Privacy-Preserving Speech Processing
via STPC and TEEs

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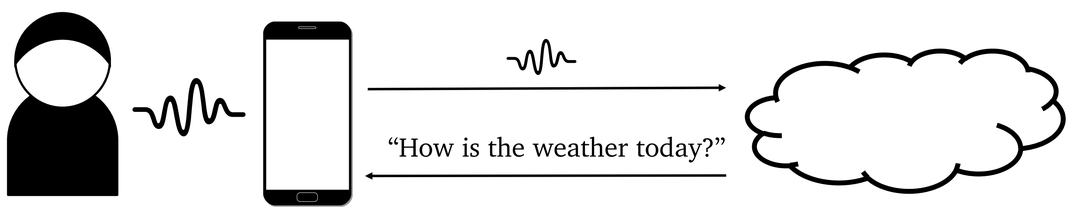
1. Motivation & Contribution

Current Situation: Voice-based Interfaces are Becoming Omnipresent

- > 2B smartphone users (Amazon Alexa, Apple Siri, Google Assistant, Microsoft Cortana)
- Increasing number of smart-home devices (Amazon Echo, Apple Home-Pod, Google Home)
- Automatic Speaker Verification (ASV) for authentication over the phone (e.g., for banking)



Risks: Voice Data Contains Sensitive Biometric Information as well as Spoken Words

➢ Impersonation attacks, extracting content, inferring sensitive data (health, ethnicity, etc.)

Problem Statement: Naïve Solution of Performing Speech Processing on Client-side fails

➢ Shipping the model parameters to the client contradicts the business interests of vendors

Contributions: Secure and Private Speech Processing Architectures

- *VoiceGuard [1]*: secure & private speech processing via Intel SGX
- *Offline Model Guard (OMG) [2]:* secure & private speech processing on mobile devices
- *Private ASV [3]* via outsourced secure two-party computation (STPC)

2. Related Work

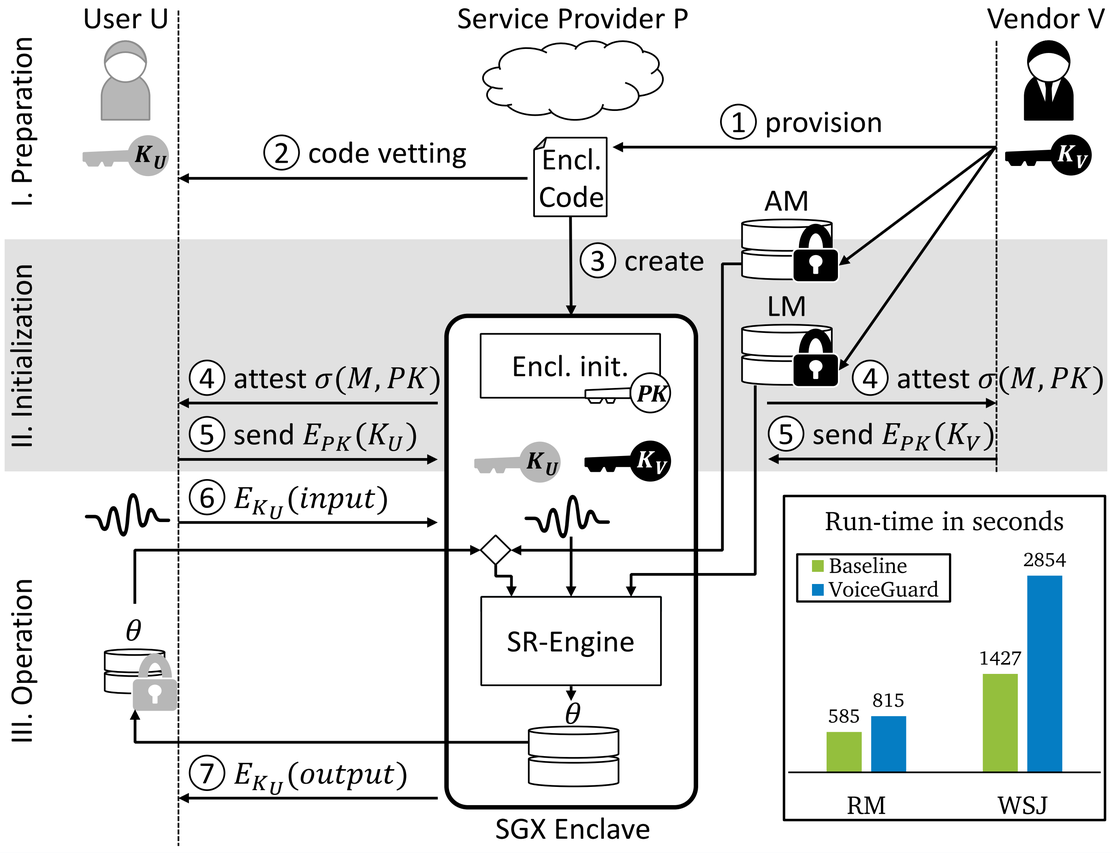
Privacy-Preserving Machine Learning

- Via *Secure Multi-Party Computation*
  - × Orders of magnitude higher communication
  - × Impractical for (large-scale) on-the-fly processing due to repeated initialization costs
- Via *Homomorphic Encryption*
  - × Orders of magnitude higher computation time
  - × Impractical for (large-scale) on-the-fly processing due to high latency

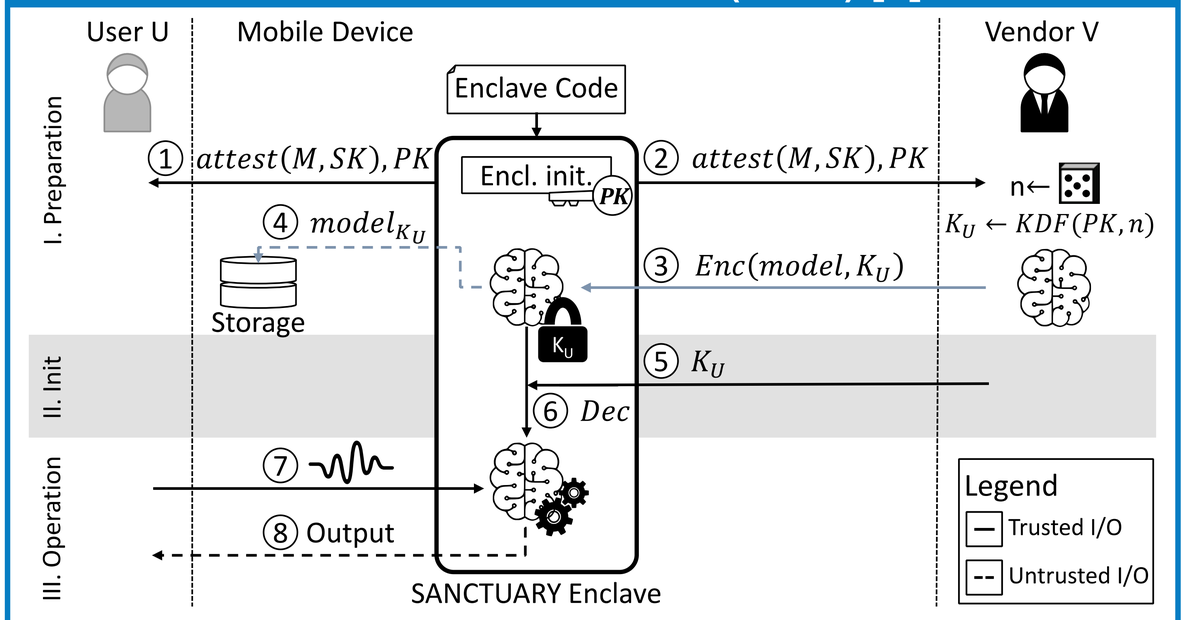
Privacy-Preserving Speech Processing (Nautsch et al., *Computer Speech and Language'19*)

- Speech processing via cryptographic means is still very inefficient
  - × Example: > 3h to encrypt 1s of audio & recognize a word out of a 10 word vocabulary
  - × Currently far from suitable for speech recognition in real time due to high overhead
- Certain tasks like ASV can be performed via HE in reasonable time
  - × PLDA ASV on i-vectors with dimension 250 takes > 6m (Nautsch et al., *Odyssey'18*)
  - × Private ASV protocols by Rahulamathavan et al. (*CyberSA'19, TASLP'19*) found to be highly insecure (Treiber & Schneider, *TPDS'19*)
- × Often, intermediate values, some model parameters, or even entire voice models of individuals are leaked (e.g., Portelo et al., *EUSPICO'14*)

3. VoiceGuard [1]



4. Offline Model Guard (OMG) [2]



Evaluation: Offline Keyword Recognition

- Based on TensorFlow Lite for Microcontrollers
- Uses spectral fingerprints & CNN architecture
- Implementation on ARM HiKey 960 development board (octo-core ARMv8 SoC, 3GB RAM)

Model Evaluation	Run-time
Baseline	379ms
Offline Model Guard	387ms

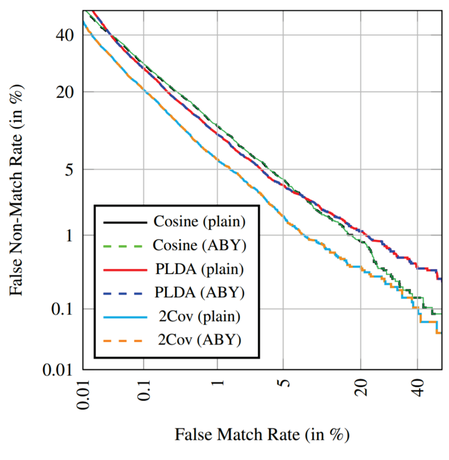
5. Private Automatic Speaker Verification (ASV) [3]

Drawbacks of Previous HE-based ASV

- High computational demand for client device & inefficient transaction times
- Threshold value, comparison score, and intermediate fixed-point exponents leaked
- No security against malicious users

Our Construction based on Outsourced STPC

- Reference embedding stored by two non-colluding servers in secret shared form
- Probe embedding secret shared during verification step, servers then compute verification in STPC
- Hides the score, intermediate results, and is secure against malicious users
- Satisfies international standards on Biometric Information Protection (ISO/IEC IS 24745)



Evaluation

- Implementation based on ABY (Demmler et al., NDSS'15) evaluated on NIST i-vector ML challenge
- Run-time: 0.5s (improvement up to 4,000x)
- Fixed-point, but retains 100% accuracy

6. Conclusion

VoiceGuard & OMG: Novel Architectures for Privacy-Preserving Speech Processing

- ✓ Protect the user's sensitive voice data & the vendor's IP (i.e., model parameters)
- ✓ Support user-specific models, such as feature transformations (e.g., fMLLR), i-vectors, or model transformations (e.g., custom output layers)
- ✓ Deployment either in the cloud or on-premises (VoiceGuard)
- ✓ Prototype implementations demonstrate applicability for speech recognition in real time
- ✓ Generic ⇒ also work for related tasks (speaker verification or voice biometrics, including emotion recognition and medical speech processing)

Private ASV: PLDA-based Speaker Verification

- ✓ Outperforms HE-based solutions both in terms of efficiency and security
- ✓ Open-source implementation (https://encrypto.de/code/PrivateASV)
- × LLR threshold precision limited to three decimal points (but sufficient for ASV)

7. References

[1] Ferdinand Brasser, Tommaso Frassetto, Korbinian Riedhammer, Ahmad-Reza Sadeghi, Thomas Schneider, and Christian Weinert. VoiceGuard: Secure and private speech processing. *INTERSPEECH 2018*.

[2] Sebastian P. Bayerl, Tommaso Frassetto, Patrick Jauernig, Korbinian Riedhammer, Ahmad-Reza Sadeghi, Thomas Schneider, Emmanuel Stapf, and Christian Weinert. Offline model guard: Secure and private ML on mobile devices. *DATE 2020*.

[3] Amos Treiber, Andreas Nautsch, Jascha Kolberg, Thomas Schneider, and Christoph Busch. Privacy-preserving PLDA speaker verification using outsourced secure computation. *Speech Communication 2019*.