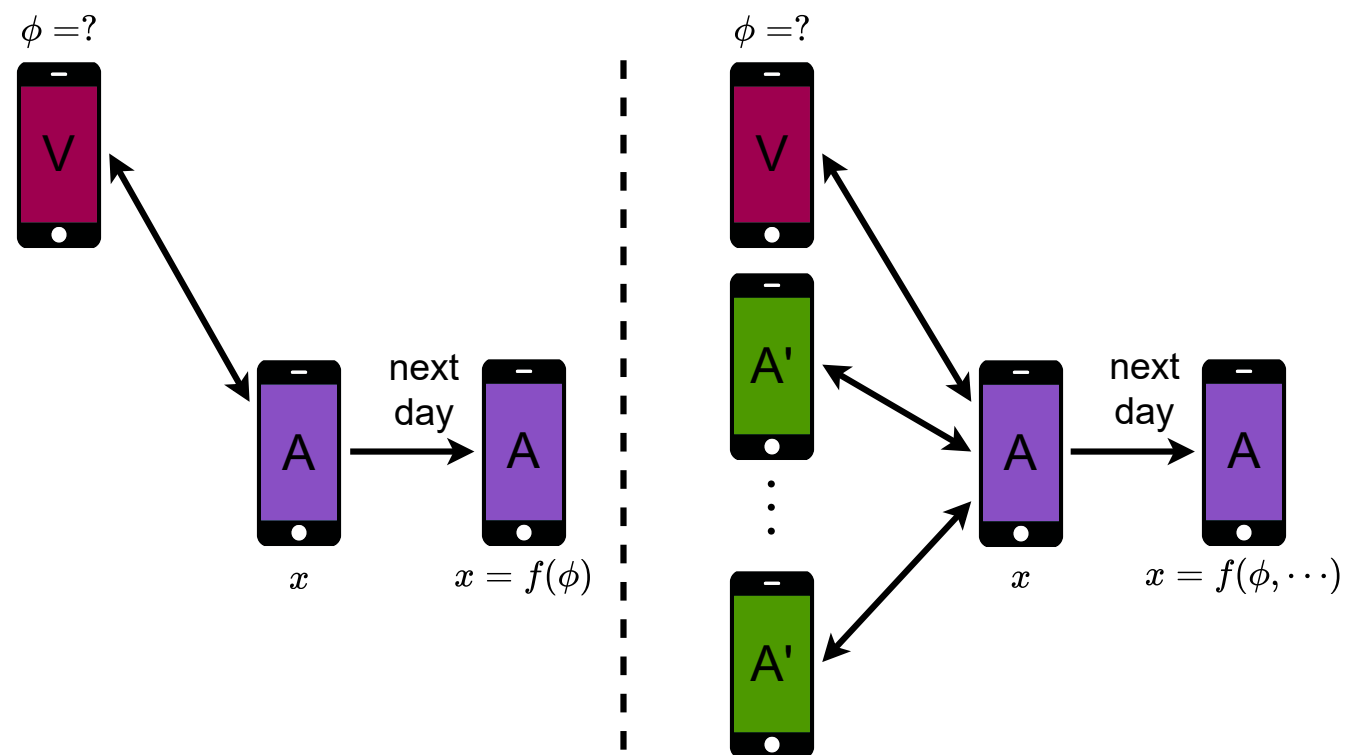


# DNA: Differentially private Neural Augmentation for contact tracing

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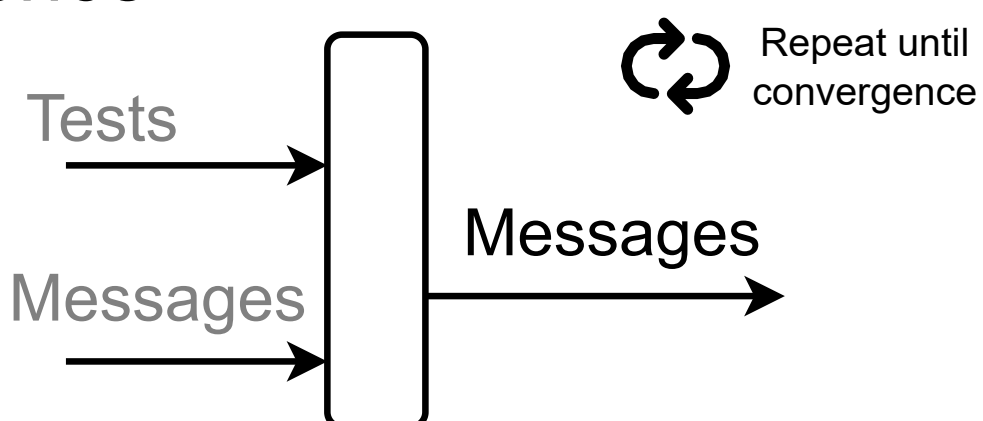
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Concerns about privacy are the main reason for low adoption of contact-tracing algorithms, even though they are shown to be effective [1,2,3]. We present a **Differentially Private (DP)** version of Neural Augmentation to improve predictions in decentralized contact tracing.

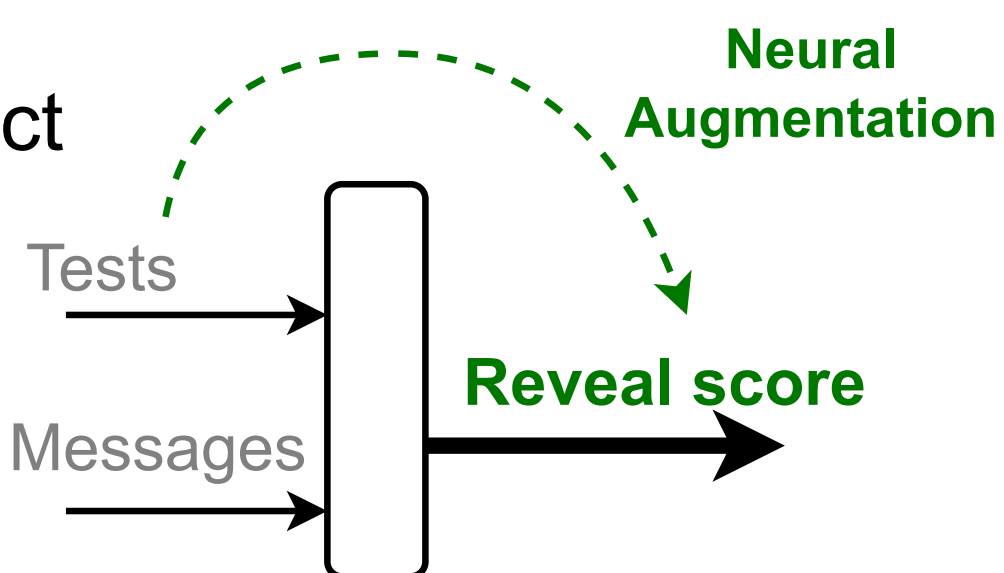


In the **attack scenario**, the Attacker can reconstruct the score of the Victim -- even in the presence of multiple contacts. Our method reveals the score under DP.

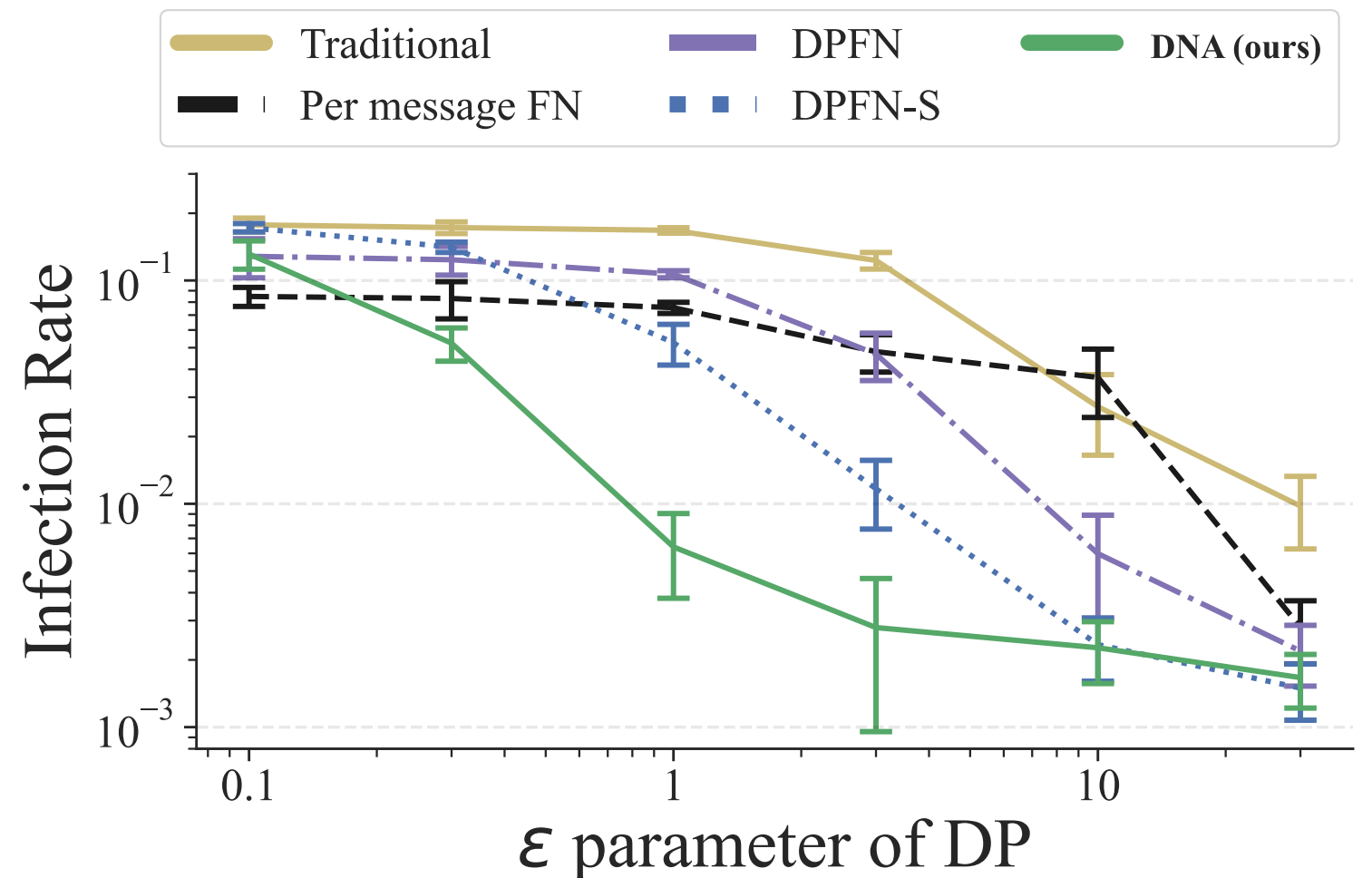
## Inference



## Predict



The reveal of the risk score is a DP function (DPFN), but the predictions can be improved with Neural Augmentation.



In the **trade-off** between privacy and the peak infection rate [4], our method achieves a significantly lower infection rate at the crucial setting of  $\epsilon = 1$  DP.

## DP definition

For  $\epsilon > 0$ ,  $\delta \in [0, 1]$ , a function  $f(\cdot)$ , for any outcome  $\Phi$ , and any two adjacent data sets  $D, D'$ , satisfies [6]:

$$p(f(D) \in \Phi) \leq e^\epsilon p(f(D') \in \Phi) + \delta$$

## Sensitivity

Maximal change with respect to one message, score  $\mu$ :

$$\Delta = \max_{\mu_1, \mu'_1} |f(\{(\mu_1, t_1)\} \cup D) - f(\{(\mu'_1, t_1)\} \cup D)| \leq p_1 \gamma_u \forall D.$$

## Neural Augmentation

The Lipschitz-constrained model has a bounded sensitivity [5]:

$$\phi = G_\theta(\{(\mu_i, t_i)\}_{i=1}^{C_T}) = g_\theta^{(2)}\left(\frac{1}{C} \sum_i g_\theta^{(1)}([\mu_i, t_i]^T)\right).$$

## Algorithm 1 DNA: Differentially private Neural Augmentation

**Require:** Dataset  $D = \{(\mu_i, t_i)\}_{i=1}^{C_T}$ , constants  $p_1, \gamma_u \in (0, 1)$ ;

$$\mu_i \leftarrow \min(\mu_i, \gamma_u)$$

$$\bar{\phi} \leftarrow F(\{(\mu_i, t_i)\}_{i=1}^{C_T}) + p_1 \times G_\theta(\{(\mu_i, t_i)\}_{i=1}^{C_T})$$

$$\phi \leftarrow \bar{\phi} + \mathcal{N}(0, \frac{2}{\epsilon^2} (\gamma_u p_1 (1 + \frac{1}{C_T}))^2 \log(\frac{5}{4\delta}))$$

The neural augmentation (operations in green) increases the sensitivity, but the required additional noise compares favorably in predictions.