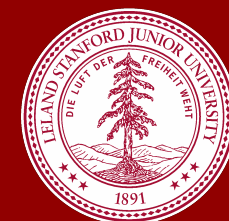


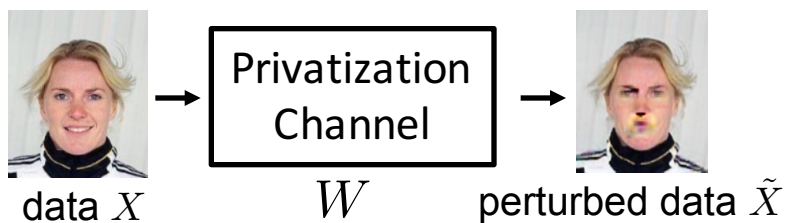


# Generative Modeling for Context-Aware Local Privacy

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## Problem Setup



Goal: erase sensitive info  $S$  (smiling or not) from  $X$  while minimizing distortion  $d(X, \tilde{X})$

## Contribution

### Related works

- Local differential privacy [1]: need data distribution, poor privacy-utility tradeoff
- Detect and perturb [2]: add random noise to sensitive parts. May not achieve minimum distortion.

### Our method

- Decentralized: trust no one even data collector
- Data driven: **do not** need data distribution
- Optimize distortion given privacy constraint

## Learning Algorithm

### Objectives

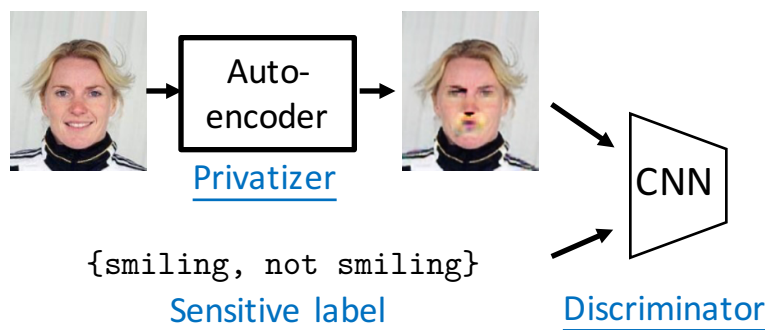
$$\begin{aligned} \min_W & \mathbb{E}_{P_{X, \tilde{X}}} d(X, \tilde{X}) \\ \text{s.t.} & \underbrace{\|P_{\tilde{X}|S=s_1} \circ W - P_{\tilde{X}|S=s_2} \circ W\|_{\text{TV}}}_{\text{Bayesian error of sensitive info. } \geq 1/2 - \epsilon} \leq \epsilon. \end{aligned}$$

### Reformulate as GAN (dual form)

$$\min_W \mathbb{E} d(X, \tilde{X}) + \lambda \left( \max_{f_\omega} \mathbb{E}_{P_{\tilde{X}|s_1}} f_\omega(\tilde{X}) - \mathbb{E}_{P_{\tilde{X}|s_2}} f_\omega(\tilde{X}) \right)$$

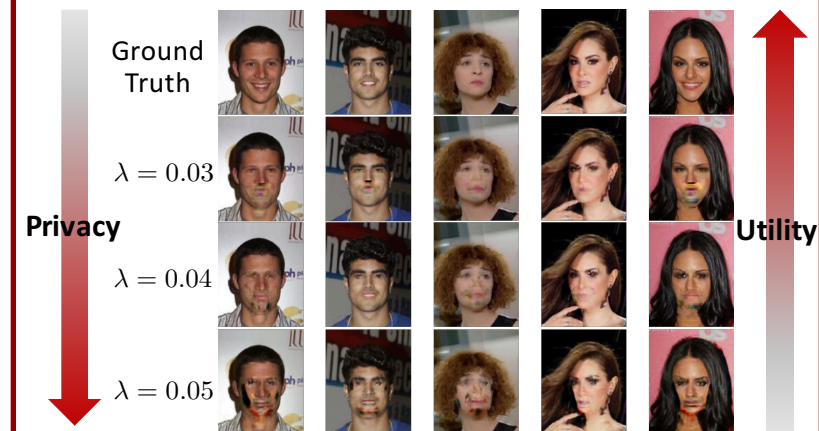
- $\lambda$ : privacy level
- $W$ : privatization channel (generator)
- $f_\omega$ : discriminator

## Training Architecture



Loss function: pixel-wise MSE  $- \lambda$  CNN's cross-entropy

## Results



## Conclusion and Future Works

- Proposed a data driven framework for context-aware privacy
- Achieved better privacy-utility trade-off with theoretical guarantee on privacy
- Can easily incorporate other utility measures
- What next: characterize the fundamental limits on privacy-utility trade-off curves

[1] John Duchi et. al, "Local privacy and statistical mini-max rates", FOCS 2013

[2] Hsiang Hsu et. al, "Discovering information-leaking samples and features", NeurIPS 2019

[3] video available at <https://youtu.be/URXQr8STJL0>