Model inversion attacks on facial and speaker recognition models

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Topic

Can we "hack" a facial recognition model and retrieve its original training data?



Facial recognition model in Mission Impossible [6]

Original paper and work

- Our choice was: "Model Inversion Attacks that Exploit Confidence Information and Basic Countermeasures" (Fredrikson et al. [2]).
- ▶ Very first paper to introduce concept of "model inversion attacks"!





Example of model inversion attack in a facial recognition model [2]

Implementation

- Started from an unofficial GitHub repository [7]
- ► Face dataset: AT&T ("ORL") [1]

We inverted three facial-recognition models: Softmax, MLP and DAE (denoising autoencoder).

Model	Paper's error	Our model's error
Softmax	7.5%	$8.1 \pm 1.2\%$
MLP	4.2%	$4.5 \pm 0.4\%$
DAE	3.3%	$8.6 \pm 1.0\%$

Each was attacked in two threat settings:

- ▶ White-box: Full access to the model's weights and gradients. We perform direct gradient-based inversion (momentum-SGD) on the loss. (Possible if the model is on your phone for example).
- ▶ Black-box: Only query access to output confidence scores.

How to invert a model? (white-box setting)

Algorithm 1 Inversion attack for facial recognition models.

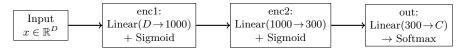
```
1: function MI-FACE(label, \alpha, \beta, \gamma, \lambda)
               c(\mathbf{x}) \stackrel{\text{def}}{=} 1 - \tilde{f}_{label}(\mathbf{x}) + \text{AuxTerm}(\mathbf{x})
 2:
 3:
              \mathbf{x}_0 \leftarrow \mathbf{0}
 4:
               for i \leftarrow 1 \dots \alpha do
                      \mathbf{x}_i \leftarrow \text{PROCESS}(\mathbf{x}_{i-1} - \lambda \cdot \nabla c(\mathbf{x}_{i-1}))
 5:
                      if c(\mathbf{x}_i) > \max(c(\mathbf{x}_{i-1}), \dots, c(\mathbf{x}_{i-\beta})) then
 6:
 7:
                             break
 8:
                      if c(\mathbf{x}_i) \leq \gamma then
 9:
                             break
10:
               return [\arg\min_{\mathbf{x}_i}(c(\mathbf{x}_i)), \min_{\mathbf{x}_i}(c(\mathbf{x}_i))]
```

Inversion attack algorithm for facial recognition models [2]

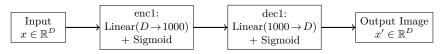
- Gradient based search approach;
- ► AuxTerm(**x**) is an extra regularizer or projection penalty to keep the image realistic;
- Stop if we reach α iterations, if the loss hasn't improved over the last β iterations or if the loss itself drops below a threshold γ .

How to invert a model? (white-box setting for DAE)

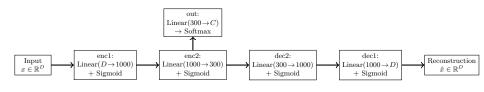
Facial recognition model for DAE:



Then, two things for two steps for the mode inversion attack:



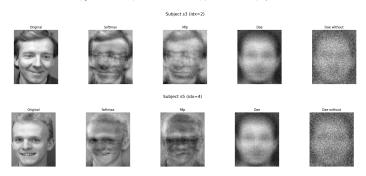
and then, for the inversion:



Results (white-box setting)

Initialization:

- ▶ Softmax: $\alpha = 50\,000, \beta = 1000, \gamma = 10^{-4}, \lambda = 0.05, \mu = 0.95$
- ► MLP: same as Softmax
- **DAE:** $\lambda = 0.1, \mu = 0.9, \alpha = 5000, \beta = 100, \gamma = 10^{-3}$



Examples of inversion attacks we have generated

Results (white-box setting)



 $Examples\ of\ inversion\ attacks\ we\ have\ generated$

How to invert a model? (black-box setting)

Algorithm 1 Inversion attack for facial recognition models.

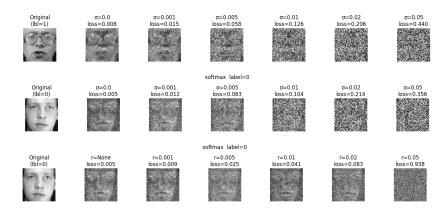
```
1: function MI-FACE(label, \alpha, \beta, \gamma, \lambda)
               c(\mathbf{x}) \stackrel{\text{def}}{=} 1 - \tilde{f}_{label}(\mathbf{x}) + \text{AuxTerm}(\mathbf{x})
  2:
  3:
               \mathbf{x}_0 \leftarrow \mathbf{0}
  4:
               for i \leftarrow 1 \dots \alpha do
  5:
                      \mathbf{x}_i \leftarrow \text{PROCESS}(\mathbf{x}_{i-1} - \lambda \cdot \nabla c(\mathbf{x}_{i-1}))
                      if c(\mathbf{x}_i) > \max(c(\mathbf{x}_{i-1}), \dots, c(\mathbf{x}_{i-\beta})) then
 6:
  7:
                              break
 8:
                      if c(\mathbf{x}_i) \leq \gamma then
 9:
                              break
10:
               return [arg min<sub>\mathbf{x}_i</sub> (c(\mathbf{x}_i)), min<sub>\mathbf{x}_i</sub> (c(\mathbf{x}_i))]
```

Inversion attack algorithm for facial recognition models [2]

- ► Instead of computing the exact gradient ⇒ approximate it!
- For small $\varepsilon > 0$, we have:

$$\frac{\partial c}{\partial y}(x) \simeq \frac{c(x+\varepsilon y) - c(x-\varepsilon y)}{2\varepsilon ||y||}.$$

Results (black-box setting)



Examples of inversion attacks we have generated

Countermeasures

How to prevent the model from model inversion attacks?

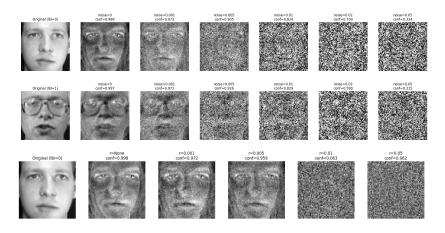
- Rounding confidences
 - Quantize

$$p_j \mapsto \left\lfloor \frac{p_j}{r} \right\rfloor \times r$$
 then re-normalize.

- Blocks SPSA inversion for $r \ge 10^{-2}$, with < 0.5% accuracy drop.
- Gaussian output noise
 - Add $\epsilon \sim \mathcal{N}(0, \sigma^2)$ to each p_j , clip to [0, 1], re-normalize.
 - Faces unrecognizable for $\sigma \ge 0.01$, with $\approx 1\%$ accuracy drop.

Defense	Block threshold	Accuracy drop
None	_	0%
Rounding (r)	$r \ge 10^{-2}$	< 0.5%
Gaussian noise	$\sigma \ge 0.01$	$\approx 1\%$

Examples of countermeasures (black-box setting)



Examples of inversion countermeasures we have generated

Speaker Recognition Model

- Can we perform the same type of model inversion on a speaker recognition model (i.e., starting from audio training data)?
- Can we create voice deepfakes of individuals in the training data using the inverted audio samples?

Speaker Recognition Model

An article already addressed all of our questions: "Introducing Model Inversion Attacks on Automatic Speaker Recognition" [4].

- ▶ Inverting audio samples: they achieved 90.48% accuracy with inverted audio samples reconstructed via model inversion attacks starting from Laplace noise.
- ▶ Creating deepfakes: the generated audio samples are not perceptually close to the originals for human listeners, but they are close enough to fool automated detection systems. However, using a vocoder, the authors were able to generate a few high-quality spoofed audio samples that resembled the original speaker.

This was done entirely in a **white-box setting** — could it also be **feasible in a black-box setting**?

Speaker recognition model: implementation

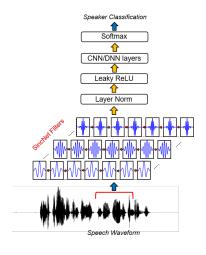
- ➤ To try model inversion in a black-box setting we had to create a speaker recognition model!
- ▶ Dataset: TIMIT [3] → broadband recordings of 630 speakers of eight major dialects of American English, each reading ten phonetically rich sentences.



Speaker recognition model described in [4]

Speaker recognition model: implementation

▶ **SincNet:** neural architecture for processing raw audio samples [5].



SincNet architecture [5]

Model Inversion Attack for Speech Recognition

Algorithm 1 Invert SincNet via Gradient Descent

```
Require: Pre-trained speaker-ID model f, target label c, iterations N, learning rate \eta
Ensure: Generated waveform x_N

    Initialize: x ← N(0, I)

                                                                                            2: for t=0 \rightarrow N-1 do
       z \leftarrow f(x)
                                                                                         ▷ logits from model
      p \leftarrow \operatorname{softmax}(z)
                                                                                         \ell \leftarrow -\log p[c]
                                                                              cross-entropy loss for target
      g \leftarrow \nabla_x \ell
                                                                                      x \leftarrow x - nq
                                                                                              ▷ gradient step
       x \leftarrow \text{clip}(x, -1, 1)

    keep in valid audio range

9: end for
10: return x
```

- ▶ Initialize: $x_0 \sim \mathcal{N}(0, I)$
- **Refine:** update x by gradient descent to minimize $\ell_{\text{CE}}(f(x), c)$
- \triangleright Clamp: project x back into the valid audio range after each step
- ▶ **Terminate:** stop when $p(c \mid x)$ exceeds a confidence threshold or max iterations reached

Thank you

Thanks for your attention!

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- [3] John S. Garofolo. TIMIT Acoustic-Phonetic Continuous Speech Corpus. Tech. rep. Linguistic Data Consortium, 1993. URL: https://catalog.ldc.upenn.edu/LDC93S1.
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- [5] Mirco Ravanelli and Yoshua Bengio. "Speaker recognition from raw waveform with SincNet". In: 2018 IEEE Spoken Language Technology Workshop (SLT). IEEE, 2018, pp. 1021–1028. DOI: 10.1109/SLT.2018.8639541.
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- [7] Zhipeng Zhang. MIA: Model Inversion Attack Toolkit. GitHub repository. Online: https://github.com/zhangzp9970/MIA (accessed 2025-05-06). 2020.