Mnemonist: Locating Model Parameters that Memorize Training Examples

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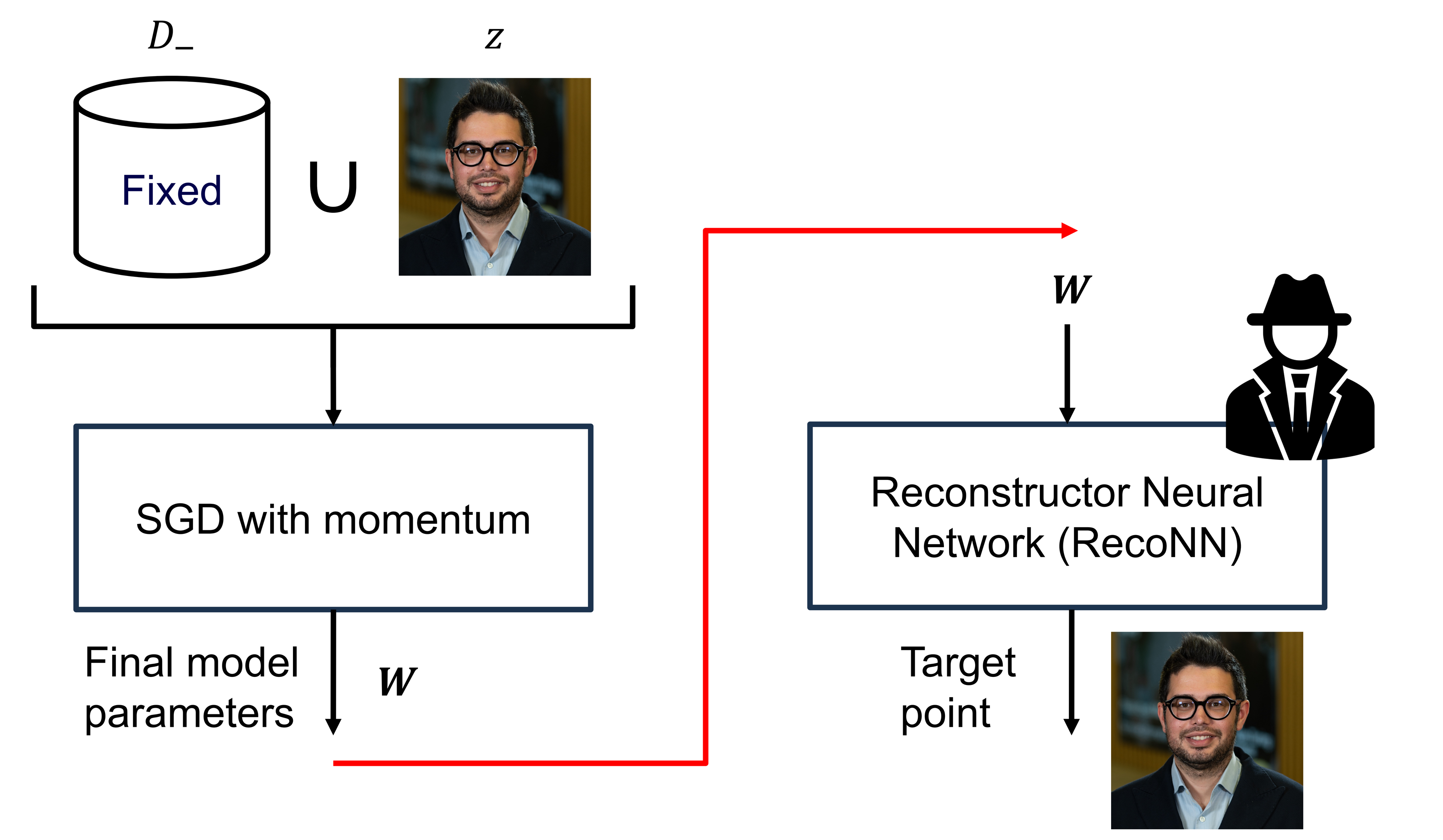
Reconstructing training data with an informed adversary

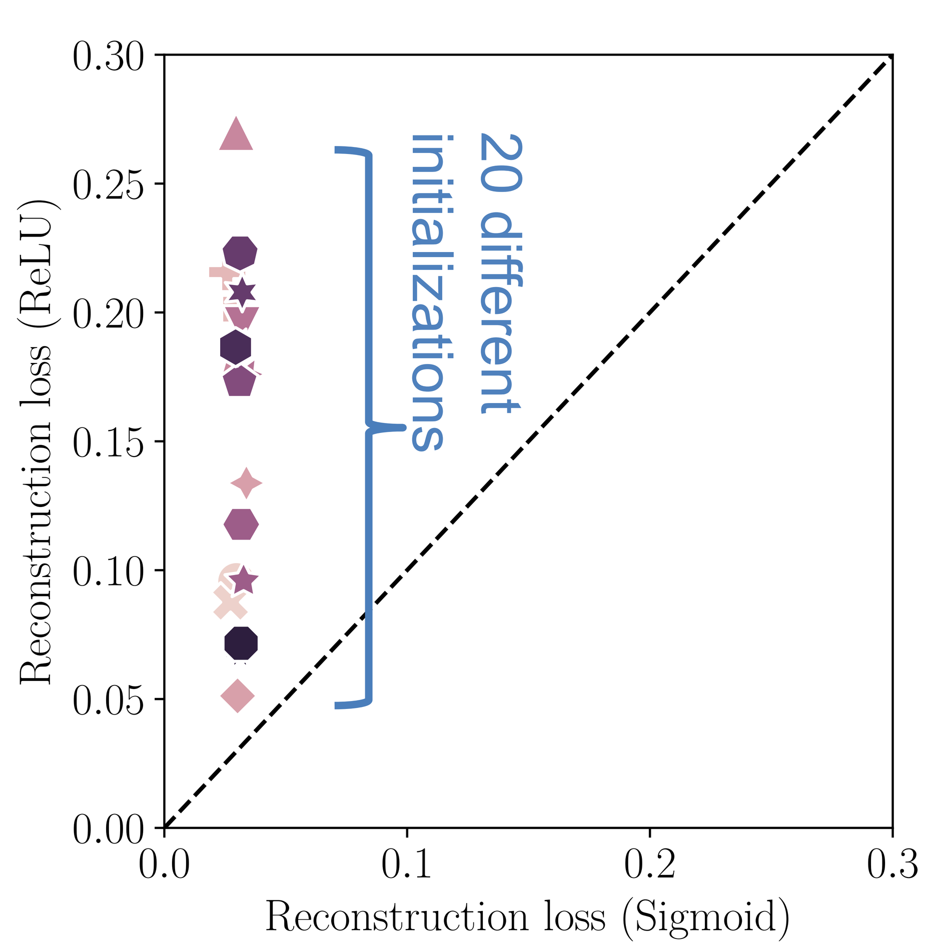


The attack consists of three steps:

1. Training **shadow models** to collect information about the impact of training examples on model parameters
   - The adversary knows $(D_-, \boldsymbol{W}, \boldsymbol{W}_{\text{init}}, S)$ + a public dataset $\bar{Z} = \{\bar{z}_i\}_{i=1}^{K}$
   - The adversary trains each shadow model, $\overline{\boldsymbol{W}}_i$, on $D_- \cup \{\bar{z}_i\}$
2. Training a **RecoNN** to output training examples from model parameters
   - Loss function: $\mathrm{MSE}(\mathrm{RecoNN}(\overline{\boldsymbol{W}}_i), \bar{z}_i) + \mathrm{MAE}(\mathrm{RecoNN}(\overline{\boldsymbol{W}}_i), \bar{z}_i)$
3. Producing a **candidate** reconstruction for the target point

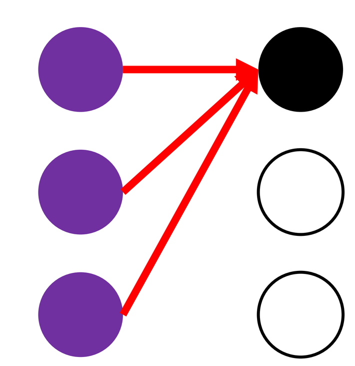
Reconstruction quality depends heavily on the activation

ReLU activations lead to **higher reconstruction loss** compared to **Sigmoid**.



Why is training data reconstruction from ReLU activated models hard?

Characterising the fundamental property of the existence of **redundant parameters** in models with ReLU activations:



Pre-activation: $h^l = w^l x + b$

Activation: $a^l = R(h^l)$

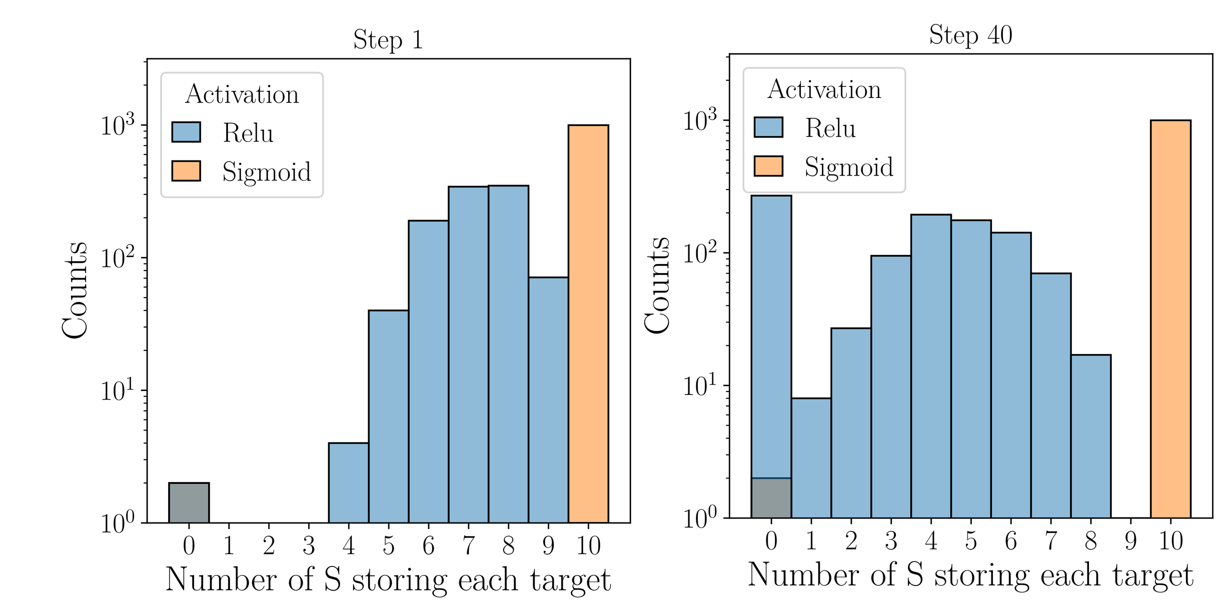
$$\frac{\partial \mathcal{L}}{\partial w^l} = \frac{\partial \mathcal{L}}{\partial a^l} \cdot \frac{\partial a^l}{\partial h^l} \cdot \frac{\partial h^l}{\partial w^l} = \frac{\partial \mathcal{L}}{\partial a^l} \cdot R'(h^l) \cdot x$$

$$\frac{\partial \mathcal{L}}{\partial w^l} = \begin{cases} 0 \\ \mathrm{scale} \cdot x \end{cases}$$

No information about the input is stored in incoming parameters to non-activate neurons

Incoming parameters to active neurons store a copy of input data

Demonstrating the existence of redundant parameters **in practice** by studying the **training dynamics**:

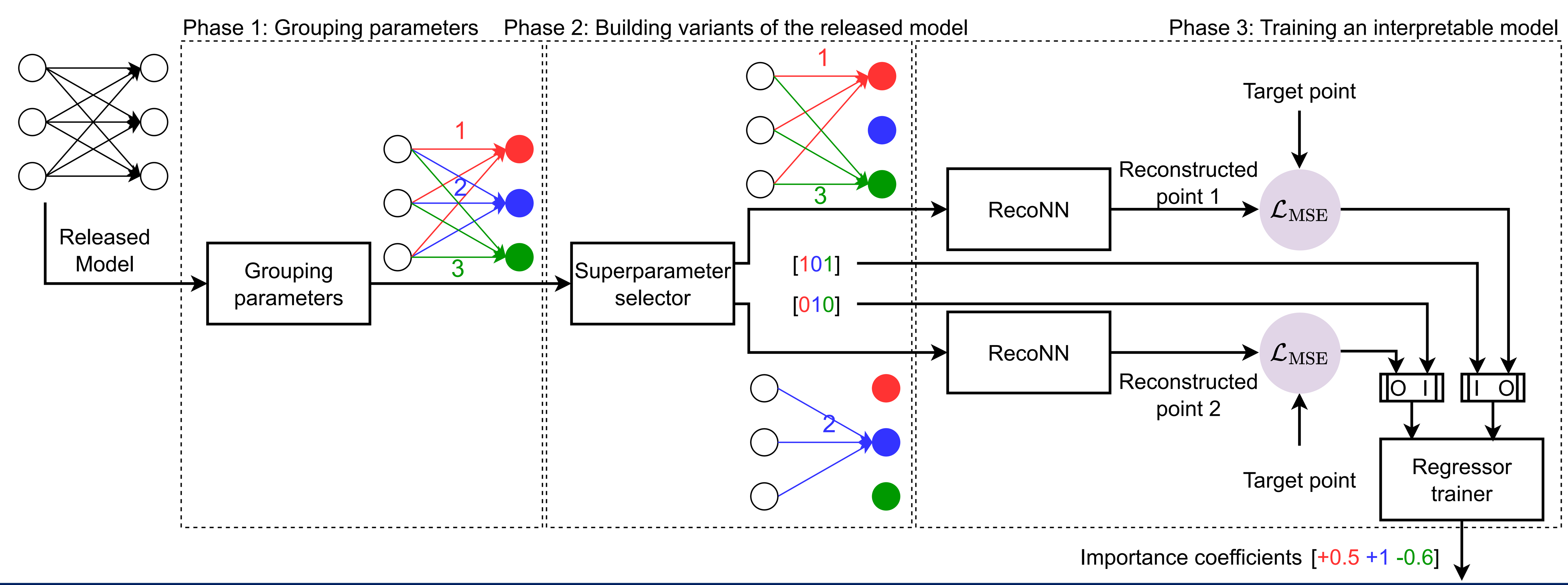


Histogram of the summation of

$$\text{Binary scale} = \begin{cases} 0 & \text{if scale} = 0 \\ 1 & \text{Otherwise} \end{cases}$$

of all rows per target point. [1k target points]

Mnemonist: finding parameters that store target examples



Mnemonist helps RecoNN to improve the quality of reconstructions

Mnemonist-RecoNN trains RecoNN only on **informative superparameters**.

Approach	run1	run2	run3	run4
RecoNN	.2040	.2705	.0908	.1315
Mnemonist-RecoNN	.1738	.2385	.0730	.1158

Algorithm 1: Mnemonist-RecoNN

Input: Fixed set D_-, K public target examples $\{\bar{z}_k\}_{k=1}^{K}$, Shadow model training Algorithm $A(\cdot)$, RecoNN training algorithm $B(\cdot)$.

Output: Mnemonist-guided RecoNN.

```
for all k ∈ range(K) do
    W̄_k ← A(D_− ∪ {z̄_k})                ▷ Train K shadow models
φ ← B({W̄_k, z̄_k}_{k=1}^K)                ▷ Train RecoNN
I ← Mnemonist(φ)          ▷ Apply Mnemonist to identify the importance of superparameters
for all k ∈ range(K) do
    W̃_k ← Selector(W̄_k, I)              ▷ Select only important superparameters
φ̃ ← B({W̃_k, z̄_k}_{k=1}^K)    ▷ Train RecoNN on the selected important superparameters
return φ̃                                 ▷ Mnemonist-guided RecoNN
```