

Post-hoc Bayesian uncertainty for a deployed tumour classifier: calibration and out-of-distribution detection under platform shift

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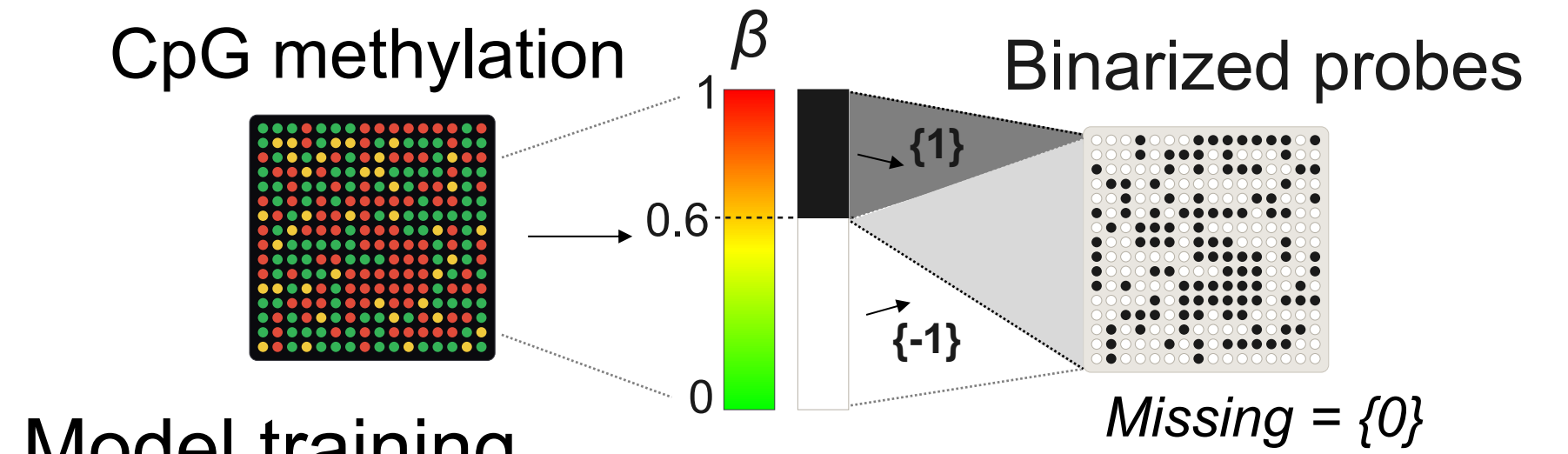
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Introduction

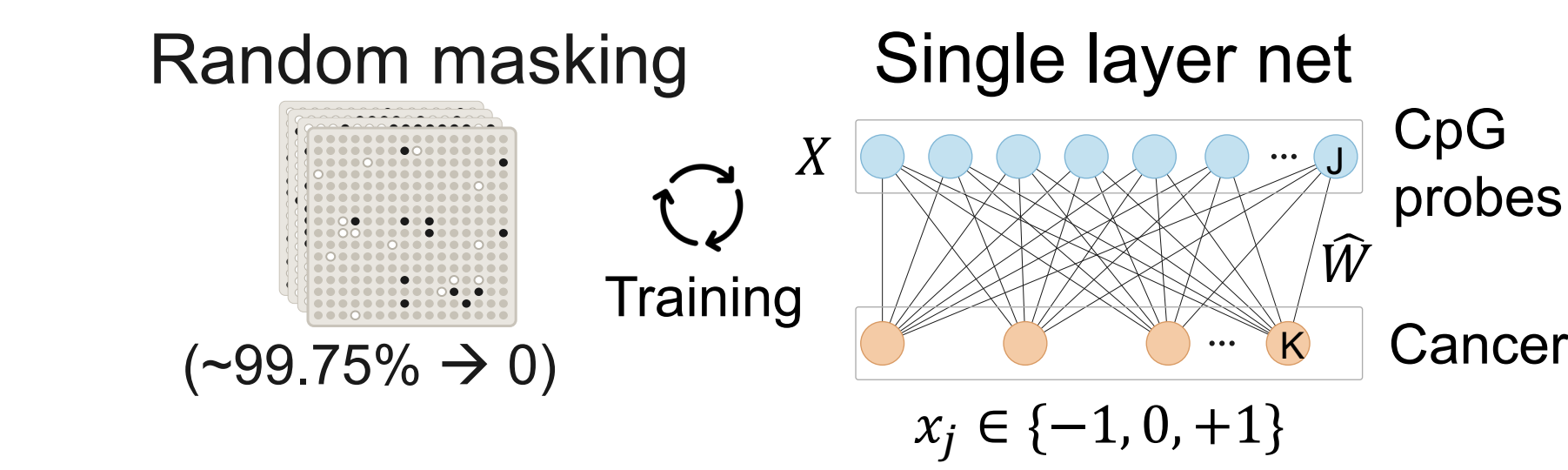
- DNA methylation signatures can classify cancers.
- Most classifiers are platform (data type) specific.
- Newly developed classifier works across all existing data types.

THE CLASSIFIER (crossNN)¹

Data Processing



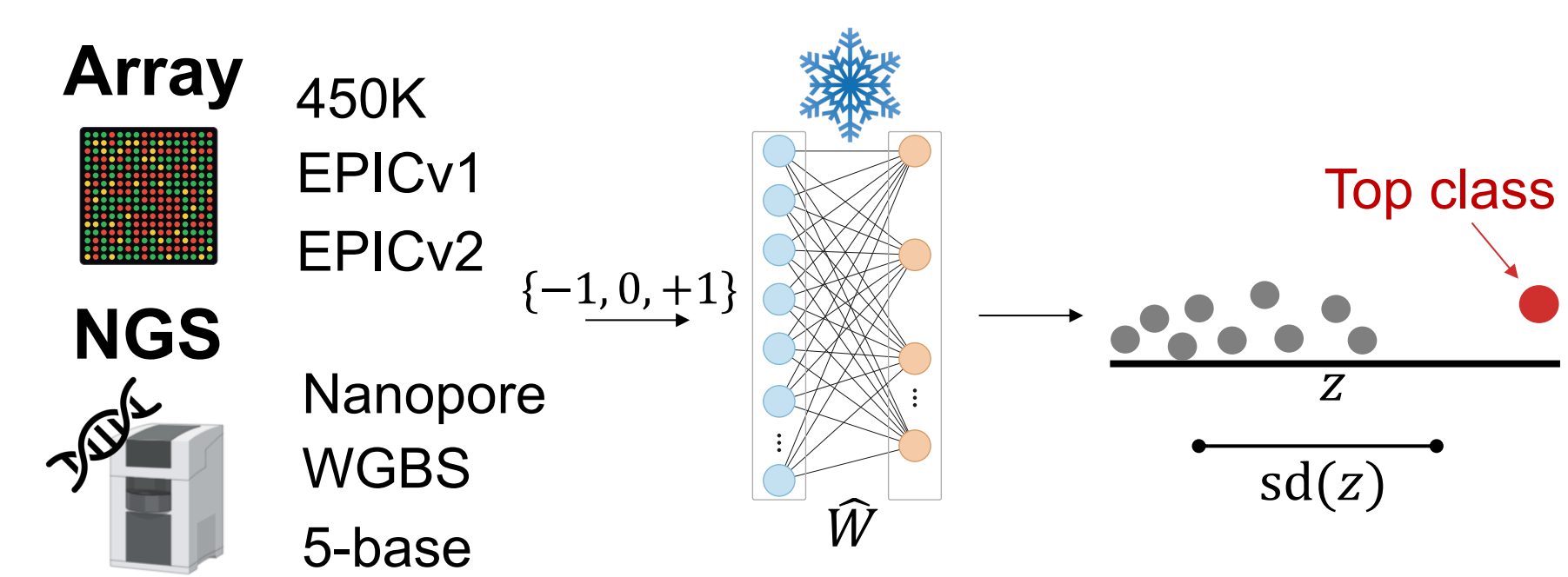
Model training



$$z_k = \sum_j \hat{W}_{\{k,j\}} x_j$$

$$\text{Confidence score: } \text{softmax}_k \left(\frac{z}{\text{sd}(z)} \right)$$

Deployment (any platform)



- Uses platform-specific **confidence score** cutoffs.
- Current values: sequencing (**0.2**) vs array (**0.4**)
- Excellent classification performance: AUROC>0.95

Rare sinonasal tumours can be classified too

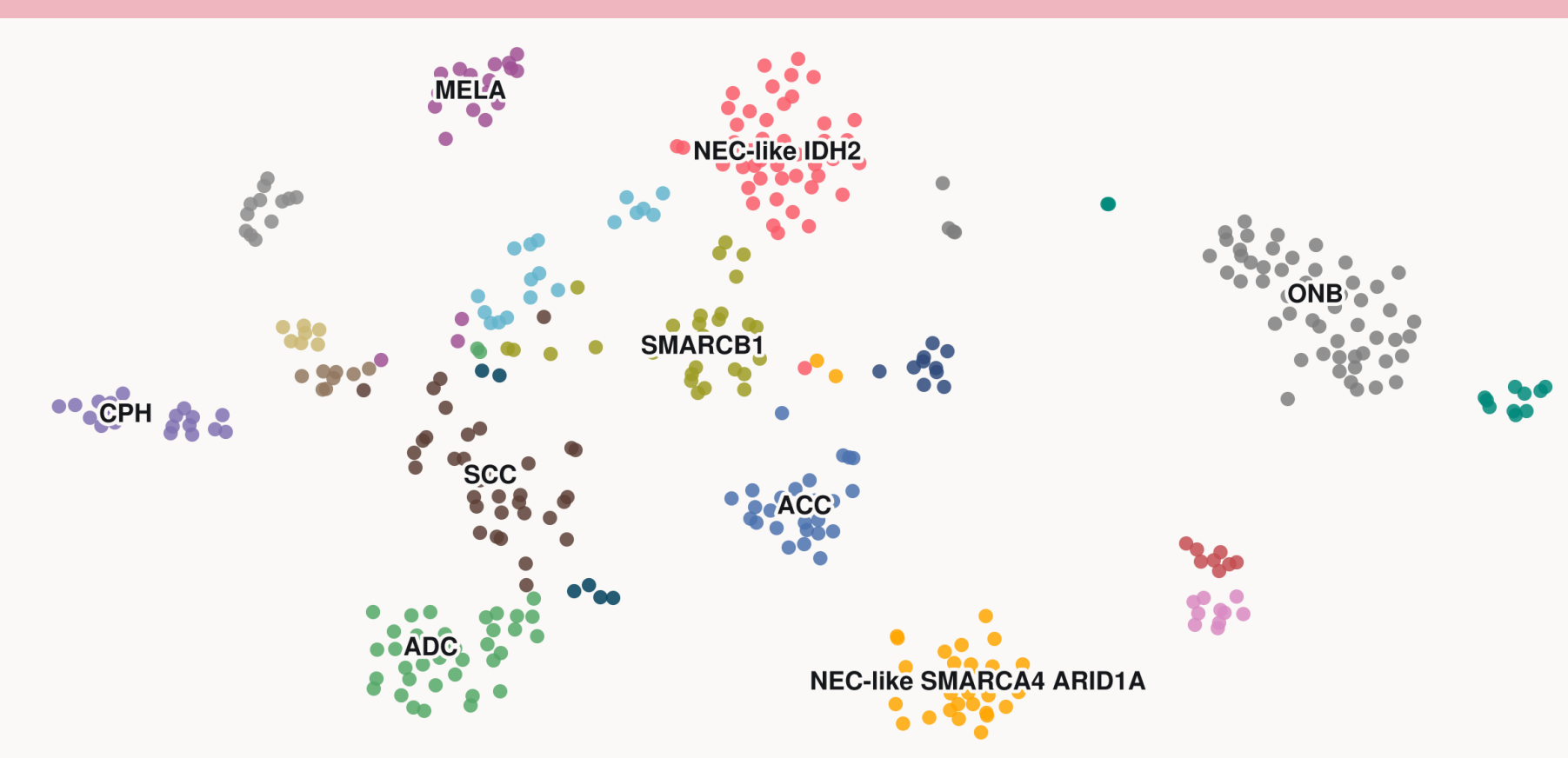


Figure 1. tSNE of methylation patterns for sinonasal tumours. Data from Jurmeister et al.² 395 reference tumours in 18 classes.

- 7 of the 18 classes hold fewer than 15 samples

Methods & Data

- Model.** crossNN¹: single linear layer on ternary features. – No model was refit to calibrate, and no diagnosis changed.
- Data.** 2,801 CNS³ and 7,001 TCGA primary tumours using released weights; 447 head & neck; 415 nanopore runs, 59 of them in known CNS classes.
- Calibration.** Measured as *top-label* ECE with 15 equal-width bins and cross-checked against the class-wise KL calibration error of a leave-one-out KDE.
- Fit.** **a** solves $E[\sigma(e(a))] = \text{accuracy}$ was set from CNS.

Result

a = 0.34 was set once on CNS and frozen; the Laplace posterior gives 0.44 with no labels

model	K	n	ECE shipped	ECE at a
CNS (their weights)	91	2,801	0.305	0.007
head & neck (ours)	18	447	0.351	0.016
pan-cancer (their weights)	178	7,001	0.403	0.032

ECE is top-label, 15 equal-width bins, and a biased low estimate. Class-wise KL error by Dirichlet-KDE, the consistent estimator, agrees: 0.046 to 0.006 on head & neck and 0.009 to 0.002 on CNS. Accuracy unchanged.

Accurate but underconfident

- Accurate: **96.2%** CNS, **98.4%** head & neck.
- Confidence score not a probability.

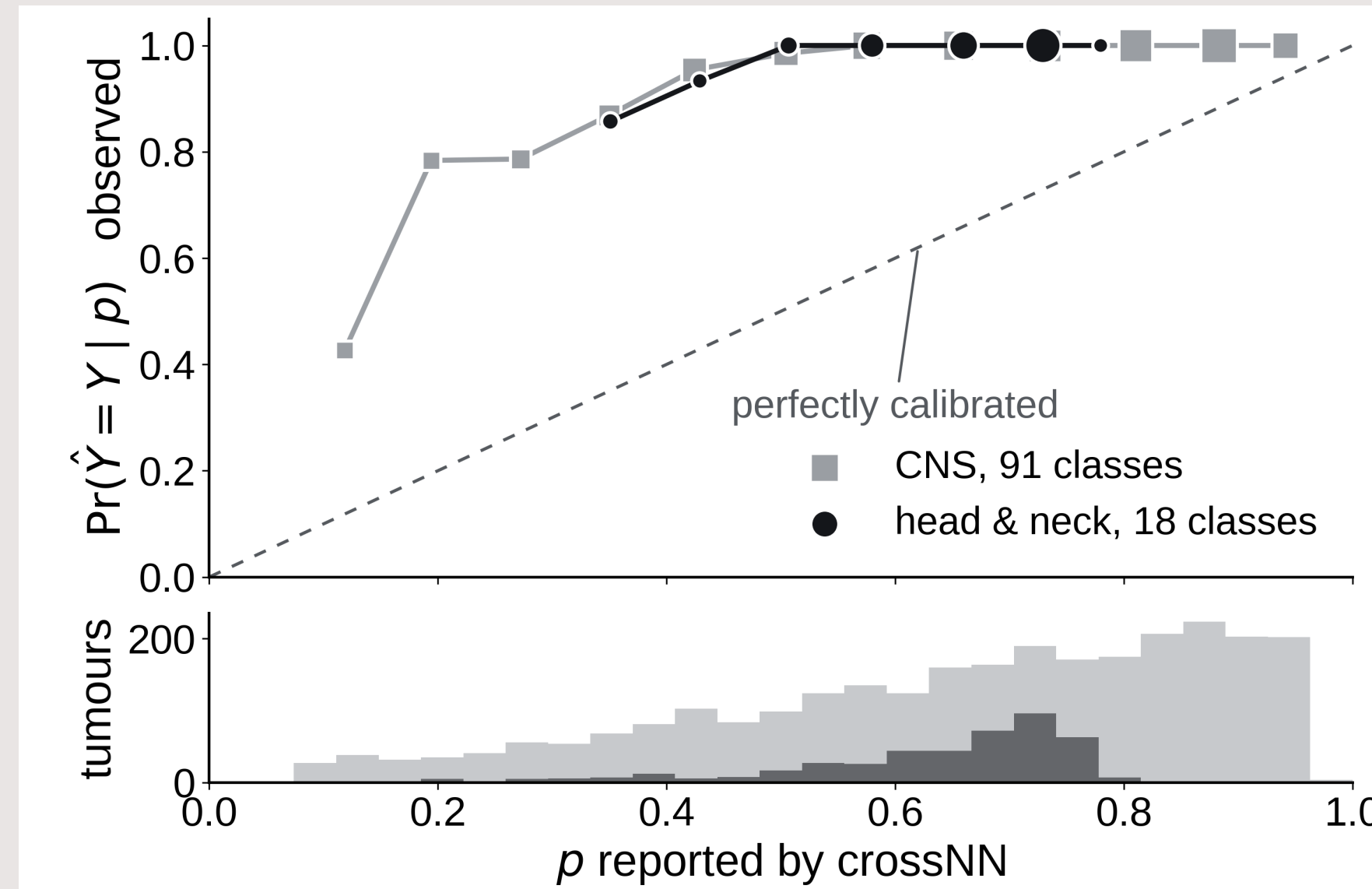


Figure 2. The score sits far below the accuracy it should report. Reliability (top) and where the scores fall (bottom). The head & neck score never exceeds 0.796, so no call reaches 90% confidence.

The missing coefficient

- Published rule: **softmax(z / sd(z))**.
- Expanded: **softmax(z / (1 · sd(z)))**, so the coefficient is 1.
- Laplace posterior on the weights do not support a=1.

$$z = Wx \quad s = \text{sd}(z) \quad \sigma(t) = (1 + e^{-t})^{-1}$$

$$p^{(a)} = \text{softmax}(z/(as))$$

$$(1) \quad \text{softmax}\left(\frac{z}{s}\right) = \text{softmax}\left(\frac{z}{1 \cdot s}\right)$$

$$(2) \quad u_k = \frac{z_{\max} - z_k}{s} \quad u_2 = \min_{k \neq \text{top}} u_k \quad \text{sd}(u) = 1 \text{ for every sample}$$

$$(3) \quad \max_k p_k^{(a)} = \frac{1}{\sum_k e^{-(z_{\max} - z_k)/(as)}}$$

$$(4) \quad = \frac{1}{\sum_k e^{-u_k/a}}$$

$$(5) \quad = \frac{1}{1 + e^{-u_2/a} N(a)} = \sigma(e(a))$$

$$(6) \quad N(a) = \sum_{k \neq \text{top}} e^{-(u_k - u_2)/a} \quad e(a) = \frac{u_2}{a} - \ln N(a)$$

$$(7) \quad E_n[\sigma(e(a))] = A \quad A = \text{accuracy}$$

$$a = 0.34 \quad 1/a = 2.9 \text{ nats}$$

Confirmed by a proper score

- Mean reported confidence = observed accuracy gives **a = 0.3404**.
- The log-likelihood puts its minimum at **0.3405**, on the same data.

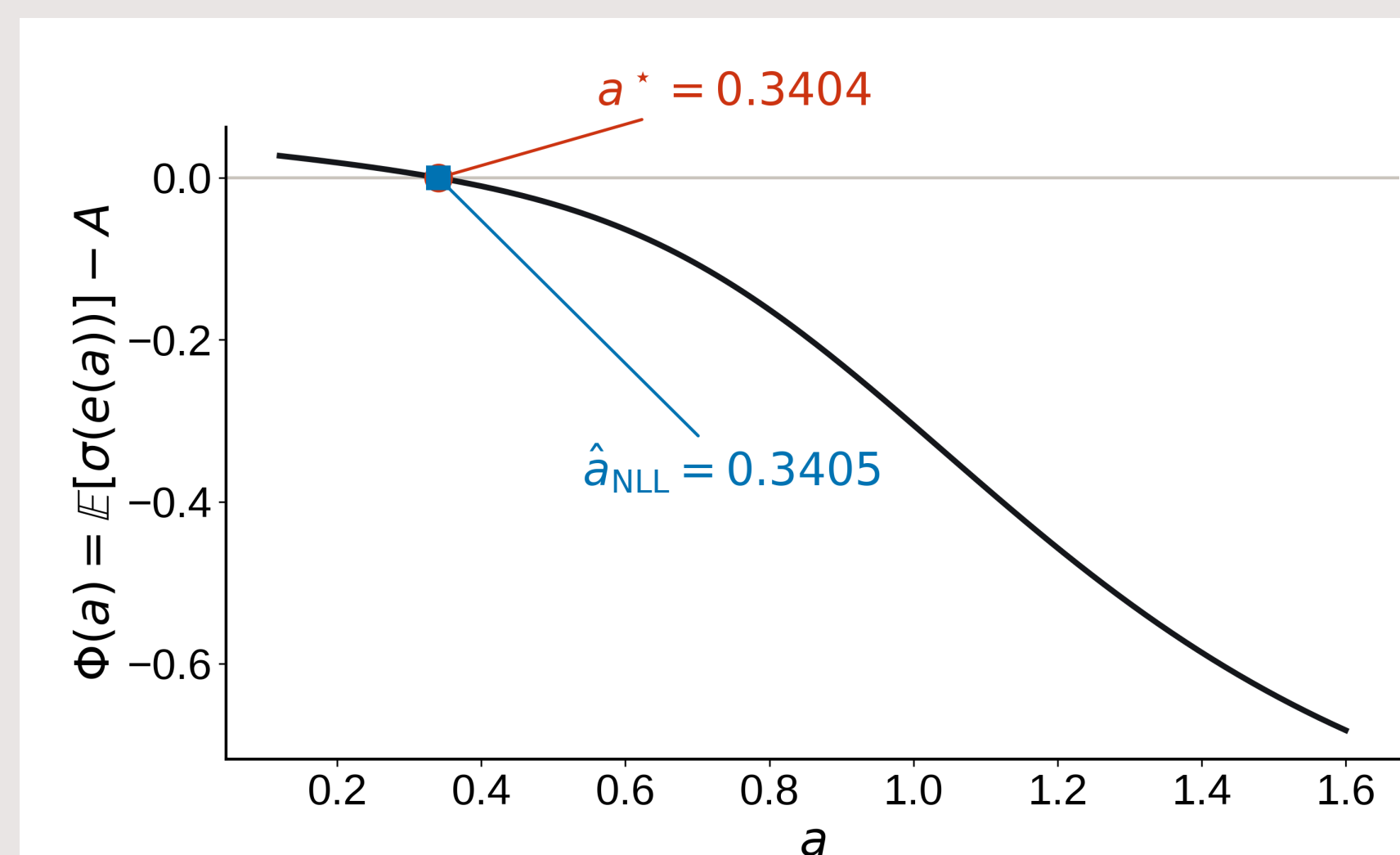


Figure 3. Two estimators agree to four decimals. $\Phi(a)$ = mean reported confidence – observed accuracy, 2,801 CNS tumours. Circle: its root. Square: the log-likelihood minimiser, on the same data.

What the cutoffs mean

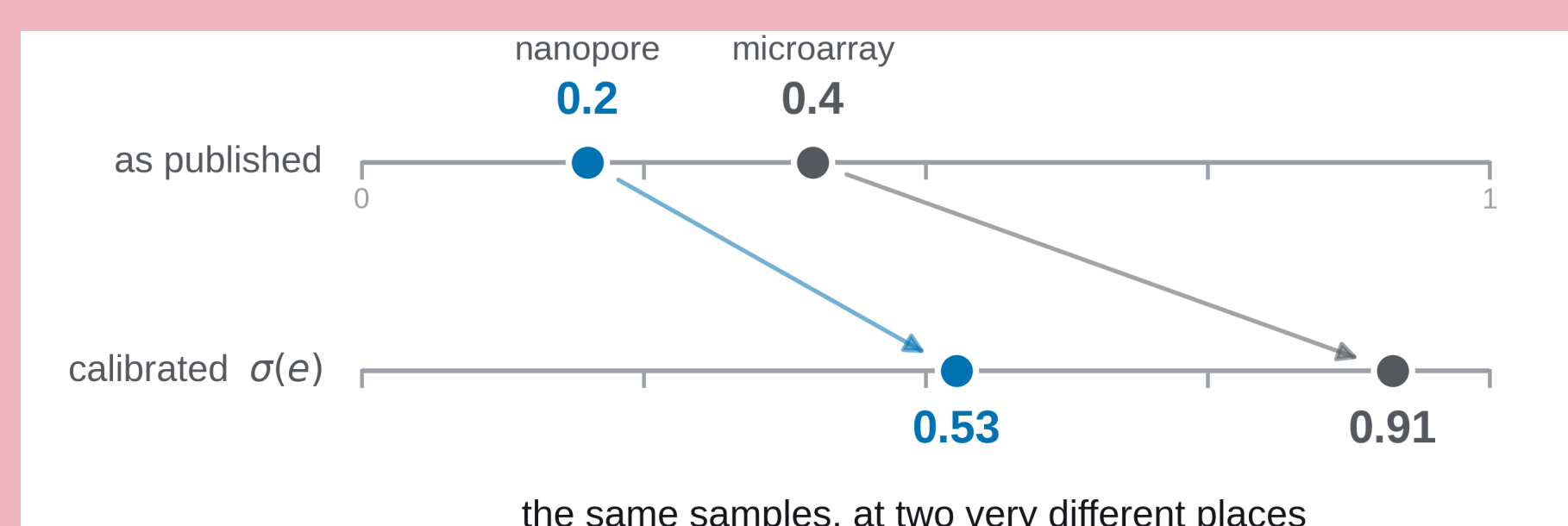


Figure 7. The two cutoffs land far apart. 0.4 and 0.2 report the same samples as 0.91 (n = 447) and 0.53 (n = 59, with only 2 samples near it).

Bayesian motivation

- Laplace posterior on the *weights*; MacKay evidence⁴ prior.
- Its probit predictive divides the logits by $\sqrt{(1 + \pi v/8)}$, which is near-constant across samples, i.e. a **temperature**.
- Set equal to a·sd(z) on CNS: **a = 0.44**, no calibration labels. Matching accuracy gives **0.34**.

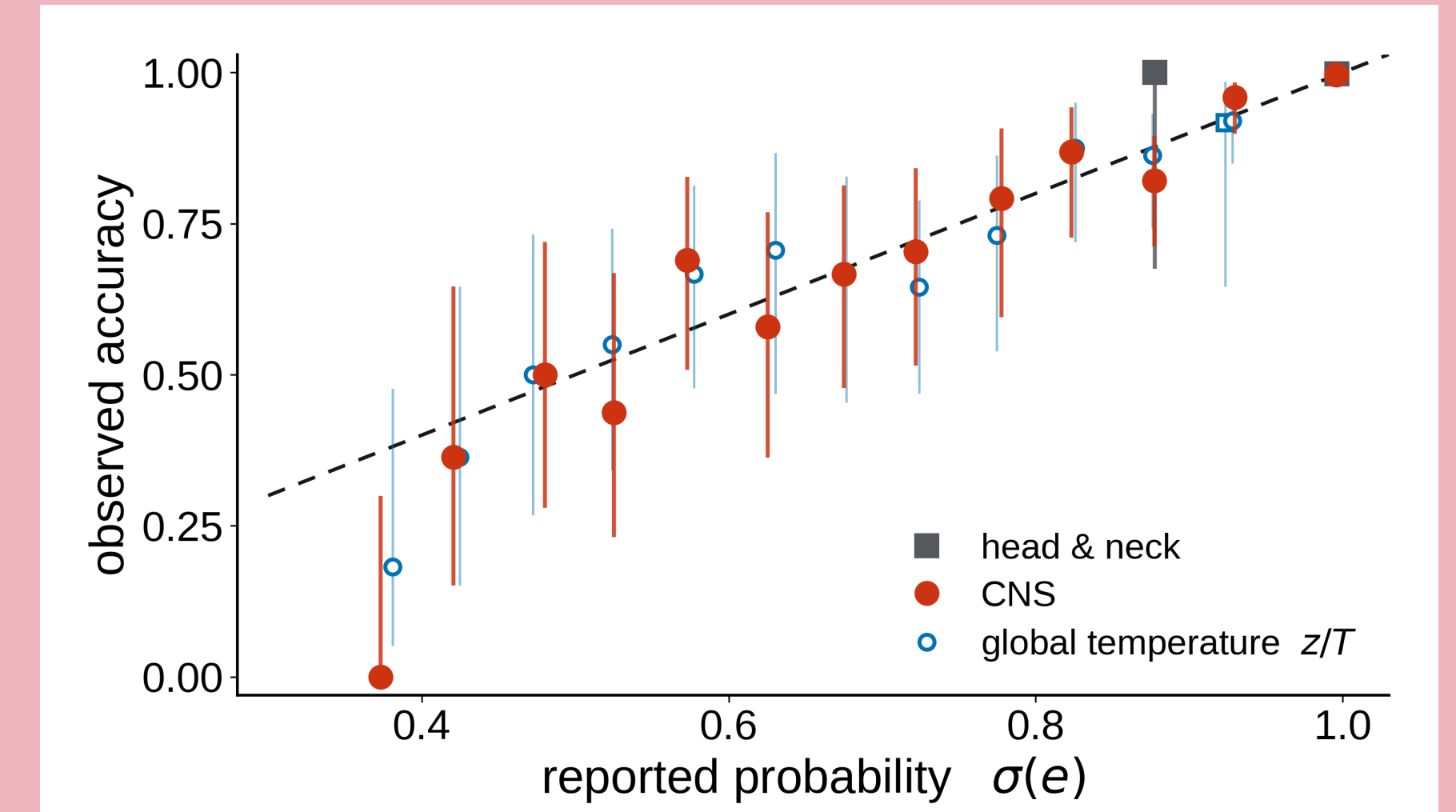


Figure 4. At full coverage both rules are calibrated. Equal-width bins, Wilson 95% intervals. ECE for $z/(a \cdot s)$ is 0.016 and 0.007, against 0.016 and 0.006 for the global temperature z/T .

Limits of the posterior

- The posterior gives the right **form**, the wrong **scale**.
- Logit is a coherent sum ($\propto |S|$); its posterior spread is incoherent ($\propto |S|^{1/2}$).
- No prior identified closes a **0.48** exponent gap.
- Curvature unusable: **71%** of samples past float64's limit.

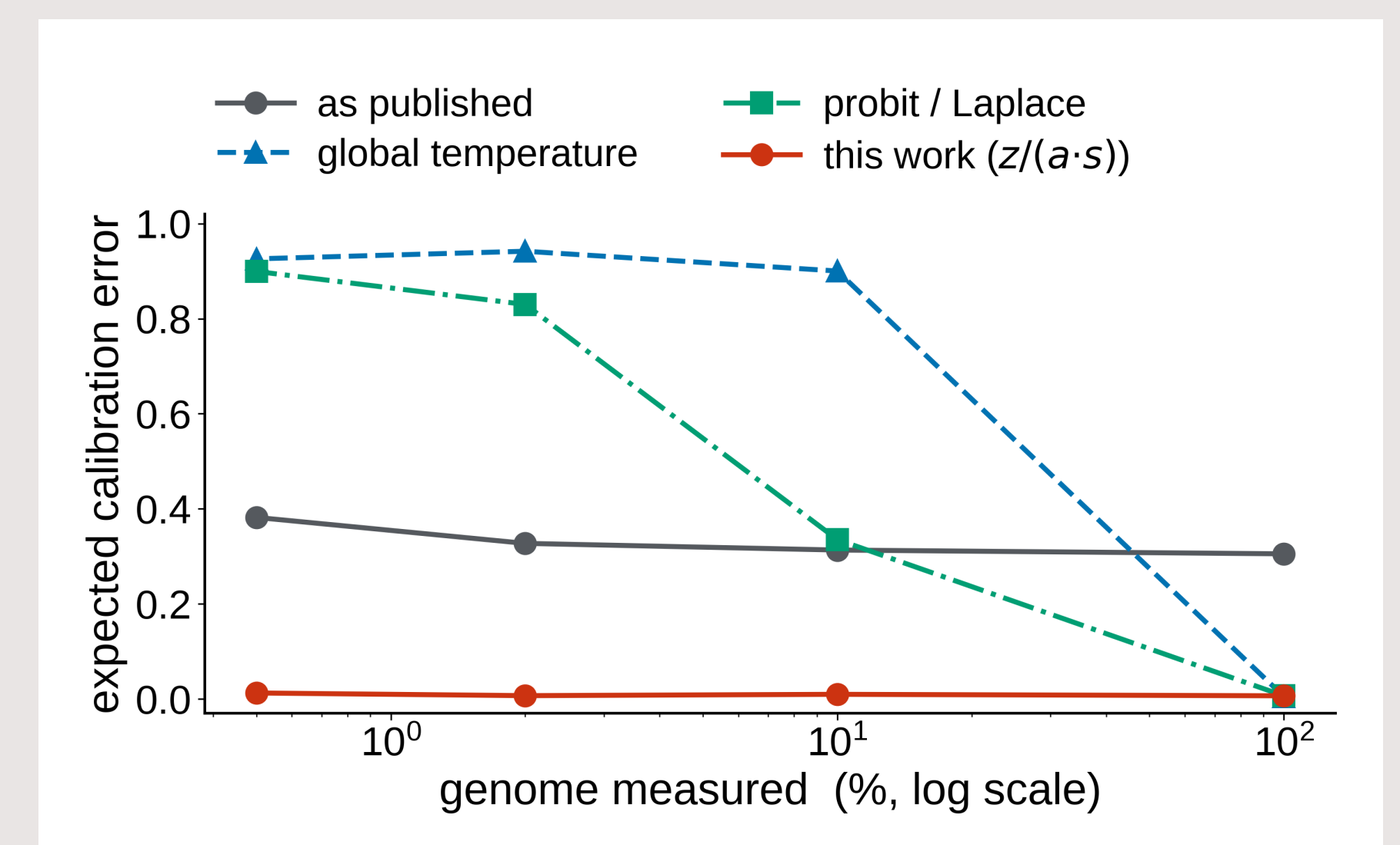


Figure 5. Only a·s survives the loss of coverage. All three alternatives are set at full coverage, then coverage is reduced.

Arrays to nanopore

- Both scalars were fitted on arrays and read unchanged on nanopore at **~1.7%** coverage.
- A temperature is calibrated only at the coverage it was fitted at; **a·s** holds.

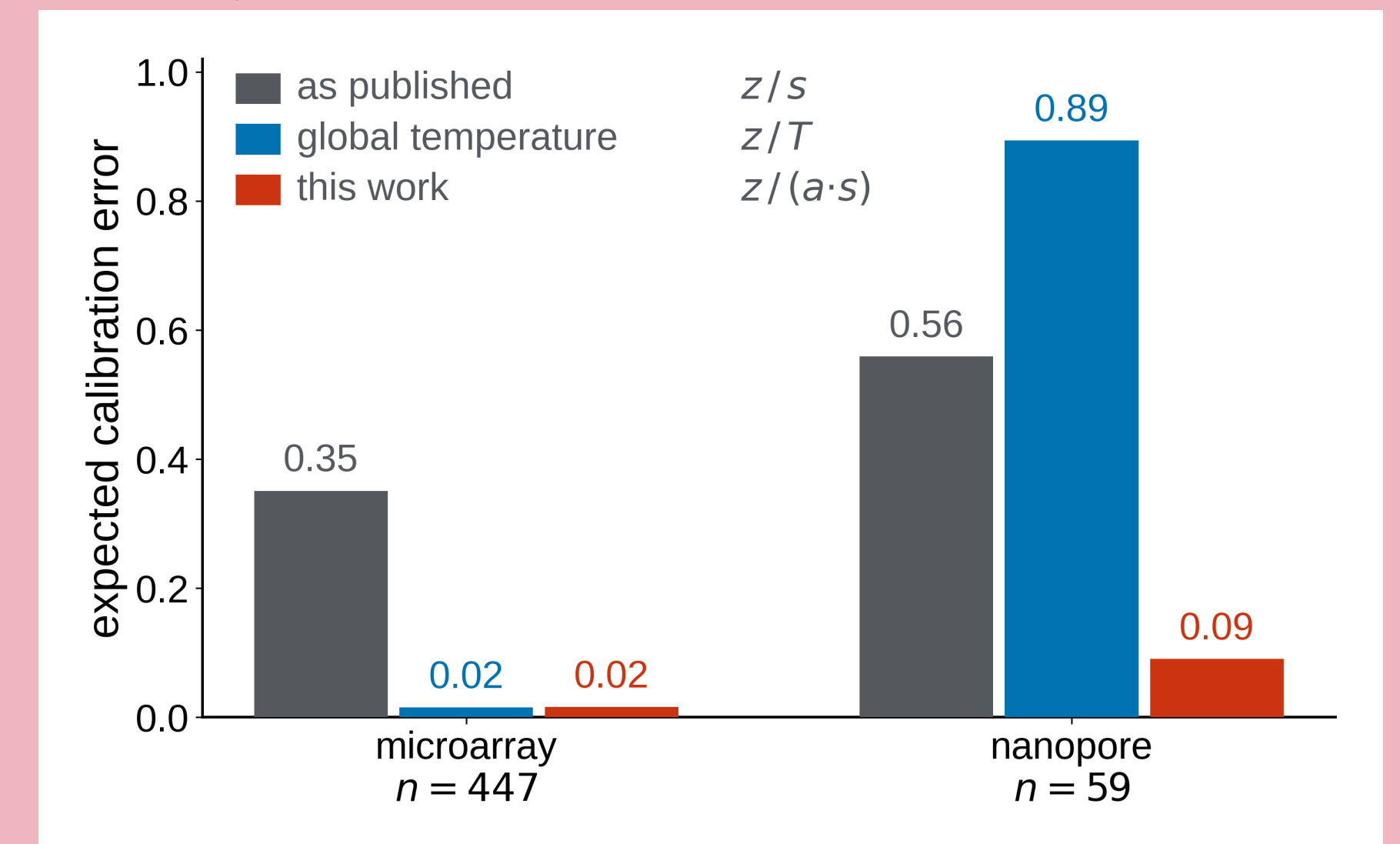


Figure 6. A temperature fitted on arrays fails on nanopore. All three rules are softmax(z / divisor); only the divisor differs. Accuracy 0.949 on nanopore, unchanged by any of them.

References. 1. Yuan D et al. Nat Cancer 6:1283–1294 (2025). 2. Jurmeister P et al. Nat Commun 13:7148 (2022). 3. Capper D et al. Nature 555:469–474 (2018). 4. MacKay DJC. Neural Comput 4:720–736 (1992). 5. Guo C et al. ICML PMLR 70:1321–1330 (2017).