Effect of Score Sampling on System Stability in Likelihood Ratio based Forensic Voice Comparison

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1. Introduction

Forensic Voice Comparison involves

- The analysis of questioned speech and known speech [6 7]

The LR framework concerns

- Similarity: how similar the questioned and know speech are [6 7]
- Typicality: how typical in a wider population [6 7]

LR framework involves two stages

- Feature to score (formants, F0, MFCC, long term F0, voice quality) [10]
- Score to LR (aka. Calibration [2] [10])

Previous studies show that system performance varies due to:

- Number of speakers used [5 8]
- Demographically matched or mismatched speakers [4]
- Speaker configurations in training, test and reference data [13]
- Different speech features used [12 14]

2. Aim

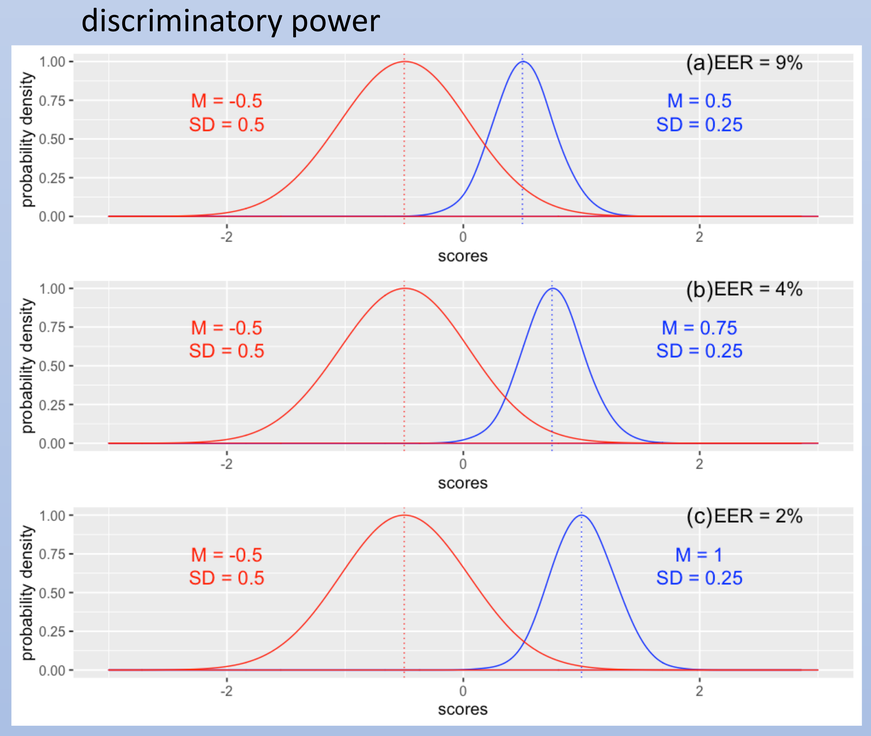
Use simulated data (highly controlled) to test the effect of speaker sampling on system performance (i.e. to avoid potential variations from sociolinguistic factors, channel mismatch, and recording devices etc.)

- How robust is a system's performance to changing which speakers are used in the training and test sets?
- Do some phonetic variables provide more or less stable LR output according to the specific sample of speakers used?

3. Method & Experiments

Data simulation

- Scores for 1000 speakers were computed from three sets of normal distributions in R [1 11]. These are referred to as set (a), set (b) and set (c)
- Different means and standard deviations used for same-/different-speaker comparisons in each set
- Different equal error rates (EER) to mimic variables with different speaker-discriminatory power



In each 100 times sampling

Sampling	Training speakers	Test speakers
Expt. 1	✓	✓
Expt. 2	✓	
Expt. 3		✓

20 test speakers

20 training speakers

Calibration[2 10]

Test scores

Training scores

LRs

C_{llr} [3 9]

4. Results

Experiment 1. Sampling training and test scores

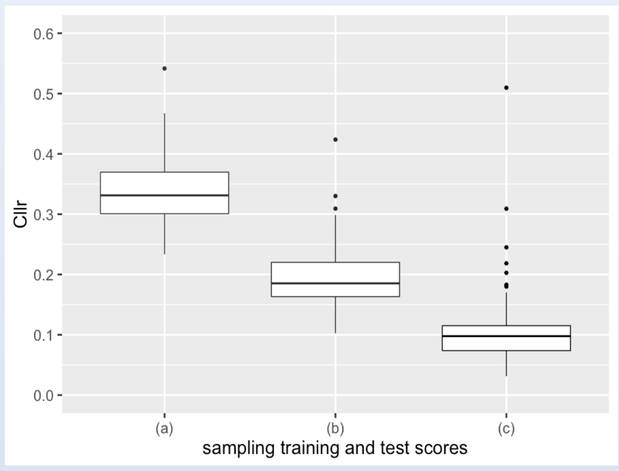


Figure 1. Variation of C_{llr}s by sampling training and test scores from pseudo-datasets (a), (b) and (c).

C_{llr}	(a)	(b)	(c)
Min.	0.23	0.10	0.03
1st Qu.	0.30	0.16	0.07
Median	0.33	0.19	0.10
3rd Qu.	0.37	0.22	0.12
Max.	0.54	0.42	0.51
IQR	0.07	0.06	0.05
OR	0.31	0.32	0.48

Table 1. C_{llr} minimum, 1st quartile, median, 3rd quartile, maximum, IQR and OR of sets (a), (b) and (c) in experiment 1.

Experiment 2. Only sampling training scores

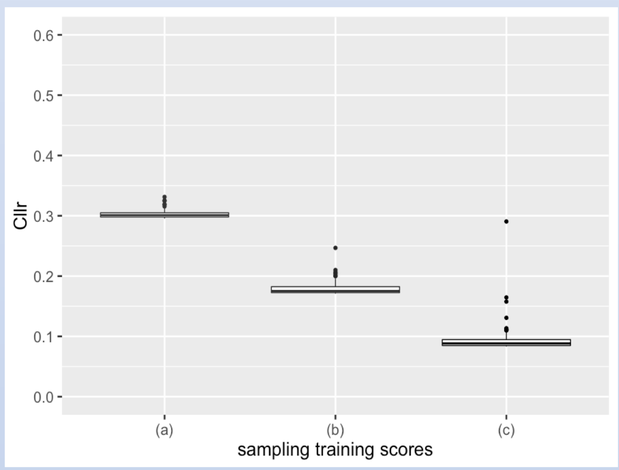


Figure 2. Variation of C_{llr}s by sampling training scores from pseudo-datasets (a), (b) and (c).

C_{llr}	(a)	(b)	(c)
Min.	0.30	0.17	0.08
1st Qu.	0.30	0.17	0.08
Median	0.3	0.17	0.09
3rd Qu.	0.31	0.18	0.09
Max.	0.33	0.25	0.29
IQR	0.01	0.01	0.01
OR	0.03	0.08	0.21

Table 2. C_{llr} minimum, 1st quartile, median, 3rd quartile, maximum, IQR and OR of sets (a), (b) and (c) in experiment 2.

Experiment 3. Only sampling test scores

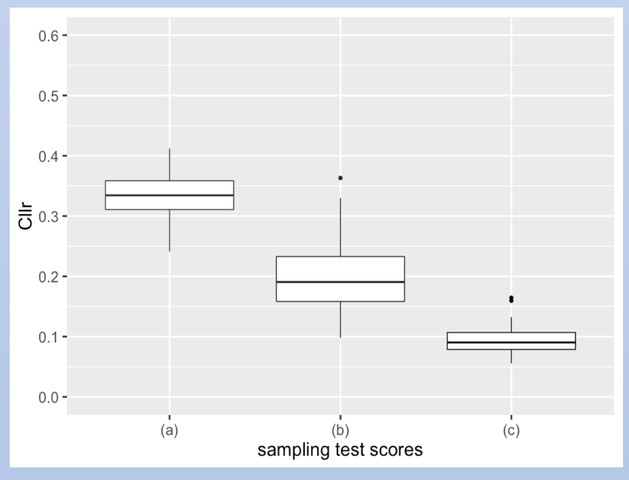


Figure 3. Variation of C_{llr}s by sampling test scores from pseudo-datasets (a), (b) and (c).

C_{llr}	(a)	(b)	(c)
Min.	0.24	0.10	0.06
1st Qu.	0.31	0.15	0.08
Median	0.33	0.19	0.09
3rd Qu.	0.36	0.23	0.11
Max.	0.41	0.36	0.16
IQR	0.05	0.08	0.03
OR	0.17	0.26	0.10

Table 3. C_{llr} minimum, 1st quartile, median, 3rd quartile, maximum, IQR and OR of sets (a), (b) and (c) in experiment 3.

5. Discussion

Experiment 1 vs Experiment 2 vs Experiment 3

- System stability varies considerably if different sets of SS and DS scores are used in each replication (Figure 1)
- Varying training scores has a limited effect on system stability (Figure 2)
- Sampling test scores has more effect on the system stability than sampling training scores (Figure 2 and Figure 3)

Set (a) vs Set (b) vs Set (c)

- Mean C_{llr} decreases as EER goes down in experiments 1, 2, and 3.
- Set (c) yielded more outliers than sets (a) and (b) in experiments 1, 2 and 3 regardless of speaker-discriminatory power (lower EER)
- The lower the EER, the lower the Cllr IQR, but not OR [Set (c)]

6. Conclusion

- Score-sampling has a marked effect on system stability regardless of speaker-discriminatory power of the feature being used
- Variables with higher speaker-discriminatory power do not necessarily yield higher system stability

8. Reference

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