

Introduction

- DNA methylation signatures can differentiate difficult-to-diagnose cancers.
- Algorithms have been developed to predict cancer classes.
- Selective prediction (abstains when unsure) is widely used.

THE CLASSIFIER (crossNN) Yuan et al. 2025

$P(y | x) = \text{softmax}(Wx)$

W: 149x226,085 CpGs
Single-layer neural network, 99.75% masking of binarized probes

- Assumes confidence corresponds to correctness of prediction.
- But, classifiers usually trained on ancestrally-skewed datasets
 - (TCGA ~80% European ancestry; Fig. 1) Carrot-Zhang et al, 2020.
- Is the **reliability** of confident calls **ancestry-dependent**?

Objective

- Audit methylation classifier for ancestry-dependent reliability of confident classification calls
- Test whether group-conditional conformal restores per-ancestry calibration.

Methods & Data

- TCGA HM450 methylation. N=7,484 cases (EUR, BAA, Asian).
- 5-fold out-of-fold logits. APS $\alpha = 0.10$ (Romano et al. 2020).

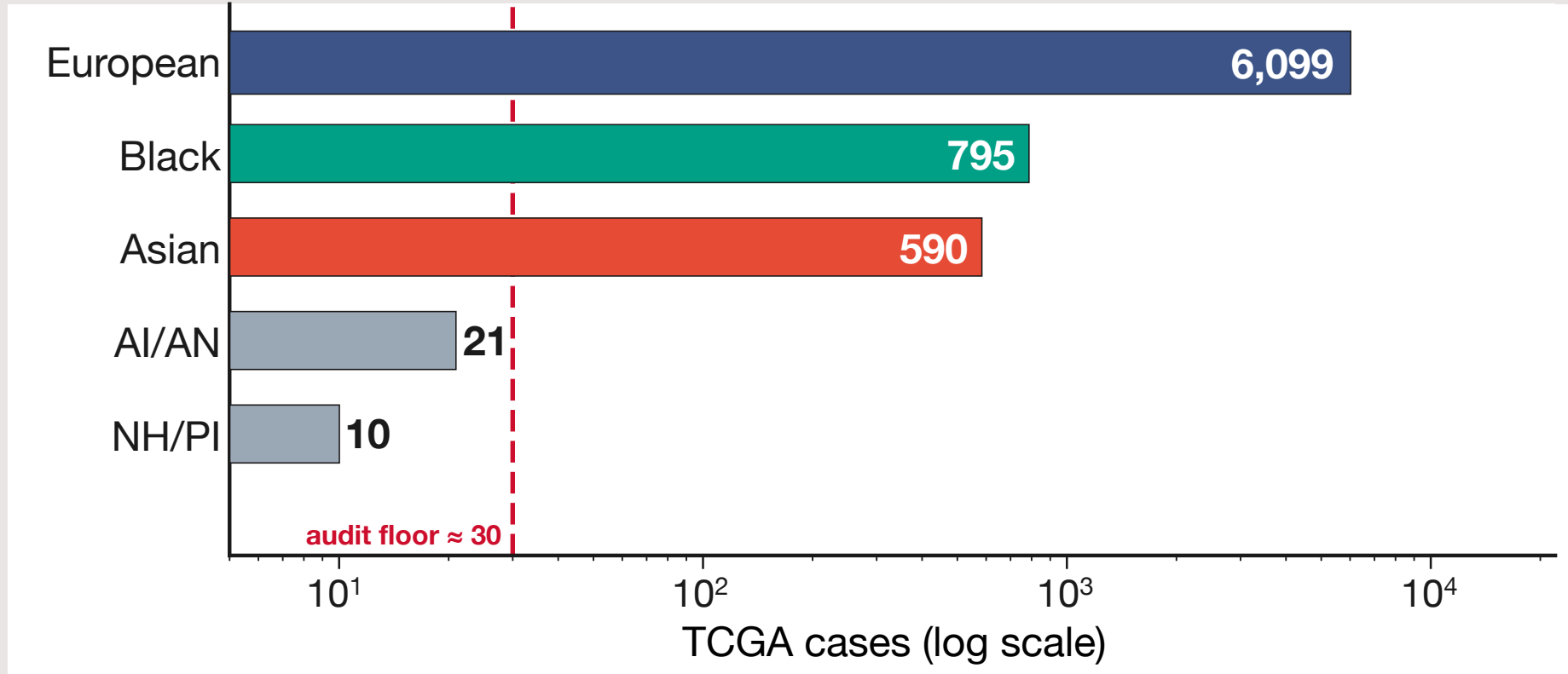


Figure 1. The methylation reference cohort (TCGA) is overwhelmingly European ancestry. Per self-reported ancestry group (log scale): European 6,099 (~80%), African 795, Asian 590. American Indian/Alaska Native AI/AN (21), and Native Hawaiian/Pacific Islander NH/PI (10) fall below the ~30-case audit floor needed to audit any single cancer (dashed line) and are excluded from subgroup testing.

Unequal reliability of confident calls

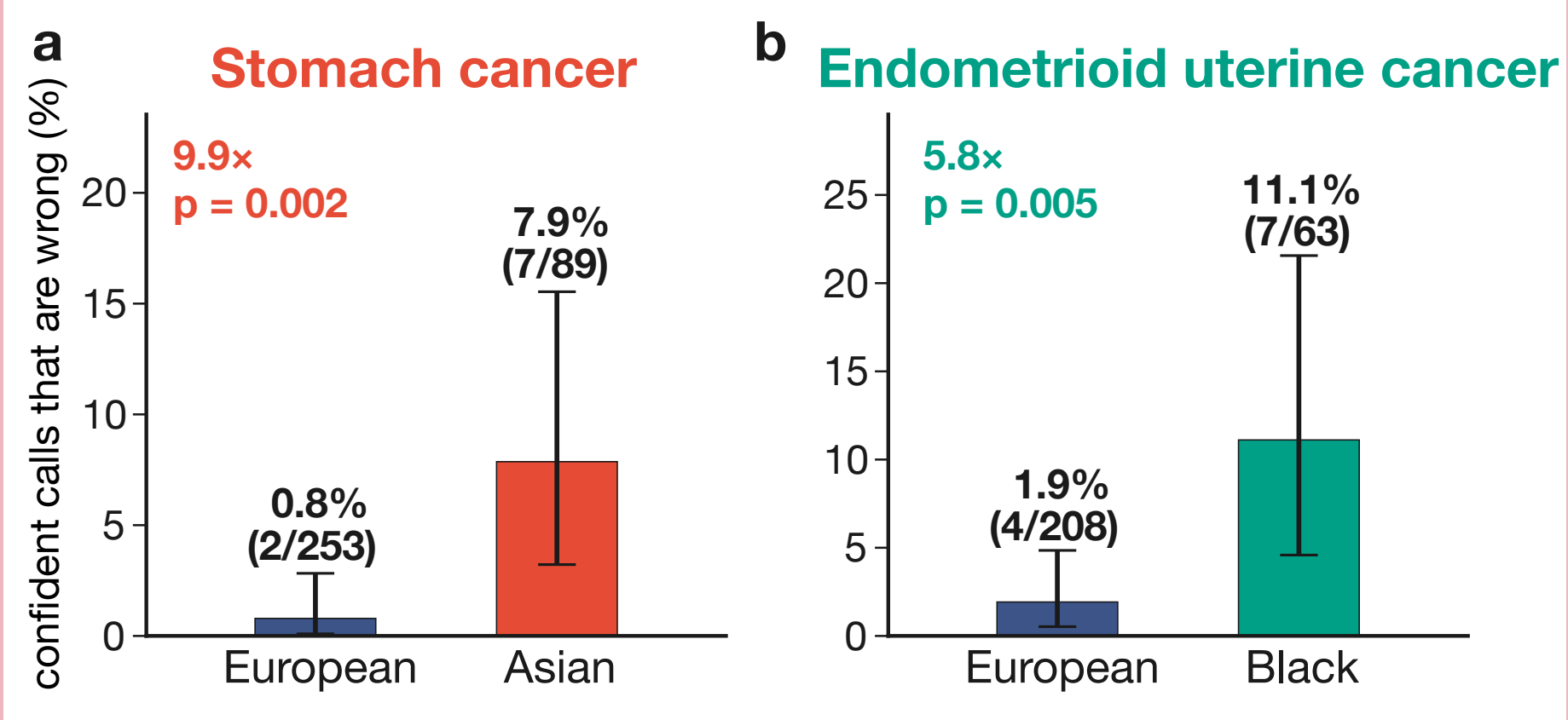


Figure 2. Within a single cancer type, confident calls fail far more often for under-represented ancestries. Observed error rate among high-confidence predictions (calibrated probability ≥ 0.8); bars are 95% CIs. (a) Stomach cancer: Asian ancestry 7.9% vs European ancestry 0.8% (9.9x). (b) Endometrioid uterine cancer: African ancestry 11.1% vs European 1.9% (5.8x). Across a 28 cell ancestry-cancer type screen, gastric cancer gap survives Bonferroni correction; the endometrioid gap survives FDR at $\alpha=0.05$.

- These classification errors are wrong but confident.
- Disproportionately impacts cancers with known existing disparities: endometrial cancer has among largest racial mortality gaps in oncology.
- Disparities persist in single cancer types; case-mix (which cancers each group gets) cannot explain observed differences (Fig. 2).

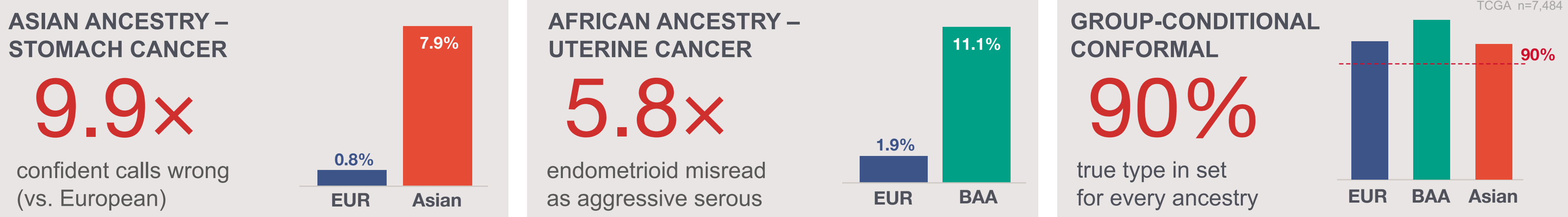
Limits of threshold-based abstention

- Abstention can only act on model confidence. If the model is confidently incorrect, then results are reported as correct.
- High-confidence errors are not identified by confidence-thresholds alone (Fig. 2).
- Raising confidence thresholds increases abstention rates on less represented populations without resolving the errors.

PRECISELY WRONG:
CONFORMAL PREDICTION FOR
HONEST PRECISION ONCOLOGY

C. Stacy¹ and S. Das¹

1.School of Pharmacy and Biomolecular Sciences, RCSI University of Medicine and Health Sciences, Dublin, Ireland.



Molecular basis of misclassification

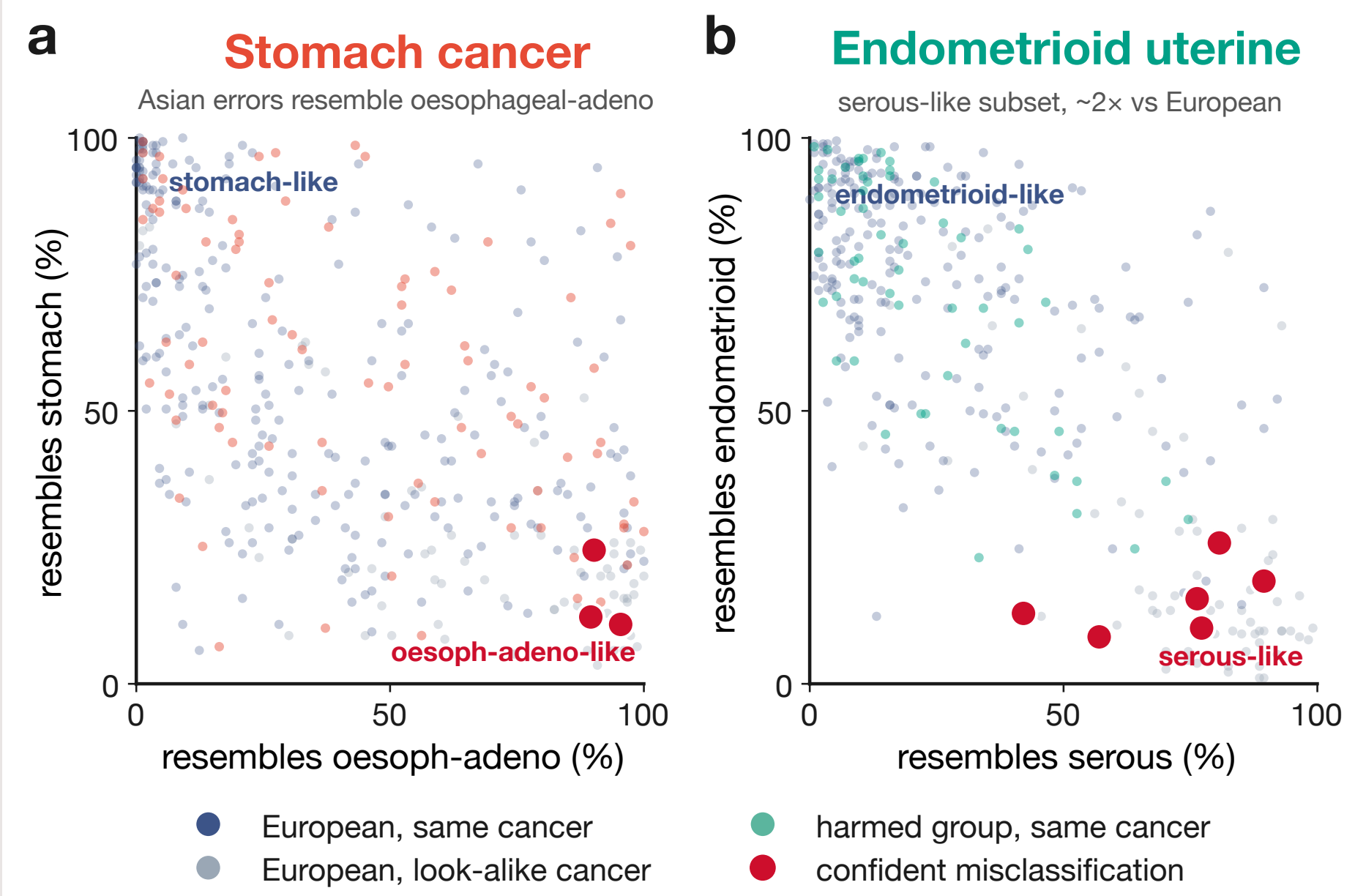


Figure 3. Misclassified tumours genuinely carry the methylation signature of the “look-alike” cancer. Each point represents one tumour, scored by how closely its methylation pattern matches markers of its own cancer type (y-axis) versus the “look-alike” type (x-axis). Confident misclassifications are enlarged with red points. (a) Stomach cancers in individuals with Asian ancestry misread as oesophageal adenocarcinoma. (b) Endometrioid uterine cancers in individuals with African ancestry misread as the aggressive serous subtype.

- Confidently misclassified tumours genuinely match the look-alike subtype (Fig. 3)
- High-confidence misclassifications are ~2x more likely in people of non-European ancestry. Matches known excess of aggressive endometrial disease in women of African ancestry
- crossNN model's own weight attribution elucidates biology
- *GRIA4* identified as top driver by model, recently validated as a methylation marker for endometrial cancer. (Chen et al., 2026)

Confounding in the fairness audit

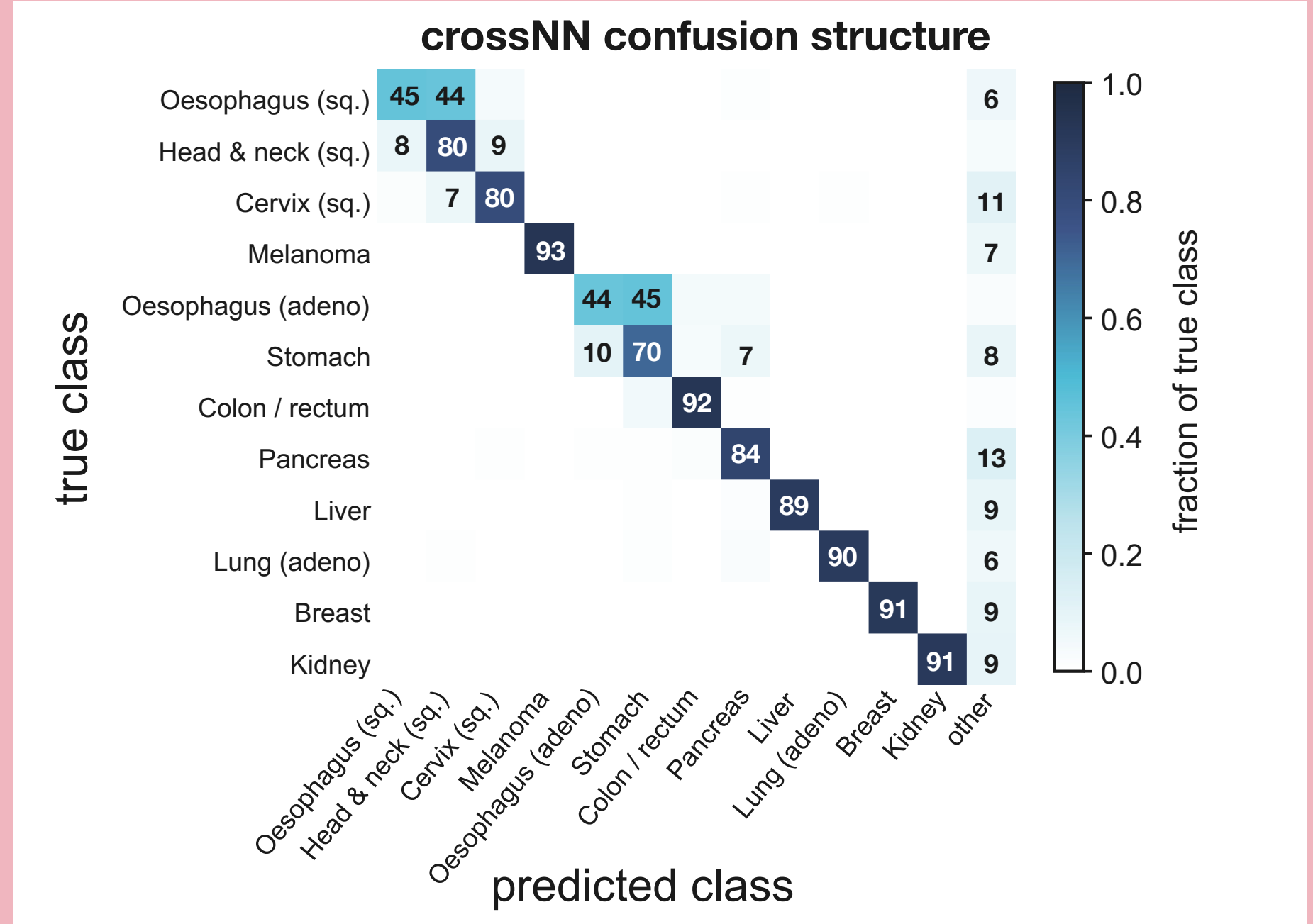


Figure 4. Misclassifications between cancer types are rarely equally bidirectional. Row-normalized crossNN confusion matrix (each row is true class, colour is the % predicted as each class). Squamous-cell (sq) and adenocarcinoma (adeno) oesophageal cancer are classified separately. Twelve classes shown; other class predictions included in right-most column.

- Common classification errors are directional: a rarer cancer is absorbed into a similar class. Squamous-oesophagus reads as head-and-neck 44% of the time and adeno-oesophagus as stomach 49%, while the reverse is <10%.
- Confusions are between cancer types, so accuracy-by-ancestry requires correcting for prevalence of classes between ancestral groups in the training dataset.

Group-conditional conformal prediction

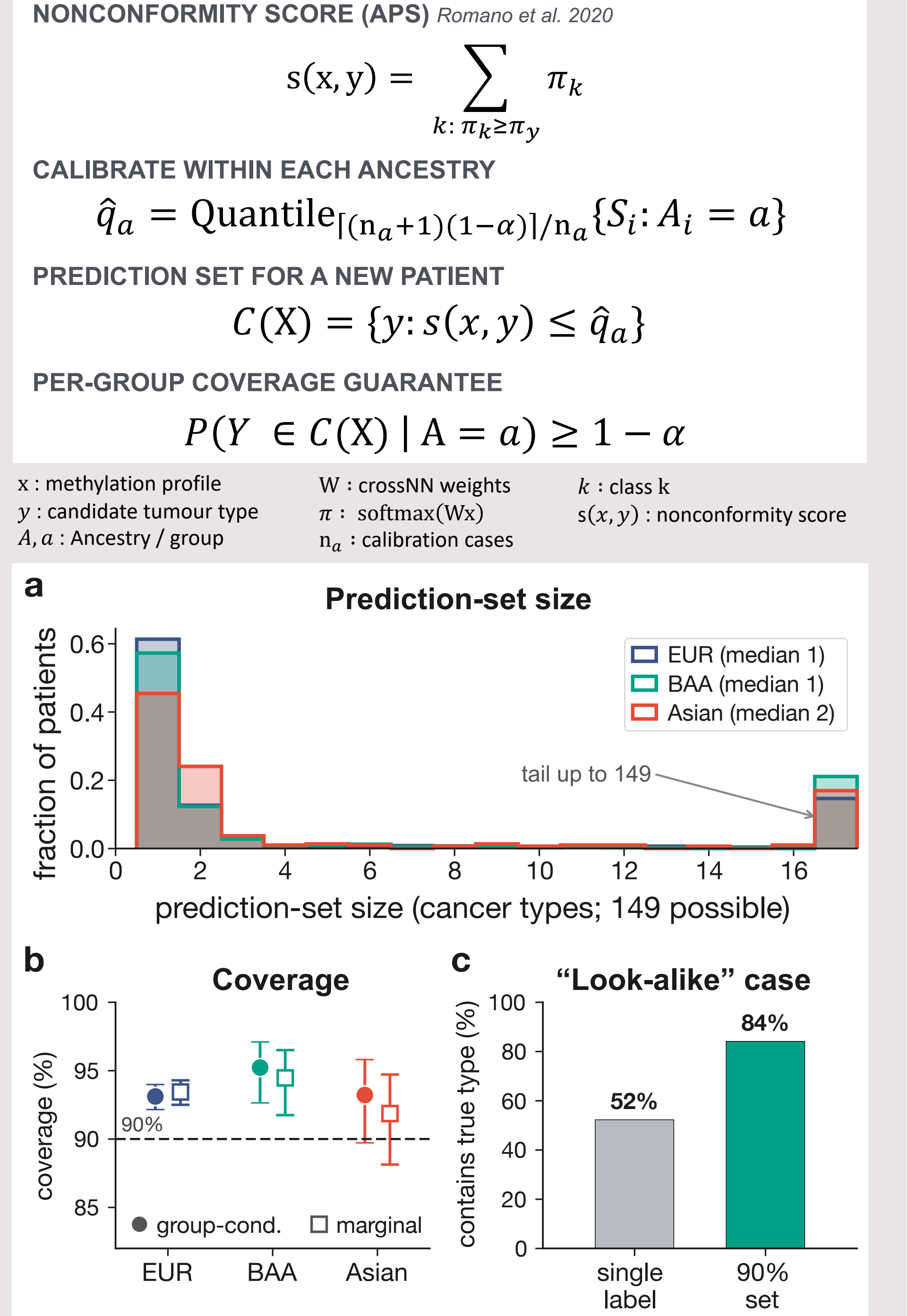


Figure 5. Group-conditional conformal returns calibrated sets that stay small for easy-to-classify cases and widen for hard cases. (a) Set size: most patients are assigned 1 or 2 classes of 149 classes across all ancestries examined with a long right tail. (b) Coverage is ~90% within every ancestry group (dashed target line). 95% CIs are wide where sample group sizes are small. Shapes show estimated group-conditional (circle) and marginal (square) true-class coverage (c) For the squamous-oesophageal look-alike case, the 90% set contains the true type 85% of the time, versus 52% for the single top-1 label.

- Conformal prediction outputs calibrated set that holds true type ~90% of cases (Fig. 5).
- Confident cases stay one class; ambiguous tumours provide appropriately cautious findings.
- Calibration within ancestry results in ~90% coverage per ancestry group, even with cohort shift (Lu et al. 2021)

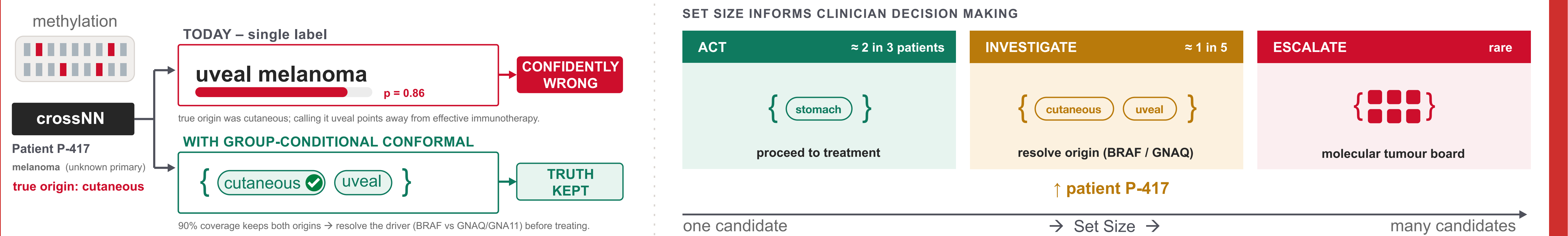
Conclusions

- Differences in molecular classifier performances are observed when comparing across ancestral groups.
- Group-conditional conformal makes the model's uncertainty more honest per ancestry, supporting replacing of abstention with widened sets.
- *Limitations:* coverage determined out-of-fold; ancestry is self-reported race.

References

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CLINICAL TRANSLATION



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