University of Glasgow | School of Computing Science

THE AWARDS 2020 | UNIVERSITY OF THE YEAR

Privacy Concerns in CDSS

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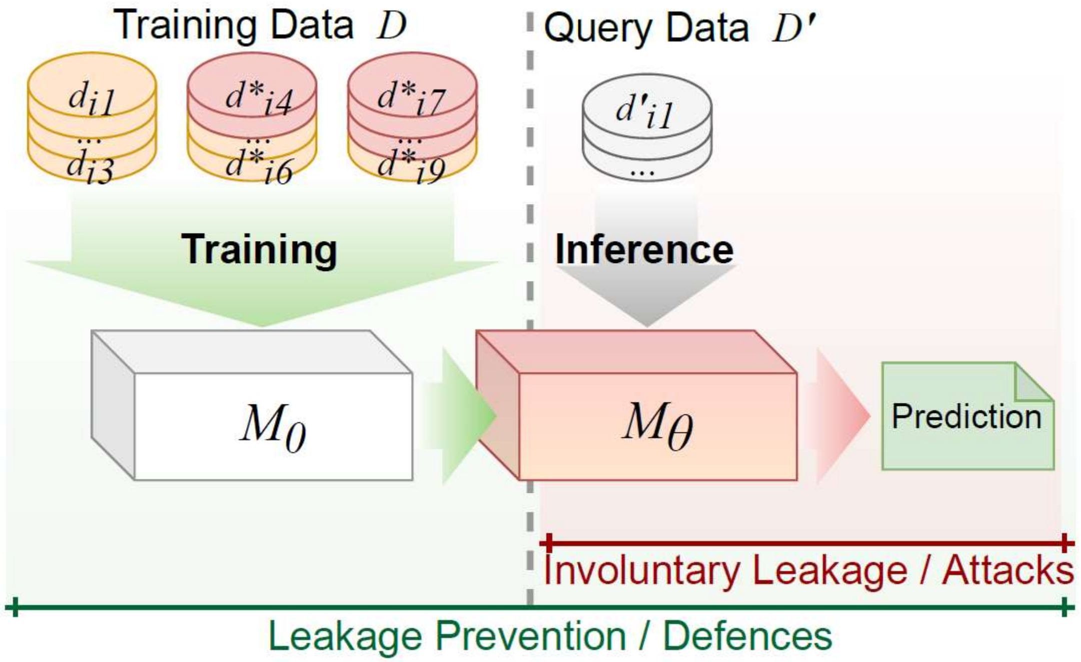
WORLD CHANGING GLASGOW

Data Leakage in Neural Networks

- Neural network inherent ability to store information
- Information is represented in the neural network weights
- Original data can be recreated with high accuracy.



Jegorova et al. ‘Survey: Leakage and Privacy at Inference Time’, https://arxiv.org/abs/2107.01614, 2021.

Privacy attacks - Datasets

Attacks against the dataset

- Re-identification attack
- Dataset reconstruction attack
- Tracking attack

Privacy attacks - Algorithmic

Attacks against the dataset

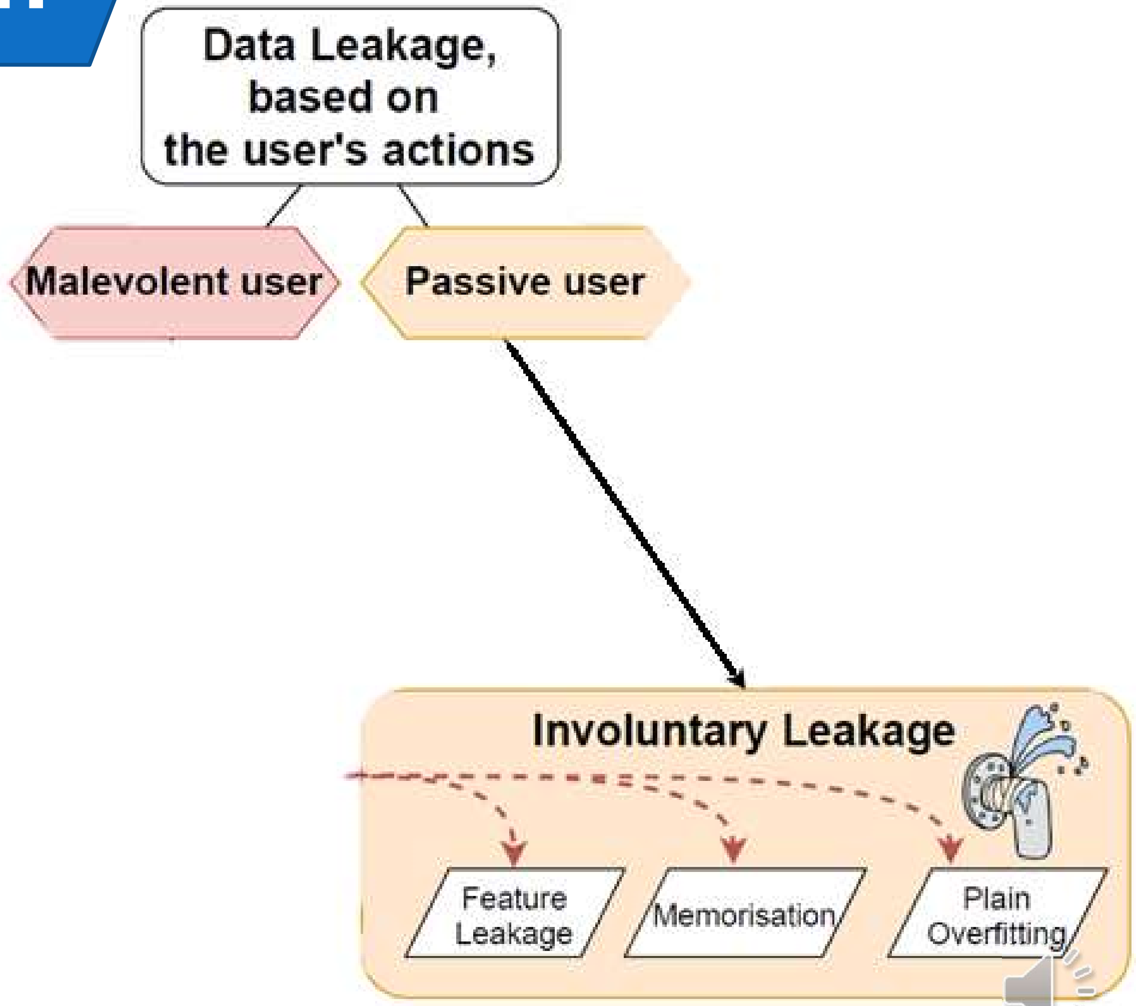
- Re-identification attack
- Dataset reconstruction attack
- Tracking attack

Attacks against the algorithm

- Adversarial attack
- Model-inversion/reconstruction attack

Leakage - Users Action

- Involuntary Leakage vs Malicious Attacks
- Data leakage can be exploited even if it is involuntary
- Feature leakage, memorization and plain overfitting are all related to the ability of deep learning models to ‘memorise’



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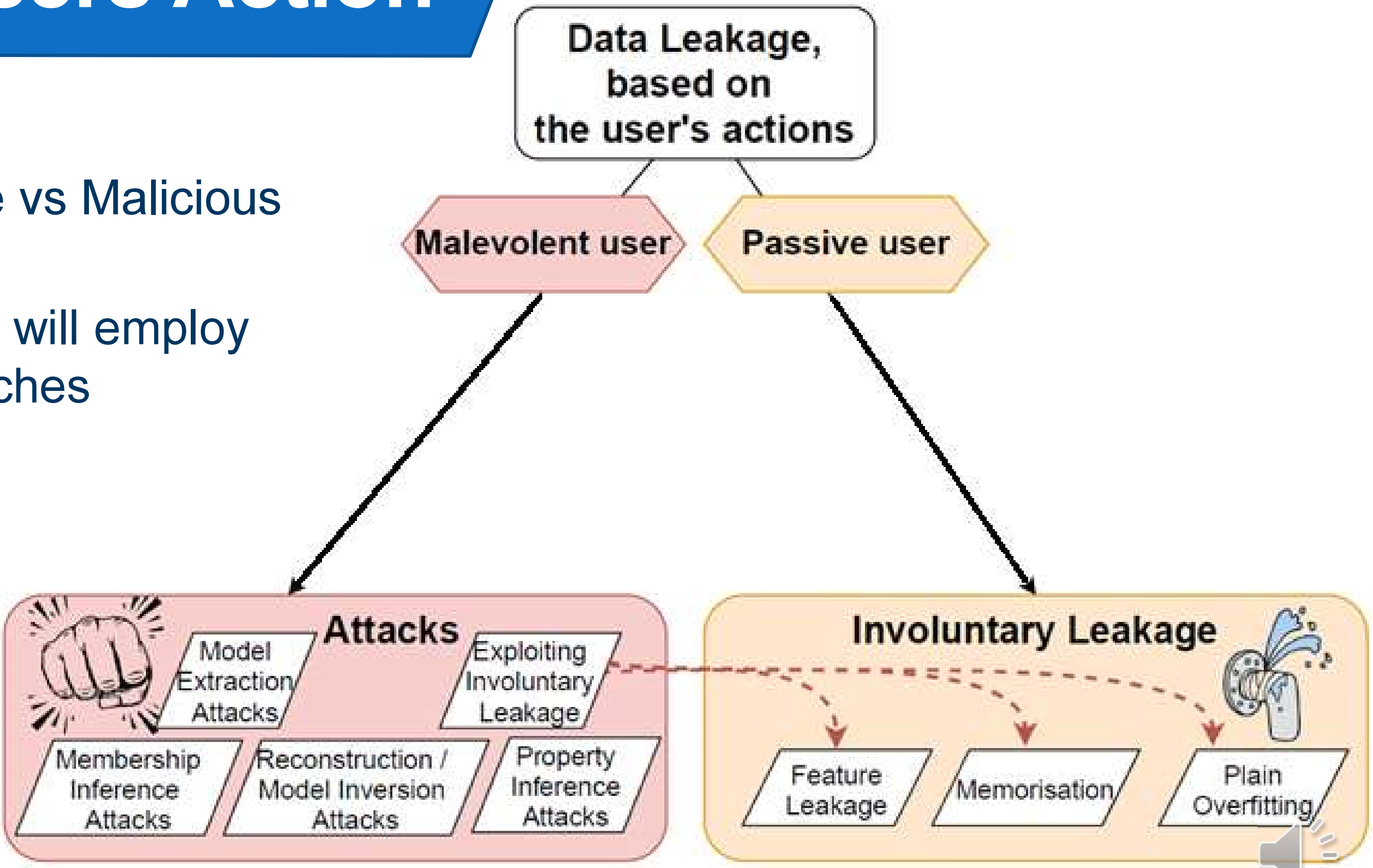
Leakage - Users Action

- Involuntary Leakage vs Malicious Attacks
- A malicious attacker will employ sophisticate approaches


Data Leakage, based on the user's actions
Malevolent user
Passive user
Attacks
Model Extraction Attacks
Exploiting Involuntary Leakage
Membership Inference Attacks
Reconstruction / Model Inversion Attacks
Property Inference Attacks
Involuntary Leakage
Feature Leakage
Memorisation
Plain Overfitting

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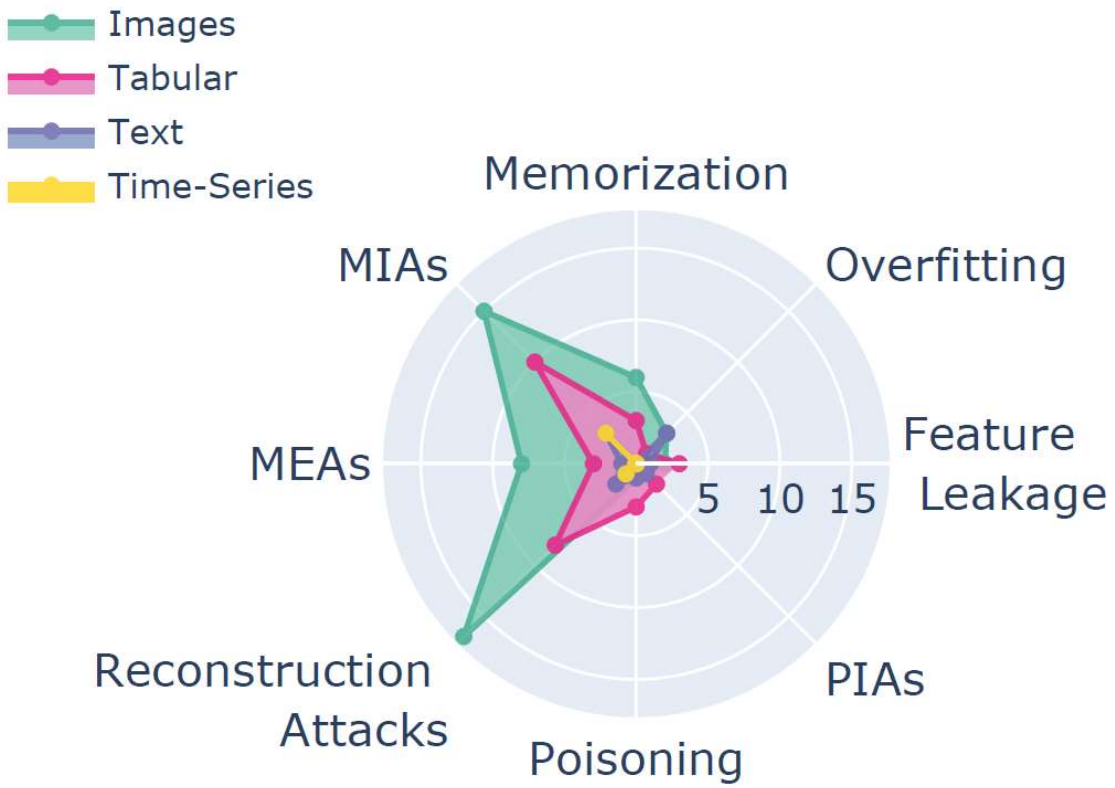
Privacy attacks - Statistics



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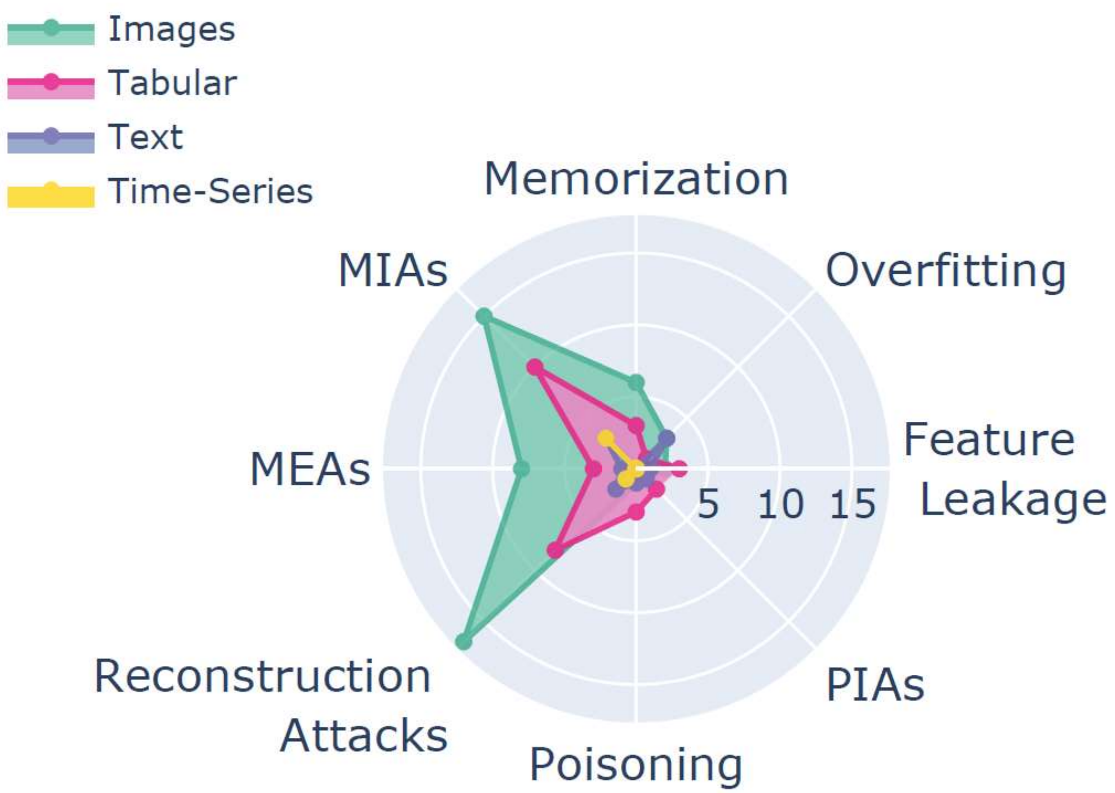
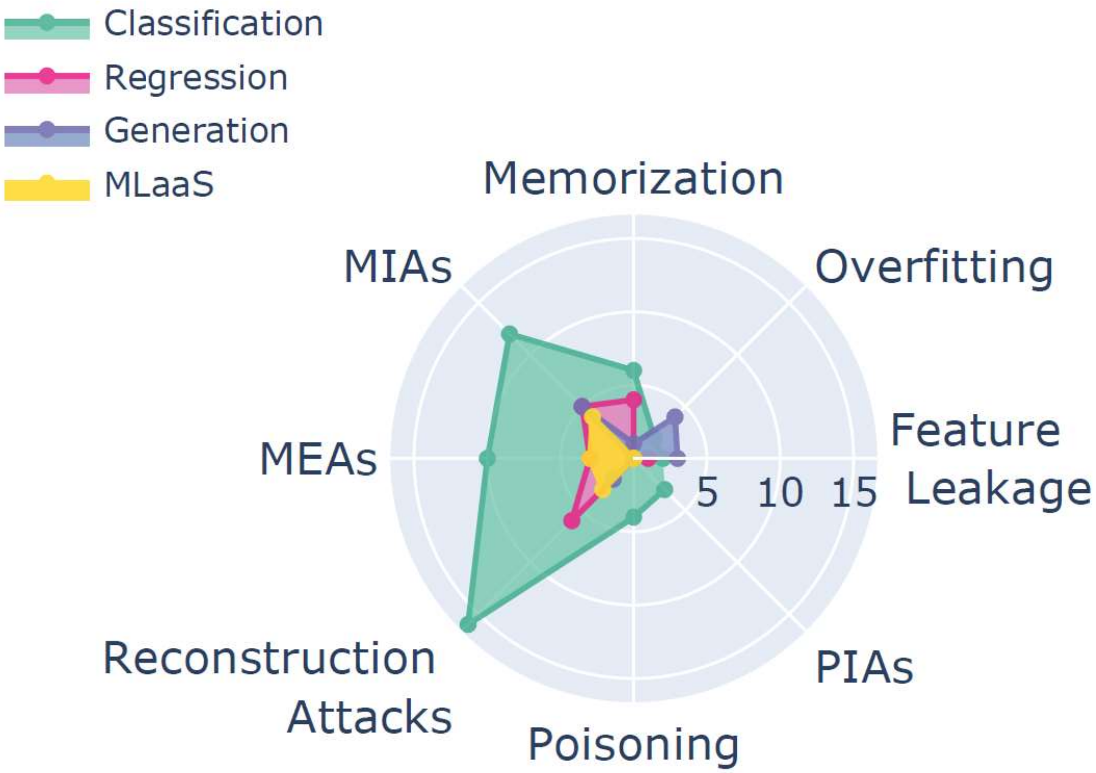
Privacy attacks - Statistics





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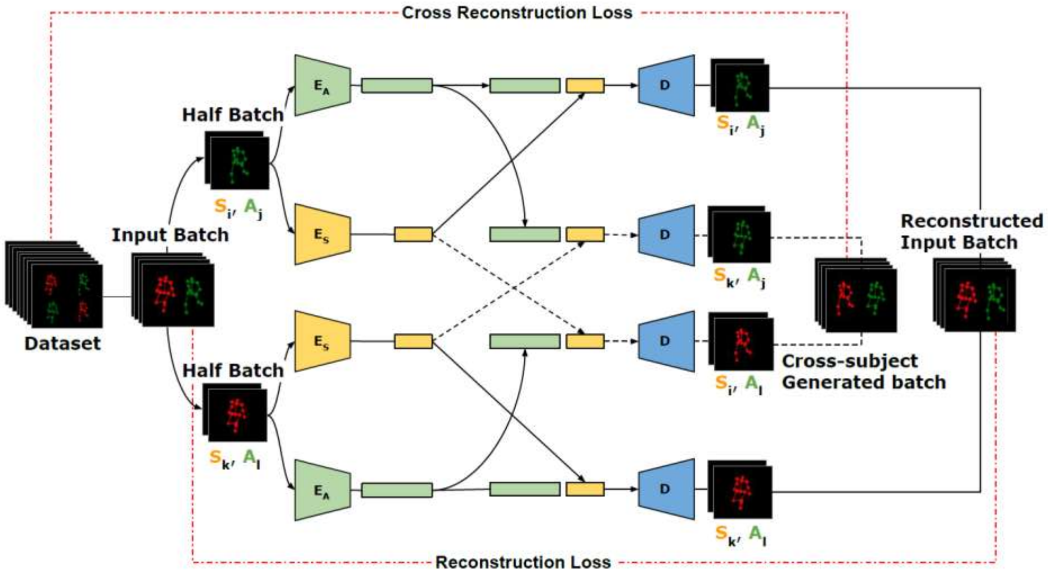
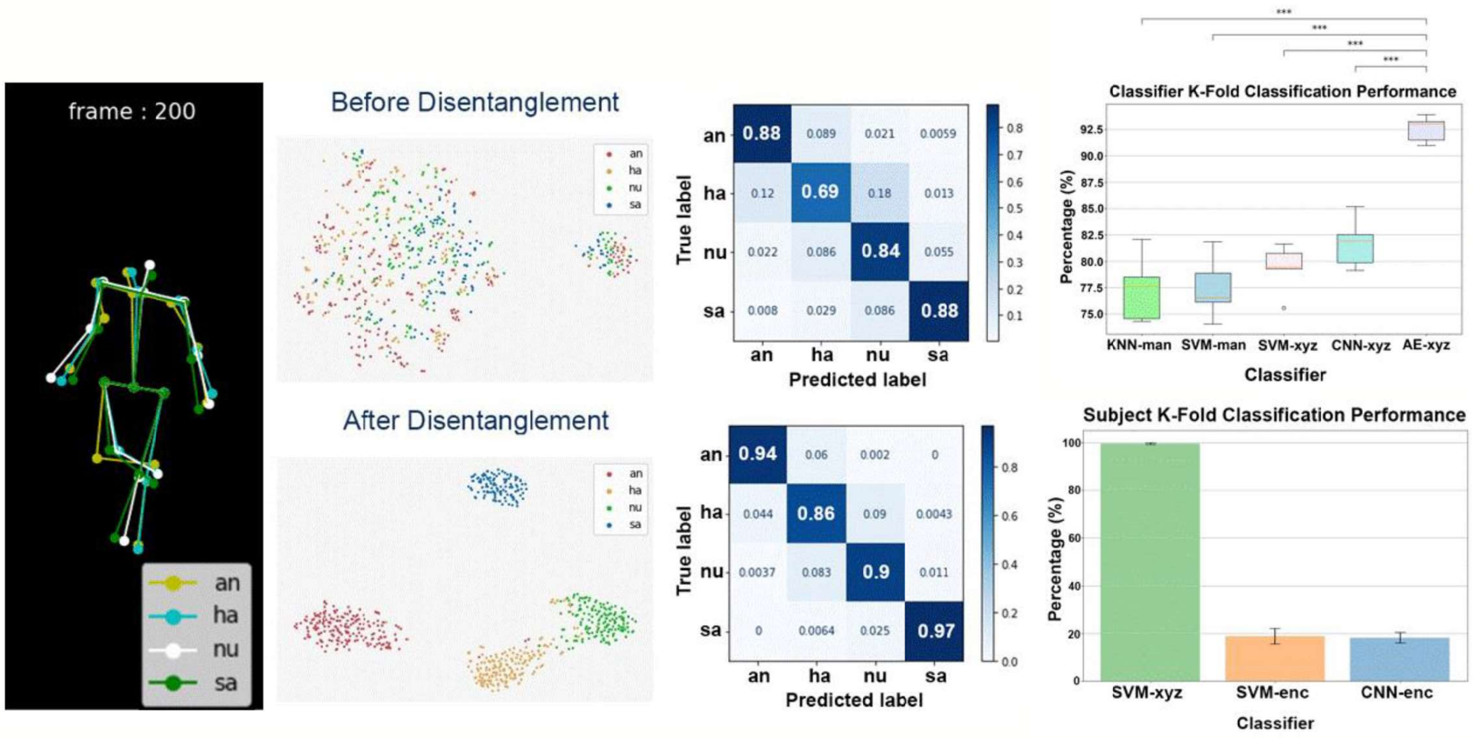
Privacy and Disentangled Representations

- Separate latent representations of identity and the characteristic of interest
- Biometrics information are filtered out in a measurable way
- Inherent designs of explainable, privacy-preserved classification



Malek-Podjaski et al. ‘Towards Explainable, Privacy-Preserved Human-Motion Affect Recognition’, IEEE Symposium Series on Computational Intelligence. https://arxiv.org/abs/2105.03958, 2021

Privacy and Disentangled Representations



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Summary

- Deep Neural Networks can memorise information with relation to the training data
- This property results in inherent vulnerabilities that can be exploited by a malicious attacker
- Considering privacy early in the development of clinical decision support systems is important
- Disentanglement can separate biometrics from the features of interest and allow to filter this information early in the processing pipeline

References

- Kaissis et al. ‘Secure, privacy-preserving and federated machine learning in medical imaging’, Nature Machine Intelligence, 2020.
- Hitaj et al. ‘Deep Models Under the GAN: Information Leakage from Collaborative Deep Learning’, ACM CCS’17, 2017.
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