IEEE Symposium on Security and Privacy
Deep Learning and Security Workshop (May 26th, 2022)

# Concept-Based Adversarial Attacks: Tricking Humans and Classifiers Alike

Johannes Schneider, Giovanni Apruzzese

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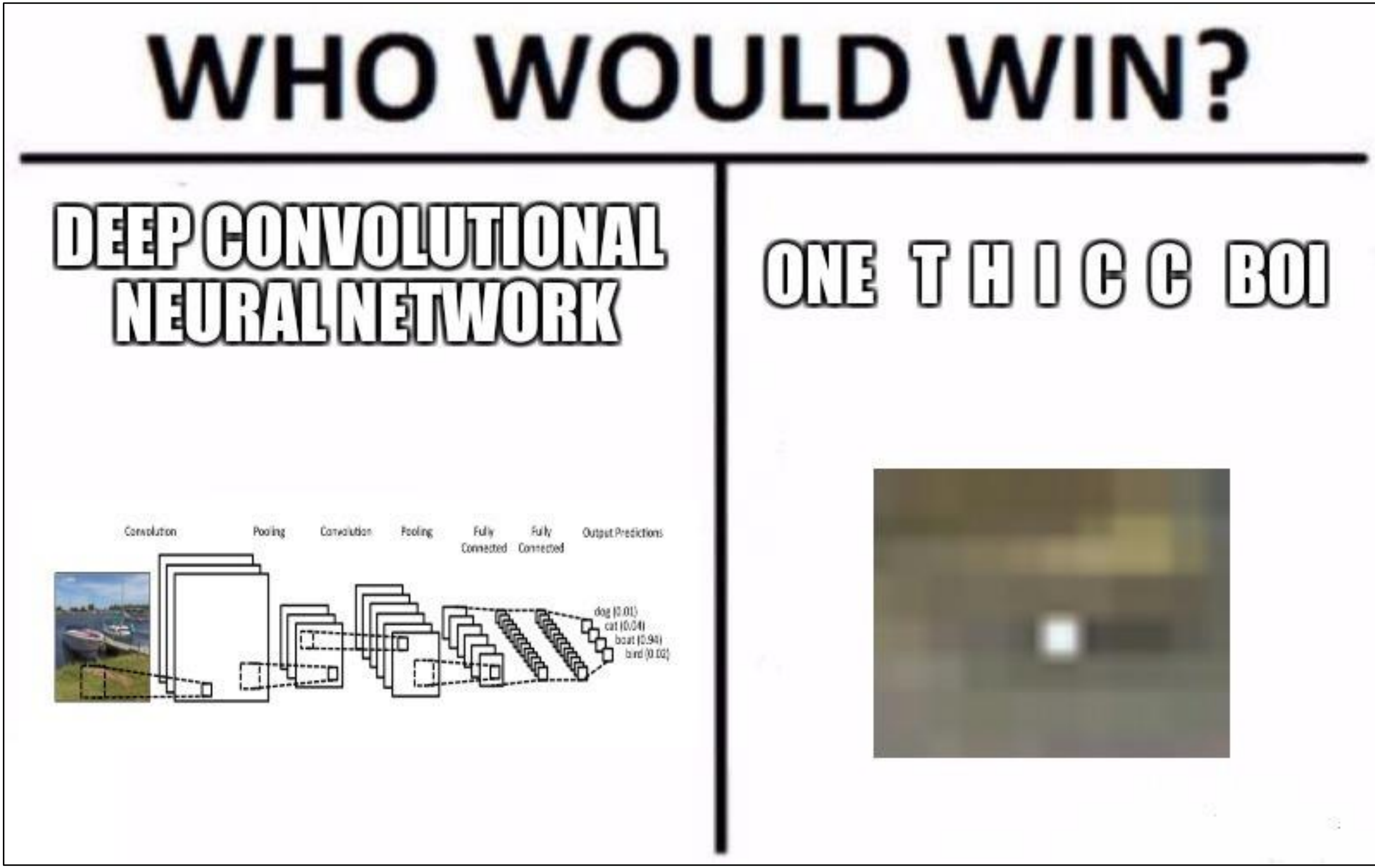

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# Scenario

- Deep Learning (DL) is used for a plethora of applications.
- In some cases, however, the "decision making" is based on:
  - The output of a *DL model*
  - The interpretation of a *human* to such output

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- Case in point: online marketplace
  - A person wants to sell an item (e.g., a car)
  - This person (i.e., the seller) uploads the images of such an item on an online marketplace
  - The marketplace automatically provides an estimate of the "value" of the corresponding item
    - This is done via DL [1]
  - Another person (i.e., a potential buyer) looks at the images, then looks at the "suggested" price, and determines whether to buy or not the corresponding item
    - The human uses the output of the DL model to make their decisions



[1] A. Varma, A. Sarma, S. Doshi, and R. Nair, "House price prediction using machine learning and neural networks," in 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT). IEEE, 2018,

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# Attack – what if…

- What if the seller has malicious intentions?

→ The seller may want to induce the DL model to estimate a higher price

- Doing this by introducing "imperceptible" perturbations may trick the DL…
- …but not the human!

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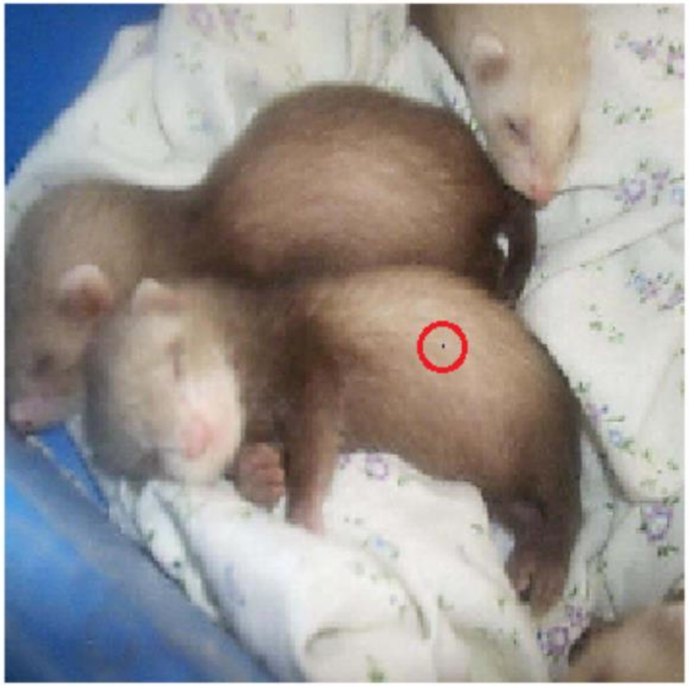

**Hamster(35.79%)**
**Nipple(42.36%)**

Reference: Su Jiawei, Danilo Vasconcellos Vargas, and Kouichi Sakurai. "One pixel attack for fooling deep neural networks." *IEEE Transactions on Evolutionary Computation* (2019)

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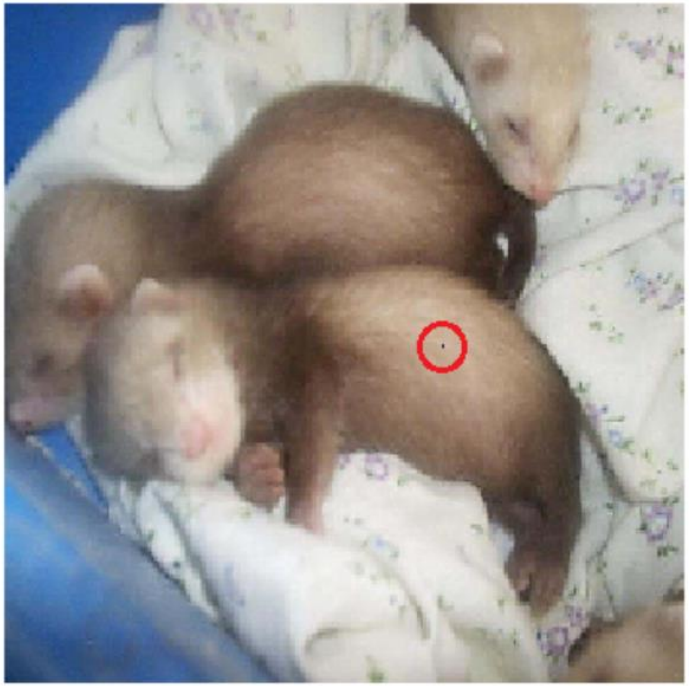

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In some cases, "imperceptible" perturbations **may not be what an attacker wants!**

↓

This is especially true when there is a "human-in-the-loop".

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# Solution (high-level)

- If humans are involved in the "decision making" process, then such humans will react to clearly incorrect outputs of DL models.
  - Humans may suspect an adversarial attack taking place; or
  - They may think that the DL model is faulty, and hence not trust/believe its output
  - Both of the above are **detrimental** for the attacker!

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  - Both of the above are **detrimental** for the attacker!

> (Malicious) solution: deceive both the human *and* the DL model!

- A DL model that thinks that a "FIAT Panda" is a "VW Polo" will output a very high price
  - But if the "perturbation" only affects a single pixel, nobody will fall for it!
- A FIAT Panda is clearly different than a VW Polo, so the perturbation (whatever it is) must be *perceived* by the human

→ The FIAT Panda must be changed in such a way that the human can be somewhat fooled
  - E.g.: the human should think that "it could be a Panda… but it could also be a Polo"

- FIAT Panda MSRP: ~10k $
- VW Polo MSRP: ~20k $

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# Solution (low-level) – How to achieve this in practice?

## Concept-based Adversarial Attacks

- The idea is using "explainability" techniques [2] to create adversarial examples.



[2] J. Schneider and M. Vlachos, "Explaining neural networks by decoding layer activations," in *International Symposium on Intelligent Data Analysis*, 2021

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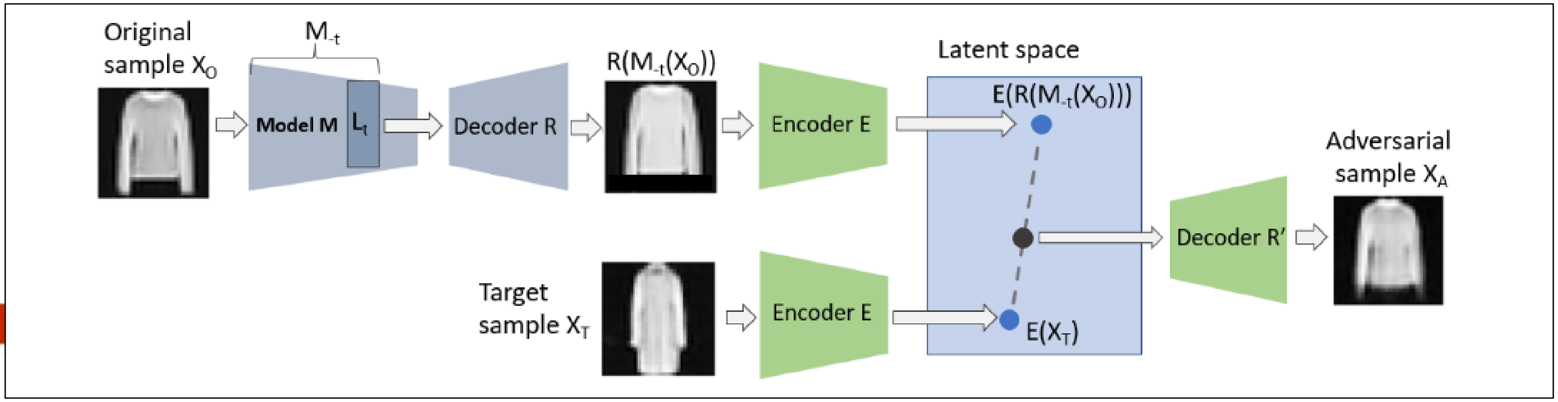
# Solution (low-level) – How to achieve this in practice?

## Concept-based Adversarial Attacks

- The idea is using "explainability" techniques [2] to create adversarial examples.
- Requirements:
  - An "original sample" (i.e., a FIAT Panda)
  - A desired "target sample" (i.e., a VW Polo)
  - A given magnitude of the perturbation (neither too big nor too small)
    - If the FIAT Panda "becomes" a VW Polo, then the adversarial attack would be unfair
    - …and the "buyer" will complain ☺
  - The details of a DL model – based on Convolutional Neural Networks (CNN)
    - These attacks can be transferred!
    - IMPORTANT: the training procedure of the targeted CNN is *not* affected!
- Output: an "adversarial example" that is a mix between the original and target sample

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# Experiments – Objectives

Given the following:

- Original sample, $\mathcal{O}$
- Target sample, $\mathcal{T}$
- Adversarial sample, $\mathcal{A}$

We design our experiments with three goals in mind:

1. *Misclassification:* the sample $\mathcal{A}$ should be classified as the class of $\mathcal{T}$ (which is different than the class of $\mathcal{O}$)

2. *Resembling the target sample*: the sample $\mathcal{A}$ should be similar to sample $\mathcal{T}$ as measured by a given function $f$ (e.g., the L2-norm)

3. *Remaining closer to the original sample:* the sample $\mathcal{A}$ should be similar to sample $\mathcal{O}$ as measured by a given function $f$ (e.g., the L2-norm)

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# Experiments – Testbed

We consider two scenarios, each associated to a given dataset: *MNIST* and *Fashion-MNIST*.

Such datasets are used to train three CNN models:

- *VGG-11* ← our baseline
- *VGG-13*
- *Resnet-10*

We will showcase the adversarial transferability by using CNN with different architectures.

We consider four methods to generate $\mathcal{A}$ by "shifting" $\mathcal{O}$ towards $\mathcal{T}$, namely:

i. Autoencoder 1 (we "deconstruct" $\mathcal{O}$ and recreate it to resemble $\mathcal{T}$)
ii. Autoencoder 2 (as the previous one, but by using different layers)
iii. Classifier encoding (i.e., we shift $\mathcal{O}$ towards $\mathcal{T}$ in the last layer of the CNN)
iv. No encoding (i.e., linear interpolation from $\mathcal{O}$ to $\mathcal{T}$)

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# Results – Qualitative

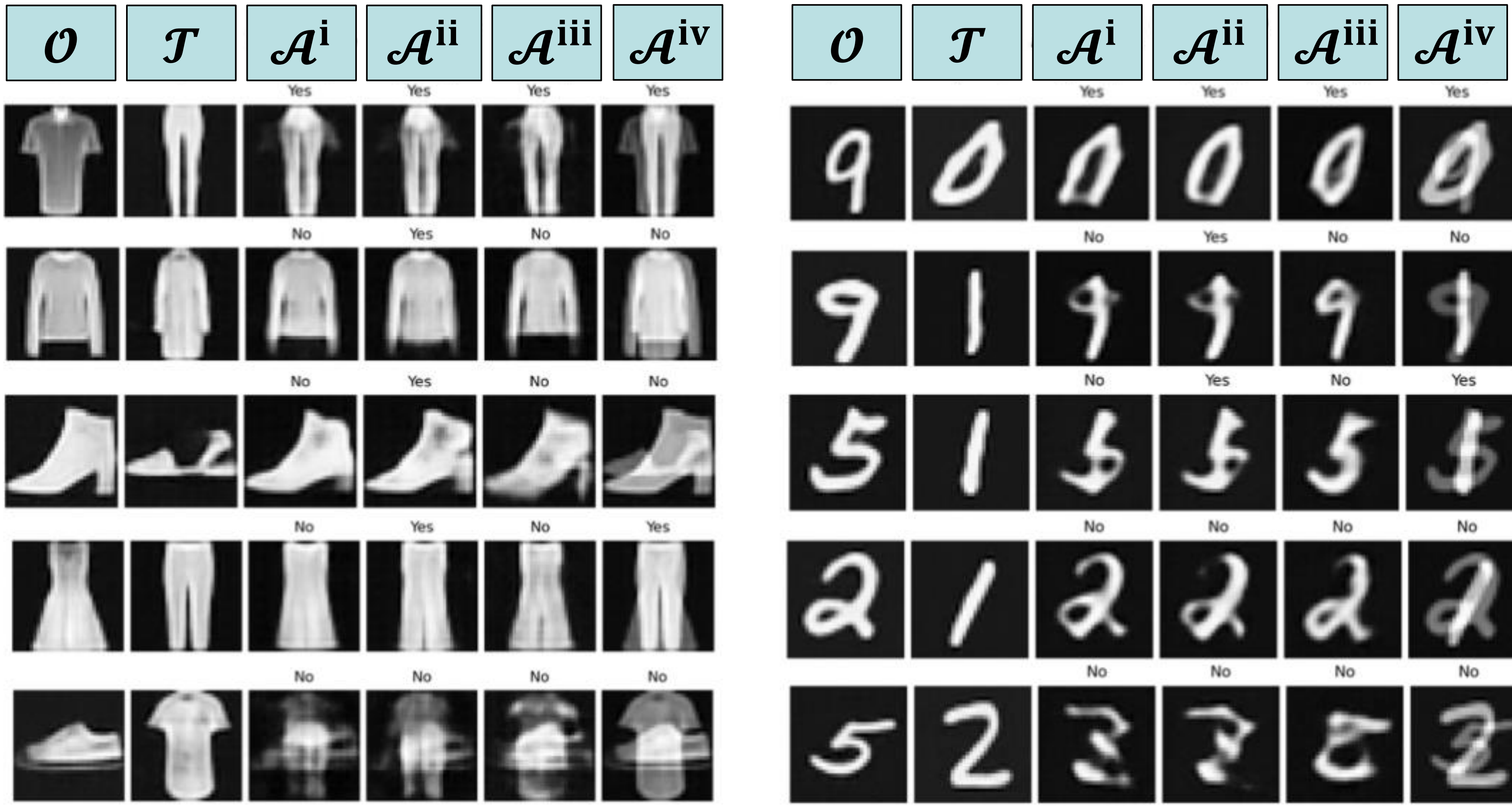


Fig. 2: Original, target and adversarial samples for different en-/decodings and interpolation for Fashion-MNIST(left) and MNIST(right). Yes/No indicates, whether the model got fooled by $X_A$, i.e. it outputs the class of $X_T$ for $X_A$

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# Results – Qualitative (takeaway)

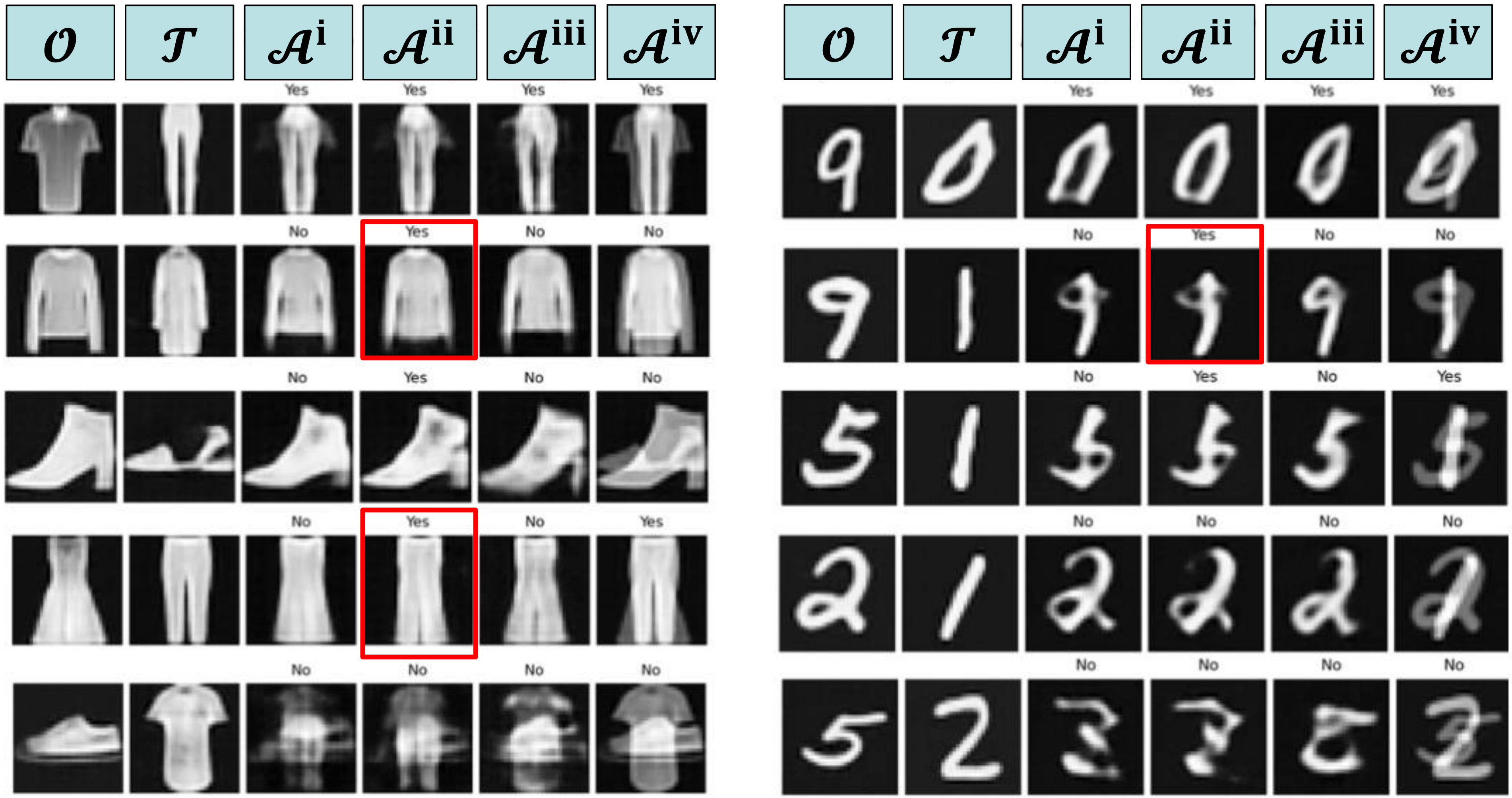


Fig. 2: Original, target and adversarial samples for different en-/decodings and interpolation for Fashion-MNIST(left) and MNIST(right). Yes/No indicates, whether the model got fooled by $X_A$, i.e. it outputs the class of $X_T$ for $X_A$

Using the Autoencoder (ii) appears to be the best method to generate a suitable $\mathcal{A}$

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# Results – Quantitative

TABLE I. Results for MNIST and FashionMNIST.

| Dataset | Generation Method | $\|\|\mathcal{A}-\mathcal{T}\|\|$ Similarity to $\mathcal{T}$ | $\|\|\mathcal{A}-\mathcal{O}\|\|$ Similarity to $\mathcal{O}$ | $Acc$(CNN) VGG-11 | $Acc$(CNN) VGG-13 | $Acc$(CNN) Resnet-10 |
|---|---|---|---|---|---|---|
| MNIST | i (autoencoder 1) | $19.87_{\pm 1.794}$ | $24.85_{\pm 0.11}$ | $0.28_{\pm 0.081}$ | $0.26_{\pm 0.079}$ | $0.27_{\pm 0.084}$ |
| | ii (autoencoder 2) | $20.41_{\pm 1.837}$ | $24.73_{\pm 0.172}$ | $0.21_{\pm 0.078}$ | $0.2_{\pm 0.077}$ | $0.2_{\pm 0.079}$ |
| | iii (classifier encoding) | $24.38_{\pm 1.71}$ | $24.71_{\pm 0.15}$ | $0.44_{\pm 0.117}$ | $0.41_{\pm 0.134}$ | $0.42_{\pm 0.124}$ |
| | iv (no encoding) | $12.42_{\pm 1.25}$ | $24.73_{\pm 0.149}$ | $0.08_{\pm 0.073}$ | $0.11_{\pm 0.075}$ | $0.09_{\pm 0.081}$ |
| Fashion-MNIST | i (autoencoder 1) | $25.22_{\pm 1.365}$ | $14.92_{\pm 0.048}$ | $0.53_{\pm 0.065}$ | $0.53_{\pm 0.065}$ | $0.51_{\pm 0.06}$ |
| | ii (autoencoder 2) | $25.84_{\pm 1.436}$ | $14.85_{\pm 0.03}$ | $0.57_{\pm 0.059}$ | $0.58_{\pm 0.057}$ | $0.56_{\pm 0.055}$ |
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- *Similarity to* $\mathcal{T}$: *classifier encoding* are the least similar to $\mathcal{T}$

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- *Similarity to $\mathcal{T}$*: *classifier encoding* are the least similar to $\mathcal{T}$
- *Similarity to $\mathcal{O}$*: all methods appear to have same results

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# Future Work

- **Human evaluation**
  - We want to submit the adversarial samples $\mathcal{A}$ to real humans and ask for their opinion
- **Defense** and **augmentation**
  - Through *adversarial training*, it is possible to use $\mathcal{A}$ to defend against similar attacks
  - Alternatively, it is possible to use $\mathcal{A}$ to augment the training dataset and (potentially) increase the baseline performance of the CNN
- **Different data**
  - We only considered MNIST and FashionMNIST, but more datasets exist (e.g., CIFAR) which can be used to devise more intriguing experiments (with real FIAT Pandas and VW Polos!)
- **Other domains**
  - We only investigated CNN that were analyzing images. However, the same principles can be applied also in other domains (i.e., malware analysis)

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