

Conformal Prediction: From Images to Agents

CVIS 2025

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Part I

**Conformal Prediction as
Uncertainty Quantification**

Part II

**Conformal Prediction for
Statistical Guarantees of
Correctness**

Part I

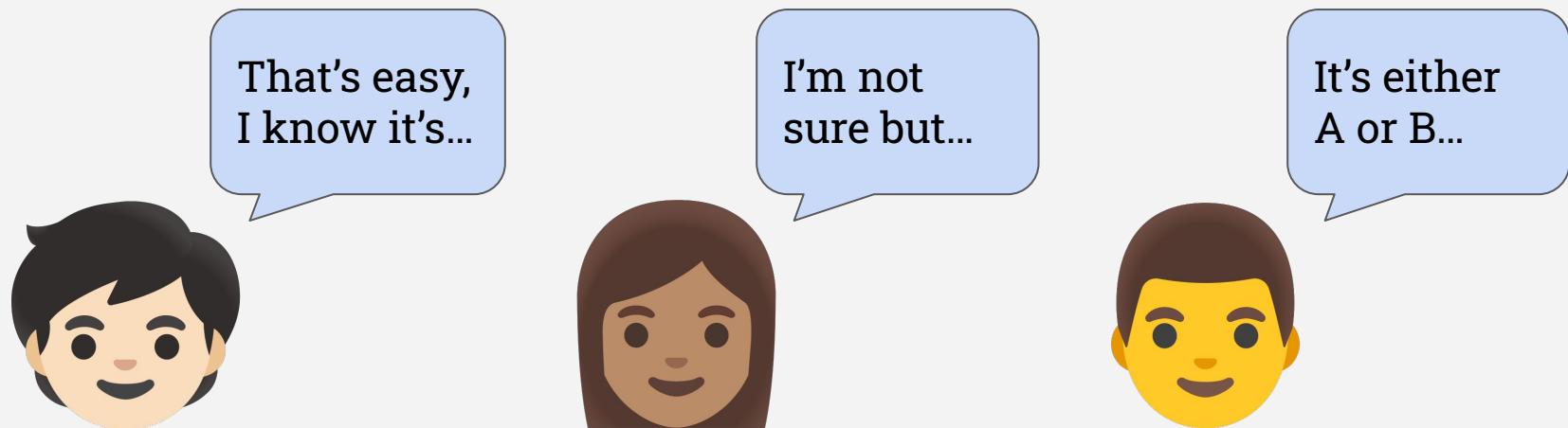
**Conformal Prediction as
Uncertainty Quantification**

Part II

**Conformal Prediction for
Statistical Guarantees of
Correctness**

Why should we quantify uncertainty?

When humans answer questions, we naturally state how confident we are.
It's a crucial aspect of decision making.



We **signal confidence**, and **offer alternatives**. Models do not.
They give you one answer every time, even when they shouldn't

Conformal Prediction

Conformal prediction is a general purpose method for transforming heuristic notions of uncertainty into rigorous ones.

Instead of outputting a single prediction, conformal prediction returns a **set**.

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Image Classification Example:

Conformal Prediction

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{Container Ship}

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Instead of outputting a single prediction, conformal prediction returns a **set**.



{Container Ship}



{Squirrel Monkey,
Spider Monkey, Lemur}

Conformal Prediction



{Container Ship}



**{Squirrel Monkey,
Spider Monkey, Lemur}**

The **size** of a prediction set **quantifies how uncertain** the model is.

When the model is more uncertain, the prediction set is larger, and this **provides alternatives** to the point prediction.

Conformal Prediction

Conformal prediction provides a statistical guarantee:

“The correct answer is in the prediction set with probability at least $1-\alpha$.”

$$\mathbb{P}(Y_{test} \in C(X_{test})) \geq 1 - \alpha$$

$1-\alpha$ can be thought of as the **success rate** - we choose it based on our error tolerance.
The technical term is **coverage**.

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Mistakes are reduced by making prediction sets larger (and therefore less useful).

Along with **statistical rigour**, conformal prediction is **versatile**, and **simple** to apply.

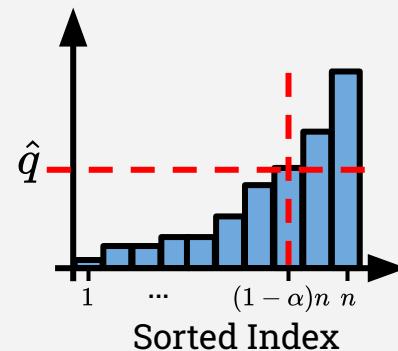
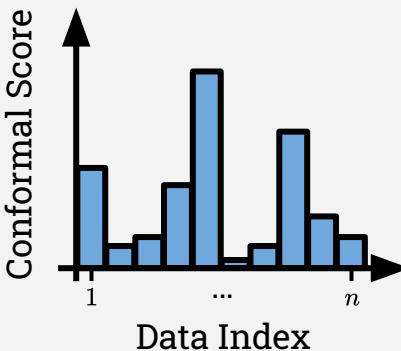
1 Define a conformal score function

$$s(x, y)$$

Larger scores indicate **worse** agreement between x and y . Classification example:

$$s(x, y) = 1 - f(x)_y$$

3 Sort scores from low to high



Compute the $1 - \alpha$ quantile. This value of the score is called the conformal threshold \hat{q}

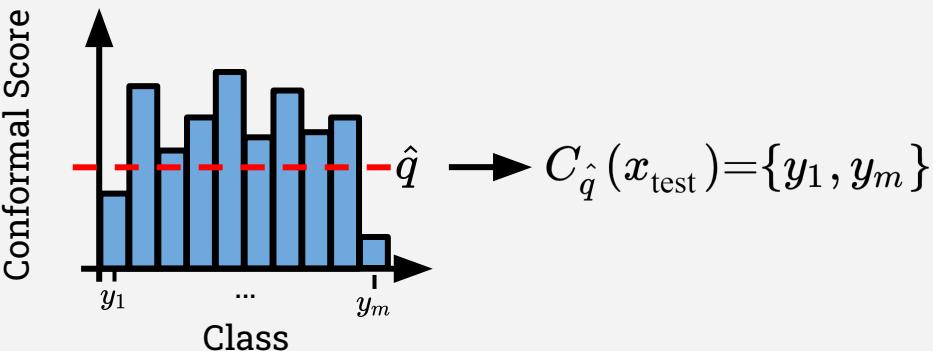
2 Given a calibration dataset

$$\{x_i, y_i\}_{i=1}^n$$

Compute conformal scores

$$s_i = s(x_i, y_i)$$

4 For new data x_{test} , return all classes with scores below the threshold



Larger set sizes indicate greater model uncertainty

Conformal Prediction

1. Define a score function
2. Compute scores on calibration data
3. Find $1-\alpha$ quantile - conformal threshold
4. On test data, return all classes with scores below threshold

Prediction sets constructed this way will satisfy coverage

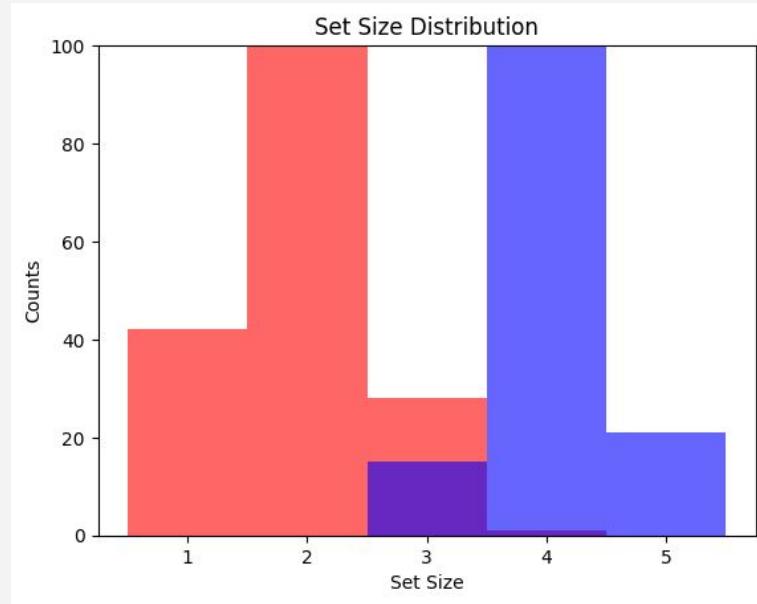
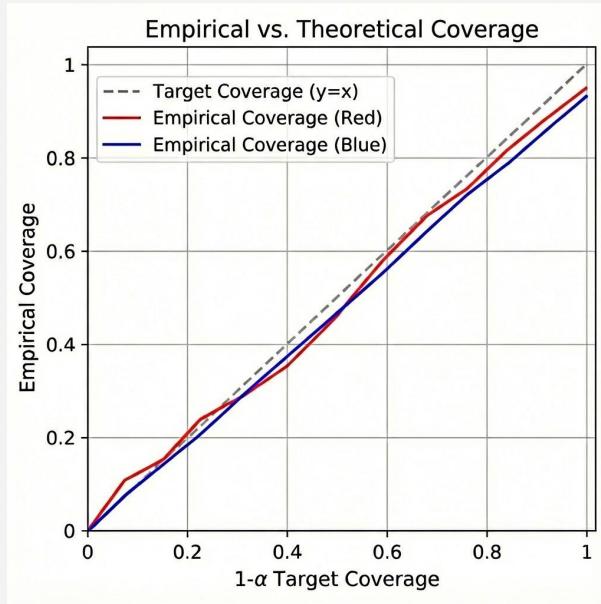
$$\mathbb{P}(Y_{test} \in C(X_{test})) \geq 1 - \alpha$$

No assumptions on:

- the model architecture
- how it was trained
- the data distribution (Gaussianity)
- how many datapoints you have (infinite data regime)

Conformal Prediction

A conformal algorithm will give coverage (in expectation) for any score function, but score functions influence the quality of sets.



Conformalized Vision Tasks

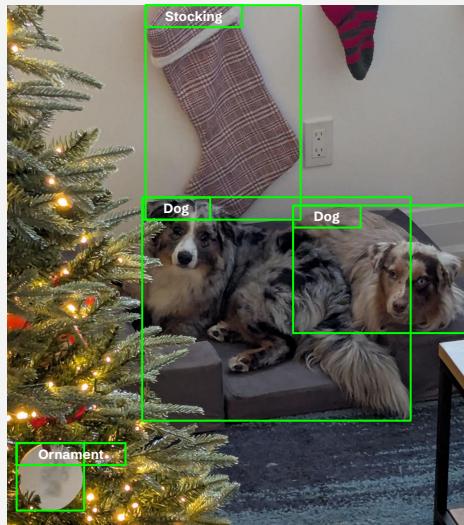
Conformal Prediction for Vision Tasks

Object Detection: Isolate and classify objects in an image

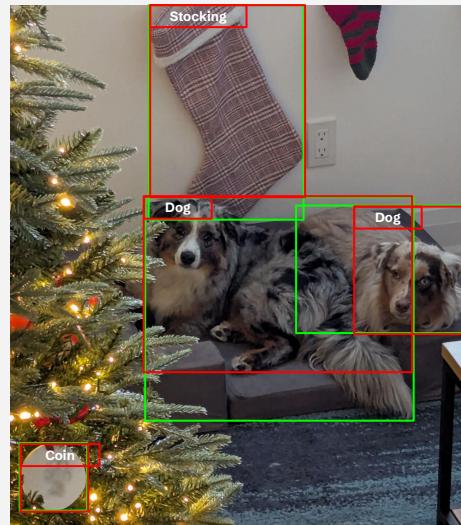
Produce a bounding box that *covers* the ground truth box, and give a label set that *covers* the ground truth label.

Larger bounding box relative to original prediction → more uncertain about location

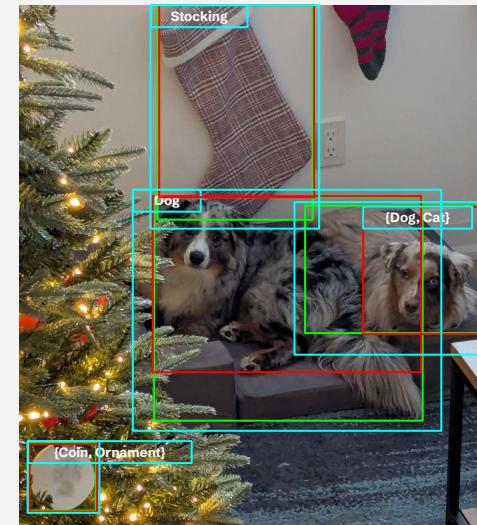
Ground Truth



Raw Prediction



Conformalized

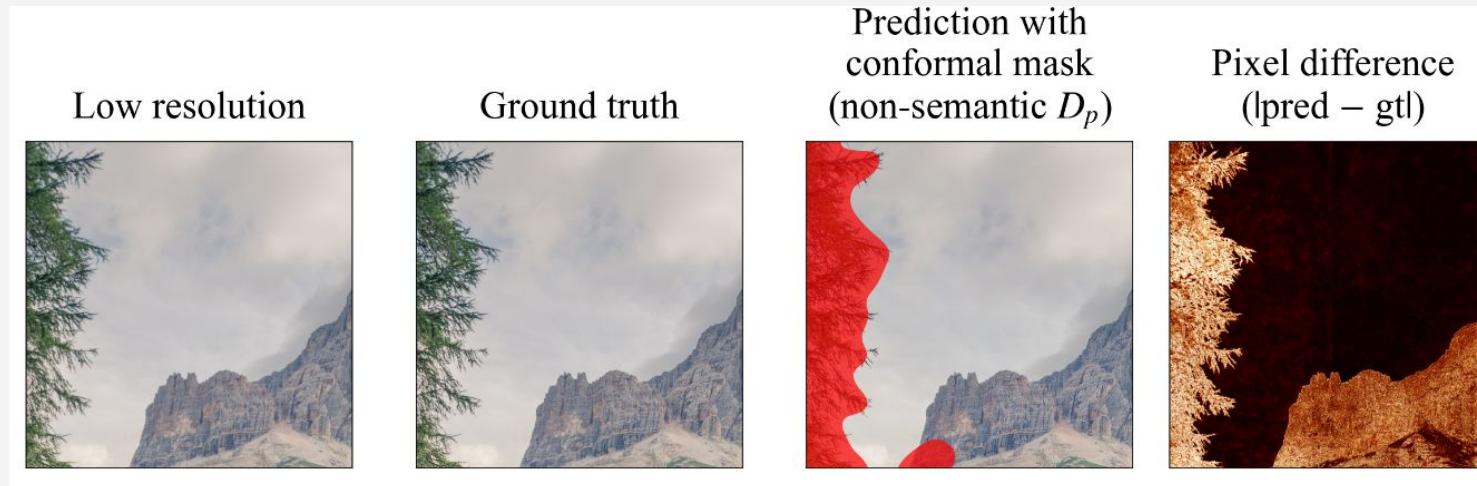


Conformal Prediction for Vision Tasks

Super-resolution: Reconstruct a high-res image from low-res inputs

Produce a mask over regions of low confidence in the reconstruction.

Masked regions should cover regions where the fidelity error is above α .



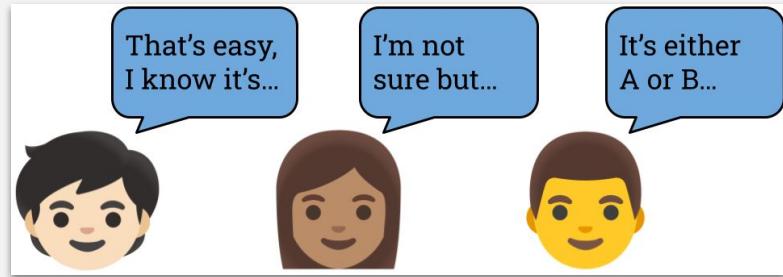
What do you do with prediction sets?

Actionable Model Outputs - Image Classification

Conformal prediction sets parallel how humans express uncertainty:

Sets signal model confidence through size.

When the model is less confident, it offers alternative.

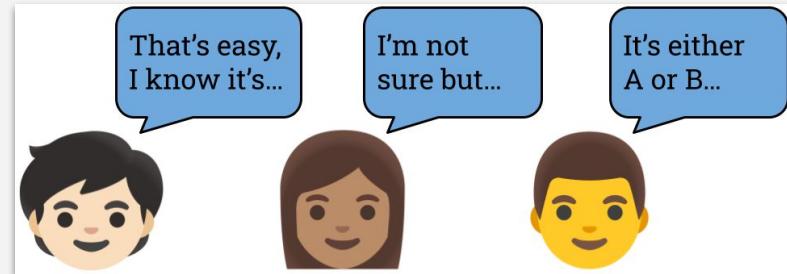


Actionable Model Outputs - Image Classification

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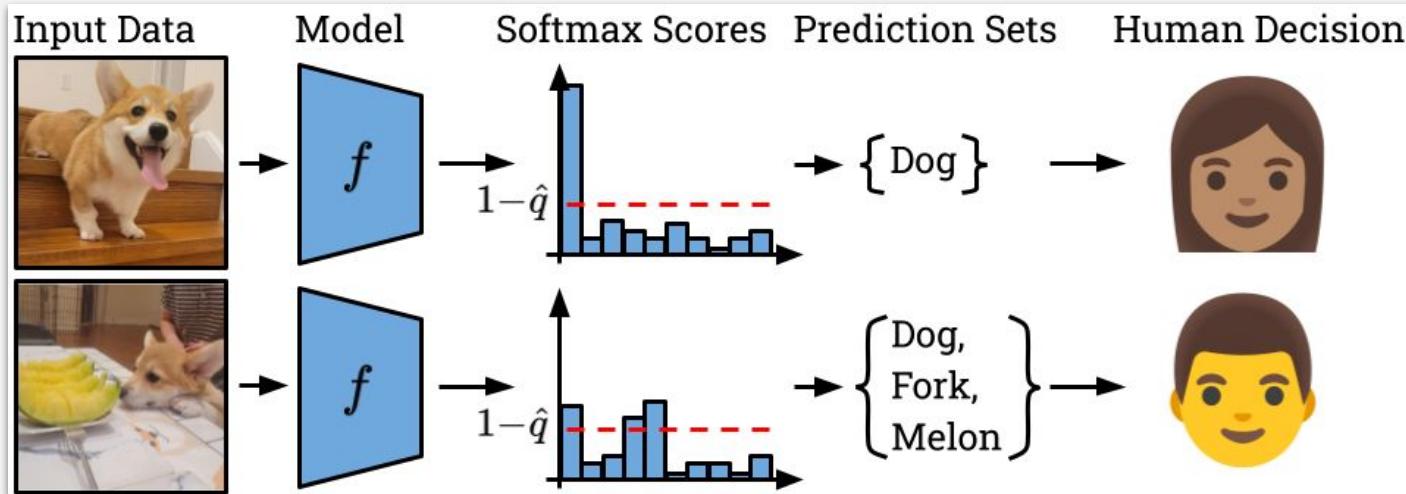
But, prediction sets are **not inherently actionable**.

Generally, we need a model to output a single prediction to automatically take an action.

Then how is conformal prediction meant to be used?

Human in the Loop Conformal Prediction

Since conformal prediction allows models to communicate in a more human way, it is natural to incorporate humans into conformal decision making pipelines.



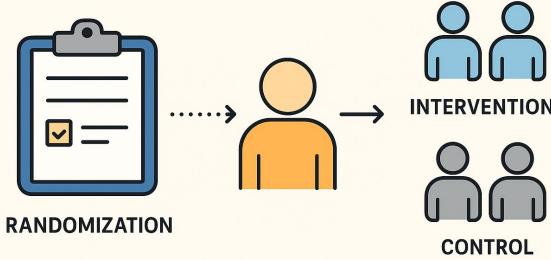
Do humans benefit from receiving conformal prediction sets?

Human in the Loop Conformal Prediction

We designed and conducted a randomized controlled trial to test two things:

Do prediction sets improve human
- accuracy?
- speed?

RANDOMIZED CONTROLLED TRIAL



Test Design

Human assigned to 1 of 3 tasks.

Tasks:

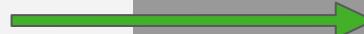
Image Classification “ObjectNet”

Sentiment Analysis

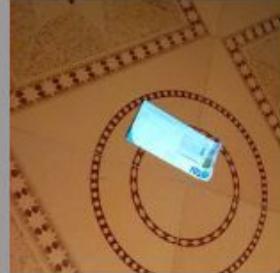
“Go-Emotions” - tweets

Named Entity Recognition

“Few-NERD” - Wikipedia



For the image below, select the most appropriate type.



AI suggestions: There is a 94% probability the answer is one of:
7. Book 16. Envelope

1. Backpack	6. Blanket	11. Broom	16. Envelope
2. Banana	7. Book	12. Bucket	17. Figurine
3. Bandage	8. Bottle	13. Candle	18. Sandal
4. Battery	9. Bottle Cap	14. Cellphone	19. Knife
5. Belt	10. Bottle Opener	15. Cellphone Charger	20. Trash Bin

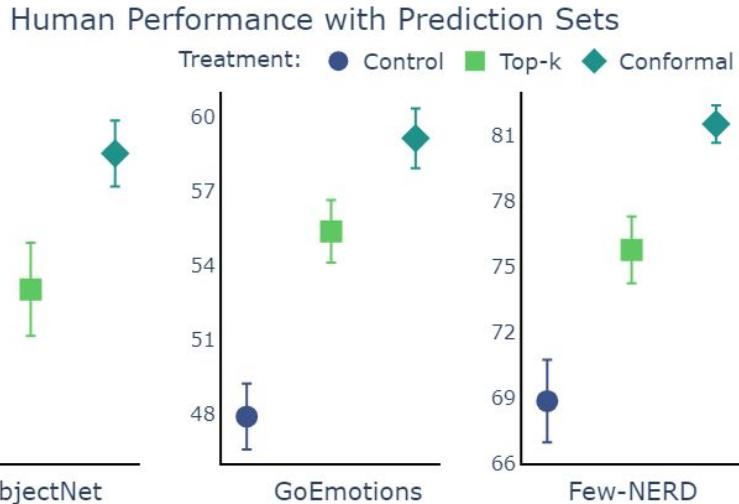
The best answer is 16. Envelope. 16 Enter a value between 1 and 20 Press SPACEBAR to continue.

Treatment: Given either no help, top 3 model predictions, or conformal set (variable size)

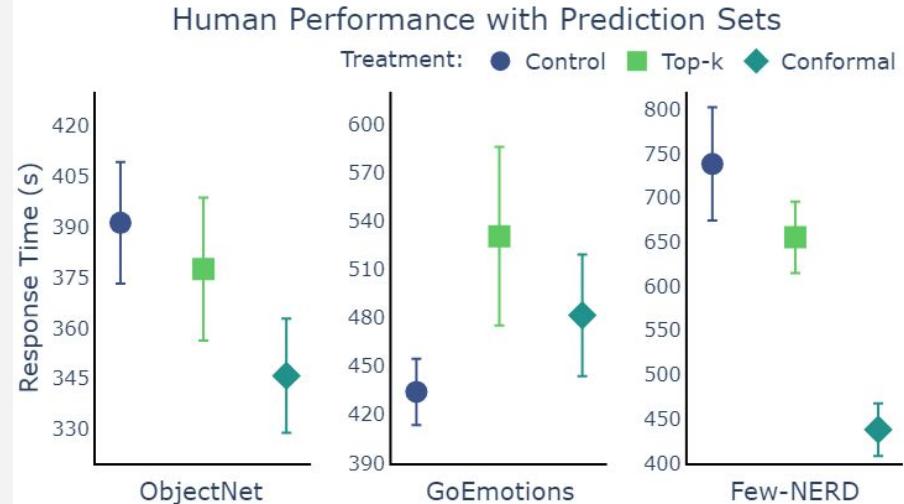
Main Results

Main results show that there is a **statistically significant and large difference in accuracy** between treatments, but no consistent trend for speed.

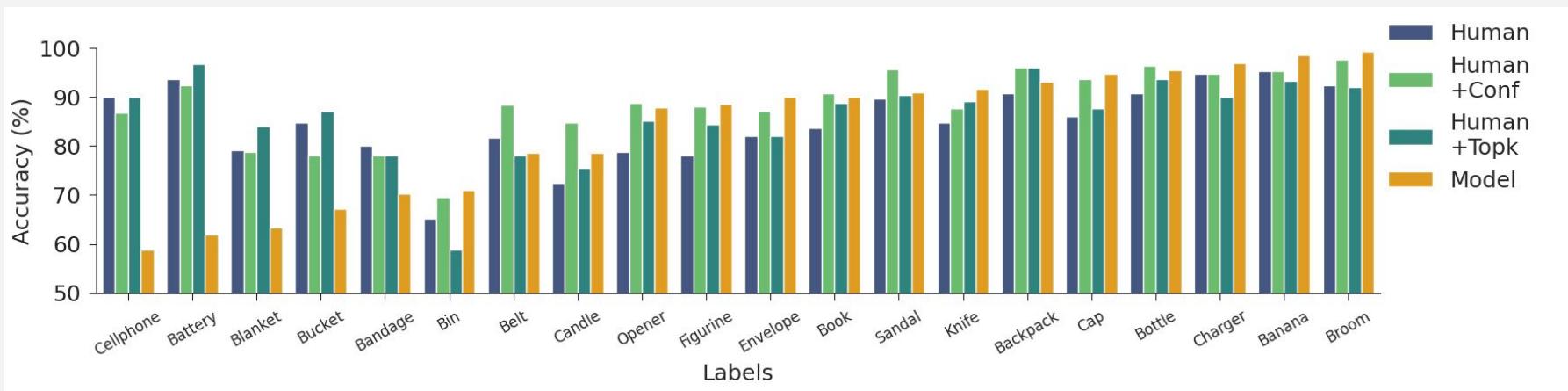
Accuracy



Speed



Fairness Concerns



Observation:

When model accuracy was **low**, Human+Conformal could be **worse** than Human.
When model accuracy was **high**, Human+Conformal was **better** than Human.

Conformal sets do not improve all classes equally - indicates Disparate Impact.

Conformal Prediction + Fairness

Suppose we have two groups within the data.

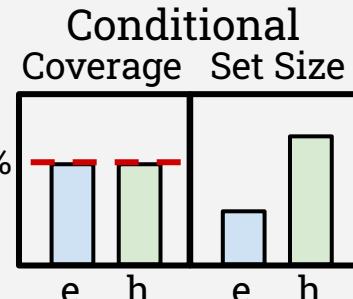
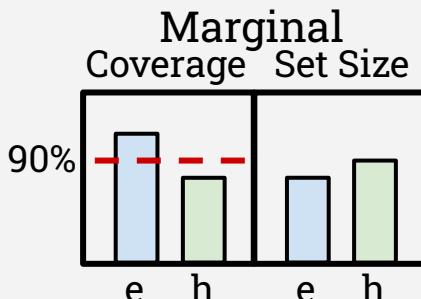
Coverage is valid *marginally*, not on each group *conditionally*.

How do you get *higher coverage* on the *undercovered group*?

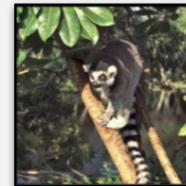
Make their prediction sets **larger**

How do you get *lower coverage* on the *overcovered group*?

Make their prediction sets **smaller**



Under-covered



{Squirrel Monkey}

Add more labels to sets

{Squirrel Monkey,
Spider Monkey,
Lemur}

Over-covered



{Cruise Ship,
Container Ship}

Remove labels from sets

{Cruise Ship}

Conformal Prediction + Fairness

Prior work argues that coverage should be equalized across groups for fairness.

Our experimental data shows that **set size matters more** for outcomes.

Equalizing Coverage across groups makes CP less fair

Equalizing Set Size across groups makes CP more fair

*Hypothesis 1 - Prediction sets given to decision makers **can cause disparate impact** in the human's performance.*

*Hypothesis 2 - Sets with Equalized Coverage **will cause greater disparate impact** than marginal coverage.*

Test Design

Human assigned to 1 of 3 tasks.

Tasks (Classification):

Image Classification “FACET”

Age = {Young, Middle, Old, Unknown}

Emotion Recognition “RAVDESS”

Gender= {Male, Female}

Text Classification “BiosBias”

Gender= {Male, Female}



For the image below, select the most appropriate option.



AI Suggestions: There is a 90% probability that the answer is one of:
6. Guard, 12. Officer

- | | | | |
|------------------|-----------------|------------------|-------------------|
| 1. Backpacker | 5. Guard | 11. Laborer | 16. Salesperson |
| 2. Boatman | 7. Guitarist | 12. Officer | 17. Singer |
| 3. Computer User | 8. Gymnast | 13. Motorcyclist | 18. Skateboarder |
| 4. Craftsman | 9. Hairdresser | 14. Painter | 19. Speaker |
| 5. Farmer | 10. Horse Rider | 15. Repairman | 20. Tennis Player |

6

Enter a value between 1 and 20

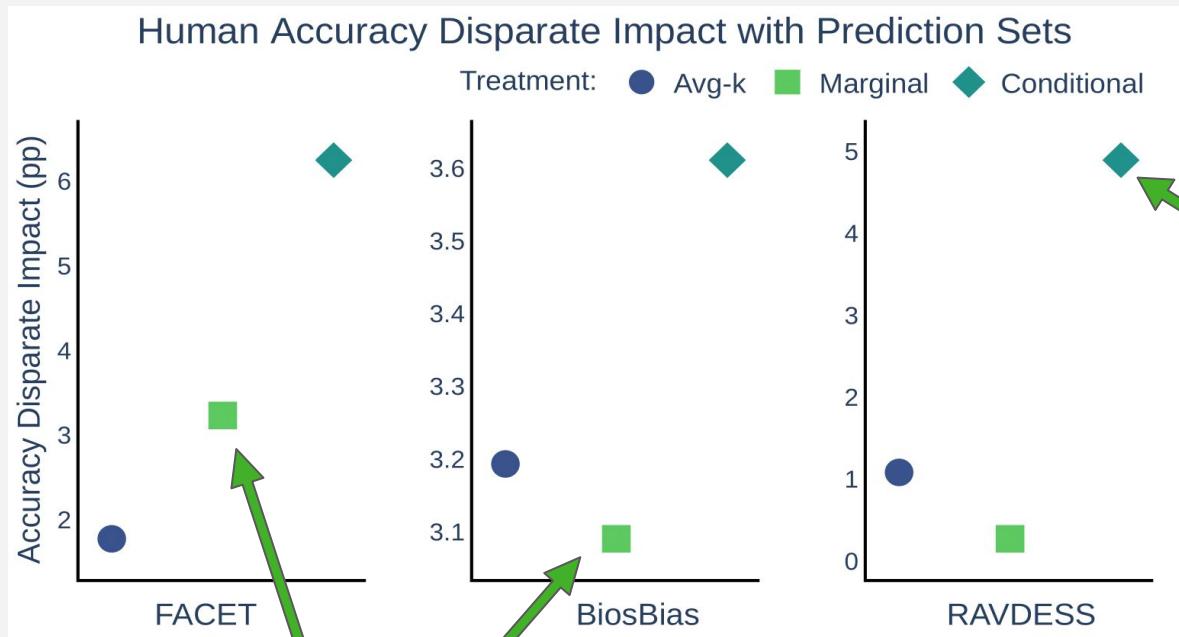
The best answer is 6. Guard.

Press SPACEBAR to continue.



Treatment: Given either no help,
marginal conformal, conditional conformal

Main Results



H1: Marginal sets caused
some **DI** in 2 of 3 tests.

H2: Conditional sets
caused much greater
DI in all tests.

Part I

Conformal Prediction as Uncertainty Quantification

Size of prediction sets indicates uncertainty

Coverage guarantee comes from calibration

Uncertainty is useful for downstream tasks

Part II

Conformal Prediction for Statistical Guarantees of Correctness

CP for Language Tasks

We can do classification, regression, set prediction. Straightforward.

How can CP be used for language tasks?

Uncertainty quantification for LLMs is an extremely important and unsolved problem.

- Hallucinations
- Abstention
- Probabilistic generation

But it may not be obvious how to apply CP...

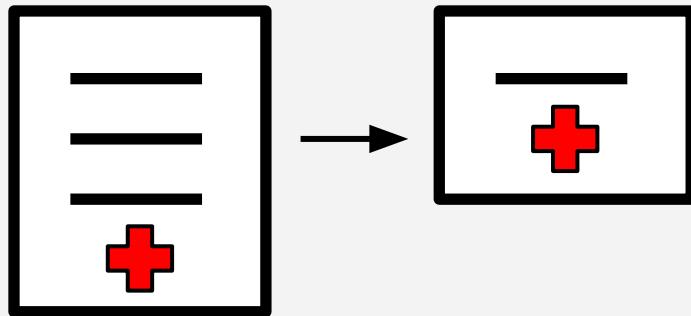
Should we generate multiple answers and return some of them as a set???

Document Summarization

Document Summarization

Summarization is an easy task nowadays - just give a document to an LLM.

But what if the document contains some critical information that must be retained?



LLM summarization gives you no guarantees that the summary

- Will contain all critical information
- Will not contain hallucinations

Extractive Summarization with Guarantees

Extractive summarization does not paraphrase, it directly extracts phrases.

By performing extraction only, no hallucinations.

We can use the principles of conformal prediction to give statistical guarantees that critical information will be retained.

EXTRACTIVE SUMMARIZATION

ORIGINAL TEXT

Machine learning is a branch of artificial intelligence that focuses on building systems that learn from data. It has applications in image recognition, natural language processing, and recommendation systems.



SUMMARY

Machine learning is a branch of artificial intelligence. It has appli-



METHOD

Selects sentences from the original text



OUTPUT

Verbatim text from source



COMPLEXITY

Simpler, less prone to factual errors

Extractive Summarization with Guarantees

Given a document x , consisting of p sentences

$$x = \{c_1, \dots, c_p\}$$

where a subset $y^* \subseteq x$ is GT important, we want to produce a summary y which contains all important information with high probability

$$\mathbb{P}[y^* \subseteq y] \geq 1 - \alpha$$

Extractive Summarization with Guarantees

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where a subset $y^* \subseteq x$ is GT important, we want to produce a summary y which contains all important information with high probability

$$\mathbb{P}[y^* \subseteq y] \geq 1 - \alpha$$

We assign an “importance score” to each sentence, and filter out sentences based on a calibrated conformal threshold.

Shorter, more concise summaries are more helpful, so aim to retain few sentences.

Conformal Importance - Calibration

1. Collect calibration data where each sentence has a binary label of importance.
2. Assign an “importance score” to each sentence (using a model).

Calibration Document #1

“Patient presented with heavy cough.”	GT=1	Importance Score = 0.7
“Patient was wearing blue socks.”	GT=0	Importance Score = 0.1
“Patient diagnosed with pneumonia.”	GT=1	Importance Score = 0.9

3. Set document-level conformal score as lowest importance score for any GT=1 sentence.

Conformal Importance - Calibration

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Calibration Document #1 - Overall conformal score = **0.7**

“Patient presented with heavy cough.” GT=1 **Importance Score = 0.7**

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3. Set document-level conformal score as lowest importance score for any GT=1 sentence.
4. Find the $1-\alpha$ quantile \hat{q} of conformal scores over the calibration dataset.

Conformal Importance - Prediction

1. Assign an “importance score” to each sentence in the same way as before.

Test Document

“Patient had a sandwich for lunch.”	GT=?	Importance Score = 0.1
“Patient to take acetaminophen daily.”	GT=?	Importance Score = 0.9
“Patient left hospital at 2:09 pm.”	GT=?	Importance Score = 0.6
“Patient advised to not consume alcohol.”	GT=?	Importance Score = 0.8

2. Sentences with importance greater than the threshold \hat{q} are kept.

Theorem: Summaries created this way contain all important information with high probability

$$\mathbb{P}[y^* \subseteq y] \geq 1 - \alpha$$

Conformal Importance - Scoring

Beyond proving mathematically that coverage holds, we proposed and evaluated various importance scoring functions.

LLM Scoring: Prompt an LLM to judge how important a sentence is from 0 to 1.

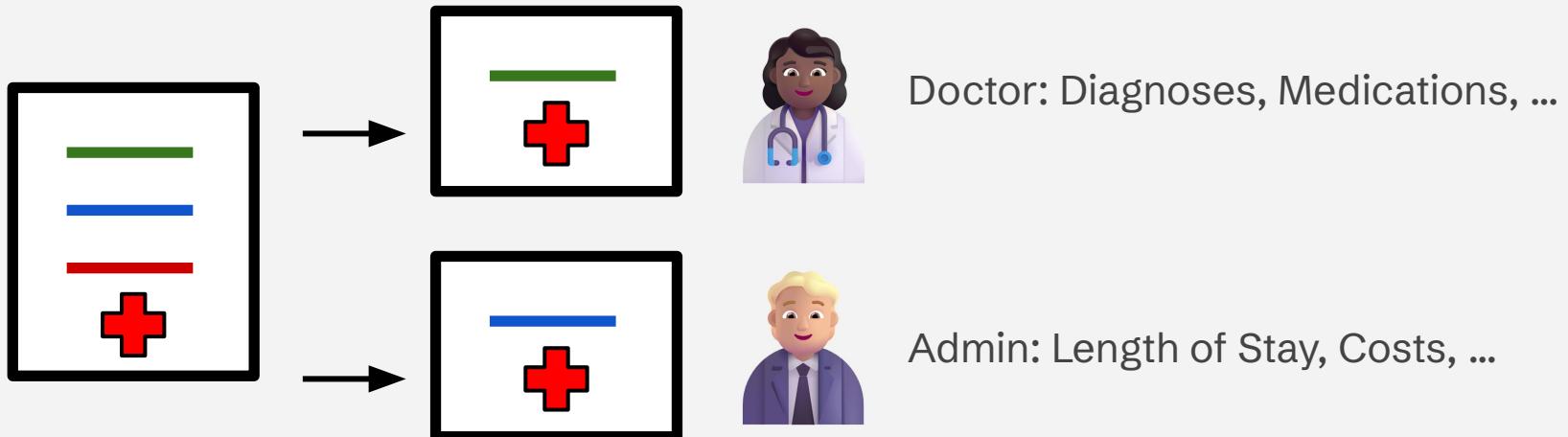
Embedding Similarity: Create sentence-level embeddings and compute distances between them to form a graph. Various NLP algorithms can compute a score based on the distance.

LLM scoring
works best!

Importance Score	AUPRC ↑					Fraction of Sentences Removed ↑				
	ECT	CSDS	CNN/DM	SciTLDR	MTS	ECT	CSDS	CNN/DM	SciTLDR	MTS
Original Article	0.10	0.27	0.10	0.06	0.81	0.00	0.00	0.00	0.00	0.00
Cos. Sim. Centrality	0.22	0.34	0.34	0.35	0.86	0.22	0.11	0.18	0.29	0.18
Sentence Centrality	0.14	0.34	0.29	0.28	0.86	0.17	0.08	0.22	0.30	0.10
GUSUM	0.21	0.44	0.33	0.21	0.90	0.11	0.24	0.27	0.15	0.13
LexRank	0.22	0.43	0.32	0.32	* ³	0.16	0.12	0.20	0.37	* ³
GPT-4o mini (binary)	0.12	0.34	0.13	0.08	0.83	0.24	0.22	0.26	0.22	0.08
GPT-4o mini	0.30	0.49	0.34	0.33	0.93	0.24	0.25	0.30	0.40	0.16
Llama3-8B	0.18	0.39	0.22	0.15	0.92	0.13	0.11	0.14	0.11	0.14
Qwen3-8B	0.17	0.38	0.22	0.16	0.91	0.13	0.11	0.09	0.14	0.22
Gemini 2.0 Flash-Lite	0.35	0.68	0.42	0.39	0.95	0.28	0.46	0.25	0.40	0.13
Gemini 2.5 Flash	0.43	0.69	0.36	0.34	0.94	0.37	0.49	0.26	0.41	0.14

Conformal Importance - Customization

Two users may have different opinions on what is important



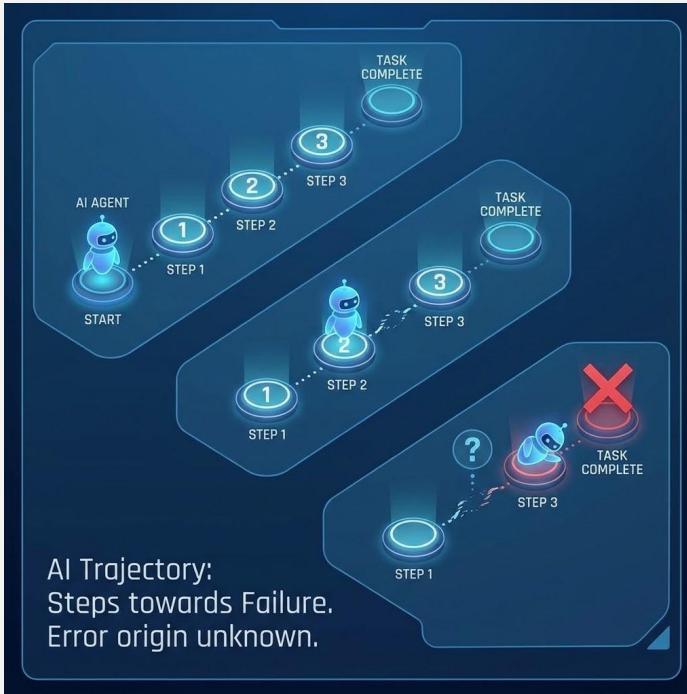
Conformal Importance can accommodate different opinions by

- Having each user annotate their own calibration set
- Defining what is considered important in the LLM scoring prompt (e.g. ICL)

Agent Error Attribution

Agent “Debugging”

When an AI agent fails at a task, how can we determine what went wrong?



Unlike traditional code, we do not see exactly which step caused the error.

A screenshot of a code editor interface, likely VS Code, showing a Python file named 'calculate_area.py'. The code defines a function 'calcul' with a typo. The error message 'TypeError: unsupported operand type(s) for +: 'str' and 'int'' is displayed, pointing to line 12 where the variable 'area' is used in a sum operation. Below the code editor, a terminal window shows the command 'main(110, 5, 4, 3)' being run, followed by the traceback and the same type error message.

```
9
10 def calcul
11     area = View Problem | Cernlonst
12     total_area = length + width * height
13
14     return total_area
15
16 print(area)
17
18
19
```

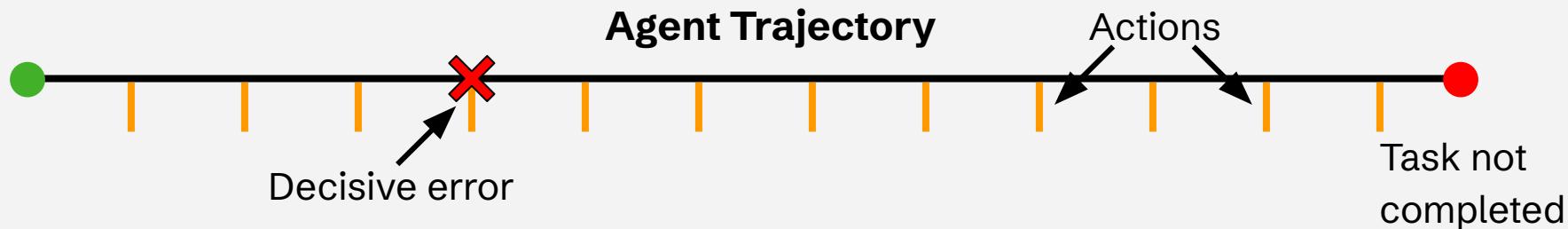
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL 1: math

```
>>> = main(110, 5, 4, 3)
total_area= length + width * height)

Traceback (most recent call last):
  File "main.py", line 5, in <module>
    calculate_area(10, "5", 2)
  File "calculate_area.py", line 12, in calculate_area
    total_area = length + width * height
TypeError: unsupported operand type(s) for +: 'int' and 'str'
```

Ln 1, Col 1

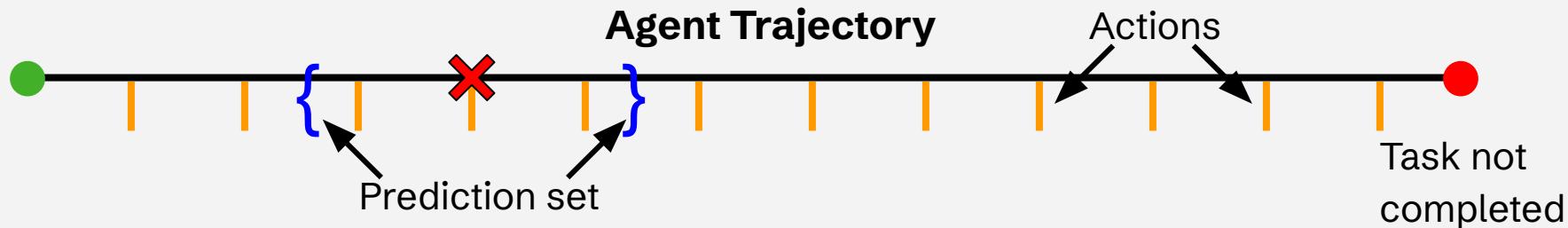
Agent Error Attribution



Imagine a web-shopping agent with a task to purchase formal black shoes. At each step it can observe a textual webpage and perform actions like clicking a mouse or typing.

Classifying exactly which step was the “decisive error” has proven to be challenging, with ~9% accuracy rates in first studies.

Agent Error Attribution



Instead, we aim to predict a (contiguous) set of steps which contains the error with high probability:

$$\mathbb{P}[y^* \subseteq y] \geq 1 - \alpha$$

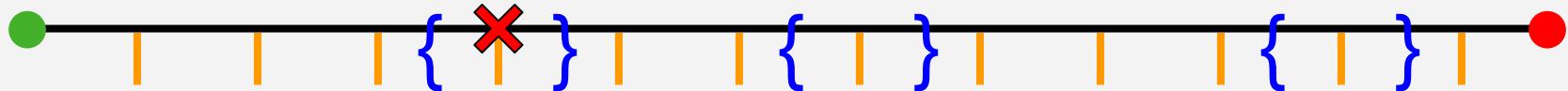
Conformal Error Attribution



This setting perfectly demonstrates the two main components of conformal systems:

1. The algorithm producing sets with a coverage guarantee,
2. The scoring function, a model of the predictive task.

Conformal Error Attribution - Algorithms



Ordinary conformal prediction for classification can be applied:

1. Define score function - how likely is a step to be the decisive error?
2. Compute scores on calibration data.
3. Find $1-\alpha$ quantile.
4. On test data, add all steps with high enough conformal score.

But this does not have the property that predicted sets be contiguous.
We are not taking advantage of the data's structure.

Conformal Error Attribution - Algorithms



Left Filtering:

1. Define score function - how likely is decisive error to be in a subsequence.
2. Filter out steps from the left that are not the decisive error. Record final score.
3. Find $1-\alpha$ quantile.
4. On test data, filter out steps until just before it drops below calibrated threshold.

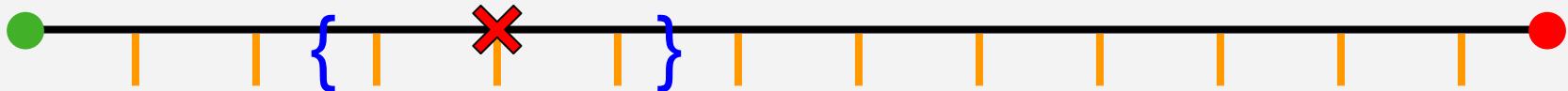
Conformal Error Attribution - Algorithms



Root-to-Leaf Tree Traversal:

1. Define score function - how likely is decisive error to be in a subsequence.
2. View the trajectory as a tree - entire trajectory = root - single step = leaf.
3. Start with single most likely leaf. Traverse up tree until decisive error contained.
4. Find $1-\alpha$ quantile.
5. On test data, traverse up tree until score surpasses calibrated threshold.

Conformal Error Attribution - Score Functions

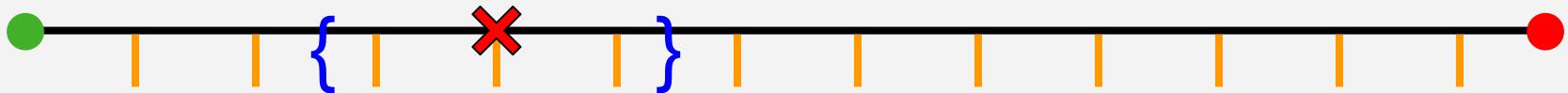


We need to assign a score to a subsequence.

You essentially need to use an LLM to handle the textual information of the trajectory:

- Task statement
- Final output (failure)
- Agent's chosen action/tool at subsequence steps
- Response from environment at subsequence steps
- Any other relevant metadata.

Conformal Error Attribution - Score Functions



All-at-Once:

Provide all the information in a single LLM call.

Pros:

- Minimal LLM calls

Cons:

- LLM can be overwhelmed by amount of detail

- Scores for nested subsequence may not be monotonic

Conformal Error Attribution - Score Functions



Aggregated Scoring:

Score each step in a subsequence individually, then aggregate the results.

E.g. **Sum** the individual scores; or take the **maximum** over scores.

Pros:

- LLM can focus on details of each step.

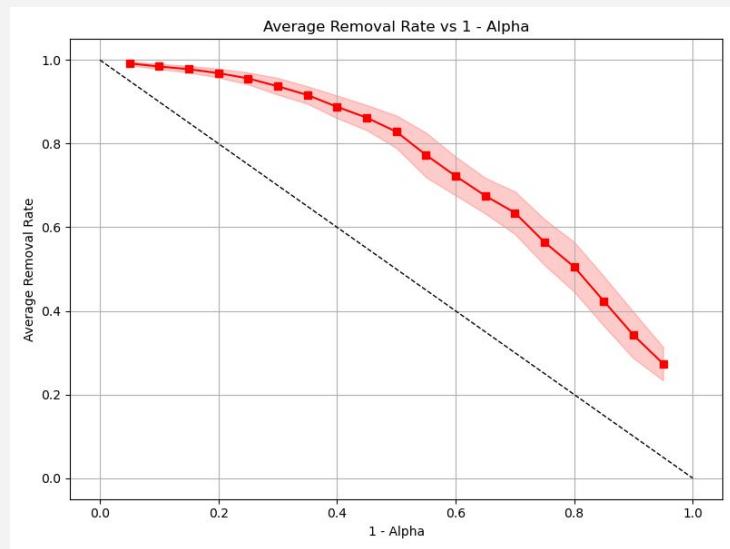
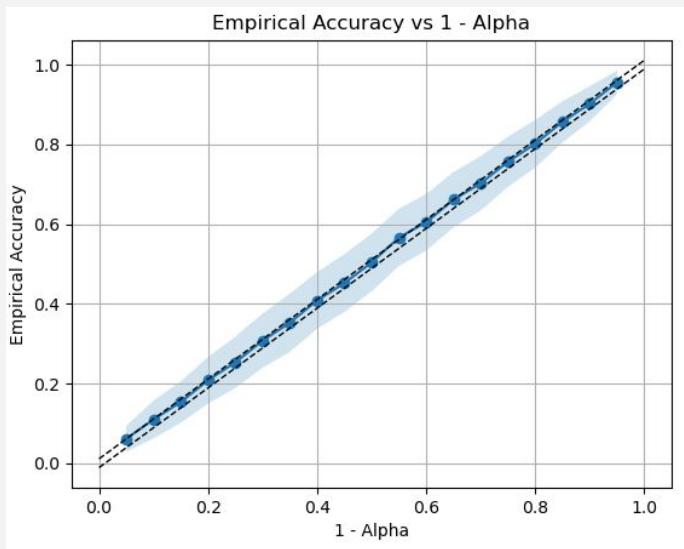
- Scores for nested subsequence can be monotonic by design.

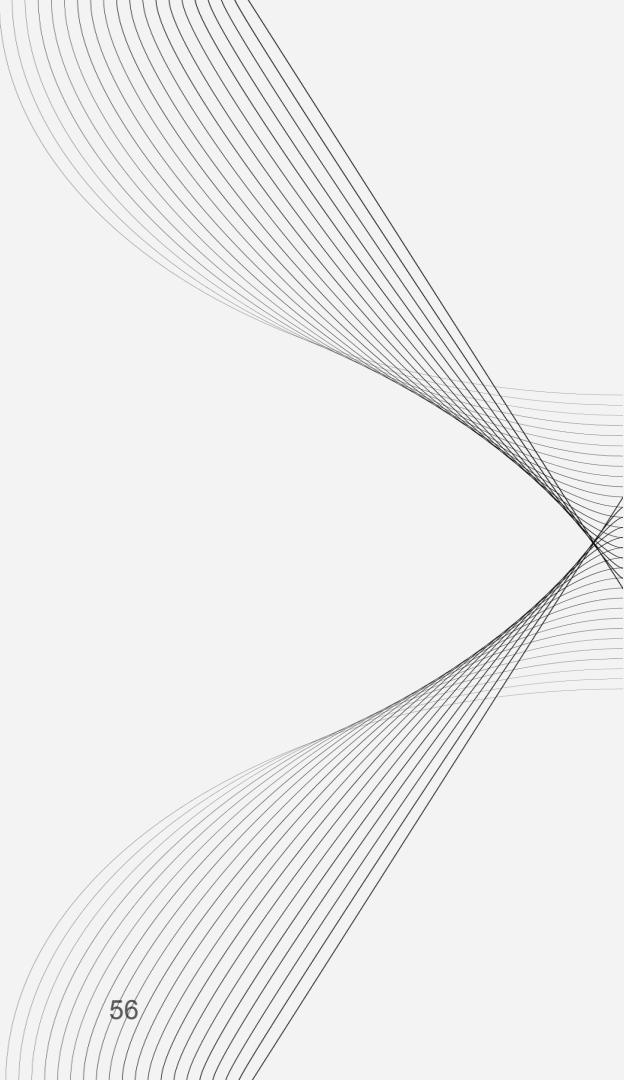
Cons:

- Several LLM calls needed.

Conformal Error Attribution

Can achieve valid statistical guarantees of coverage while narrowing down the prediction set to 20-30% of total steps.





Conclusions

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Conformal prediction is not just a method for generating sets, or quantifying uncertainty.

It is a flexible framework for providing statistical guarantees on various forms of correctness. Tight guarantees hold with minimal assumptions.

By being creative with how score functions are defined, we can adapt conformal prediction to new settings, like document summarization, and agent evaluation.

Layer 6 is hiring for

- Research Machine Learning Scientists
- Machine Learning Engineers
- Technical Product Owners

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with me at the break!

Thank you!



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