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Towards End-to-End Private Automatic Speaker Recognition

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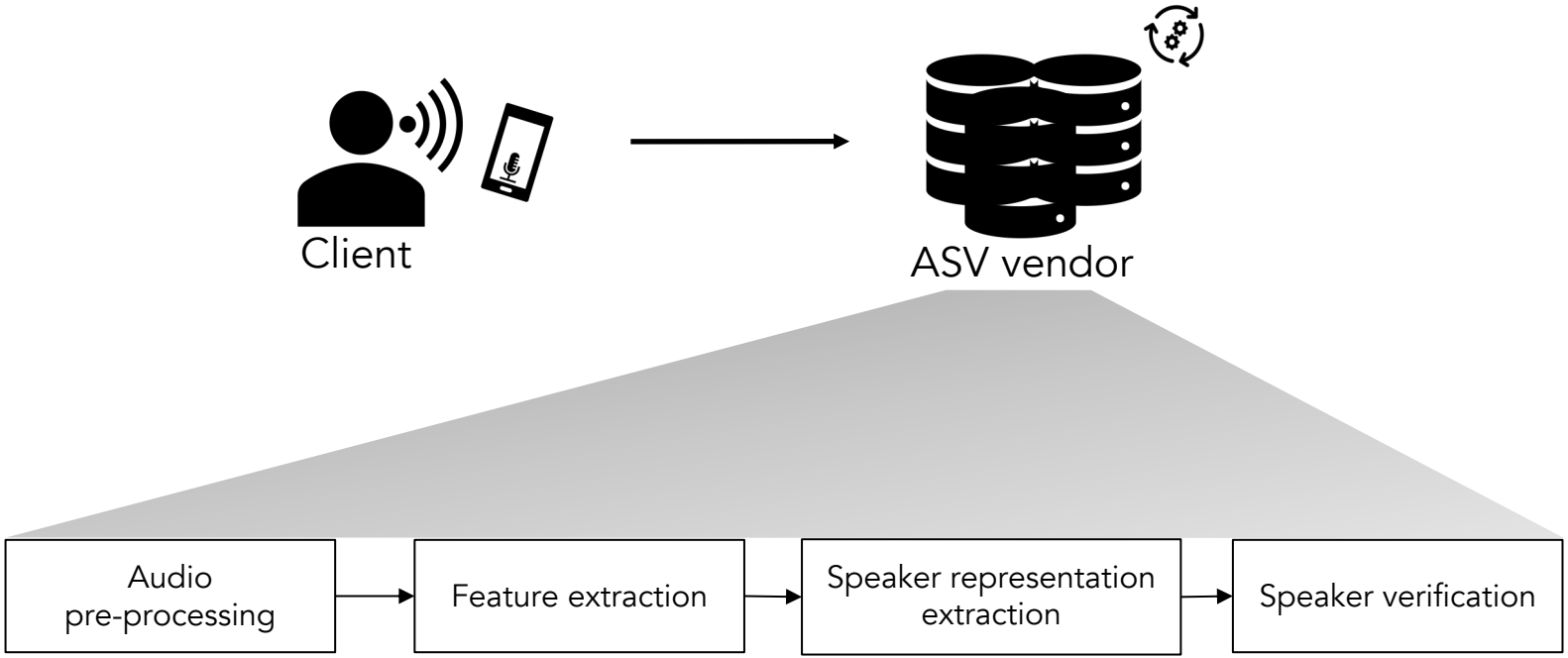
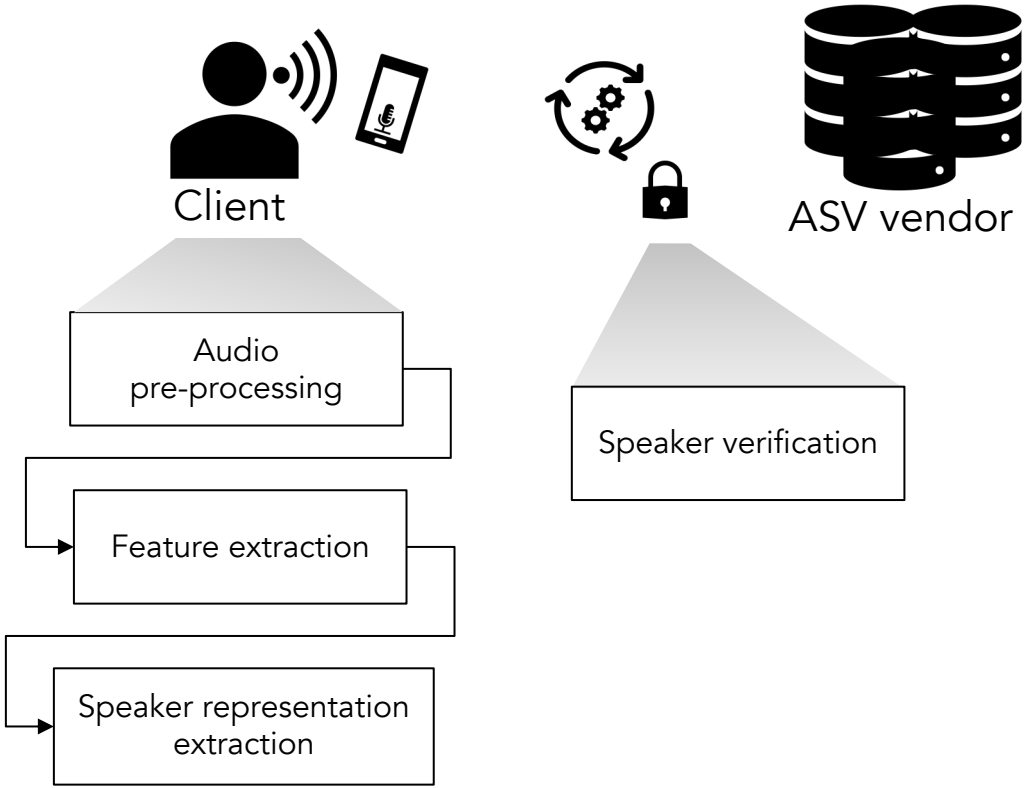
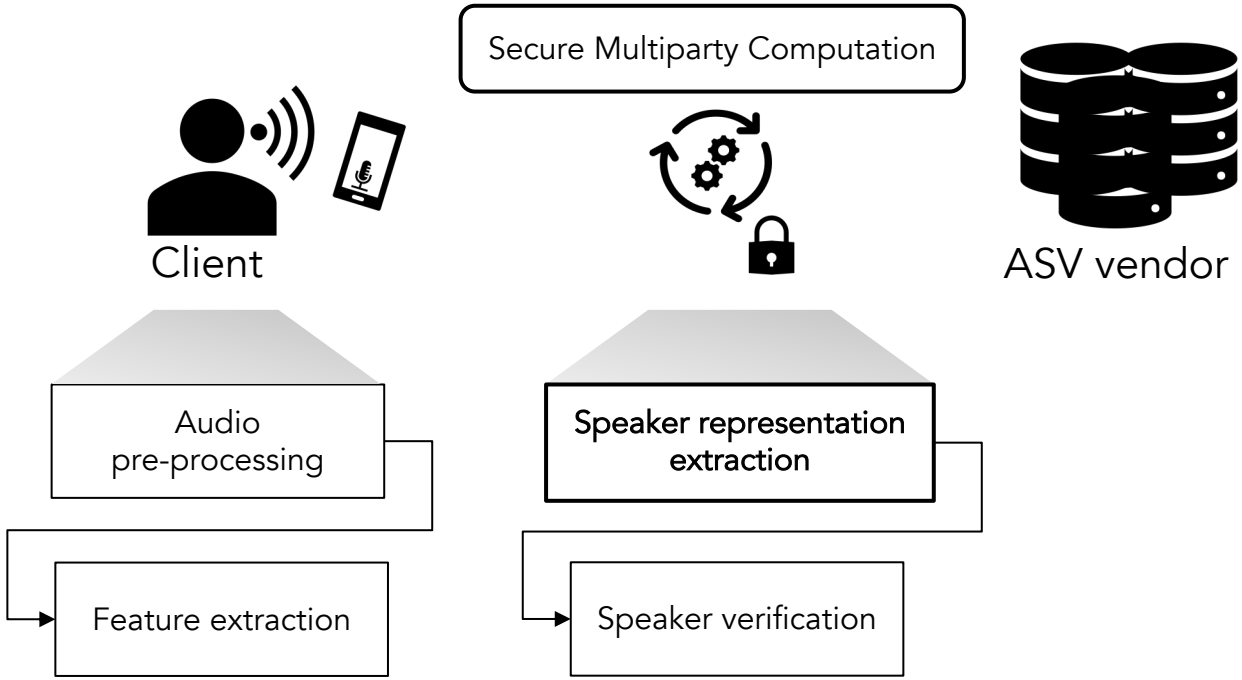
Motivation: Problem setting



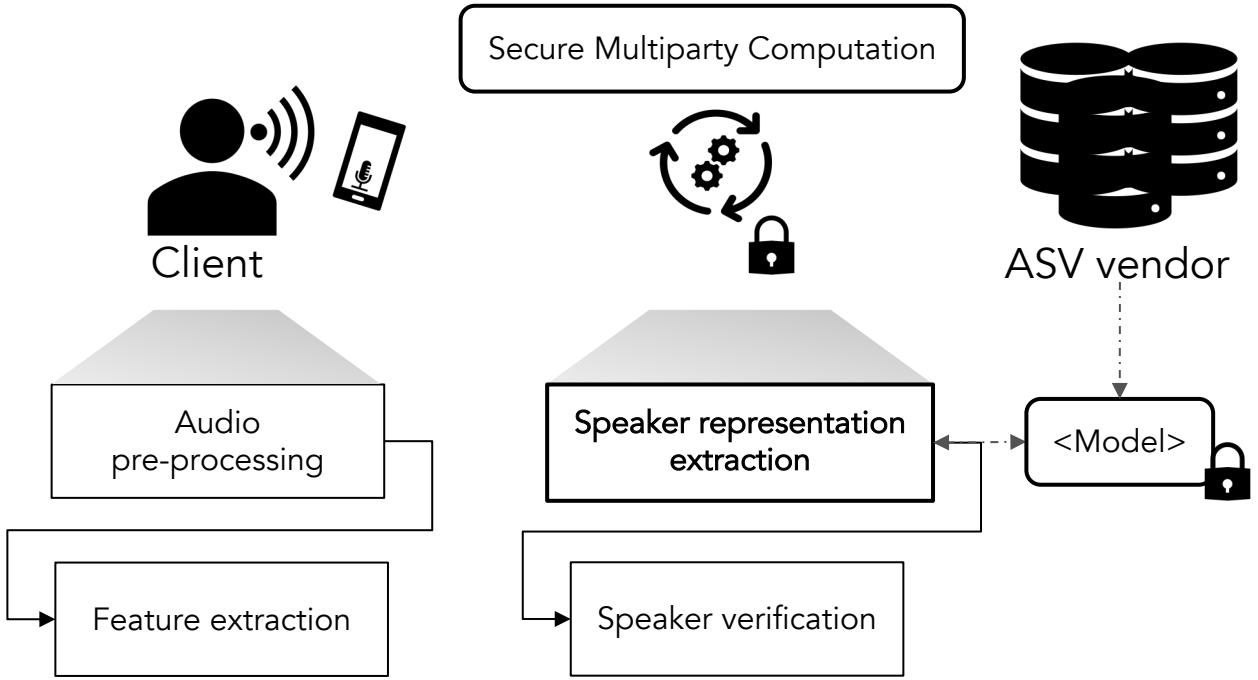
Motivation: State-of-the-art



Motivation: Proposed solution



Motivation: Proposed solution



Outline

- Motivation
- Secure Multiparty Computation
- Privacy-preserving speaker embedding extraction: security settings
- Implementation and experimental setup
- Results
- Conclusions and future work

Secure Multiparty Computation (SMC)

- **Family of cryptographic protocols** that allow two or more parties to interactively (and privately) compute functions, e.g.:
  - Arithmetic Secret Sharing
  - Boolean Secret Sharing
  - Garbled Circuits

- **Arithmetic Secret Sharing:**

P1	P2
Input: x	Input: y
$\langle x \rangle_1 = r_x$	$\langle y \rangle_1 = r_y$
$\langle x \rangle_2 = x - r_x$	$\langle y \rangle_2 = y - r_y$

Secure Multiparty Computation: Arithmetic Secret Sharing

- *n*-party setting: the owner of the data generates *n-1* random values, with each *secret share* being defined as:

$$\langle x \rangle_n = x - \sum_{i=1}^{n-1} r_i \qquad x = \sum_{i=1}^{n} \langle x \rangle_i$$

- It is then possible to perform operations over multiple shared values:
  - Additions can be performed locally;
  - Multiplications require *multiplication triples* (also called *Beaver triples*).

Secure Multiparty Computation: *Multiplication Triples*

We want to compute $\langle z \rangle = \langle x \rangle \times \langle y \rangle$

- Assume we have *pre-computed* secret-shared values $\langle a \rangle$, $\langle b \rangle$ and $\langle c \rangle$, such that:

$$\langle c \rangle = \langle a \rangle \times \langle b \rangle$$

- To perform a *multiplication* each party sets local shares $\langle e \rangle_i, \langle f \rangle_i$ as:

$$\langle e \rangle_i = \langle x \rangle_i - \langle a \rangle_i \qquad \langle f \rangle_i = \langle y \rangle_i - \langle b \rangle_i$$

- All parties then interact to reconstruct *e* and *f*, and set their share of $\langle z \rangle$ to

$$\langle z \rangle_i = i \cdot e \cdot f + f \cdot \langle a \rangle_i + e \cdot \langle b \rangle_i + \langle c \rangle_i$$

Secure Multiparty Computation: Boolean Secret Sharing

- The previous representation is easily adaptable to binary representations:

$$\langle x \rangle_n = x \oplus \sum_{i=1}^{n-1} s_i \qquad x = \langle x \rangle_1 \oplus \langle x \rangle_2 \oplus \ldots \oplus \langle x \rangle_n$$

- Similarly to Arithmetic Secret Sharing:
  - XORs can be computed locally;
  - AND operations require *multiplication triples.*

- We can convert between Arithmetic and Boolean domains using pre-computed values shared in both domains (e.g. *daBits*, *edaBits*).

Secure Multiparty Computation: Replicated Secret Sharing

- A (more efficient) variant of the previous secret sharing protocol:
  - Instead of having a single share, each party holds a *set* of shares per value.

e.g. consider three parties, and a secret-shared value x:

$$x = \sum_{i=1}^{3} \langle x \rangle_i$$

P1 will hold: $\langle x \rangle_1, \langle x \rangle_2$

P2 will hold: $\langle x \rangle_2, \langle x \rangle_3$

P3 will hold: $\langle x \rangle_3, \langle x \rangle_1$

Secure Multiparty Computation: Replicated Secret Sharing

- A (more efficient) variant of the *vanilla* secret sharing protocol:
  - Additions are performed locally by each party.
  - Multiplications **no longer** require *multiplication triples.*

e.g. Simple multiplication protocol for three parties ($\langle z \rangle = \langle x \rangle \times \langle y \rangle$):

- Each party multiplies the shares it holds for each value locally and obtains:

$$z_1 = \langle x \rangle_1 \langle y \rangle_1 + \langle x \rangle_1 \langle y \rangle_2 + \langle x \rangle_2 \langle y \rangle_1$$
$$z_2 = \langle x \rangle_2 \langle y \rangle_2 + \langle x \rangle_2 \langle y \rangle_3 + \langle x \rangle_3 \langle y \rangle_2$$
$$z_3 = \langle x \rangle_3 \langle y \rangle_3 + \langle x \rangle_3 \langle y \rangle_1 + \langle x \rangle_1 \langle y \rangle_3$$

- *Re-sharing* protocol is required.

Secure Multiparty Computation: Security models

- *Honest-but-curious* model:
  - Parties are assumed to follow the protocol, but to try to get as much information as possible.

- *Malicious* model:
  - Parties are assumed to try to thwart the protocol to gain more information.

  - Requires specific protocols to ensure all parties are "behaving" correctly, e.g.:
    - Cut-and-choose methods;
    - Zero-Knowledge (ZK) proofs;
    - Message Authentication Codes (MACs).

- Honest majority vs dishonest majority

Privacy-preserving speaker embedding extraction

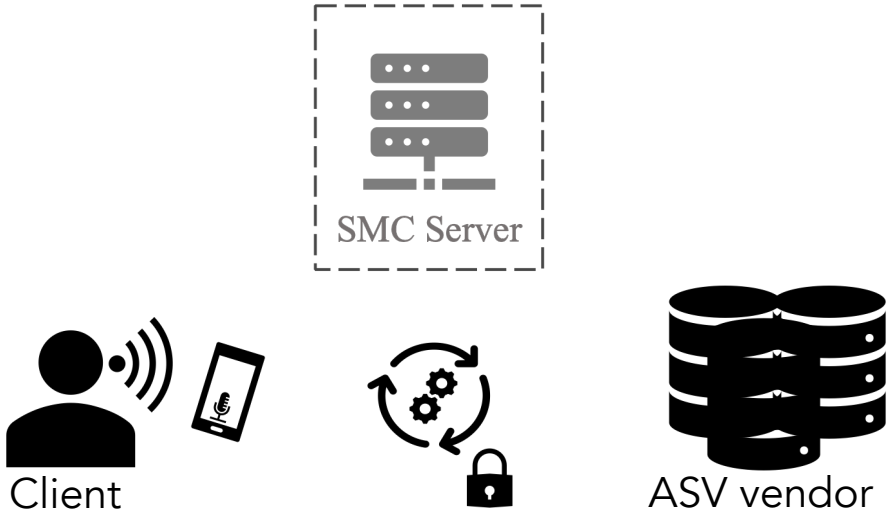
Privacy-preserving speaker embedding extraction: Security setting

2-party setting

Simplest/most natural setting

- Honest-but-curious security
- Malicious security

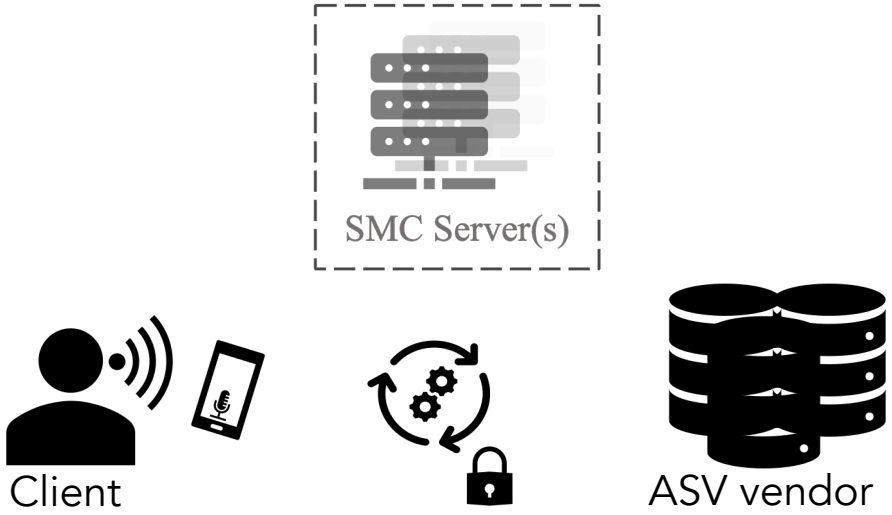
Privacy-preserving speaker embedding extraction: Security setting



3-party setting:

- Allows the instantiation of more efficient protocols

Privacy-preserving speaker embedding extraction: Security setting



4-party setting:

- 4-party Replicated Secret Sharing Protocol of Dalskov et al. [1].
- Provides honest-majority security against one malicious party.

Experimental setup

- Pre-trained SpeechBrain *x-vector* speaker embedding extraction model [2]:
  - 3.2% EER on Voxceleb 1 test set
- MP-SPDZ library [3]:
  - Implements linear and non-linear operations required for the *x-vector* extraction network.
- Protocols used:
  - *Semi*$_2^k$: 2-party semi-honest protocol [4]
  - 3-party RSS: semi-honest protocol (Araki et al. [5])
  - 4-party RSS: malicious protocol w/ honest majority (Dalskov et al. [1])
  - SPDZ$_2^k$: 2-party malicious protocol [4]

#	Layer	Input	Output	Kernel	Dilation
1	TDNN 1	24	512	5	1
2	TDNN 2	512	512	3	2
3	TDNN 3	512	512	3	3
4	TDNN 4	512	512	1	1
5	TDNN 5	512	1500	1	1
6	Statistics Pooling	1500	3000	-	-
7	Linear	3000	512	-	-

Table 1: *x-vector* extractor architecture

Experimental setup: Fixed-point representations

- In neural networks, weights are **floating-point** numbers.
- Shares in Arithmetic Secret Sharing protocols are **integers.**
  - It is not possible to compute random *real* numbers **uniformly** over an interval.
- In our implementation we use MP-SPDZ's **fixed-point** number representation:

$$x = y \cdot 2^f$$

  - *f* represents a fixed precision
  - *y* is a secret-shared value
- Additions can be computed without changes.
- Multiplications require an extra division/truncation by *f*.
  - Implemented as binary left-shift operation or specific *probabilistic truncation* protocol.

Results

Protocol	Security model	Time (s)		Communication (MB)	
		Pre-processing	Online	Pre-processing	Online
2-party Semi$_2^k$ [4]	Semi-honest	>2 hours	≅19	≅1.6 TB	≅12.6 GB
2-party SPDZ$_2^k$ [4]	Malicious	>1 day	≅126	≅21 TB	≅27 GB
3-party RSS [5]	Semi-honest w/ honest majority	≅0.18	≅11	15	118
4-party RSS [1]	Malicious w/ honest majority	≅1.2	≅17	27	333

Table 2: Computational and communication costs for the extraction of speaker embeddings from 3-second long speech recordings.

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Conclusions & Future Work

- In this work we have shown that it is possible to extract *x-vector* speaker embeddings using Secure Multiparty Computation.
- By using SMC we are able to protect both the privacy of the speaker's voice as well as the ASV vendor's model.
- As future work it would be important to explore:
  - Techniques to reduce the size of the *x-vector* extraction network
  - Other security models that better fit real world scenarios (e.g. *covert security*).
- This work has also been recently applied to Automatic Speaker Diarization in the context of the CMU Portugal project PrivaDia.

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Thank you!

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References

[1] Dalskov, A., Escudero, D. and Keller, M. "Fantastic Four: Honest-Majority Four-Party Secure Computation With Malicious Security." 30th USENIX Security Symposium (USENIX Security 21), 2021.

[2] Parcollet, T., et al. "Speechbrain: A general-purpose speech toolkit." (2022).

[3] Keller, M. "MP-SPDZ: A versatile framework for multi-party computation." Proceedings of the 2020 ACM SIGSAC conference on computer and communications security. 2020.

[4] Cramer, R., Damgärd, I., Escudero, D., Scholl, P. and Xing C., “SPD Z2k : Efficient MPC mod 2k for dishonest majority,” in Annual International Cryptology Conference. Springer, 2018, pp. 769– 798.

[5] Araki, T., Furukawa, J., Lindell, Y., Nof, A. and Ohara, K. “High- throughput semi-honest secure three-party computation with an honest majority,” in SIGSAC. ACM, 2016, p. 805–817.