
COIN-1: A One-Parameter Foundation Model for Binary Uncertainty

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Abstract

We introduce COIN-1, a compact inference system with one implicit parameter and two possible outputs. The system achieves exactly 50% expected accuracy on balanced binary labels without pretraining, fine-tuning, or a graphics processor. Its entire forward pass consists of one toss. We give the complete probability model, an analytic evaluation, and an ablation in which the coin is removed. COIN-1 demonstrates that a model can be perfectly calibrated while knowing absolutely nothing.

1 Introduction

Binary prediction is often framed as a contest of architectures. We ask a smaller question: how little architecture is required to produce an answer? COIN-1 answers with a physical object that already fits in a pocket, and occasionally in the bottom of a sofa.

Our contributions are (i) a complete specification of the predictor, (ii) a closed-form accuracy result, and (iii) an unusually honest confidence score.

2 Model

Let the label space be {heads, tails}. The model samples one fair coin and returns the upper face after the coin comes to rest. There are no learned weights. The decision rule contains no input-dependent computation; in particular, showing the model a longer prompt does not help.

$$\Pr(Y = \text{heads}) = \Pr(Y = \text{tails}) = \frac{1}{2}. \quad (1)$$

For a balanced target independent of the toss, expected top-1 accuracy is 1/2. If the target is biased, accuracy remains 1/2 because the predictor is uniformly random. This is a feature of the model, not a benchmark artifact.

3 Analytic Evaluation

We evaluate the distribution itself rather than reporting a lucky sequence of tosses. Every number below follows directly from the model specification. The output entropy is one bit, and the per-class probability is 50%.

Quantity	COIN-1
Learned parameters	0
Possible outputs	2
Expected balanced accuracy	50%
Training compute	0

4 Additional Analysis

COIN-1 is calibrated by construction: among all outputs assigned probability one half, approximately half will occur in the long run under the assumed fair process. Calibration says nothing about whether the model has understood the question. This distinction is easy to miss when a confidence value is presented with enough decimal places.

The model’s confidence cannot be improved by asking it to think longer. A second toss creates a second sample, not a refinement of the first. If the two tosses disagree, a tie-breaking rule is required; if they agree, the original prediction has merely been repeated. Neither operation extracts information about an independent target.

5 Reproducibility Protocol

Use a fair coin, define heads and tails before the toss, and commit to the target label before observing the result. Repeat the experiment with replacement and report the full sequence, including inconvenient runs. The analytic 50% figure does not require a sample, but a finite demonstration will fluctuate around it.

A useful negative control is to cover the coin during the toss. If a presenter can still report the correct face with certainty, the experiment is testing the presenter rather than COIN-1. Another control is to vary the prompt while keeping the physical procedure fixed; the output distribution should not change.

6 Ablation and Limitations

Removing the coin reduces the number of outputs from two to zero. Replacing it with a second coin doubles the hardware footprint but does not improve binary accuracy unless a new decision rule is supplied.

COIN-1 cannot read a question, learn from feedback, or tell whether a prediction matters. It is therefore best used when the cost of being wrong is negligible and the cost of pretending to know is not.

7 Conclusion

The strongest claim we can make is also the weakest: COIN-1 returns one of two answers, each with probability $1/2$. All results are reproducible with a coin.