



Babol Noshirvani
University of Technology

Privacy Preserving Machine Learning

Mohammad Hoseinpour

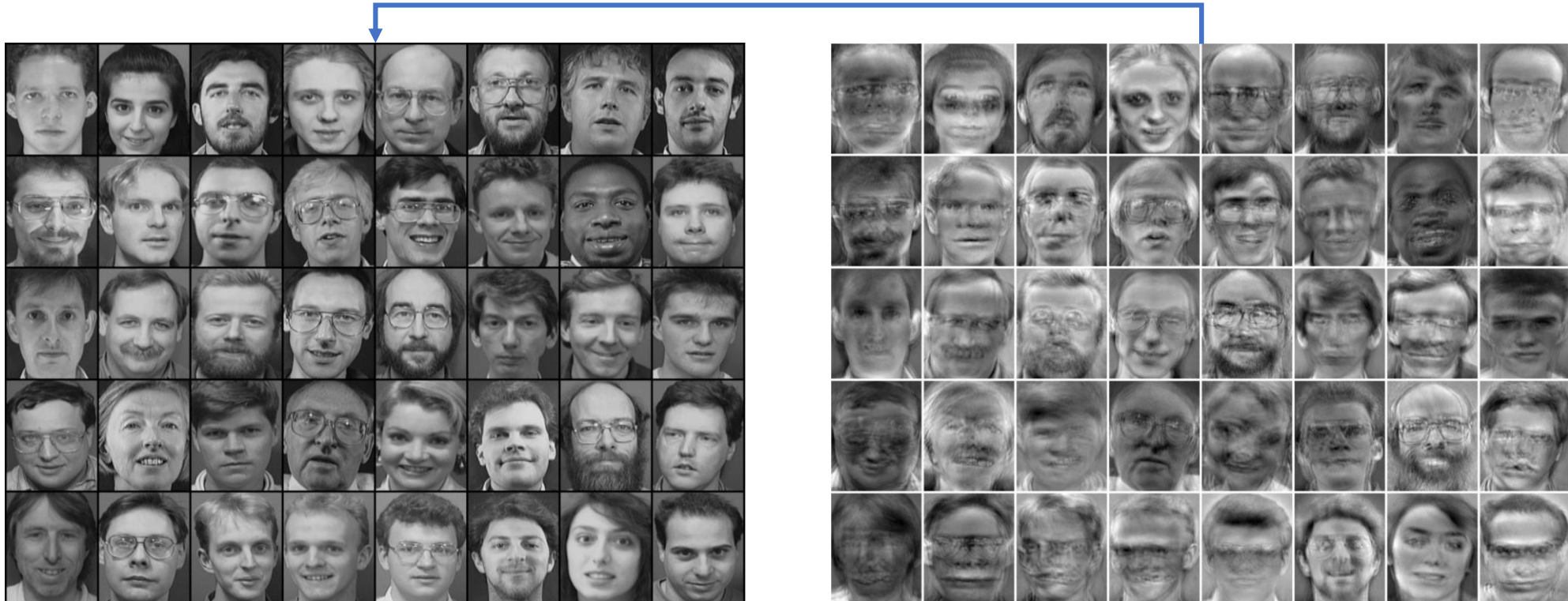
Supervisor : Prof. Ali Aghagolzadeh

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Motivation

- Machine Learning (ML) models can **memorize** training datasets
- Training ML models over **private datasets** can **violate** the **privacy of individuals**
- **Training data extraction attacks:**
 - Fredrikson et al. (2015), “Model Inversion Attacks that Exploit Confidence Information and Basic Countermeasures”

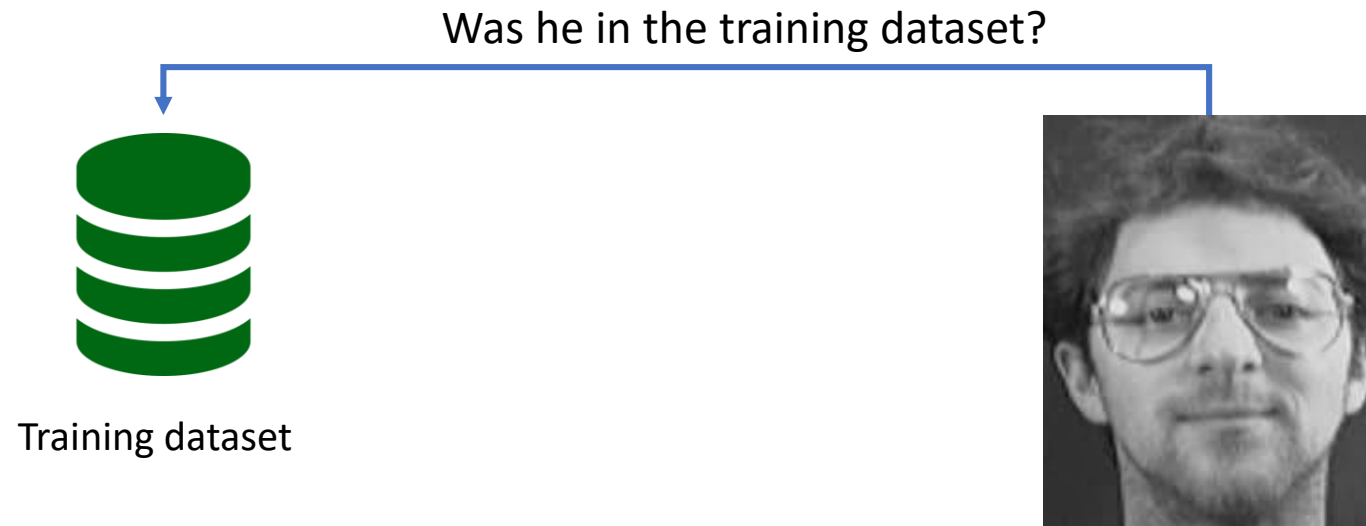
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An example of model inversion attack

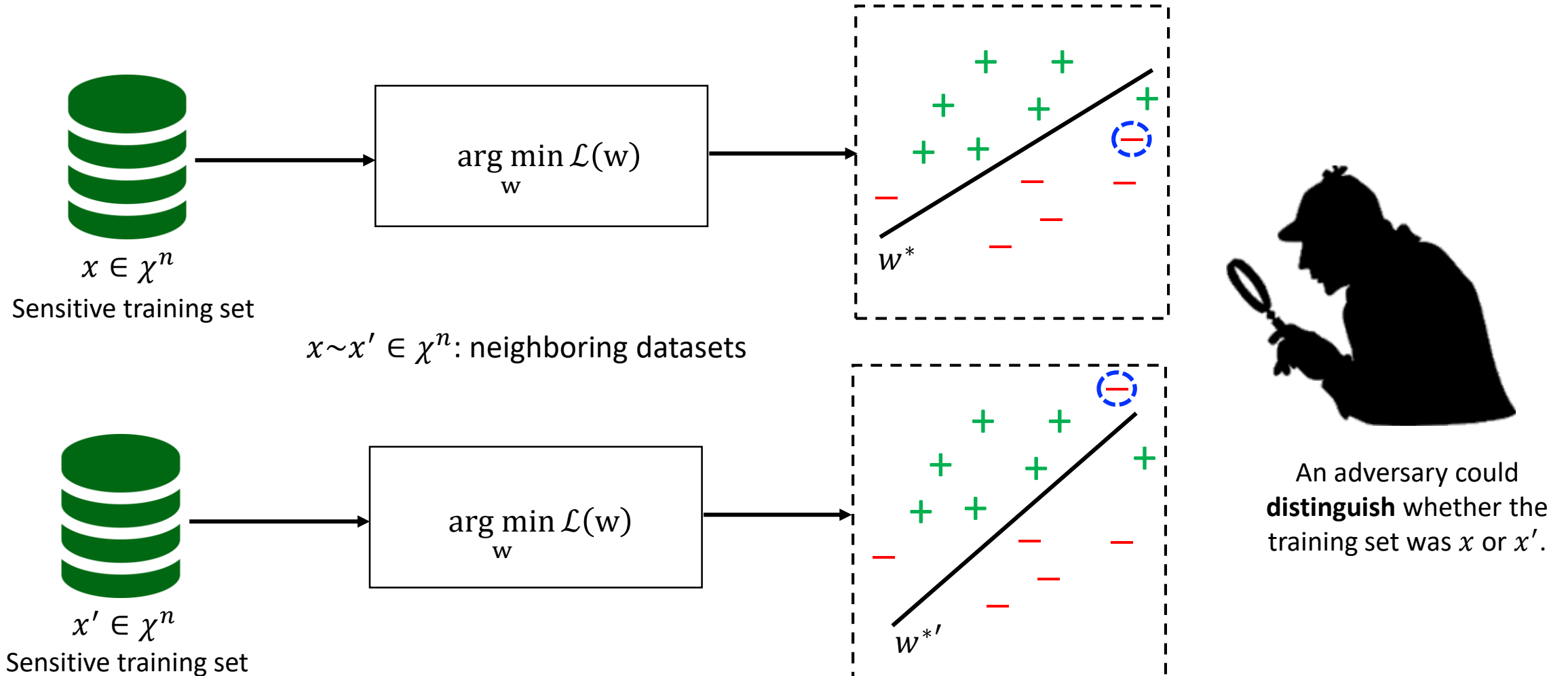
Motivation

- Machine Learning (ML) models can **memorize** training datasets
- Training ML models over **private datasets** can **violate** the **privacy of individuals**
- **Membership inference attacks:**
 - Shokri et al. (2016), “Membership Inference Attacks Against Machine Learning”



Non-Private Logistic Regression

- The **decision boundary** of the classifier is **sensitive to the individual data points** in the training set.



Private Logistic Regression

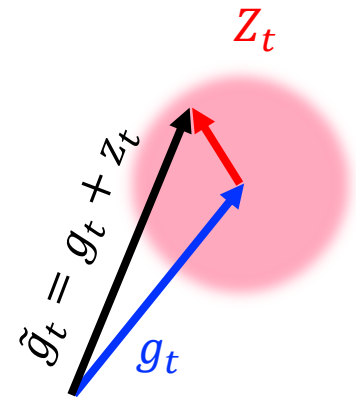
- We apply **Gaussian mechanism** for privatizing the **updating rule** of the gradient descent

$$\text{Empirical Risk: } \mathcal{L}(w) = \frac{1}{n} \sum_{i=1}^n \ell(w, (x_i, y_i)) + \lambda R(w)$$

Algorithm 1 Noisy Projected Gradient Descent $(\mathcal{L}, \mathcal{C}, \eta, \sigma)$

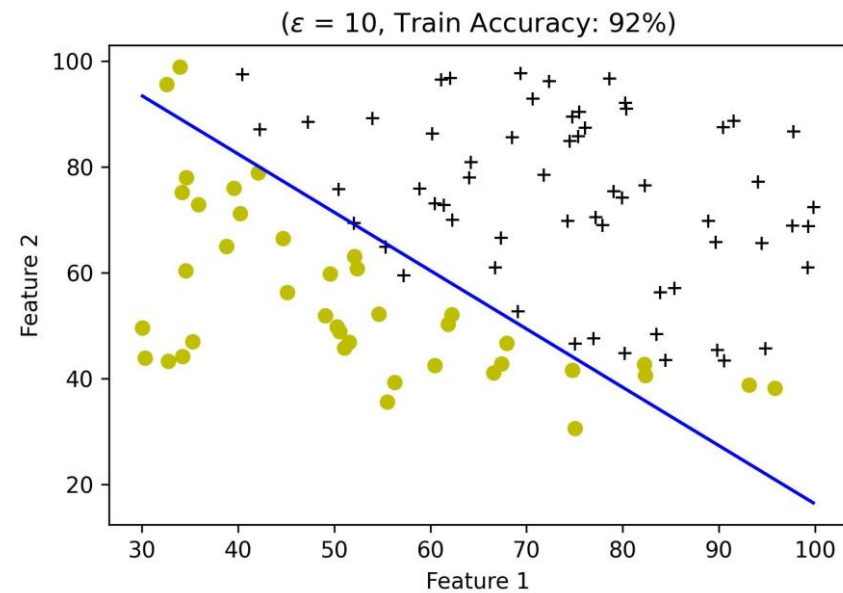
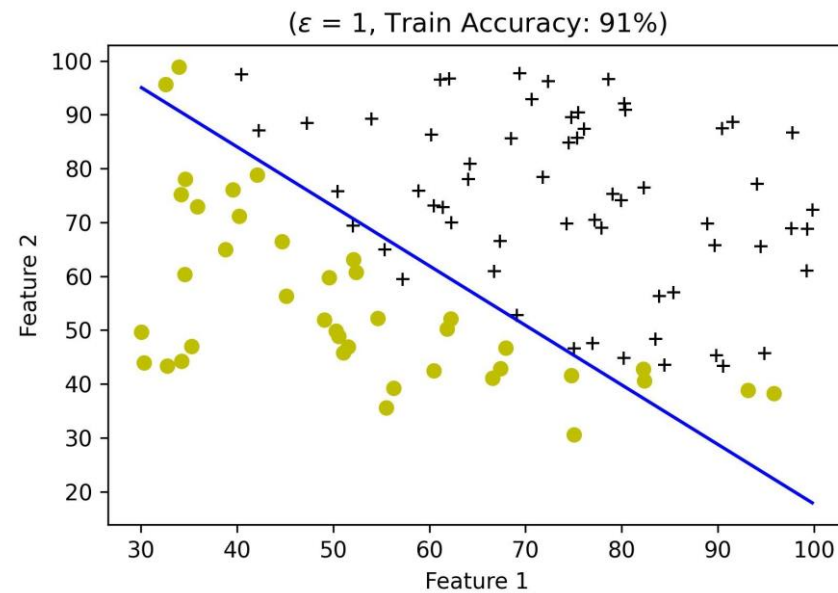
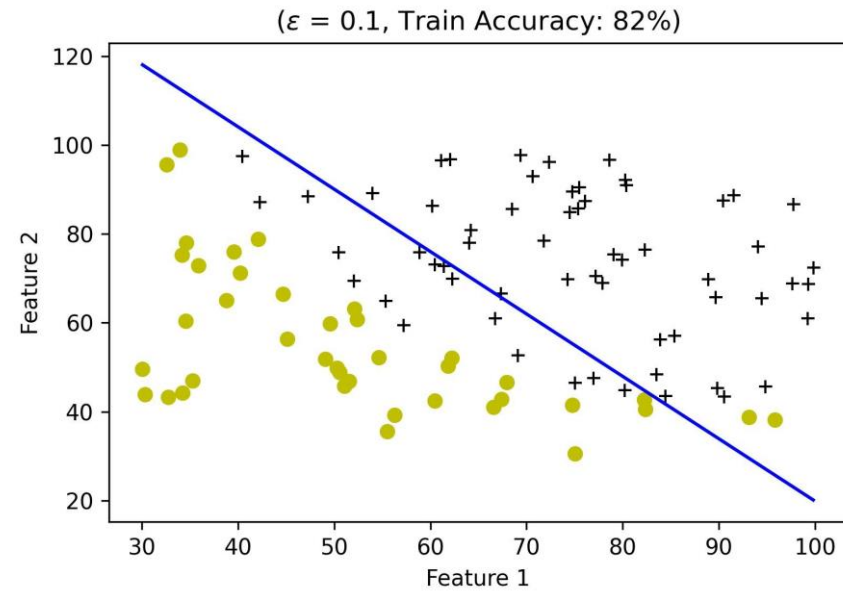
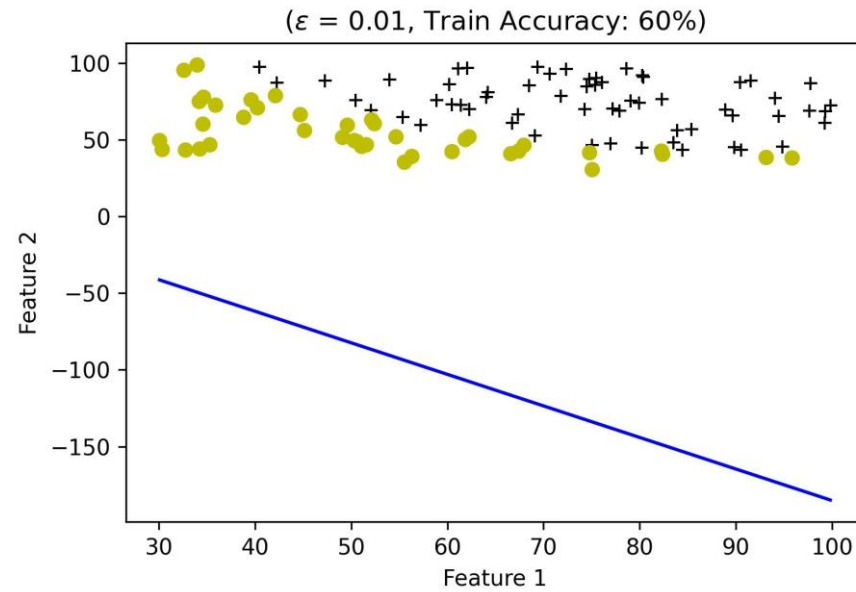
Inputs: Set $\mathcal{C} \subseteq \mathbb{R}^d$, noise parameter σ , learning rate η , loss function $\mathcal{L}(w)$.

```
1:  $w_0 \leftarrow$  arbitrary point in  $\mathcal{C}$ ;  
2: for  $t = 1, 2, \dots, T$  do  
3:    $g_t \leftarrow \nabla \mathcal{L}(w_{t-1})$ ;  
4:    $\tilde{g}_t \leftarrow g_t + \mathcal{N}(0, \sigma^2 I_d)$ ;  
5:    $u_t \leftarrow w_{t-1} - \eta \tilde{g}_t$ ;  
6:    $w_t \leftarrow \Pi_{\mathcal{C}}(u_t)$ ;  
7: end for  
8: return  $w_T$ ;
```



Perturbed gradient vector due to the additive Gaussian noise

Results



Thank You