System performance as a function of calibration methods, sample size and sampling variability in likelihood ratio-based forensic voice comparison

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Introduction

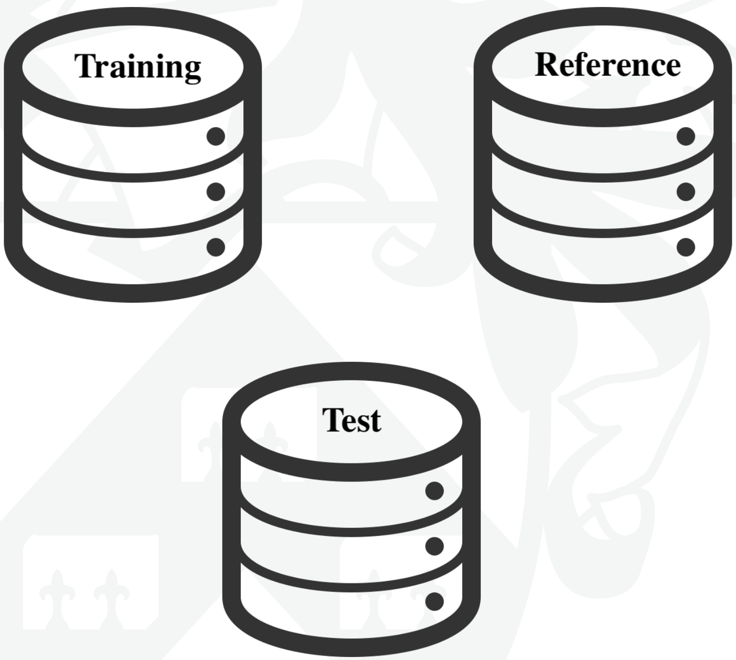
In Forensic Voice Comparison (FVC)

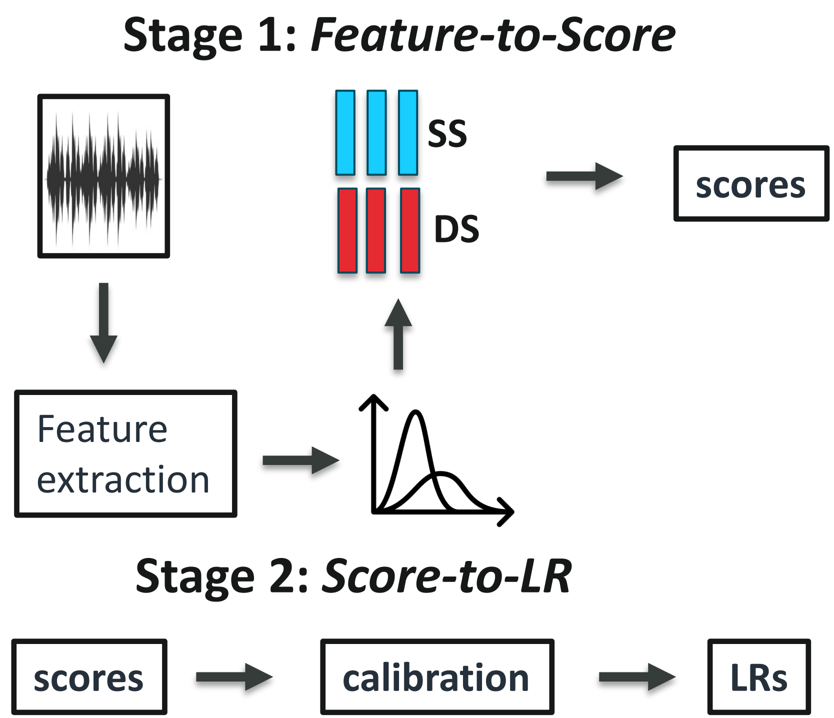
VS.

In recent years,

- Likelihood ratio (LR) framework
- Growing pressure on experts
- Established procedures

Introduction



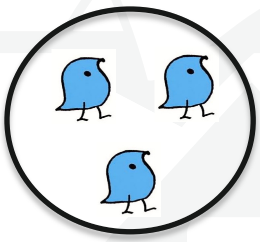


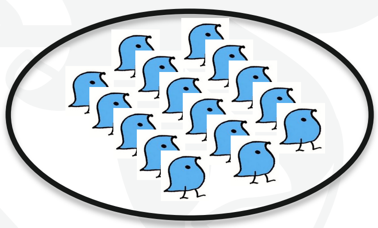
- Objectivity **vs.** Subjectivity

Introduction

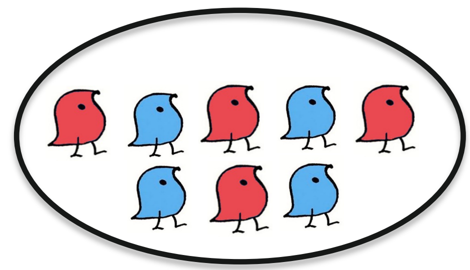
Previous LR-based FVC studies looked in the effect of

- size of training, test and reference data [1,2,3]





- configurations of training, test and reference data [4,5]



Showing that the effect of sampling variability is inevitable regardless of

- the size of training, test and reference data

&

- configurations of training, test and reference data

Questions

System performance **<==>** sampling variability

Can calibration reduce the level of uncertainty?

Previous studies [6, 7] have tested the effectiveness of different calibration methods. However,

- limited sets of data
- scores → Gaussian distribution

Questions

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Given the limit of sample size in the real world, how does system perform when

- scores are skewed

&

- sample size is limited ?

Can we incorporate uncertainty into the LR itself in LR computation?

Can certain calibration methods reduce the level of uncertainty when the sample size is small?

Current study

We simulated scores from skewed distributions to test four calibration methods:

- Logistic regression [8]
- Empirical lower and upper bound (ELUB) [9]
- Regularised logistic regression [7]
- Bayesian model [10]

Claimed to incorporate uncertainty into the LR itself, such that LRs will be closer to 1 when uncertainty is high (i.e. when sample size is small).

Aiming to investigate:

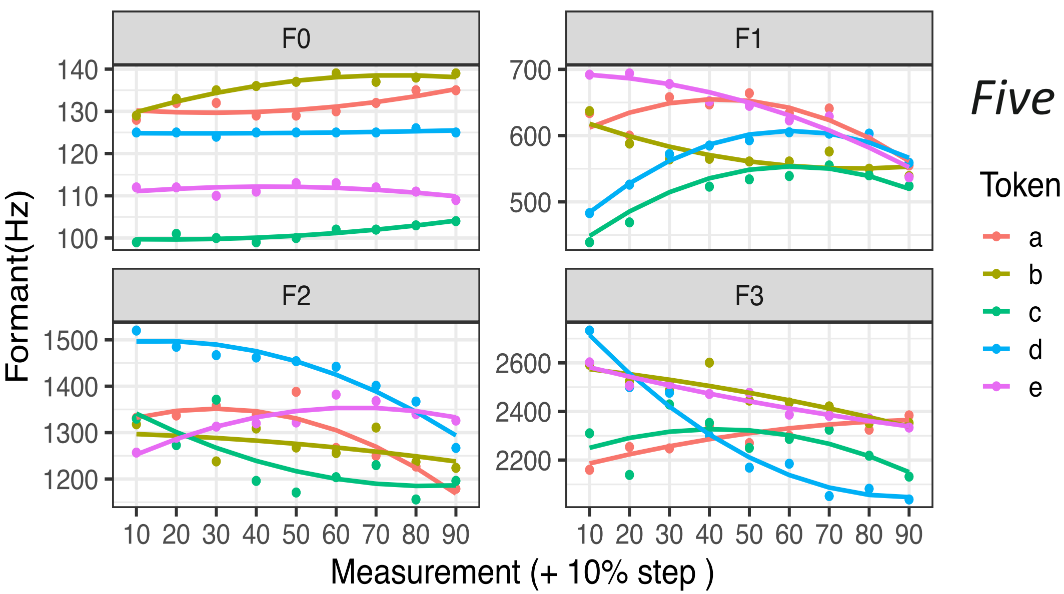
a. overall system validity
and
b. the reliability of the system validity

Methods

Data

Skewed scores simulated from the acoustics of filled pause ***um,***

- 90 SSBE speakers from DyViS [11]
- Quadratic curves → F1, F2, F3 and f0
- Multivariate kernel density (MVKD) [12]



Five tokens, speaker 114 DyViS.

Methods

Data

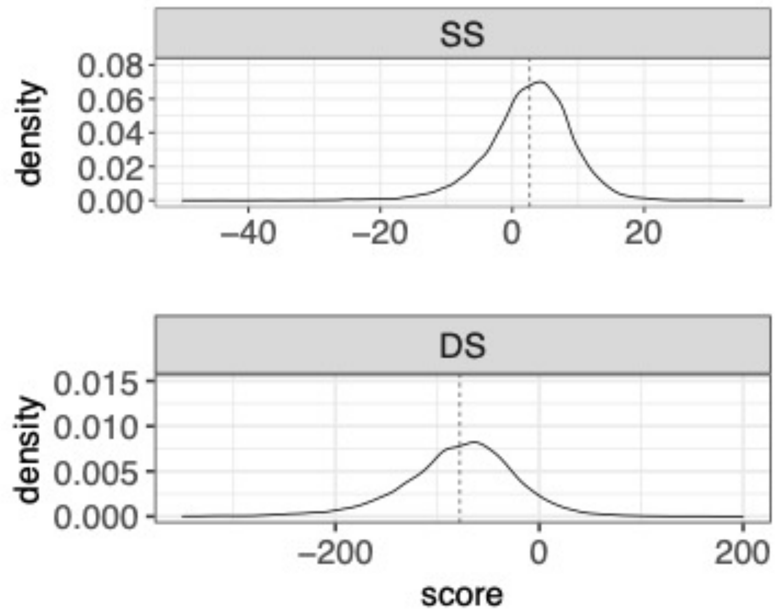
Score simulation:

- Distribution parameters
- `sn`[13] function in R[14]

Distribution parameters for score simulation.

um score	Mean	SD	Skewness	Kurtosis
Log SS	2.6	6.6	-0.7	3.5
Log DS	-78	56.6	-0.7	3.1

Distributions of simulated SS and DS log scores (1000 samples per set).



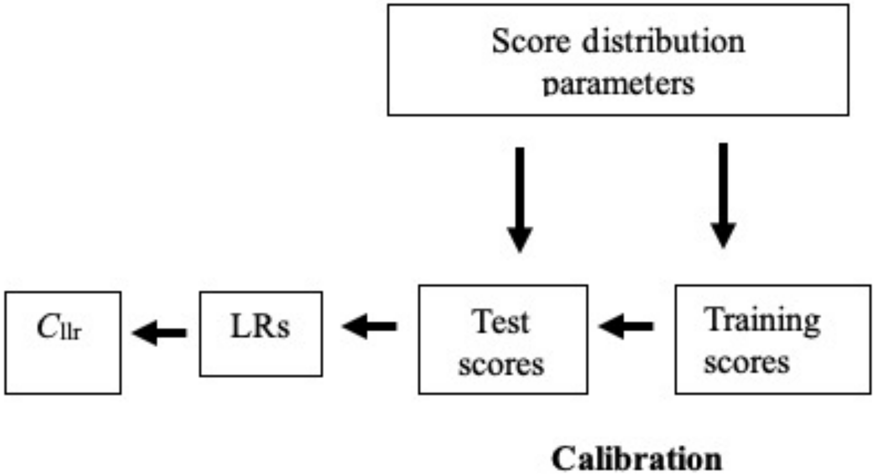
Methods

Sample size

training and test scores were sampled 100 times per sample size:

- 20 to 100 speakers
- 10-speaker increasements
- SS scores 20 ~ 100
- DS scores 380 ~9900

Schematic of the simulation process using score distribution parameters, replicated 100 times for each sample size.



Calibration

Calibration was replicated 100 times using four calibration methods for each sample size.

Methods

Evaluation

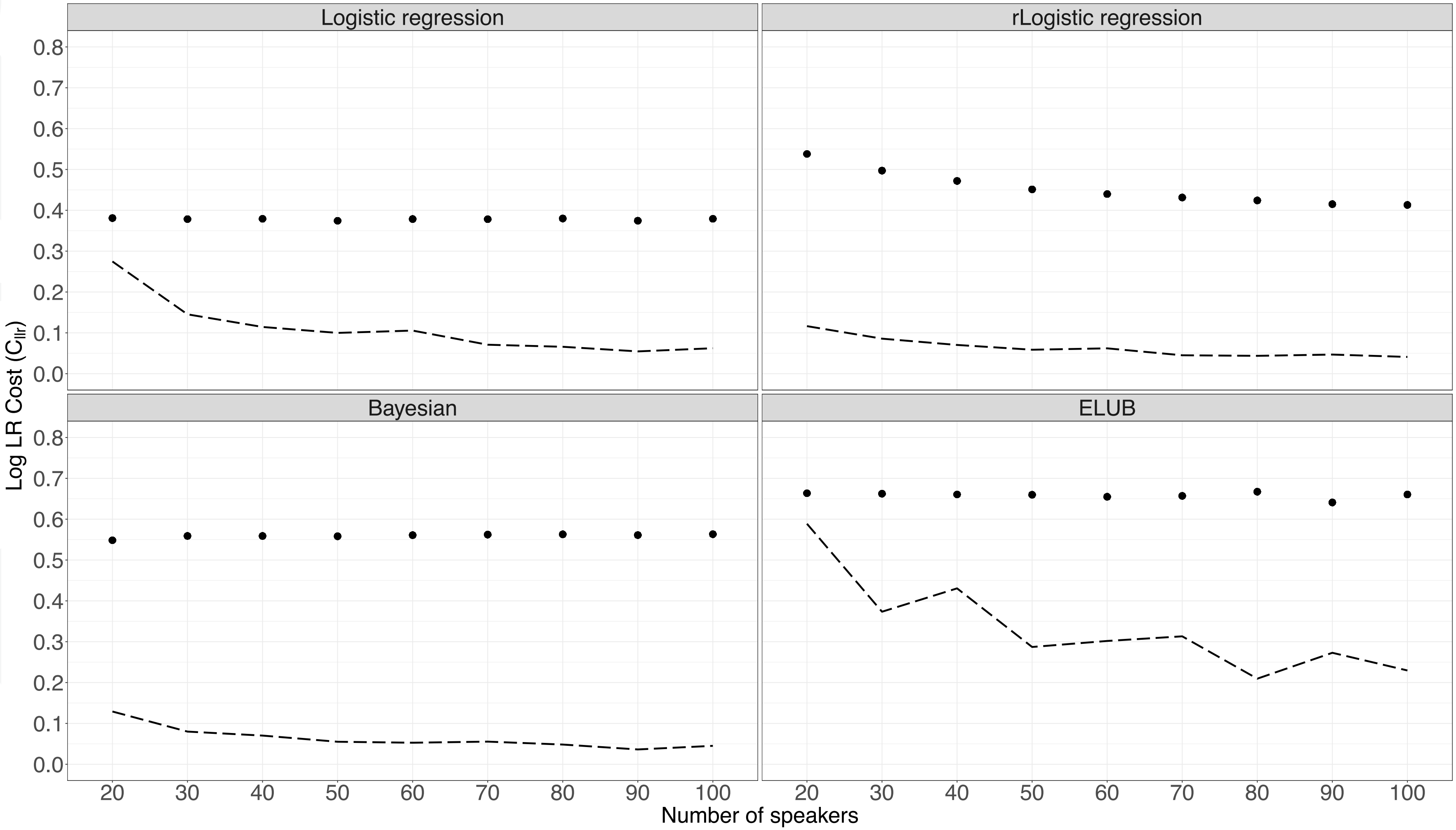
System validity: Log LR cost (C_{llr}) mean of 100 replications.

System reliability: C_{llr} range, Max. C_{llr} – Min. C_{llr} in 100 replications.

A C_{llr} of less than 1 indicates that the system is capturing useful information.

Systems with better performance should yield both lower C_{llr} mean and range.

Results


Logistic regression
rLogistic regression
Bayesian
ELUB
Log LR Cost (C_{llr})
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
20
30
40
50
60
70
80
90
100
Number of speakers

Take-home message

- Calibration methods ***vs.*** score skewness ***vs.*** sample sizes

- System validity (C_{llr} mean) ***vs.*** reliability (C_{llr} range)
  - e.g., logistic regression ***vs.*** rlogistic regression/the Bayesian model

- Experts' decisions
  - lower uncertainty **>** higher validity (i.e. the potential of a very low C_{llr})

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