Reducing the degree of uncertainty within automatic speaker recognition systems using a Bayesian calibration model

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1. Introduction

Forensic validation

-Validity: a measure of discrimination, i.e., how good or bad the system is at separating two samples
- Repeatability: intra-examiner reliability
- Reproducibility: inter-examiner reliability

Most forensic validation implicitly focuses on
- Overall performance of methods under casework conditions
- Discriminability (see Smith & Neal 2021) with different methods chosen, or decisions made
- Based low values for the validity metric used

However, the expert's primary concern should be to reduce uncertainty (Morrison & Enzinger 2016, Ramos et al 2021).

Source of uncertainty

- Subjective decision: varies from features used for analysis to statistical models, reference population used
- Variation in the disputed sample
- Variation in the known sample
- Sampling variability

Problems:

- Each case is unique in terms of case materials/conditions,

Questions:

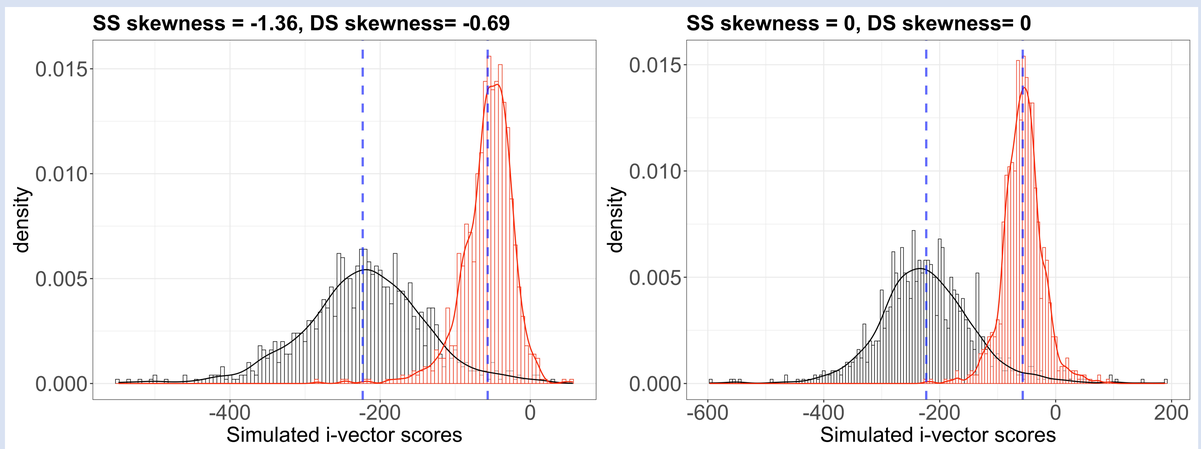
- Is reproducibility possible?
- What happens to the reliability caused by uncertainty on system performance?

2. Aim

- Use simulated score to demonstrate the variability in validation results as a function of sampling variability
- Demonstrate how Bayesian calibration (Brümmer & Swart 2014) may reduce such uncertainty.

3. Method

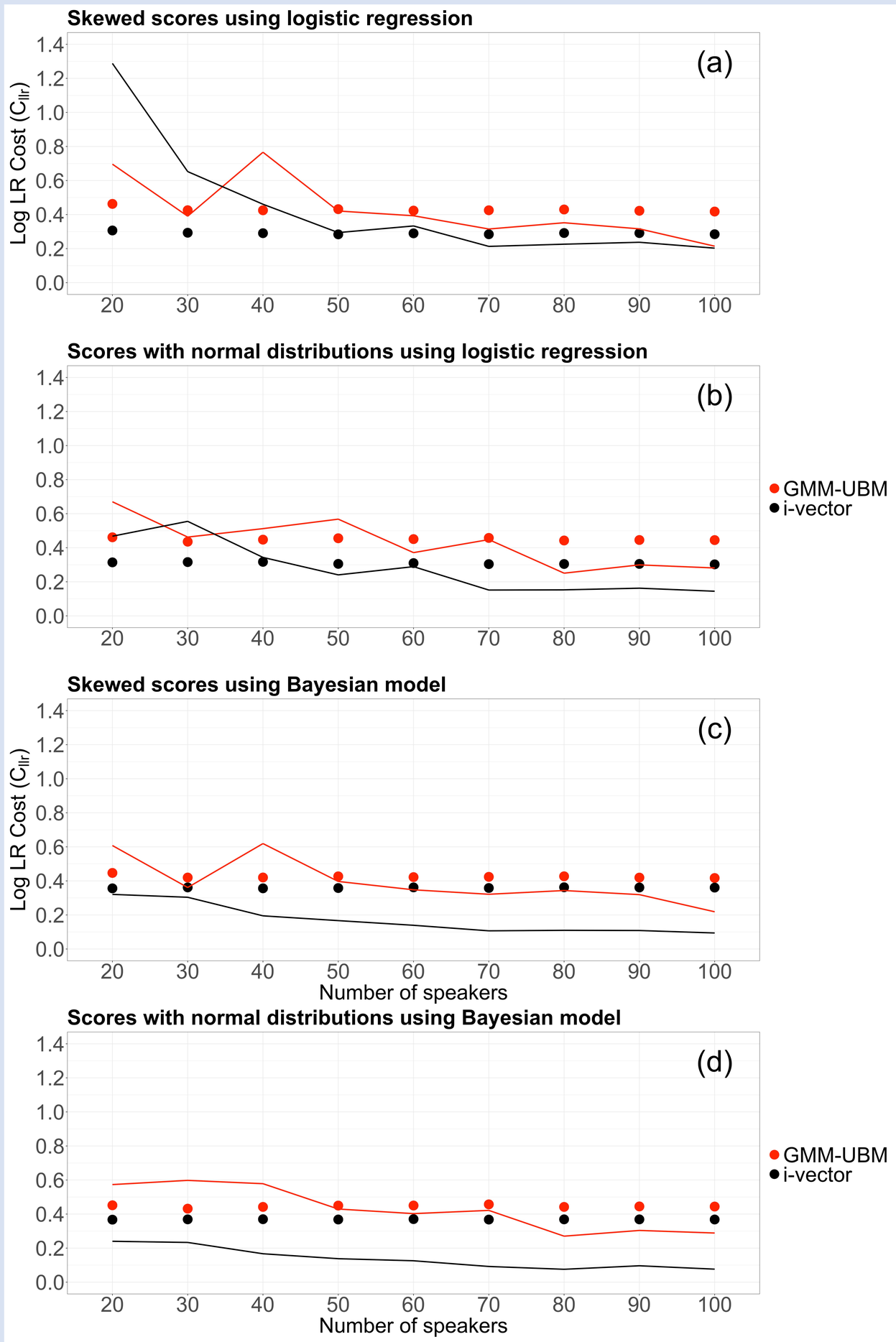
- Scores were simulated based on score distribution parameters obtained from (Enzinger & Morrison, 2016; Morrison & Pho, 2018).
- The skewness for both SS and DS scores were changed to 0 (i.e., normal distribution) while the kurtosis, mean and standard deviation were kept fixed.
- Calibration (i.e., logistic regression and Bayesian model) conducted 100 times for scores with normal and skewed distribution with different sample size respectively



Examples of simulated i-vector (top panel) and GMM-UBM (bottom panels) scores, sample size = 1000 in each of the SS and DS scores. Blue dashed lines indicate the mean.

4. Results

Validation in experiment



C_{llr} mean (dots) and range (lines) as a function of score skewness, sample size and calibration methods.

5. Take home message

- Recognise that forensic comparison is a process involving numerous decisions which introduce uncertainty via both systematic and random factors

- Be explicit about the decisions made at each stage of the process and the implications of such decisions for uncertainty in terms of the results LRs **and** overall method validity

- In the forensic context, it is not the case that the modern 'state-of-art' system which is capable of the best validity is necessarily the optimal choice.

- Rather, this choice is dependent on sample size, score skewness, and the choice of calibration method (likely amongst of considerations).

6. References

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