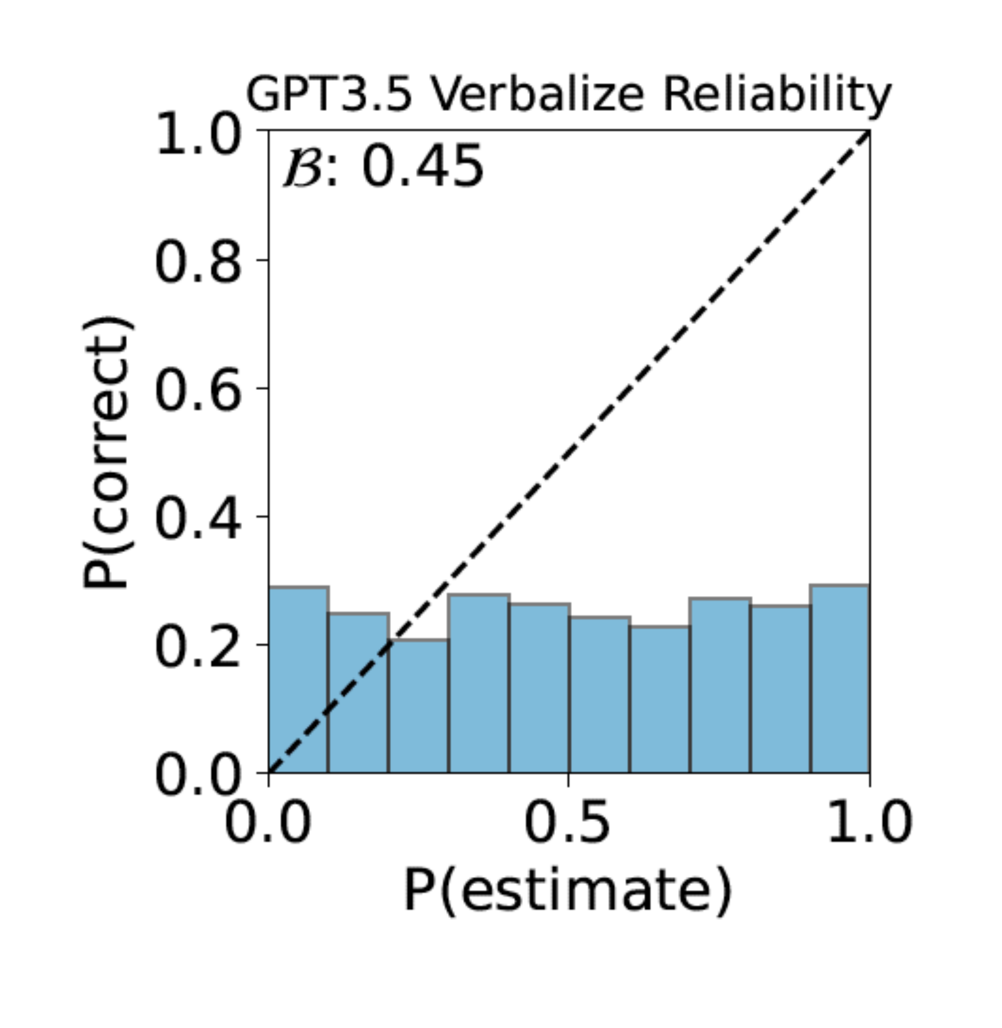
Calibration Measures



Calibration Measures

$$ECE = \sum_{all\ buckets\ b_i} \frac{|b_i|}{n} * |correct(b_i) - confidence(b_i)|$$



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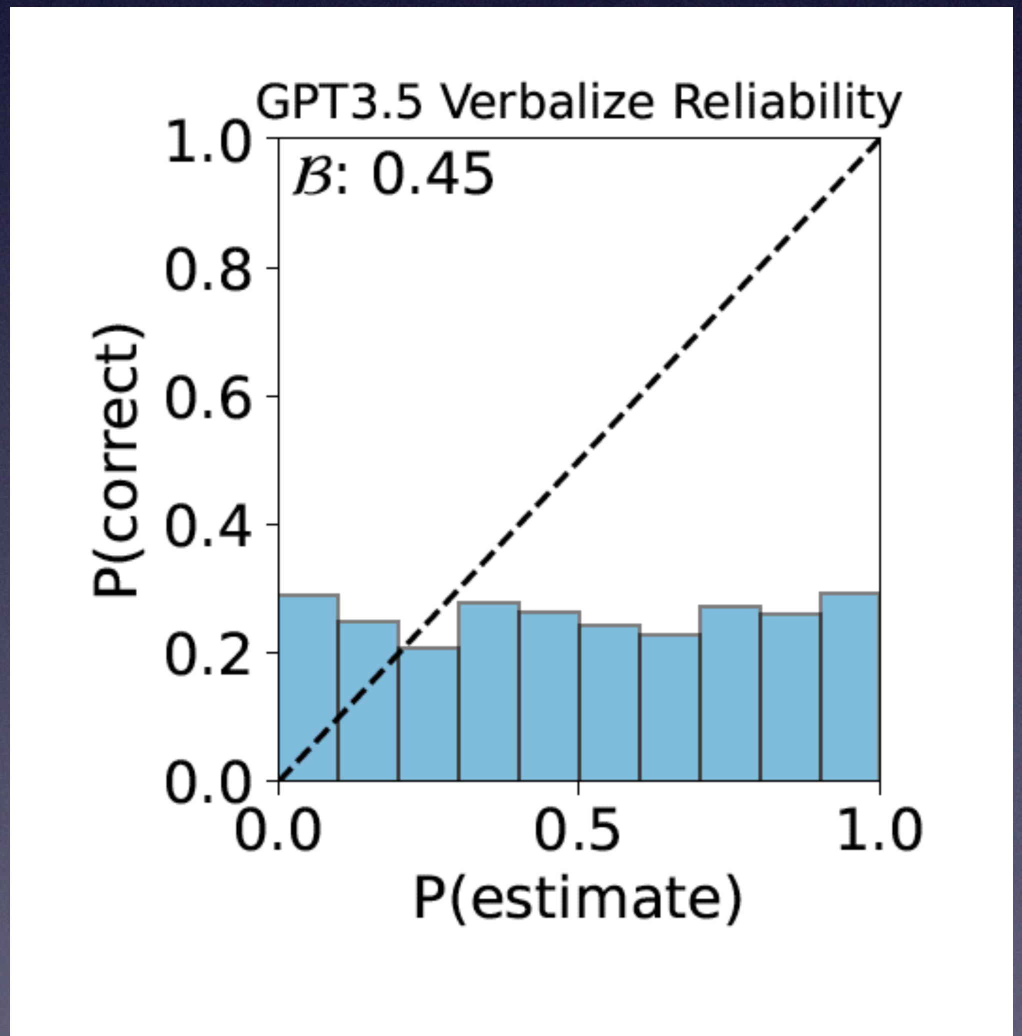

Can “CHEAT”: low ECE by always giving base-rate as Confidence

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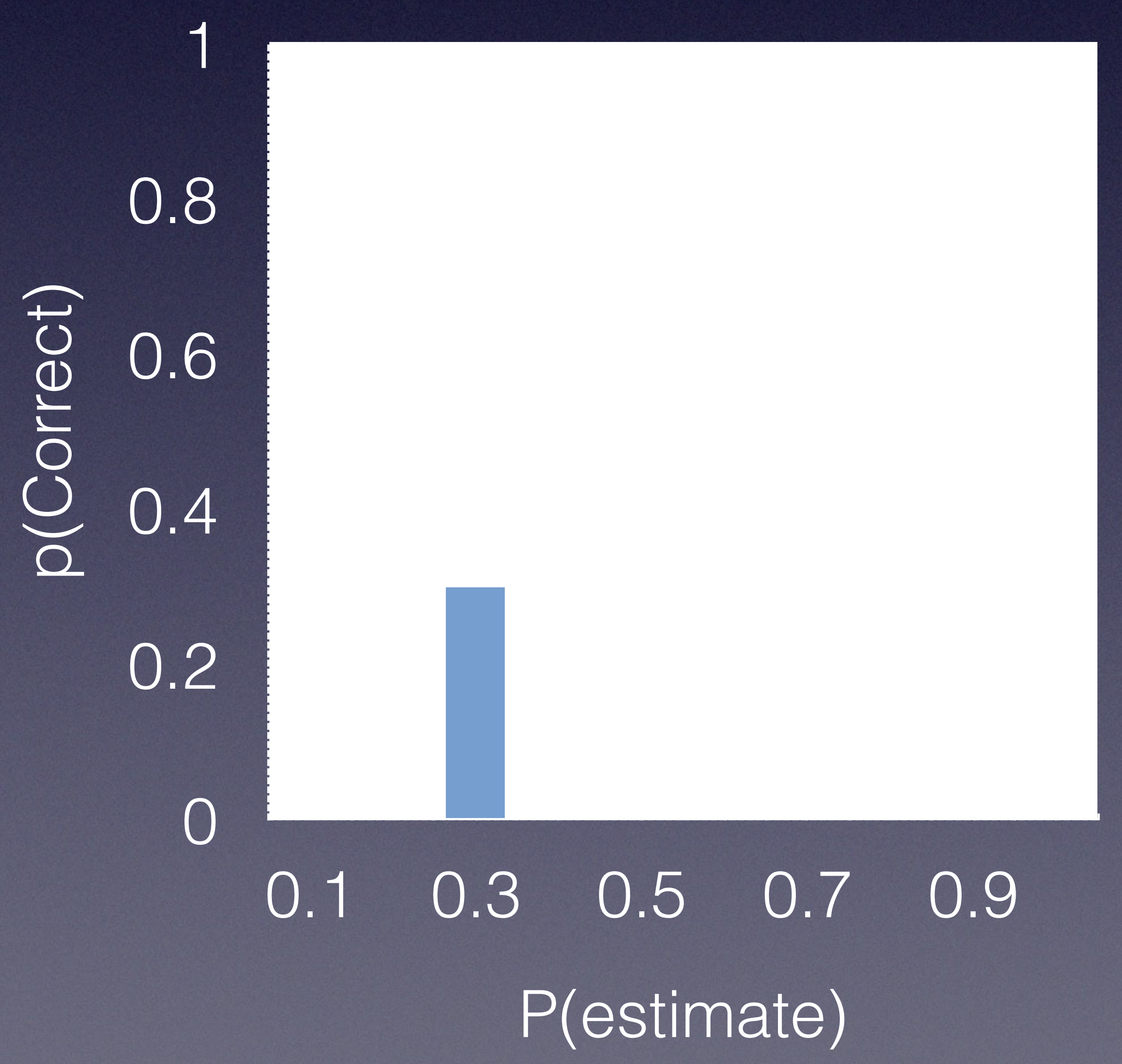

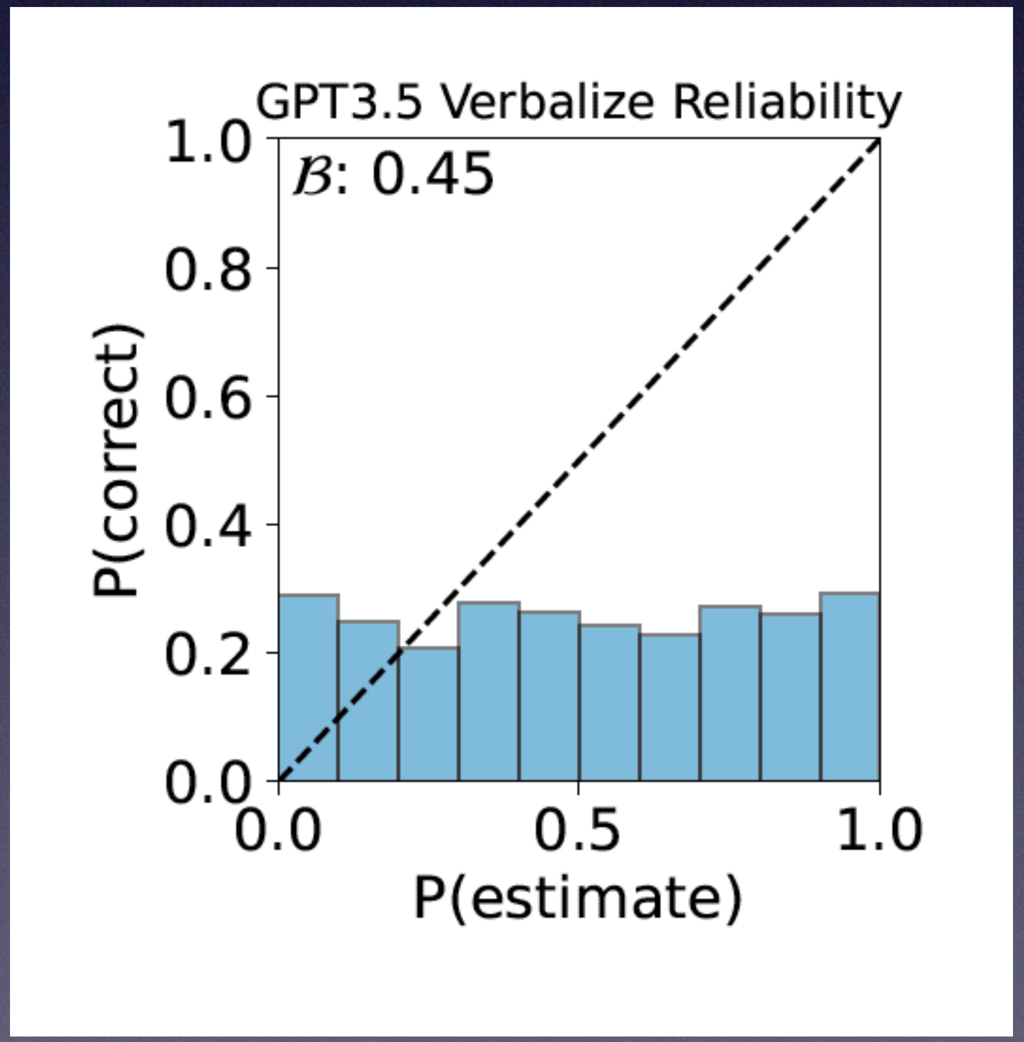

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$$B_{actual} = \frac{1}{n} \sum_{all\ \ n\ samples\ x} \begin{cases} p_{\mathscr{M}}(x, \hat{y})^2 & \text{if prediction } \hat{y} \text{ wrong} \\ (1 - p_{\mathscr{M}}(x, \hat{y}))^2 & \text{otherwise} \end{cases}$$

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$$B_{ref} = p_{br} * (1 - p_{br})$$

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Can't Cheat!! $B_{ref} = p_{br} * (1 - p_{br})$

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Calibration Measures

Skill scores *(between -∞ and 1)*

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Out of the Box, LLM probabilties are negative skill.

Calibration and Correctness of Language Models for Code

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ICSE 2025, to appear

Datasets

Task	Dataset	Dataset Size	Correctness Measure	Confidence Measure	Calibration Metric
Function synthesis	HumanEval	164	Test-passing Correctness	Average Token Probability, Generated Sequence Probability, Verbalized Self-Evaluation, Question Answering Logit	Brier Score, ECE
	MBBP Func	880			
Line-level Completion	DyPyBench	1,988	Test-passing Correctness, EM		
Program Repair	Defects4J 1-line	120			
	ManySStubs4j	3,000	Exact-Match (EM)		

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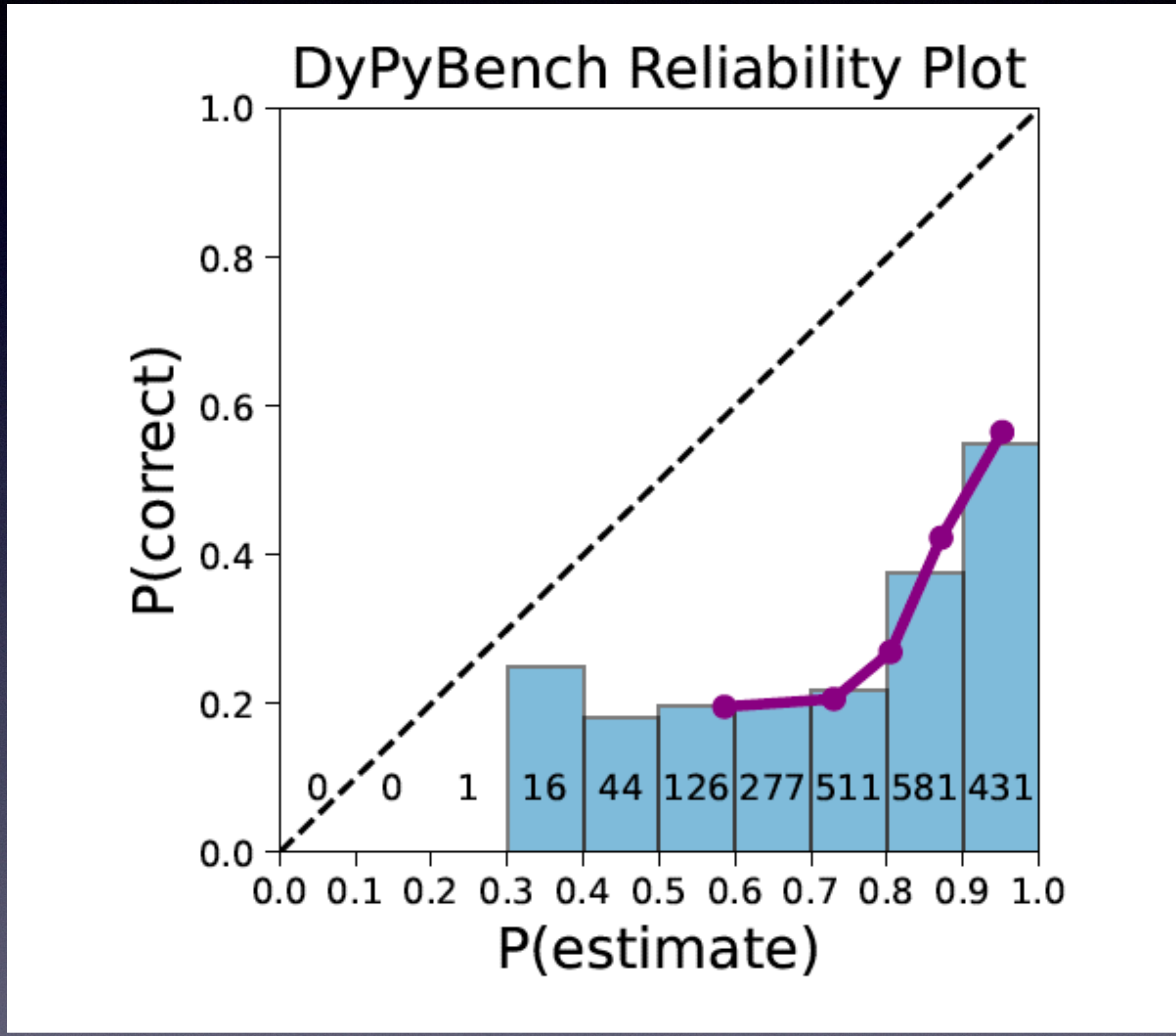
- SStubs4J does not have tests, only exact-match

Models

	All Pass@1			Exact-Match		
	CodeGen2	Codex	GPT-3.5	CodeGen2	Codex	GPT-3.5
SStubs	-	-	-	0.73%	**27.77%**	20.27%
DyPyBench	28.84%	32.96%	**33.22%**	19.68%	23.60%	**23.96%**
Defects4J	0.00%	**23.33%**	19.17%	0.00%	**19.17%**	15.00%
HumanEval	23.17%	47.24%	**64.60%**	-	-	-
MBPP	29.08%	61.79%	**72.04%**	-	-	-

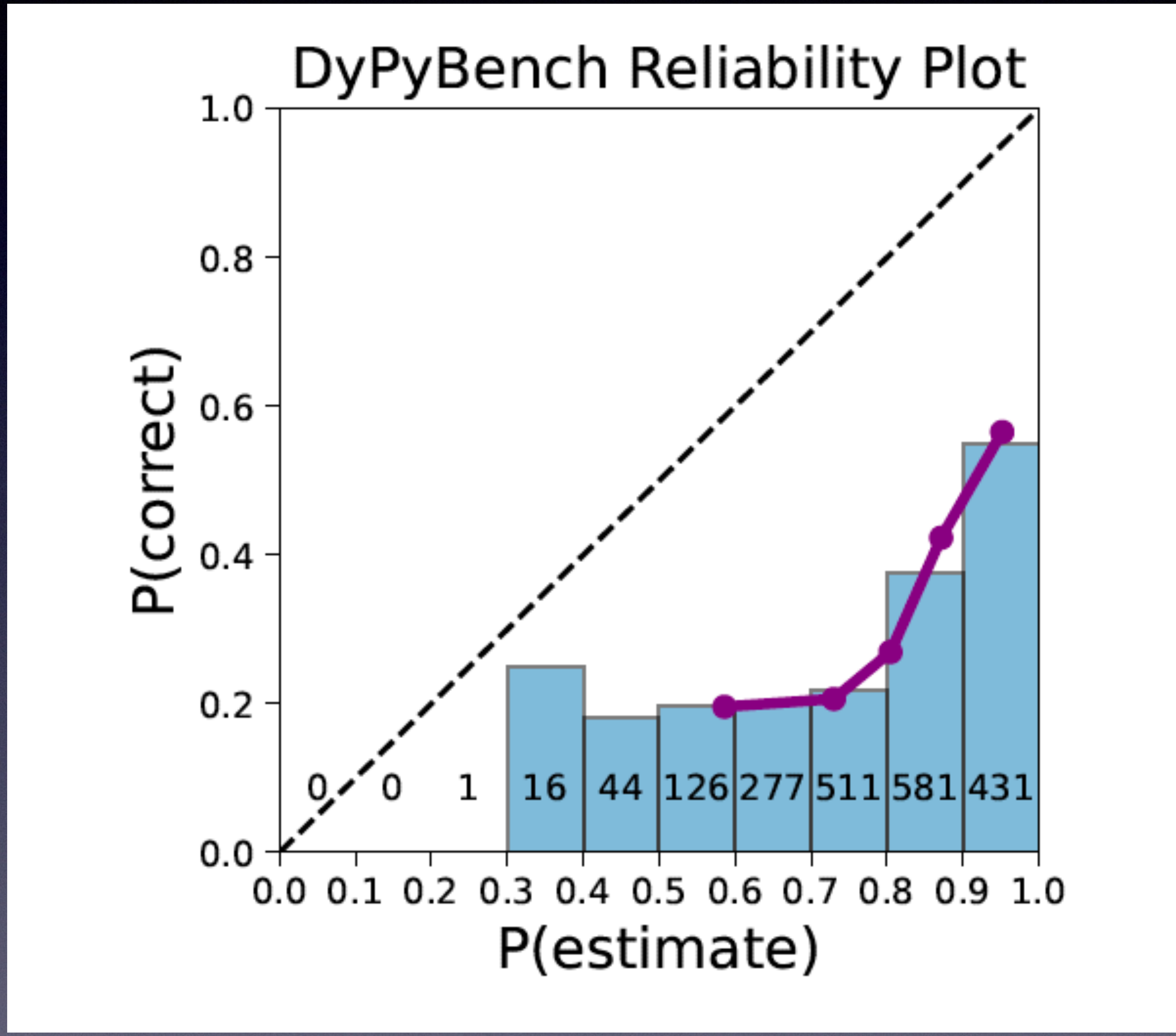
- Each cell ~ the *base rate*
- *Thus All Pass @1 Brier Ref Score for DyPyBench, Codex = 0.33*0.67 = 0.22*

GPT 3.5, Line Completion



Correctness: Test Passing, ***Confidence:*** Avg Per-token probability

GPT 3.5, Line Completion



ECE = *0.15*

Correctness: Test Passing, ***Confidence:*** Avg Per-token probability

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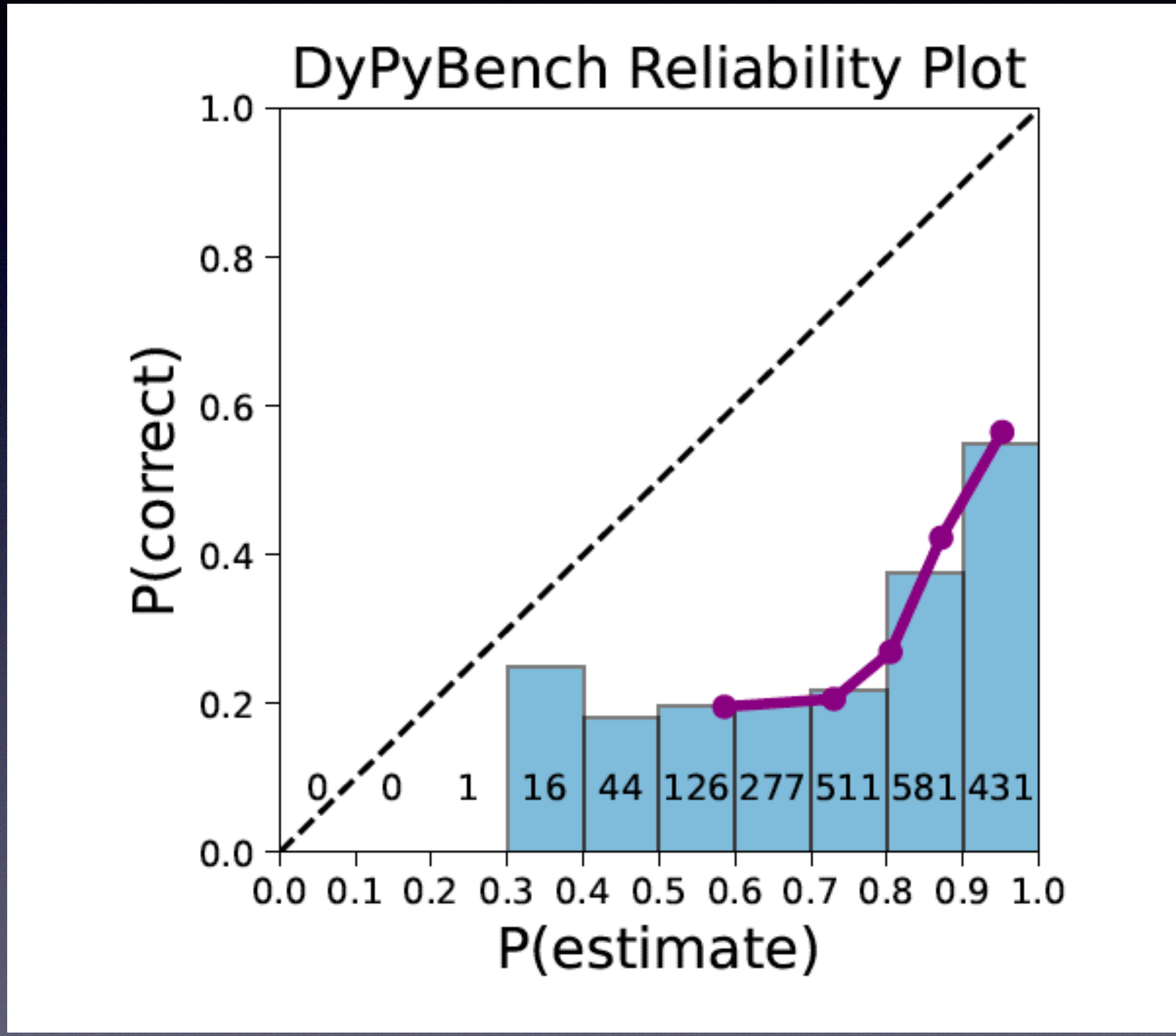

ECE = *0.15*
Brier (actual) = *0.41*

Correctness: Test Passing, ***Confidence:*** Avg Per-token probability

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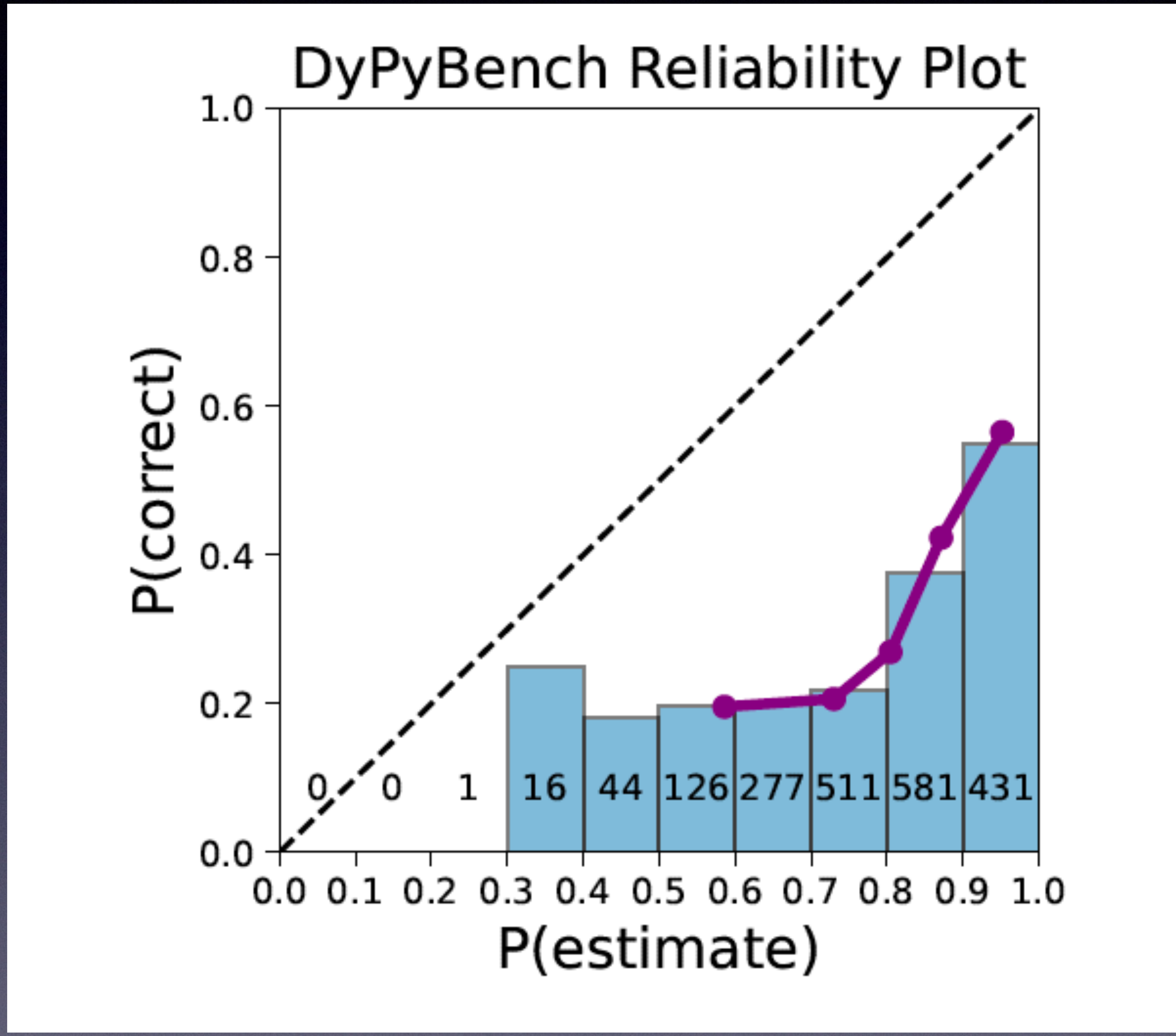

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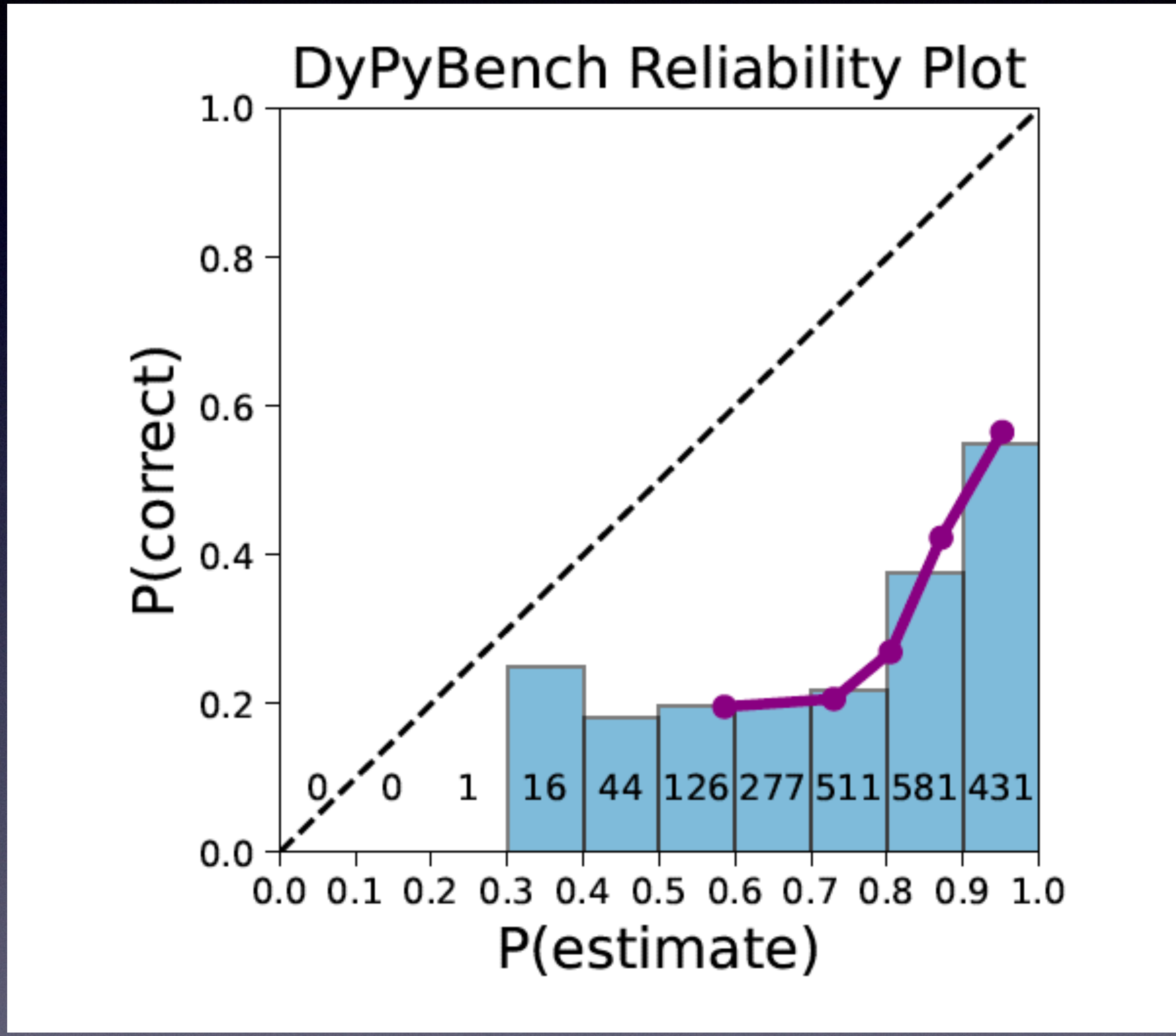
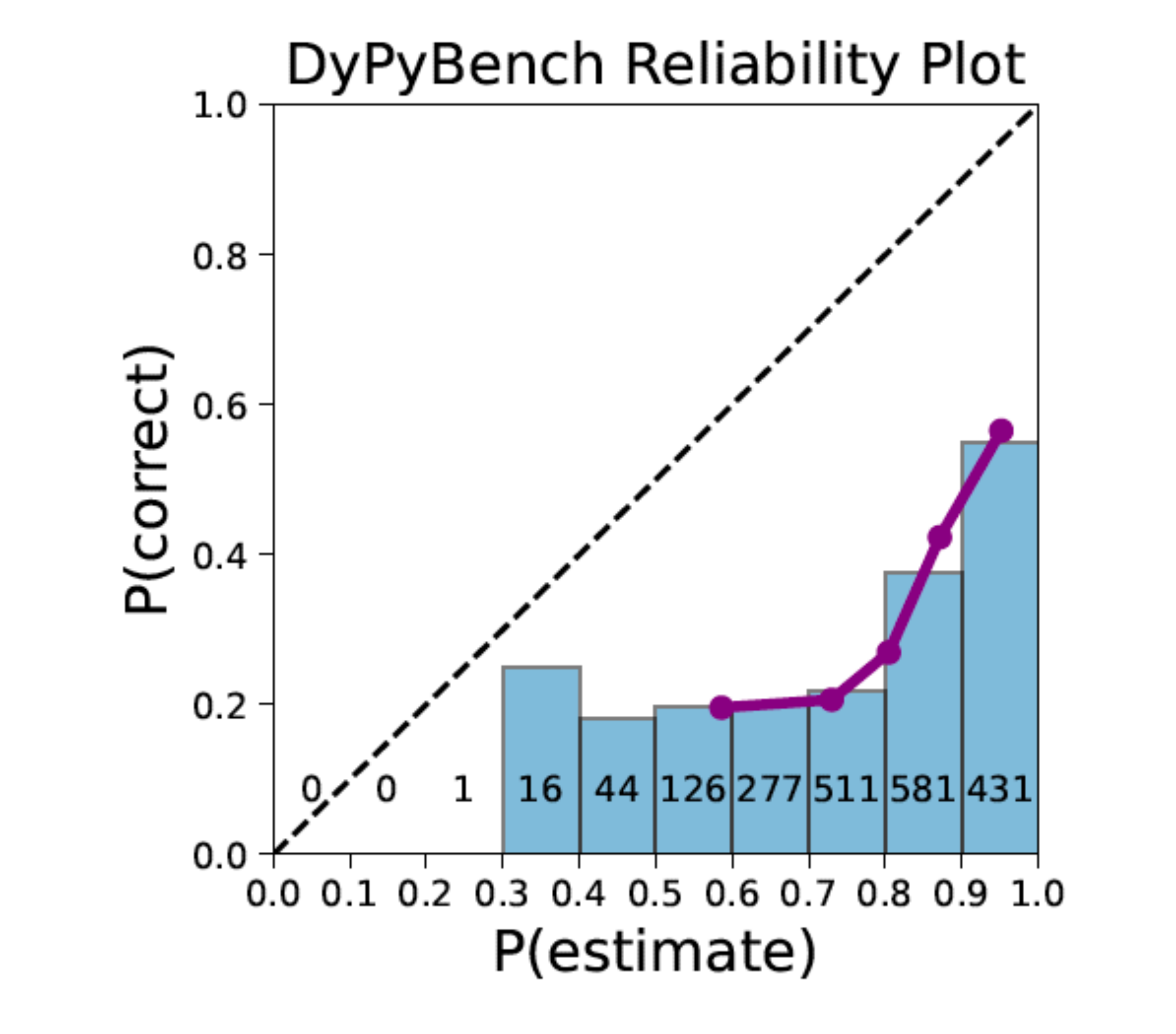


ECE = *0.15*
Brier (actual) = *0.41*
Brier (ref) = *0.22*
Skill Score = *-0.87*

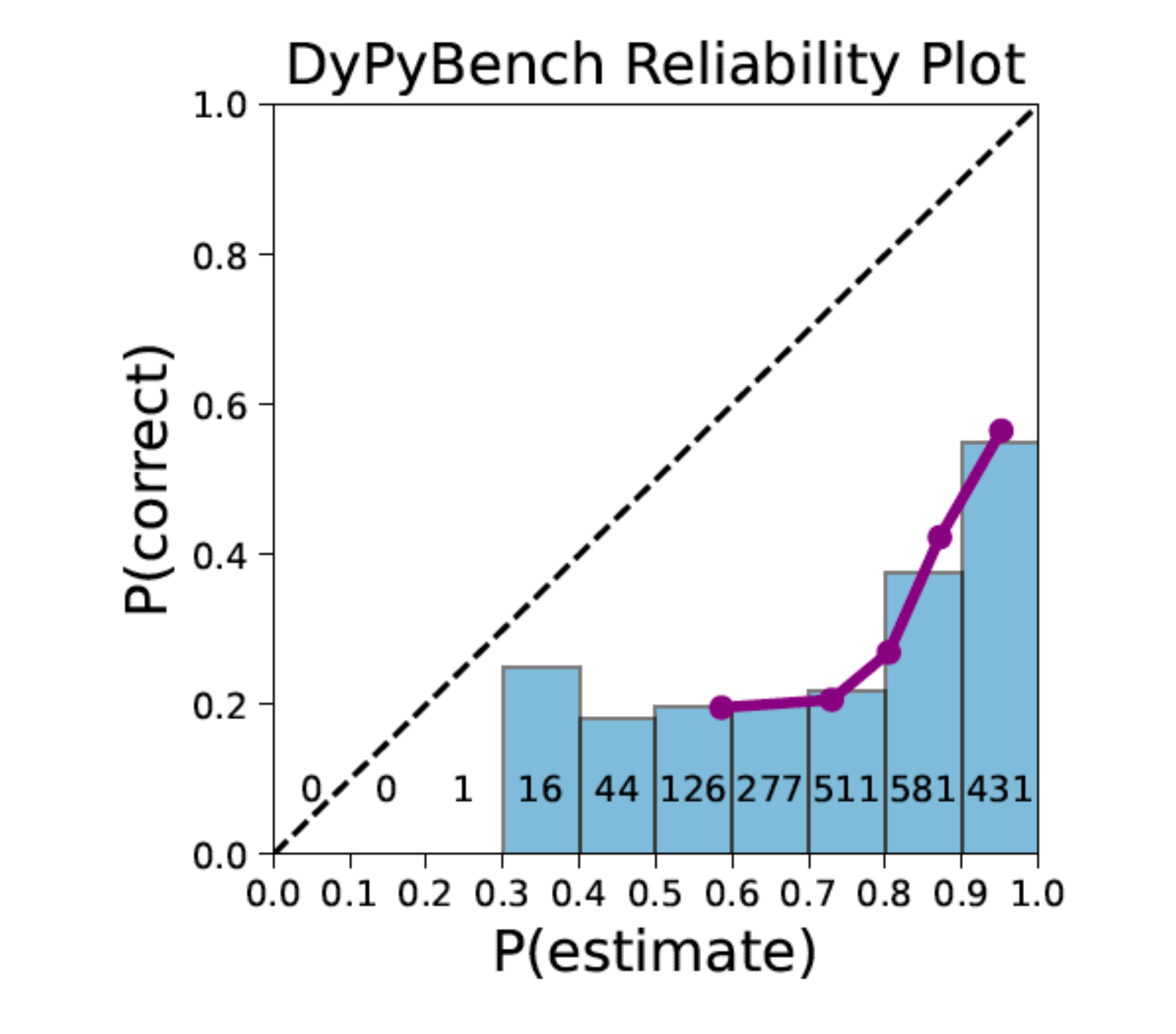
Correctness: Test Passing, ***Confidence:*** Avg Per-token probability

Recaling the Confidence



Recaling the Confidence

Platt Scaling: fit a logistic regression using ***some*** datapoints to better match the actual correctness response.



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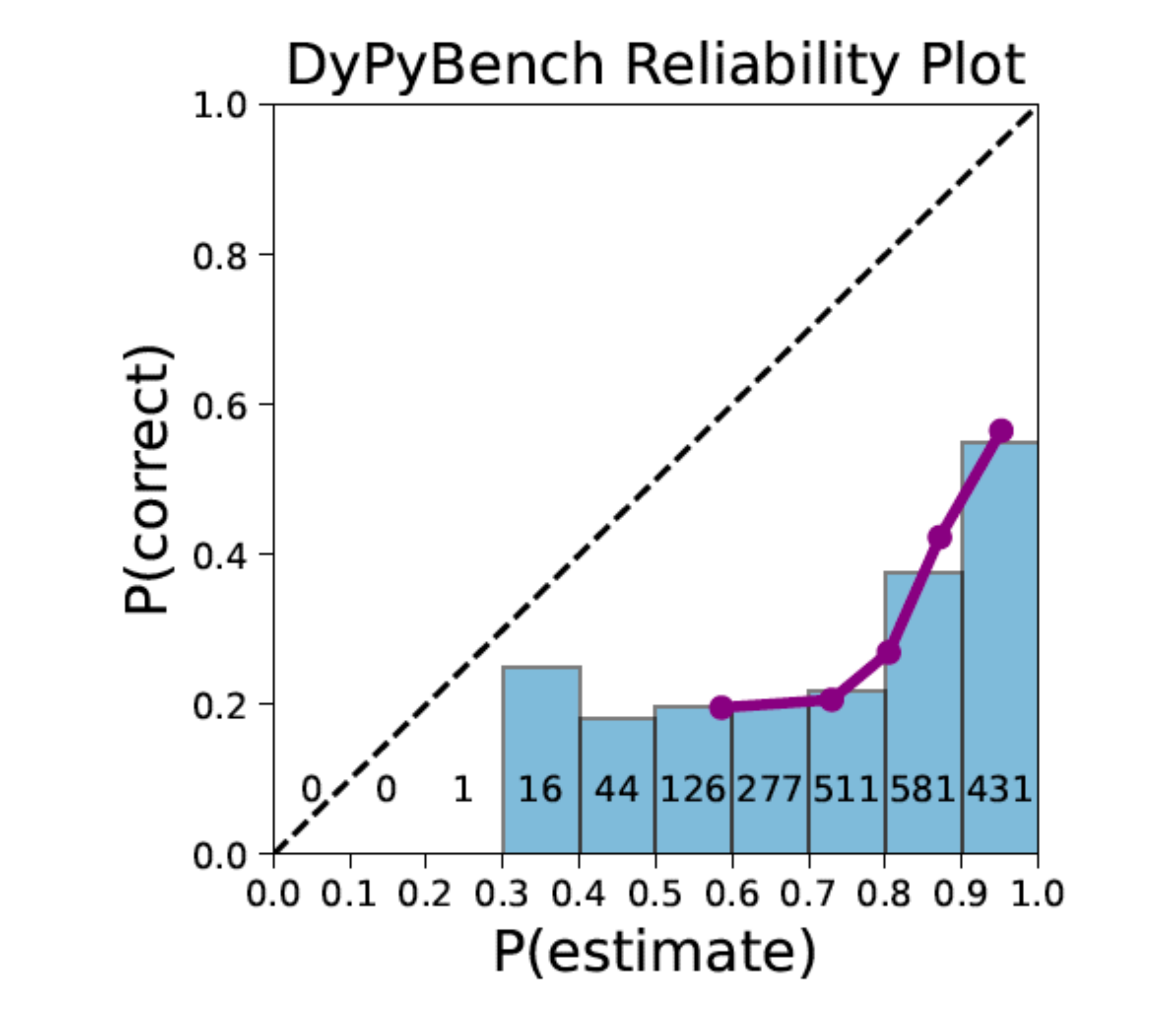
- ***RESPONSE:*** The actual correctness value (y axis)



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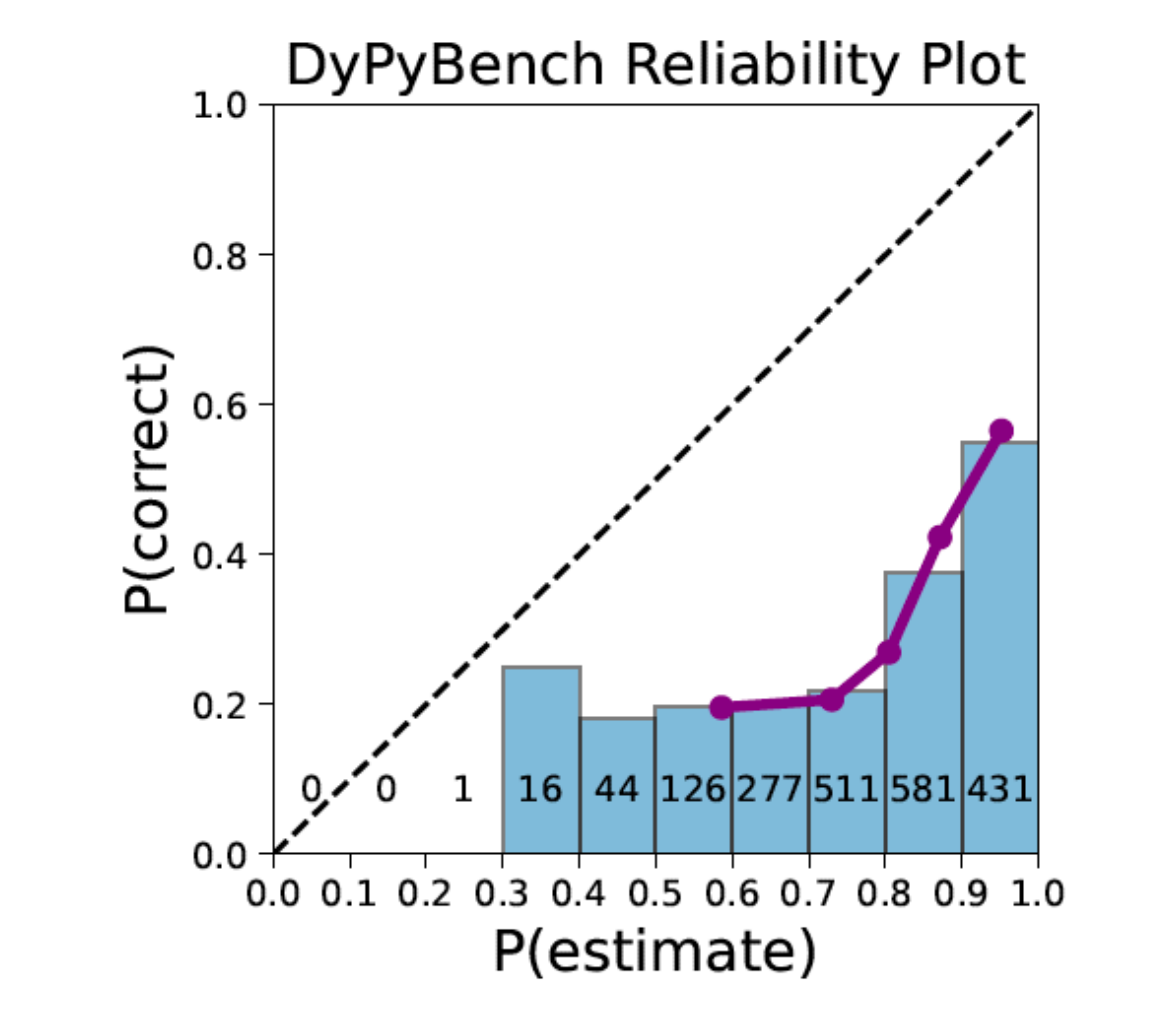

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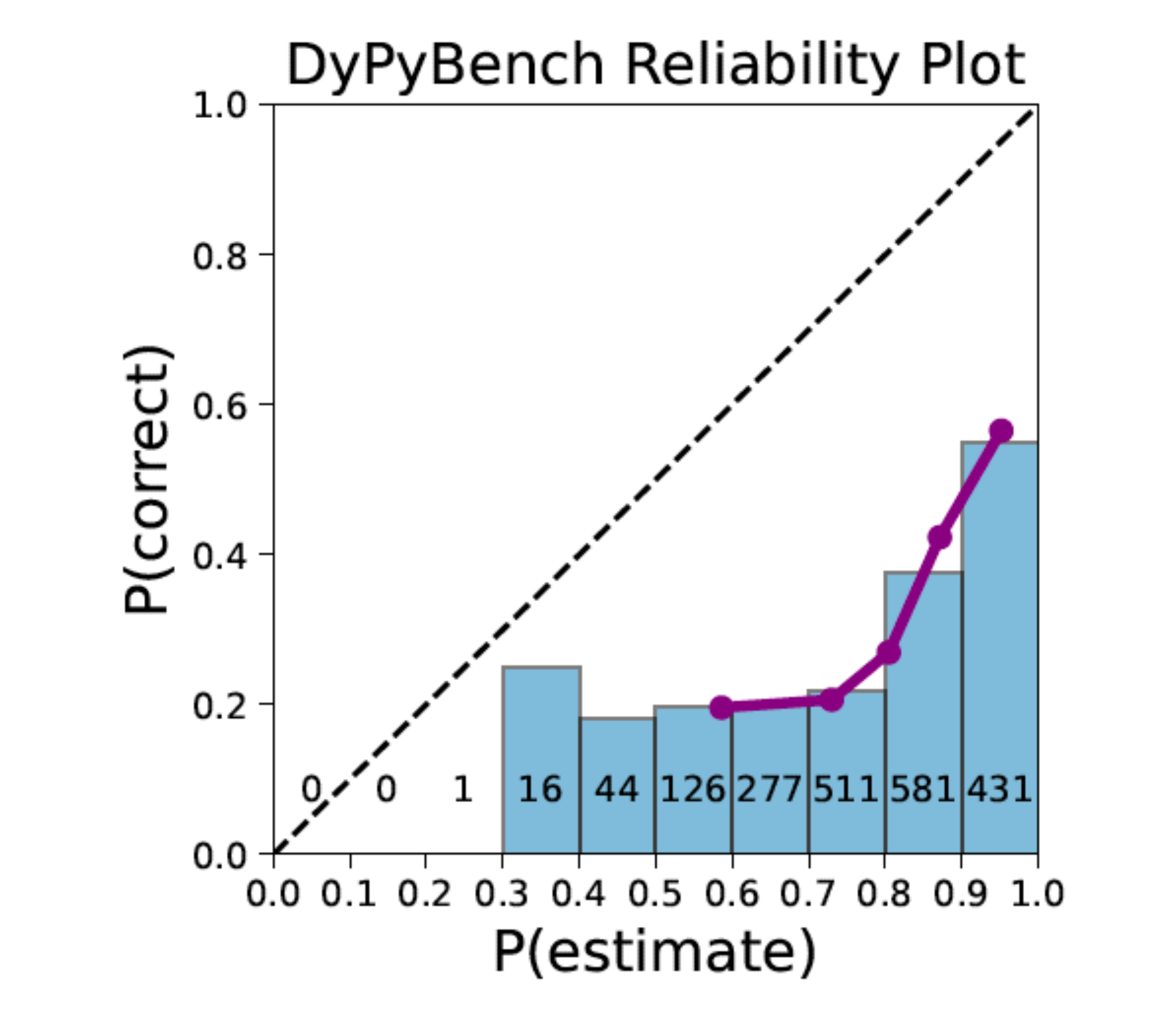
- ***PARAMETERS:*** Two, scaling value + bias



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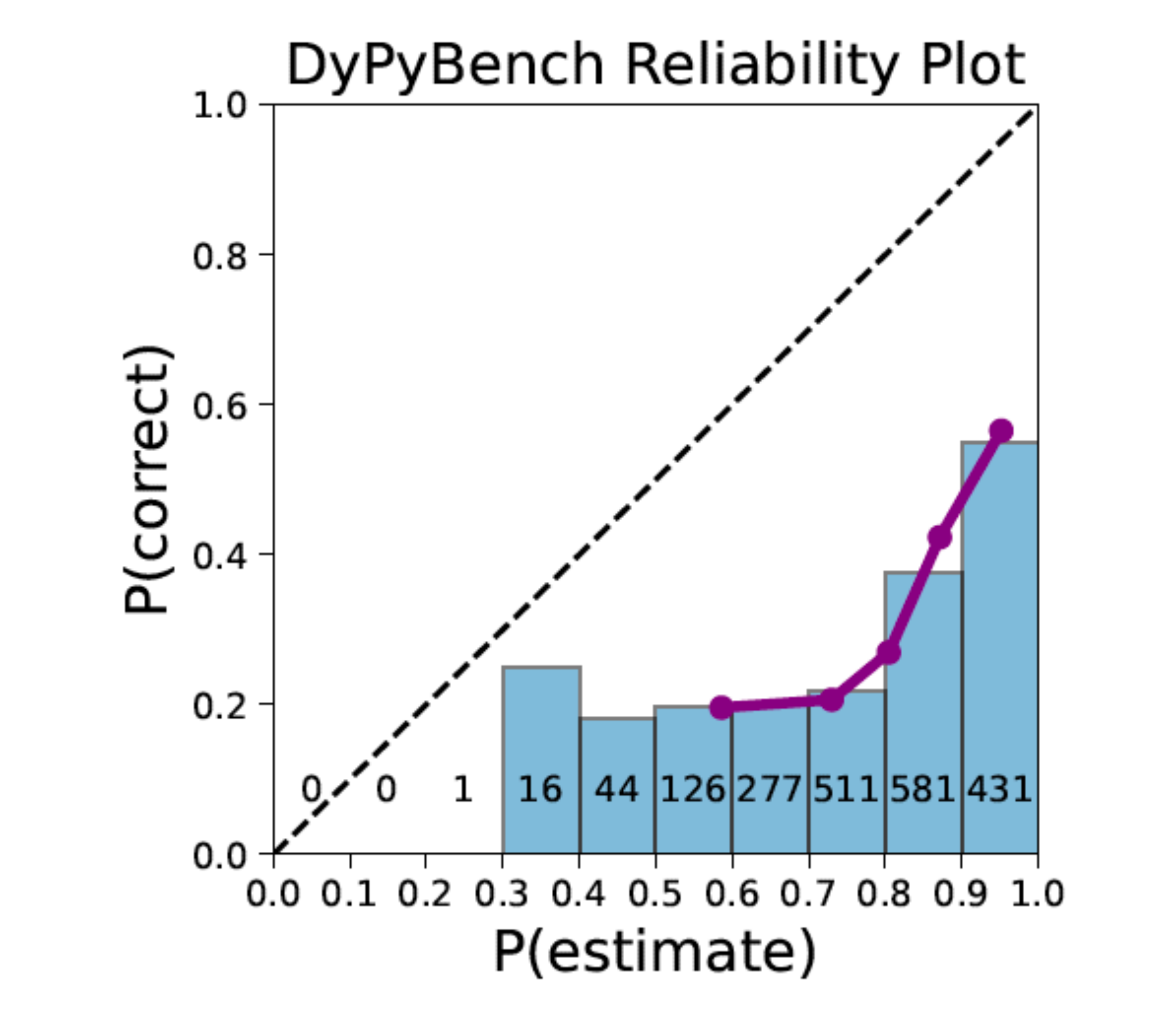

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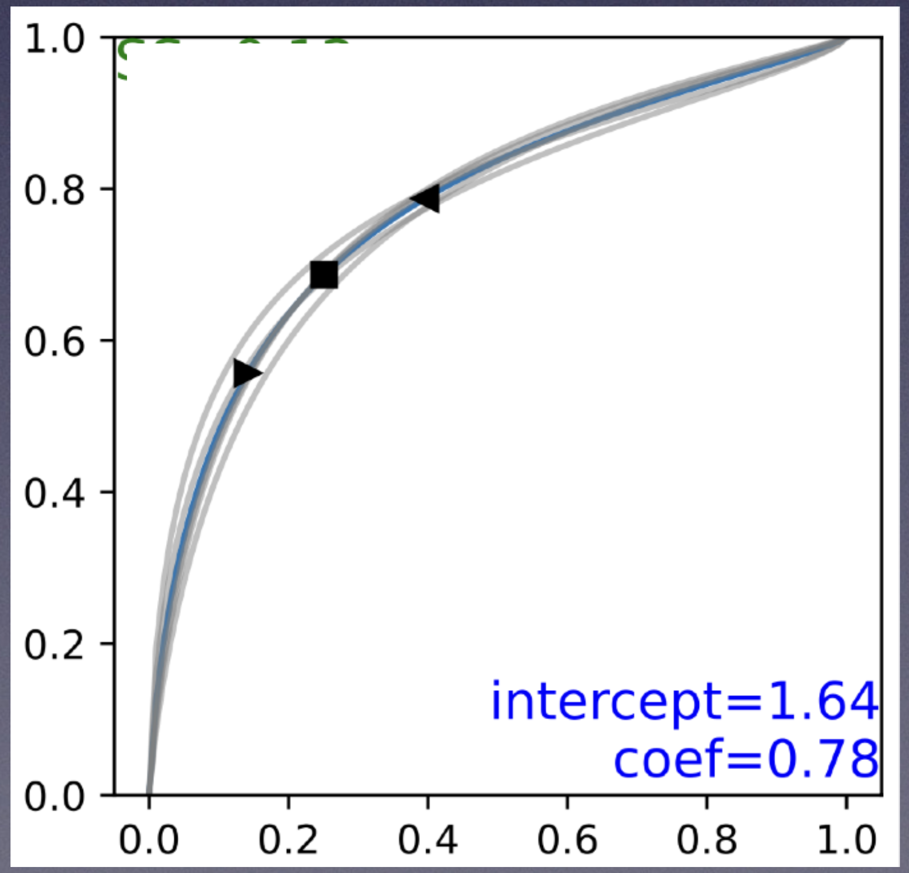

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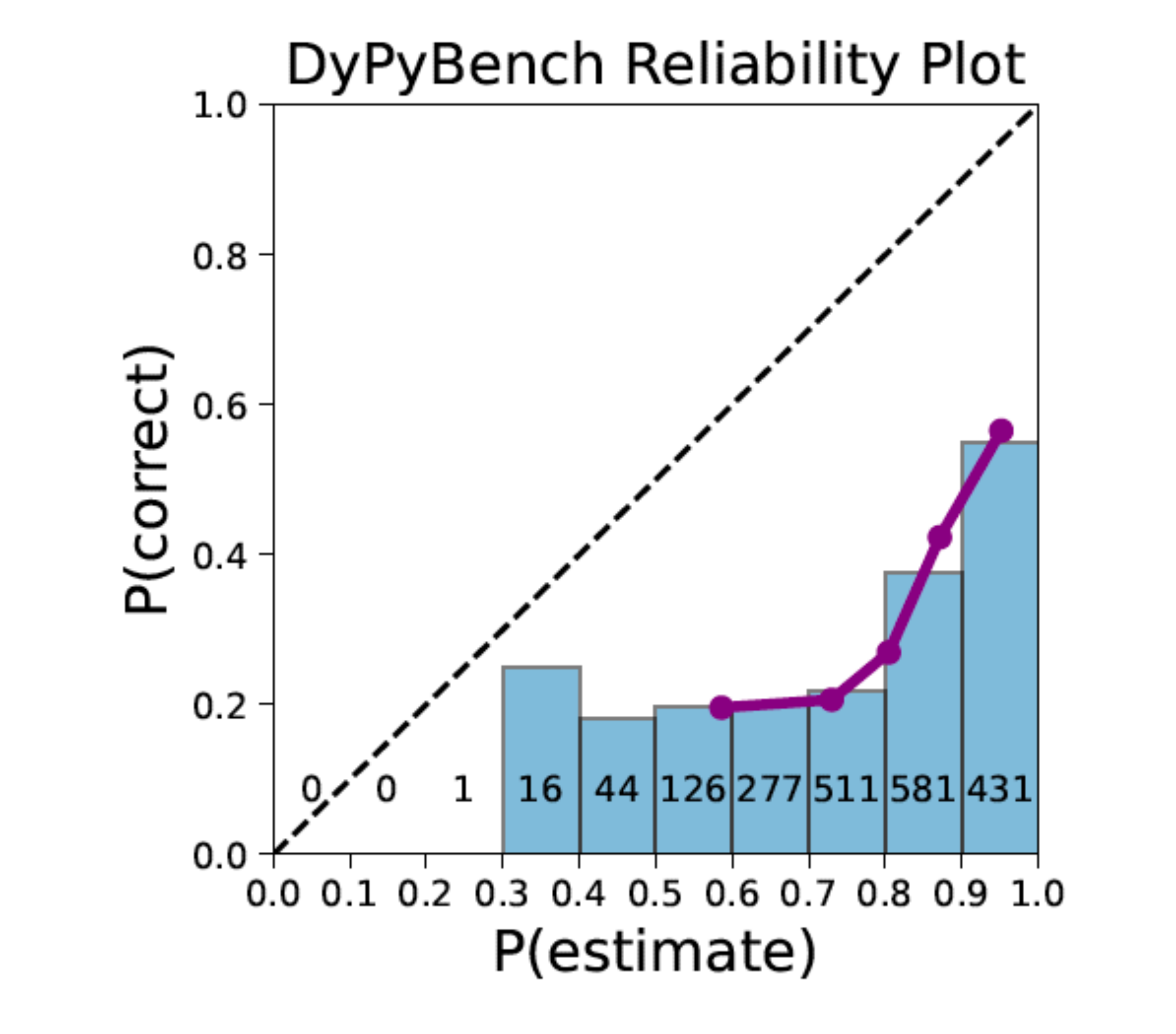
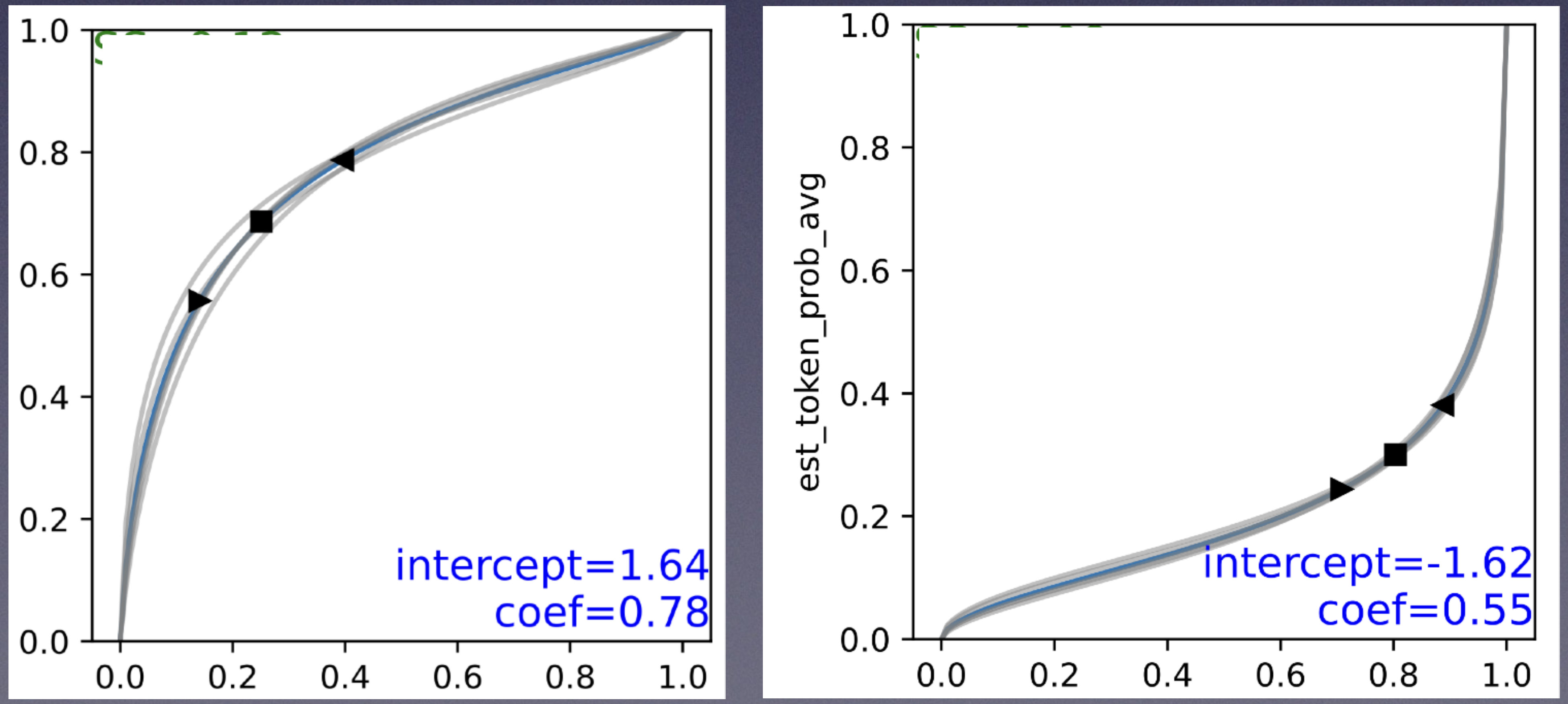




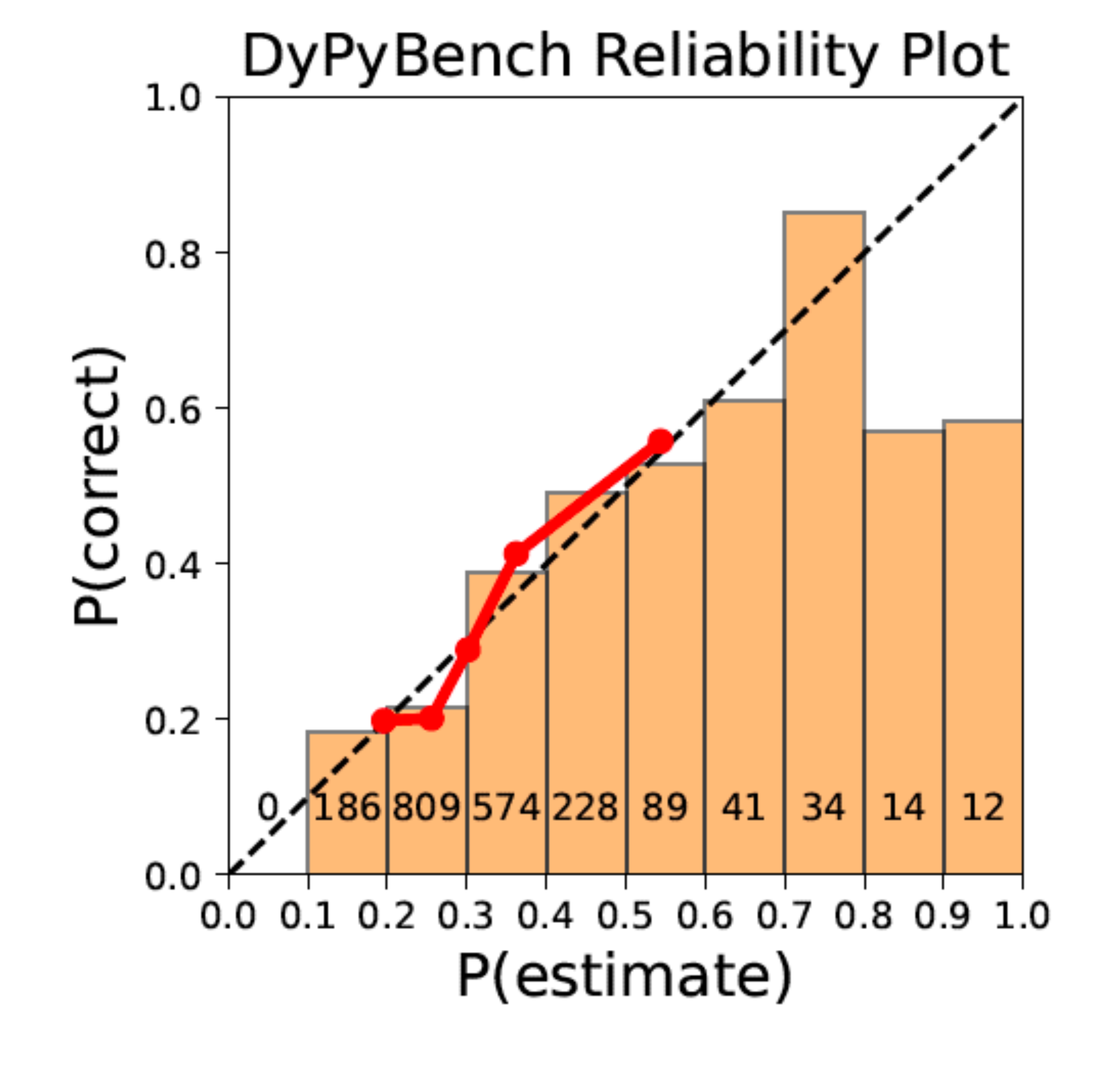
GPT 3.5, Line Completion *(Platt rescaling)*

ECE = *0.04.* *(was 0.15)*

B (actual) = *0.20.* *(was 0.41)*

B (reference) = *0.22*

Skill Score = *+0.08.* *(was -0.87)*



Beyond Intrinsic Confidence

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- ***Reflective Verbalized Self Ask:*** Ask the model, given it's own response, to output a probability of correctness.

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- ***Reflective True/False Logit:*** Ask the model if it's own response is correct, output True/False and take the logistic probability of True, normalized with False.
- ***Few-shot:*** Same as above, except we provide few-shots (both RAG and random.

Reflective Verbalized Self-Ask

We have the following python code implementing a method.

```
from typing import List

def below_zero(operations: List[int]) -> bool:
   ””” You're given a list of deposit and withdrawal operations on a bank
account that starts with zero balance. Your task is to detect if at any point
the balance of account fallls below zero, and at that point function should
return True. Otherwise it should return False.
>>> below_zero([1, 2, 3])
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>>> below_zero([1, 2, -4, 5])
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   “””
   balance = 0
   for op in operations:
      balance += op
   if balance < 0:
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   return False
```

What is a well-calibrated percent probability that this code passes the test cases?
Probability:

Reflective Verbalized Self-Ask

We have the following python code implementing a method.

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True or False, this code matches intent and is bug-free. Answer: **True**

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Logit

TL;DR Findings

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- ***Verbalized Self Ask:*** Not much better.
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- ***Few-shot:*** RAG with BM25 *(next slide)*

Few-shot Reflective, for Code Completion

Confidence Measure	$\mathcal{B} \downarrow$	$SS \uparrow$	$ECE \downarrow$
0-Shot Reflect	0.25	-0.15	0.15
0-Shot Reflect (Rescaled)	0.22	0.00	
FS Random	0.29	-0.29	0.21
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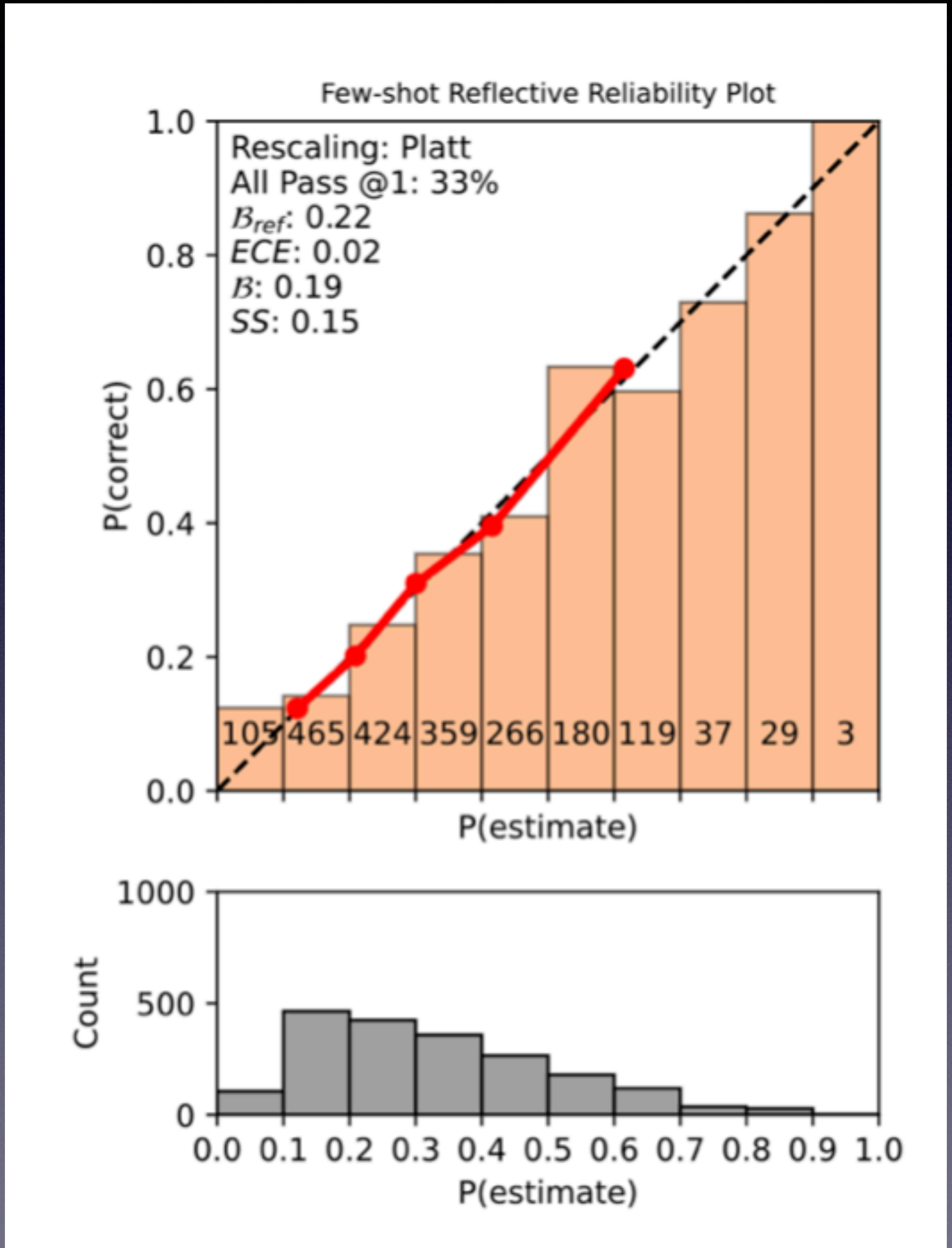

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def Convert2Base7(num):
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Summary

- The “Last Mile” is challenging
- Hypothesis: More information would lead to rational decision making and better outcomes.
- Well Calibrated Confidences are possible
- Need to do some User Studies. (*Collaborators ?)*