Anomaly Detection in Computer Vision and Thermal Imaging for Battery Monitoring

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Overview

- My education & experiences background
- Part 1: Introduction to Computer Vision
  - What is Machine Learning (ML)
  - What is Computer Vision (CV)
  - Common CV tasks
  - Types of learning in ML
  - Types of ML model

Overview

- Part 2: Introduction to Anomaly Detection
  - Anomalies
  - Anomaly Detection (AD)
  - Application of AD
  - Challenges of AD
  - AD method
    - One-class
      - Model-based
      - Data augmentation-based
      - Framework (model + data augmentation)
    - Zero-shot
  - Summary and food for thought

Overview

- Part 3: Anomaly Detection for Battery Monitoring System
    - AD for thermal image battery
    - Challenges
    - One-shot method
    - Zero-shot method
    - Ongoing challenges

My education & experiences background

9.2011

Undergraduate
- Multimedia Nusantara University, Indonesia
- Thesis topic: embedded system (non-AI topic)

9.2015

Master
- University of Science and Technology, South Korea
- Research topic: neural network compression (image classification application)

9.2017

PhD
- University of Science and Technology, South Korea
- Research topics: **anomaly detection for surveillance camera**, **augmentation**, domain adaptation, semi-supervised learning

3.2023

My education & experiences background

4.2023

Postdoctoral researcher

- Interdisciplinary Centre for Security, Reliability and Trust (SnT), University of Luxembourg, Luxembourg
- Research topic: **audio-visual/audio/visual deepfake detector**,
  [from October 2024] battery SoX prediction & **battery thermal image anomaly detection**

7.2025

AI research consultant

- Helmholtz AI, Germany
- Research topic: AI in health

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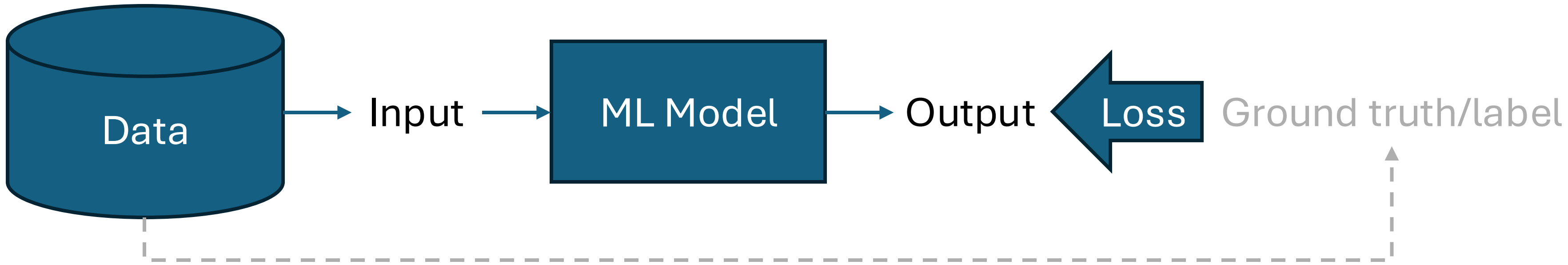
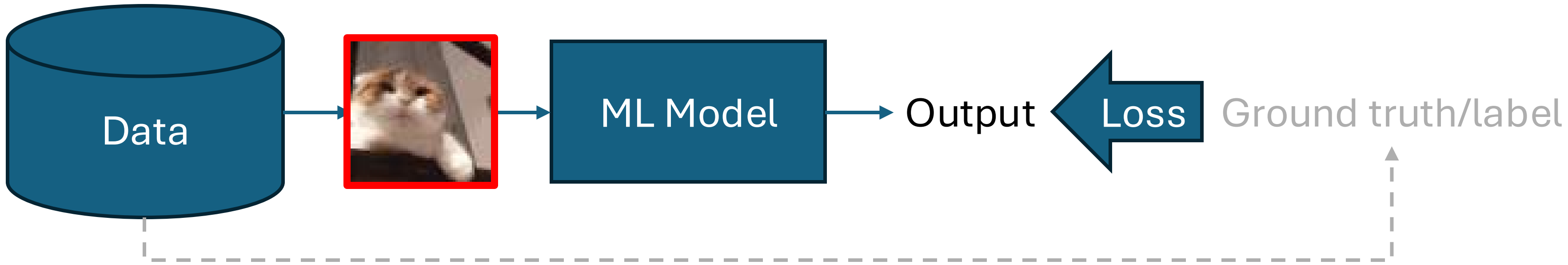
What is Machine Learning (ML)

- Computer learns from data
  - **Data** may/may not provide ground truth
  - **ML model** is the processor from input to output
  - **Loss** is the objectives (what ML model should learn from the data?)



What is Computer Vision (CV)

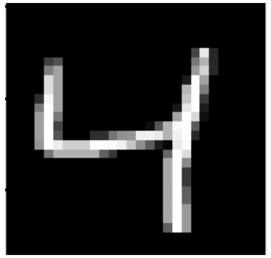
- ML to process visual data (image/video)



Non-ML CV (Sobel edge detection, etc.) exists, but not our focus

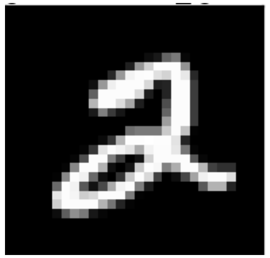
Common CV tasks

- Image/video classification



“4”

“dancing”



“2”

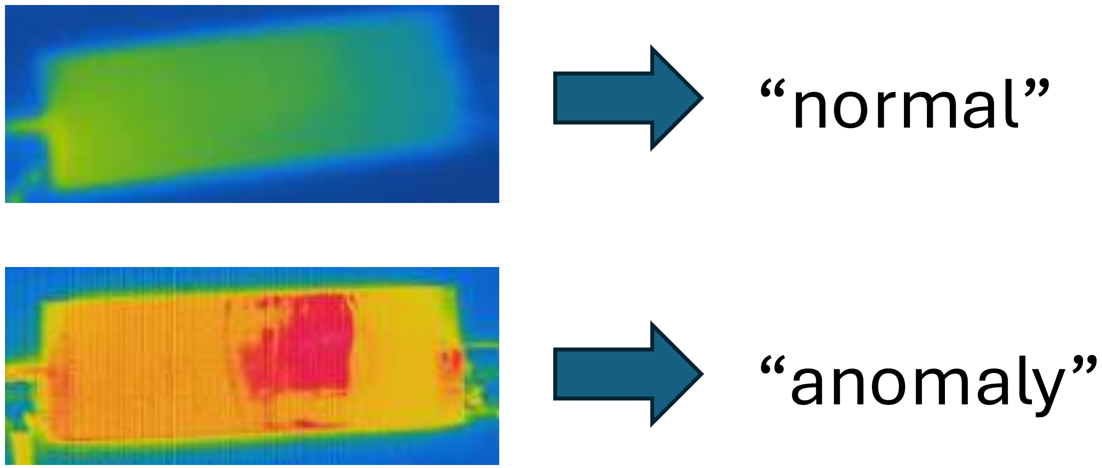
“shaking hands”

Handwritten digit classification

Action classification

Common CV tasks

- Image/video classification



Anomaly detection

Common CV tasks

- Object detection

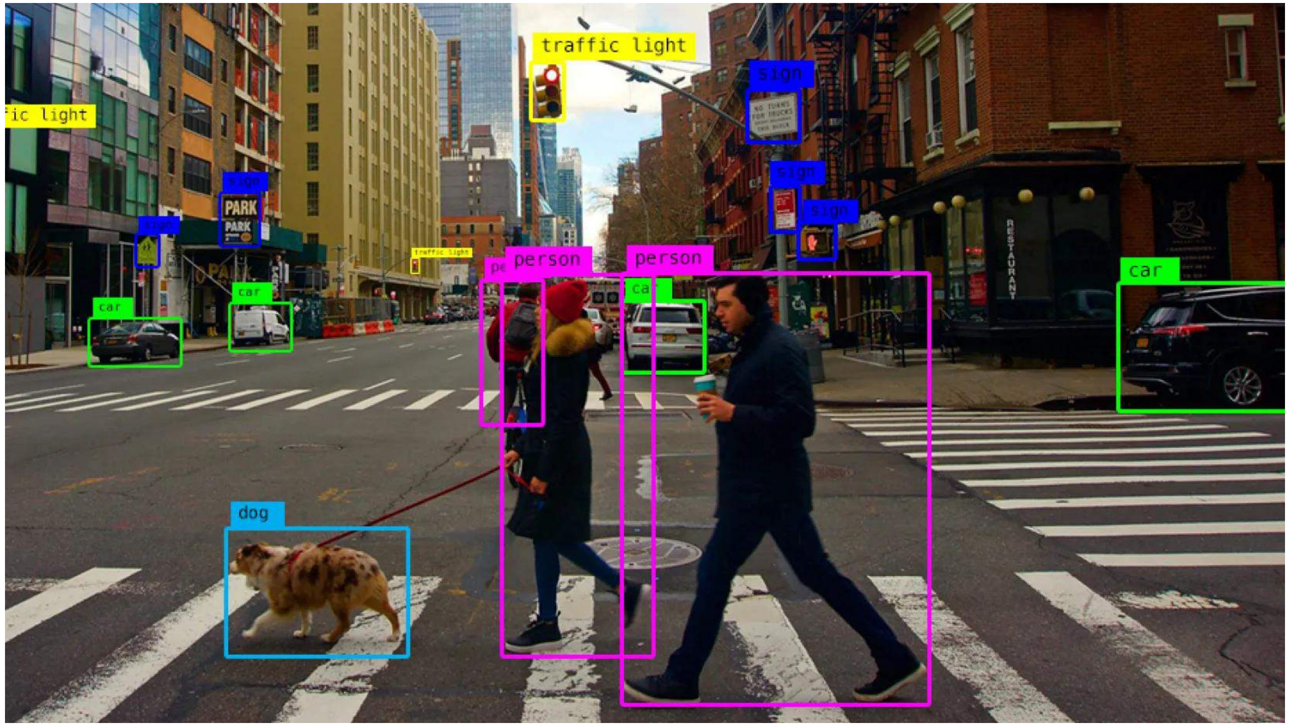
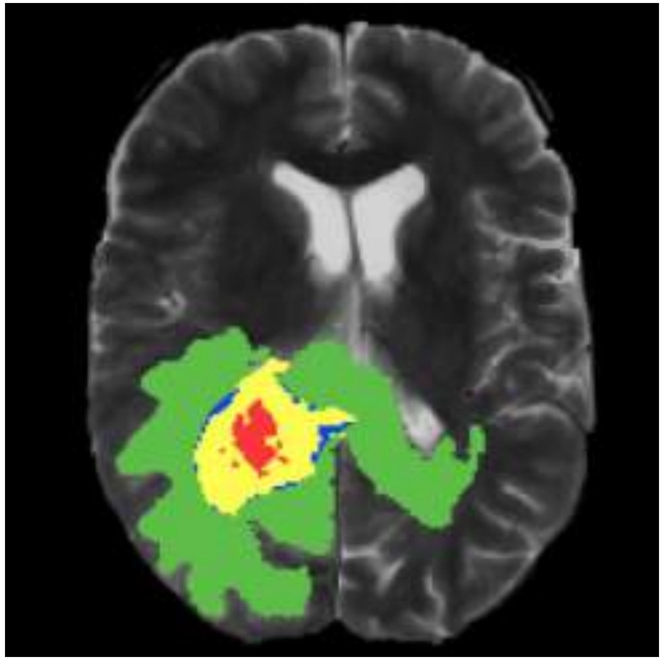


Image source: https://www.augmentedstartups.com/blog/how-to-implement-object-detection-using-deep-learning-a-step-by-step-guide

Common CV tasks

- Segmentation

Object segmentation



Brain tumor (anomaly) segmentation

Image source: https://medium.com/visionwizard/object-segmentation-4fc67077a678, https://paperswithcode.com/task/brain-tumor-segmentation

Common CV tasks

- Tracking

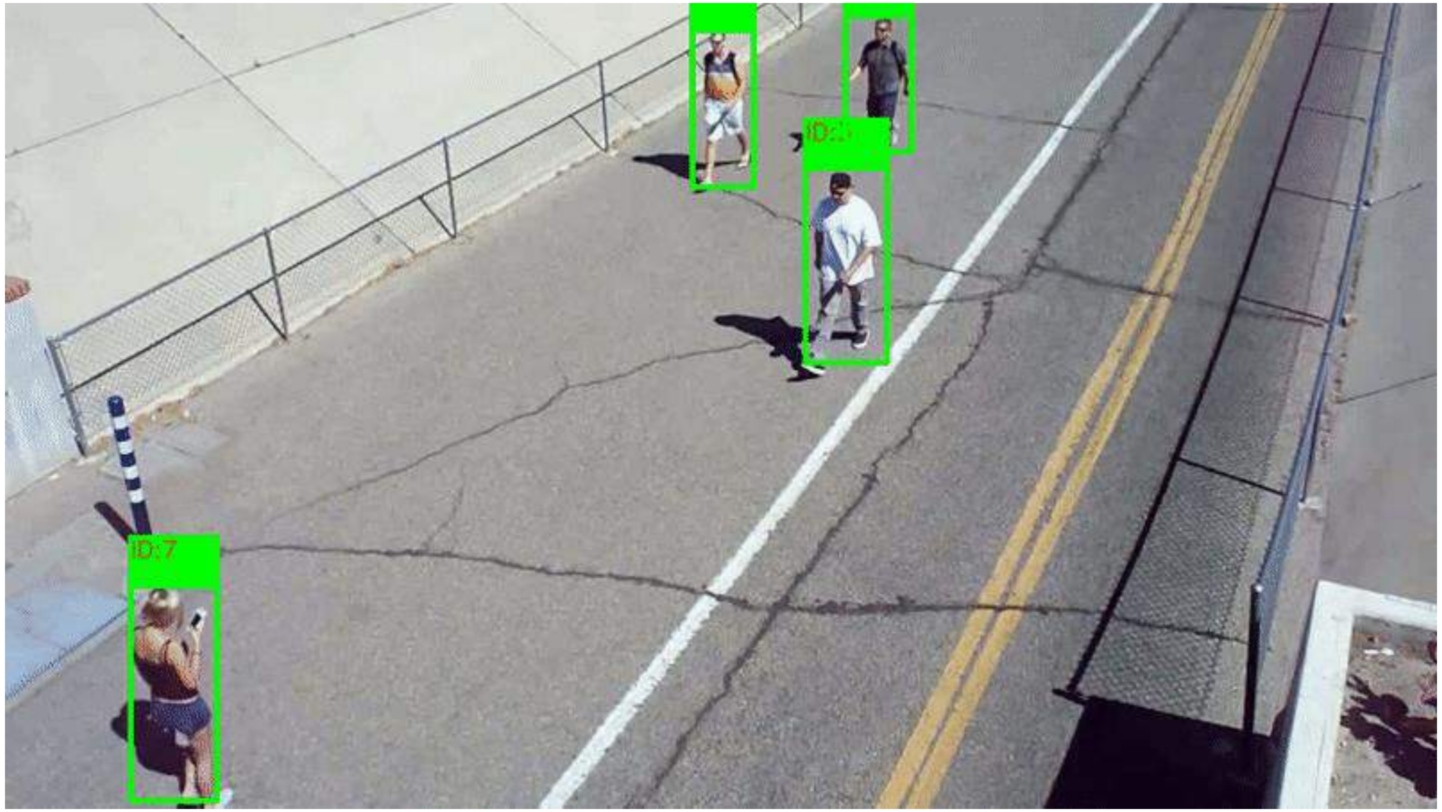


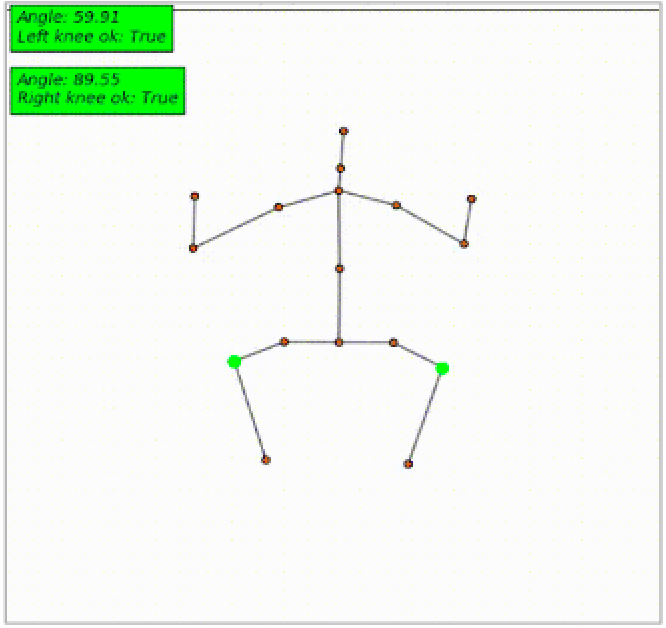
Image source: https://www.comet.com/site/blog/an-introduction-to-object-tracking-in-computer-vision/

Common CV tasks

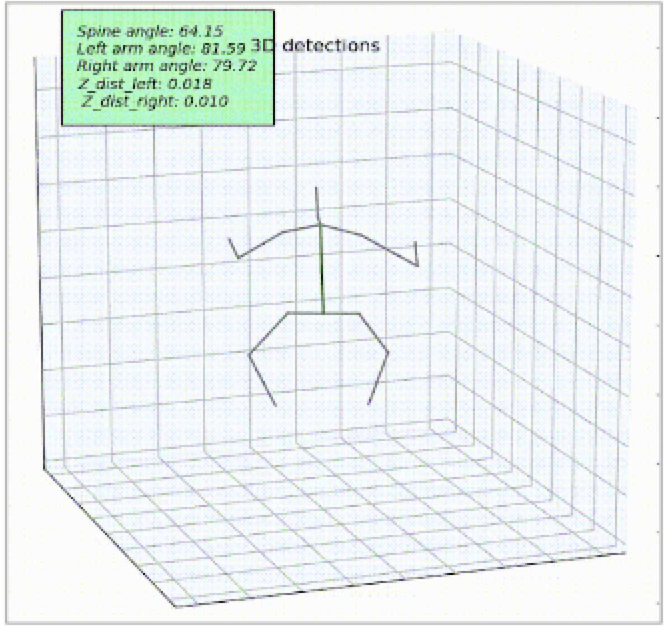
- Pose estimation

Original image

Result of 2D Pose Estimation work



Result of 3D Pose Estimation work



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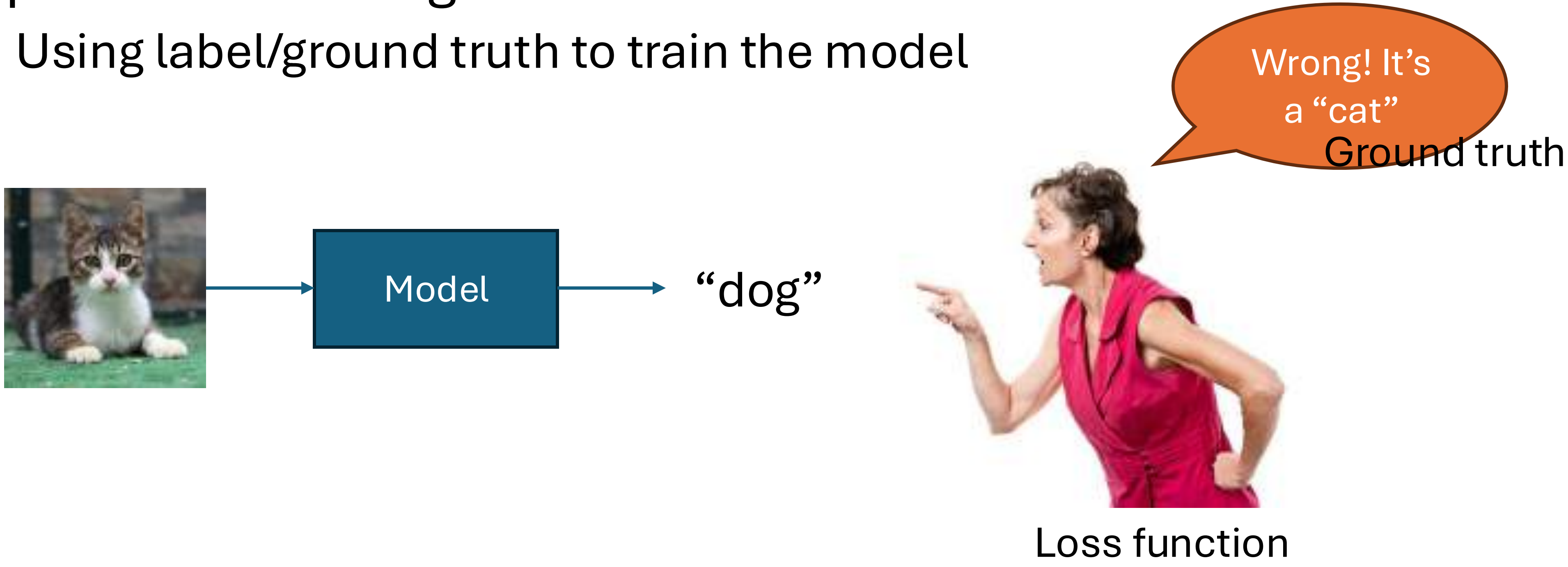
Types of learning in ML

- Supervised learning
  - Using label/ground truth to train the model



But labels are expensive!

Especially labels that require expertise

Types of learning in ML

- Semi-supervised learning
  - Train using small amount of labeled data + huge amount of unlabeled data

Pseudo-label

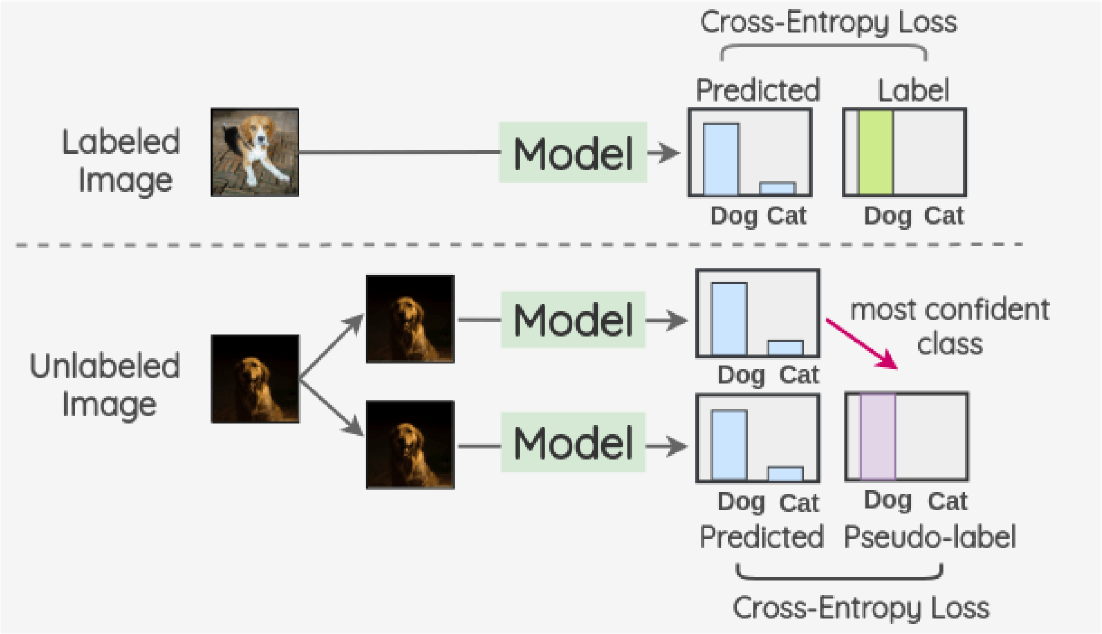
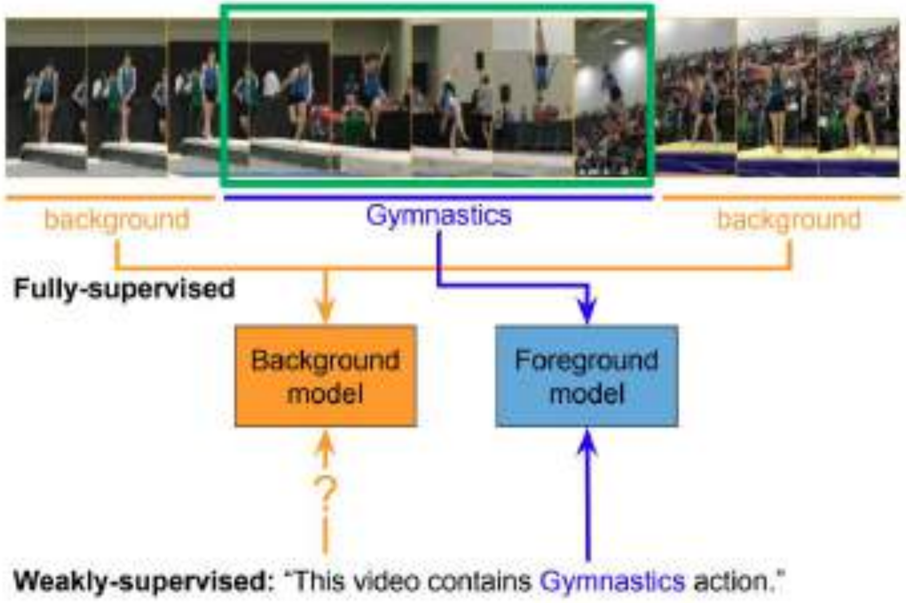


Image credits: https://amitness.com/2020/07/semi-supervised-learning/

Types of learning in ML

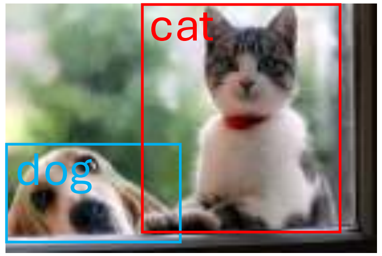
- Weakly-supervised learning
  - Using lower quality/cheaper labels

Action localization



Object detection

Fully supervised



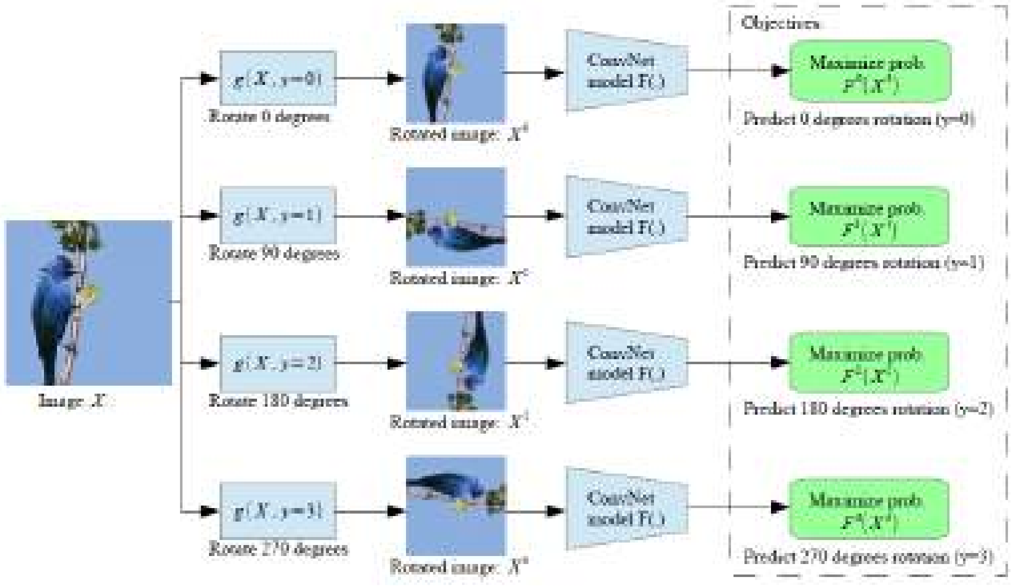
Weakly supervised

Label: cat, dog

Source: Nguyen, P.X., Ramanan, D. and Fowlkes, C.C., 2019. Weakly-supervised action localization with background modeling. In *Proceedings of the IEEE/CVF international conference on computer vision* (pp. 5502-5511).

Types of learning in ML

- Unsupervised learning
  - No labels in the training data
    - Labels can be generated automatically from the input (self-supervised learning)
    - Can be combined with supervised learning in the 2^{nd} stage of training



Source: Gidaris, S., Singh, P. and Komodakis, N., 2018. Unsupervised Representation Learning by Predicting Image Rotations. In *6th International Conference on Learning Representations* (ICLR 2018).

Types of learning in ML

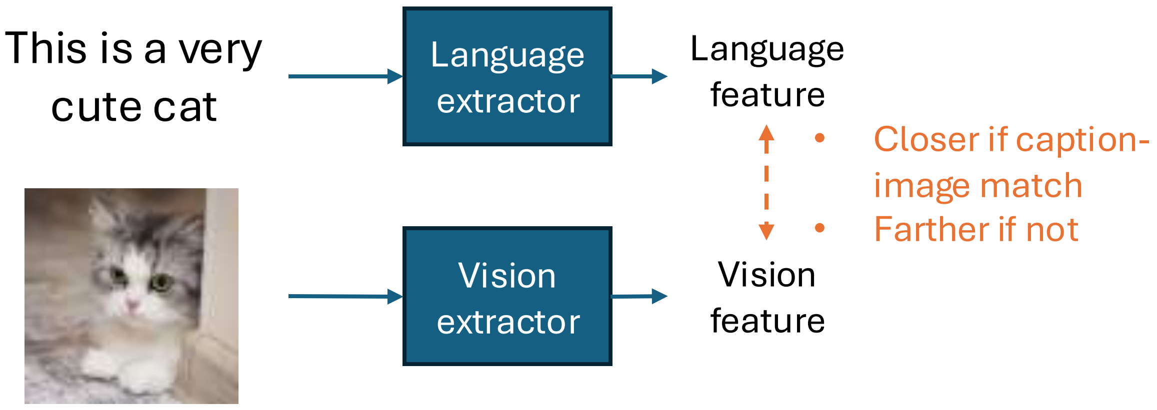
- Few-shot learning
    - Recognizing new class with only few amount of labeled data

New class (1 data):

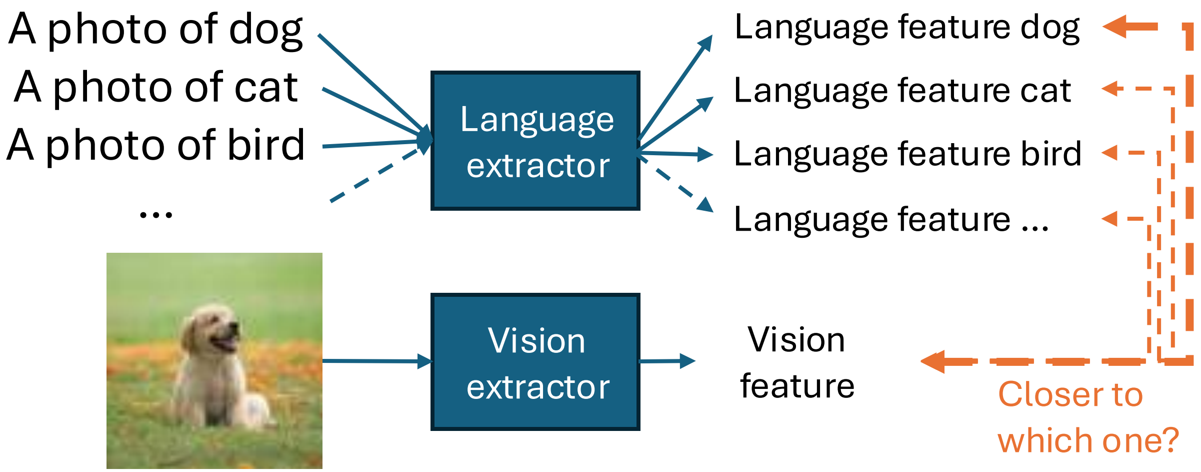
Source: Koch, G., Zemel, R. and Salakhutdinov, R., 2015, July. Siamese neural networks for one-shot image recognition. In *ICML deep learning workshop* (Vol. 2, No. 1, pp. 1-30).

Types of learning in ML

- Zero-shot learning
  - Training with other tasks than the test
  - For example, Contrastive Language-Image Pretraining (CLIP):



Training with image-caption pairs



Zero-shot for image classification

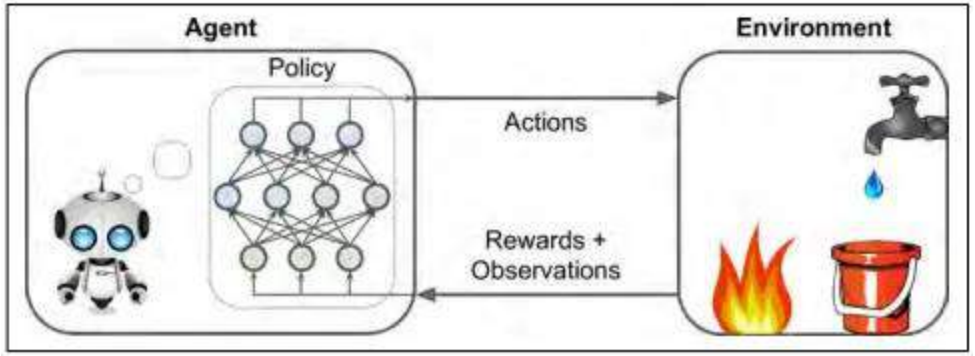
Source: Radford, A., Kim, J.W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., Sastry, G., Askell, A., Mishkin, P., Clark, J. and Krueger, G., 2021, July. Learning transferable visual models from natural language supervision. In *International conference on machine learning* (pp. 8748-8763). PmLR.

Types of learning in ML

- One-class classification
  - Specific to anomaly detection → will discuss later

Types of learning in ML

- Reinforcement learning
  - Learning by interacting with environment



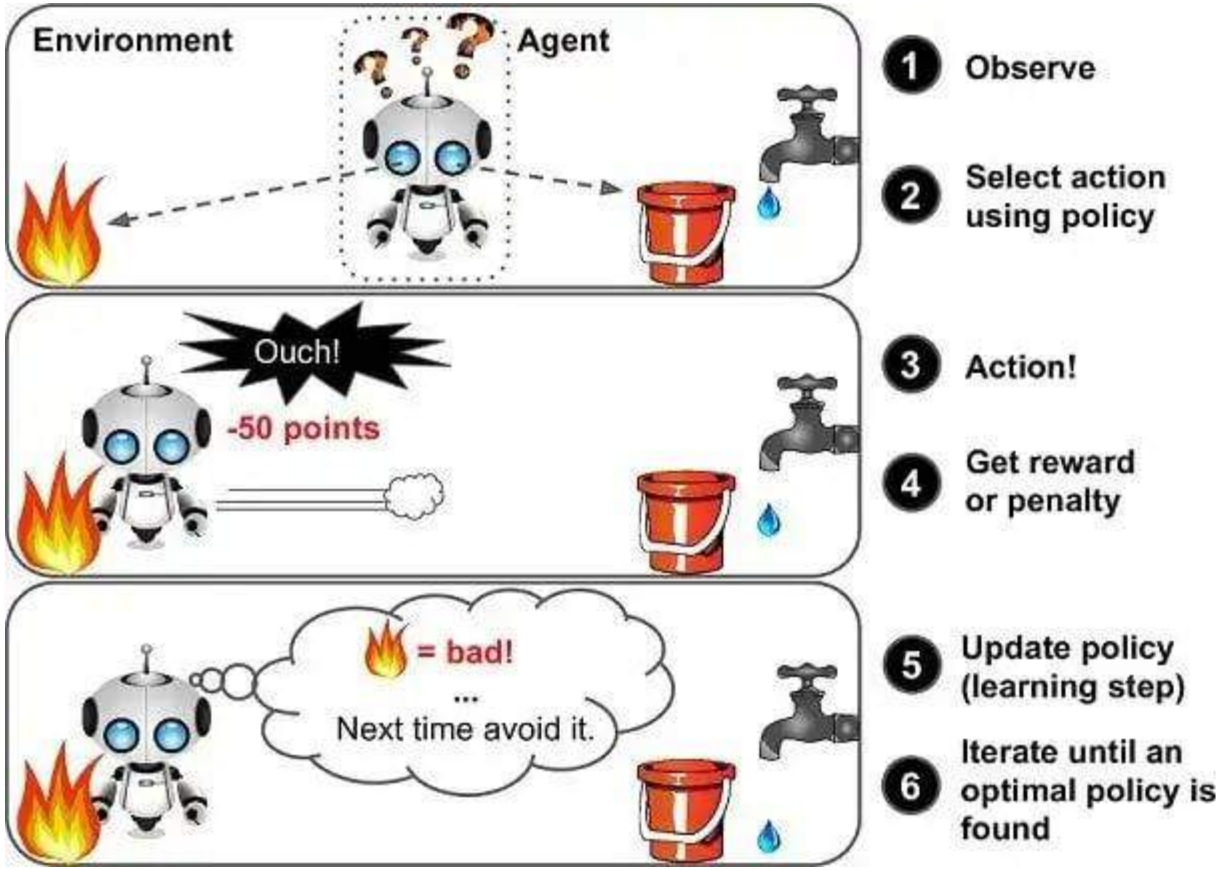
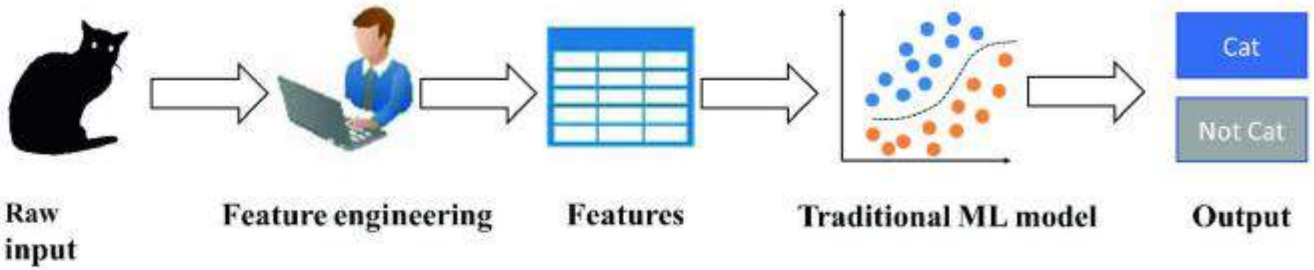


Image source: https://fritz.ai/introduction-to-reinforcement-learning/, https://www.odinschool.com/blog/top-100-reinforcement-learning-real-life-examples-and-its-challenges

Types of ML models

- Traditional ML
  - Feature (e.g. edge, blobs) are mostly hand-crafted
  - Non-neural network model



- Deep learning
  - Neural network model (inspired by neural system)

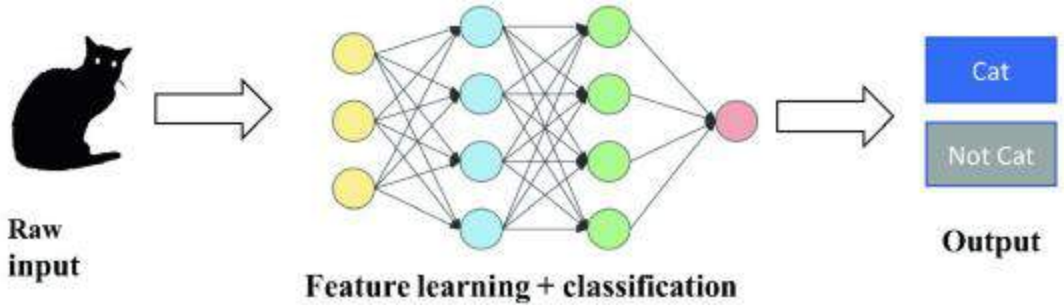


Image source: Wang, S. and Cao, J., 2021. AI and deep learning for urban computing. Urban informatics, pp.815-844.

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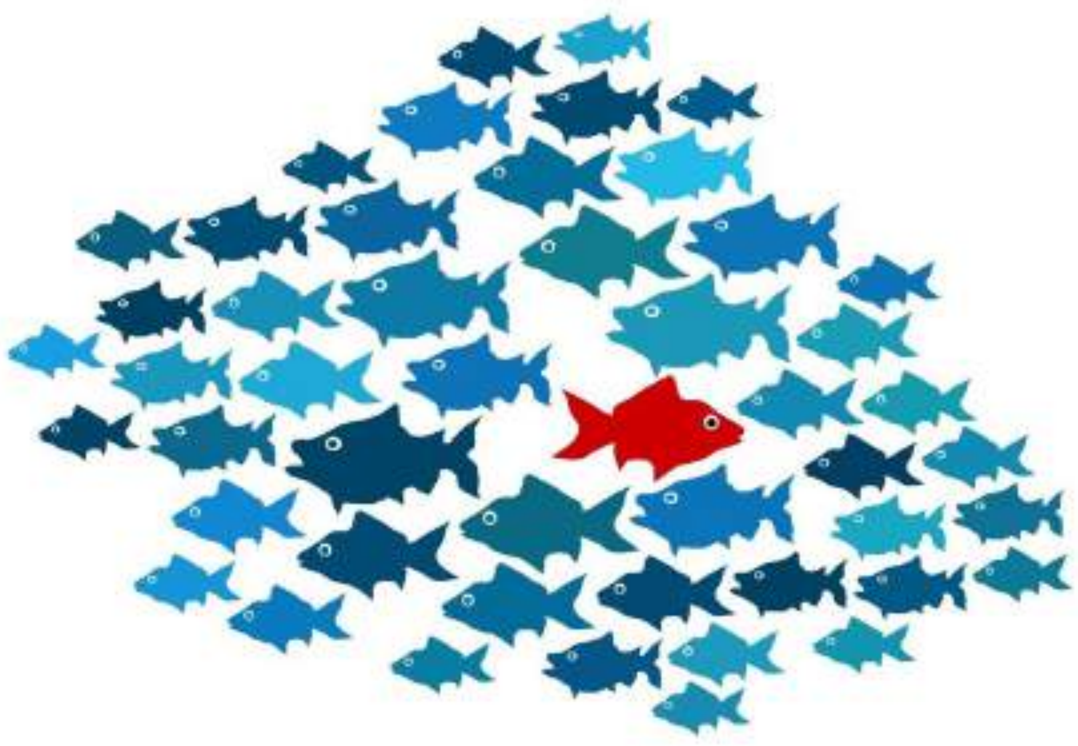
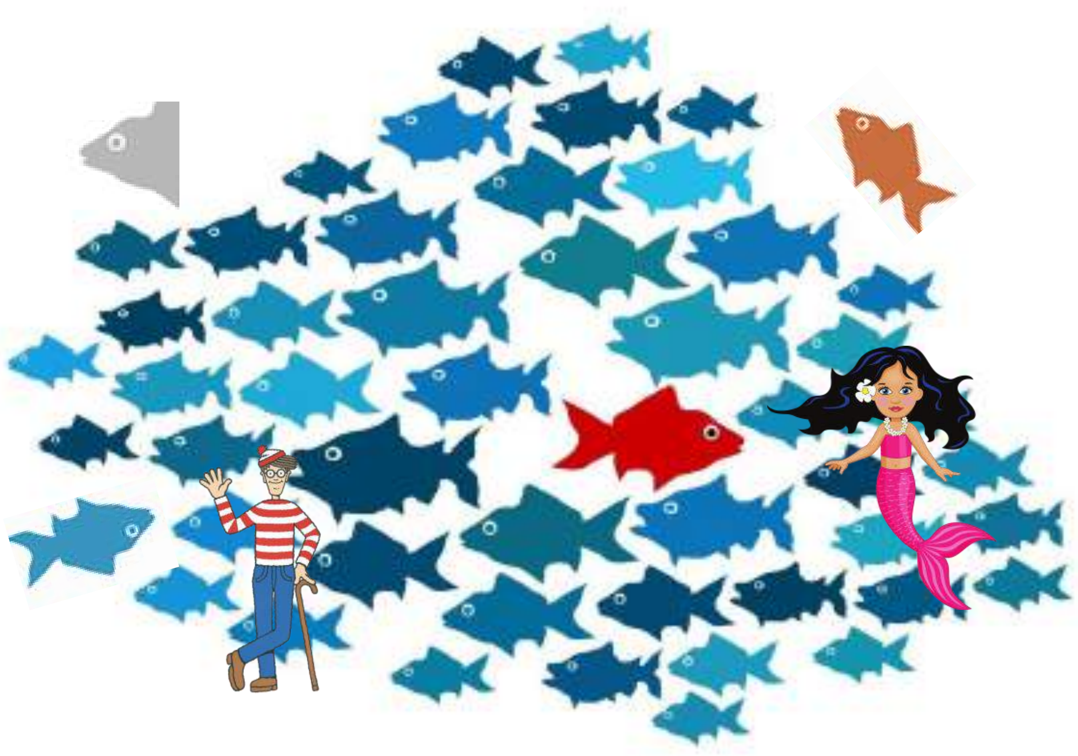
Anomalies

- Different from normal pattern



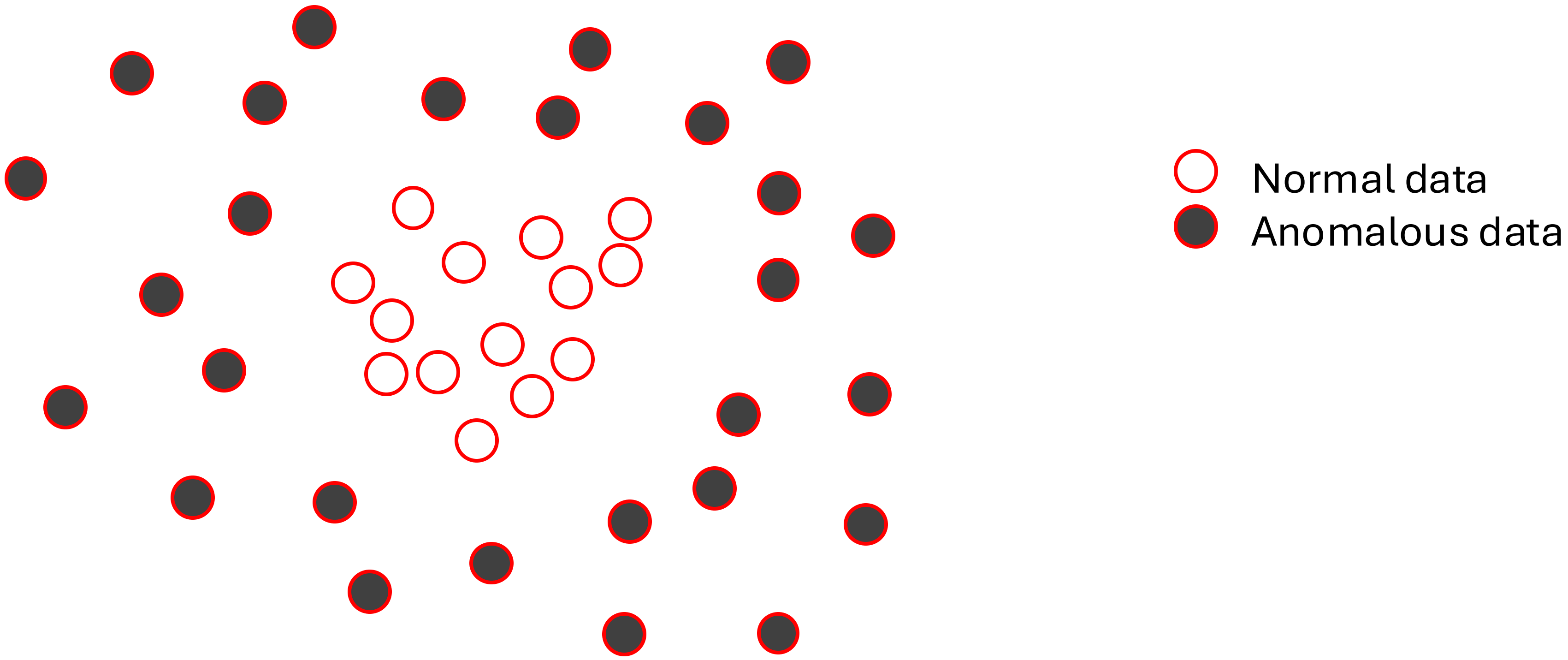
Anomalies

- Different from normal pattern + have unlimited varieties



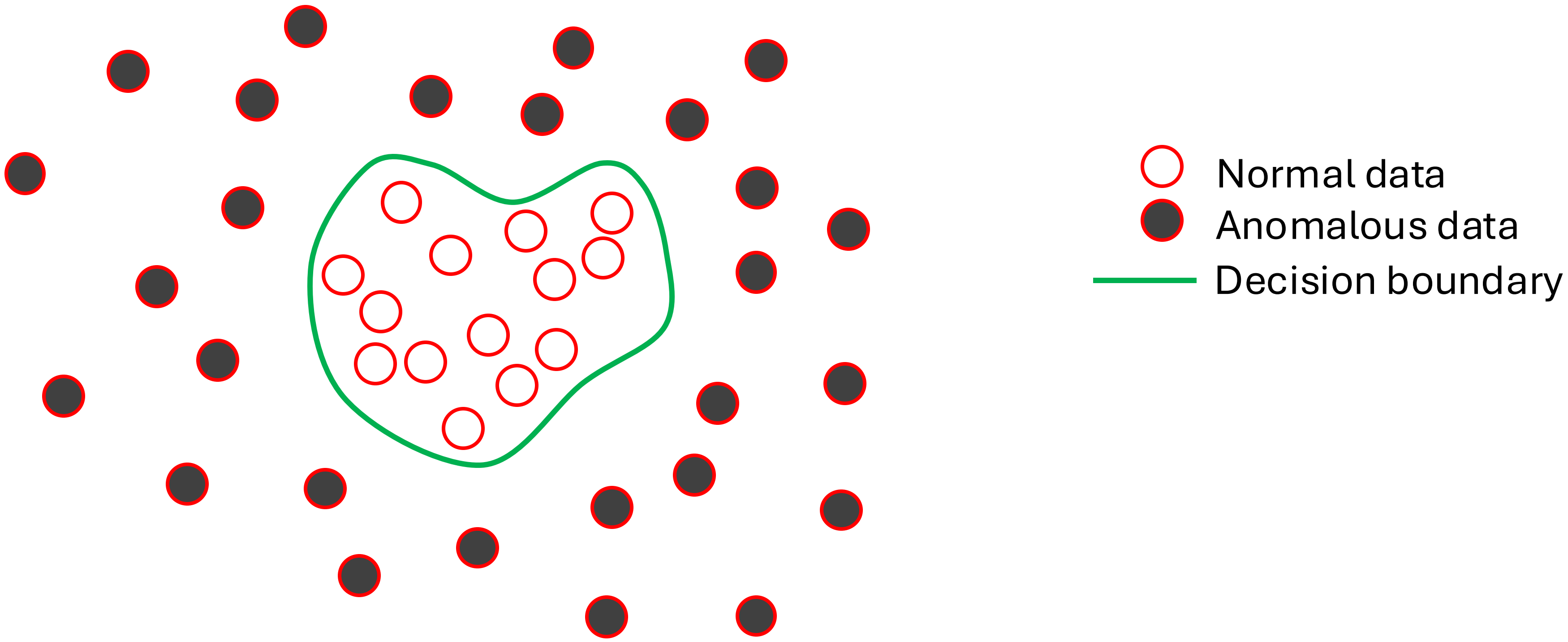
Anomalies

Anomalies



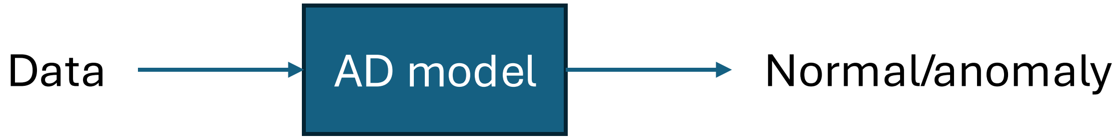
Anomaly Detection (AD)

- Normal / not normal classification



Anomaly Detection (AD)

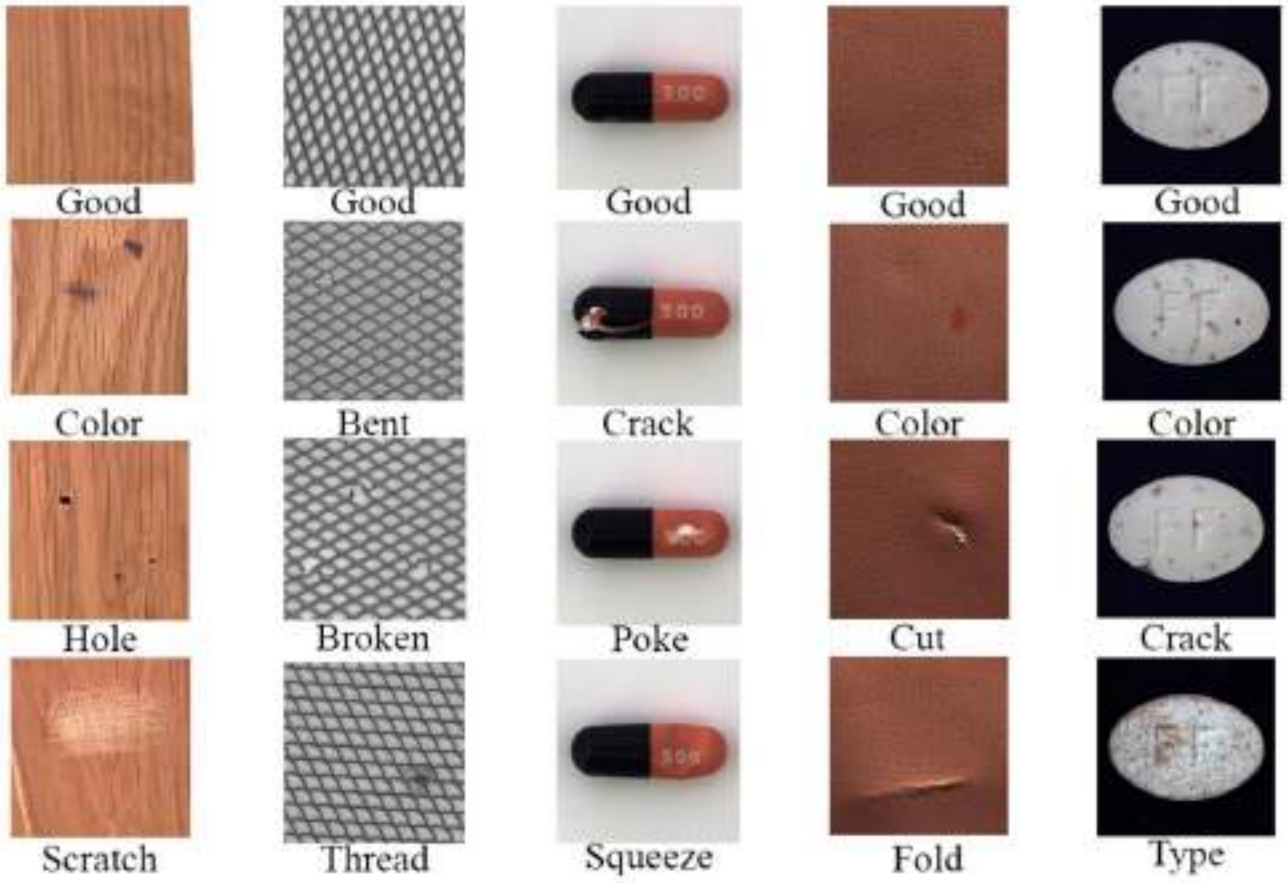
- Normal / not normal classification



Applications of AD

- Defect detection

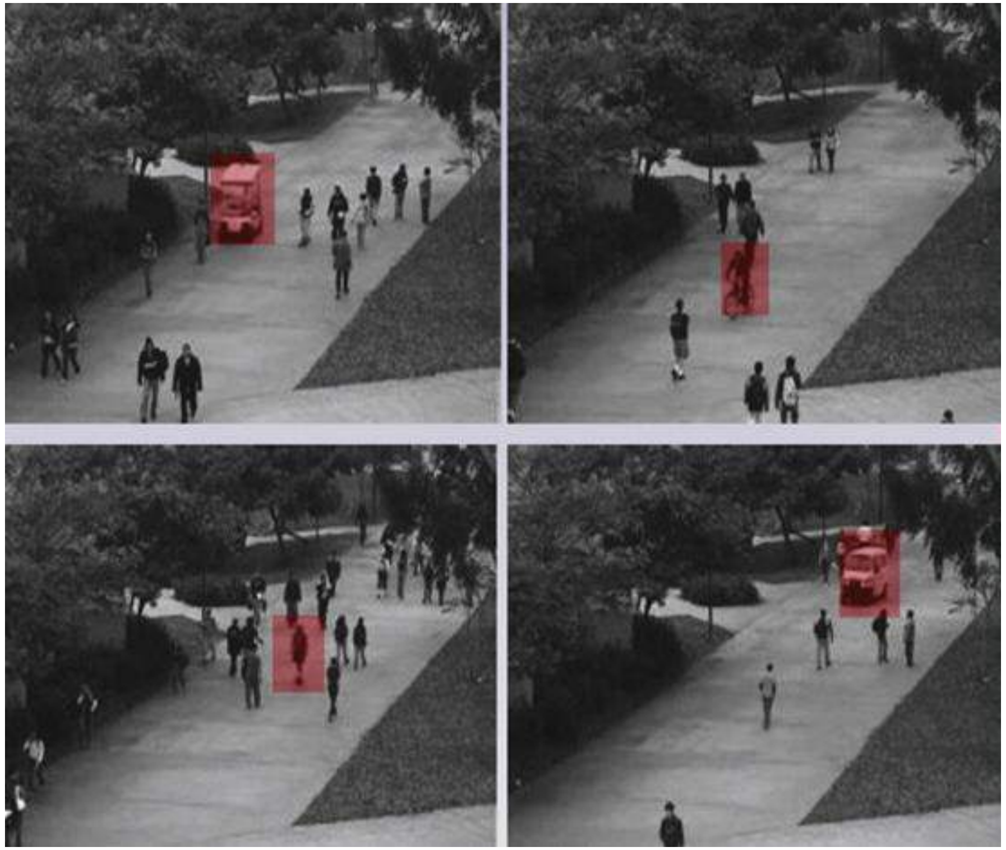
defect



Can have unlimited number of defect types

Applications of AD

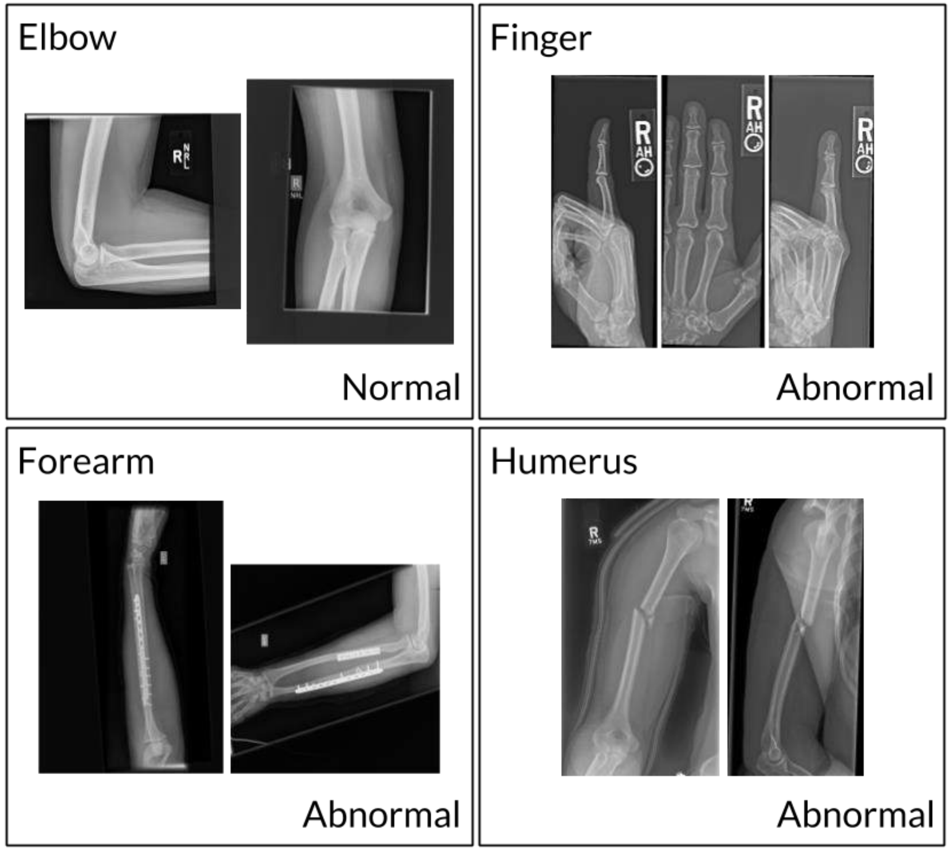
- Surveillance



Can have unlimited number of anomalous behavior

Applications of AD

- Medical

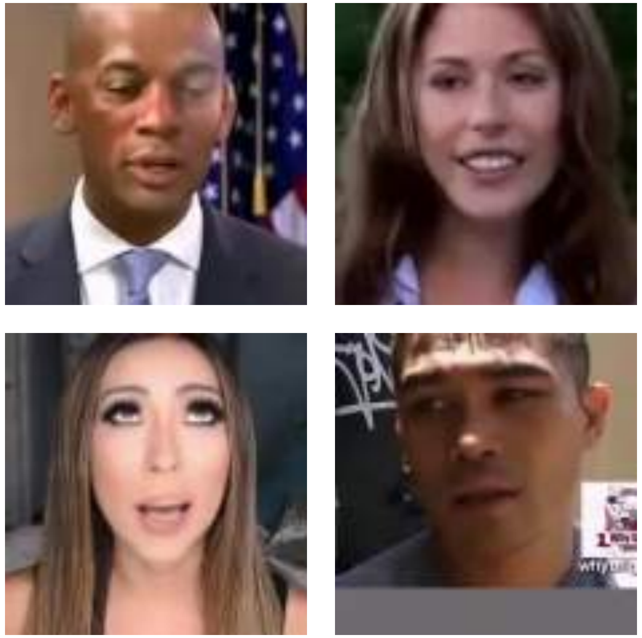


Can have unlimited number of disease

Applications of AD

- Deepfake detection

Real (normal)



Fake (anomaly)

Can be made by unlimited number of generative methods

Challenges of AD

- Anomalous data is difficult to get
  - Quantity-wise
  - Variety-wise

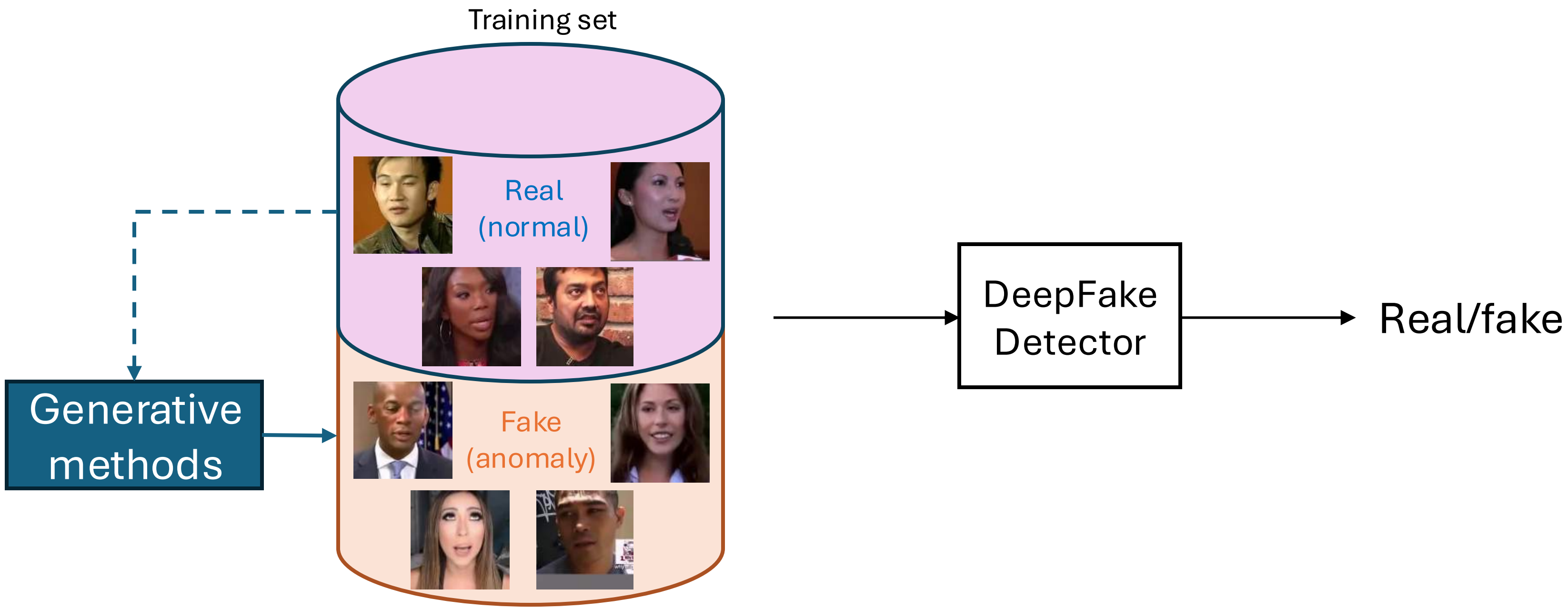
e.g. in surveillance

Escaping Puma
(video not found)

... etc.

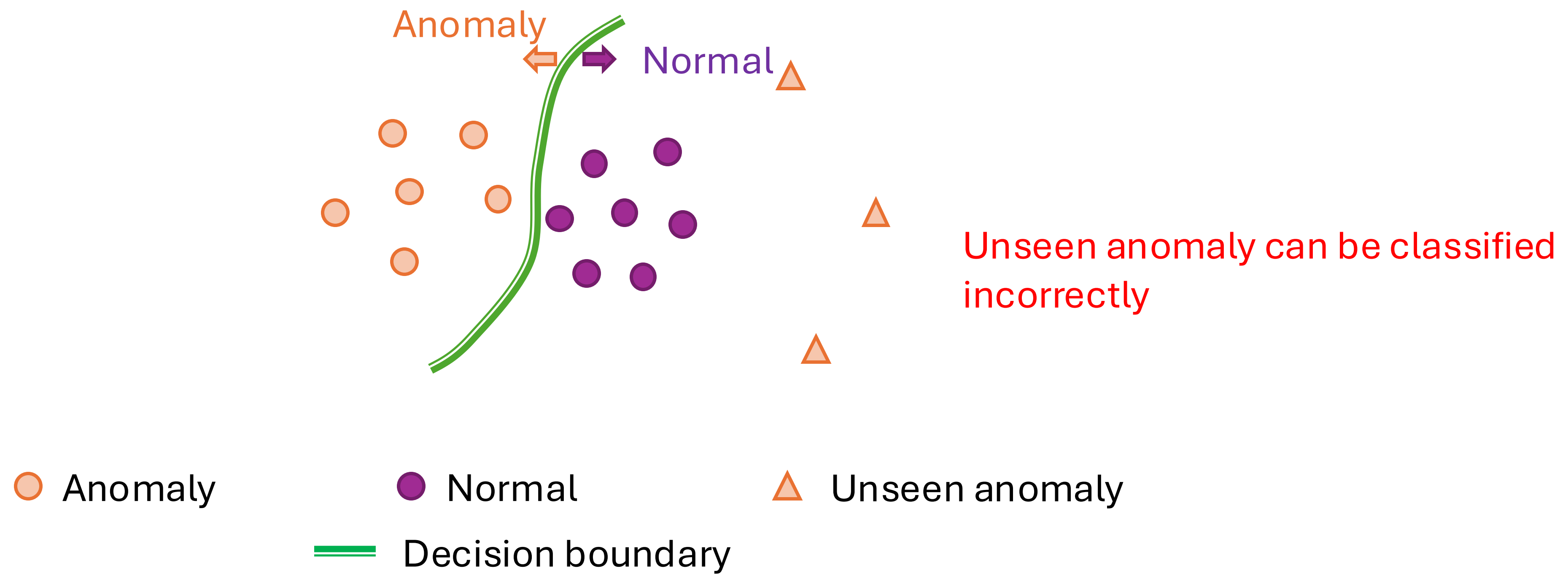
Challenges of AD

- Supervised learning is difficult
  - Possible application with supervised learning:
    Deepfake detection → can easily create fake data with available generative models



Challenges of AD

- Supervised learning is difficult
  - Possible application with supervised learning: Deepfake detection
    - BUT! Even when we have **quantity**, the **variety** may not be enough for generalization to unseen fake



Overview

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    - One-class
      - Model-based
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      - Framework (model + data augmentation)
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AD method

- One-class
  - Training with only normal data
  - Some papers claim as “unsupervised” (although I disagree)
- Zero-shot
  - no training on anomaly detection task
- Weakly-supervised
- Semi-supervised
- Unsupervised

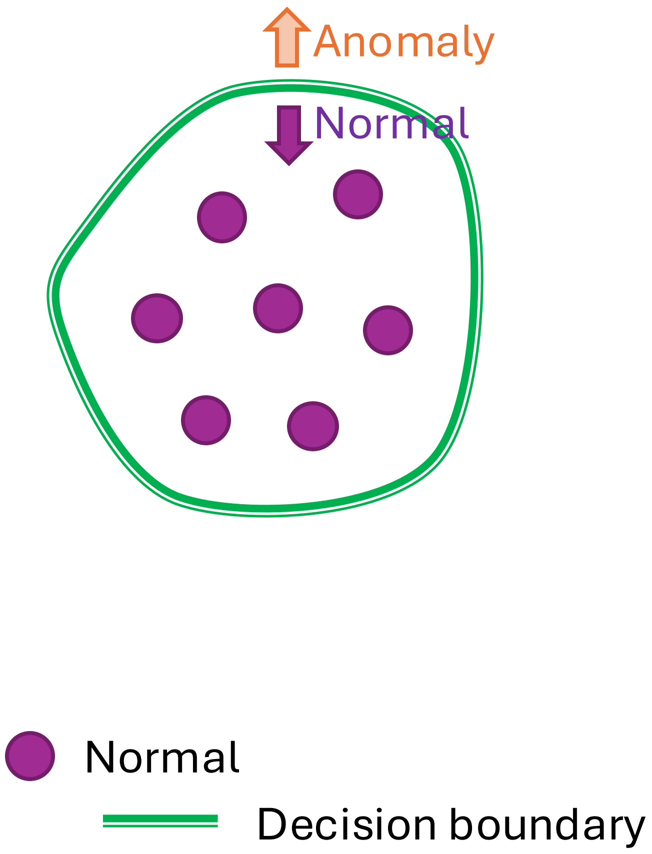
Will not be discussed in this lecture

AD method: one-class

- Model
  - How to train with only one-class (normal) data
- Data augmentation
  - How to add more data to train (especially anomalies)
- Framework: model + data augmentation

AD method: one-class: model

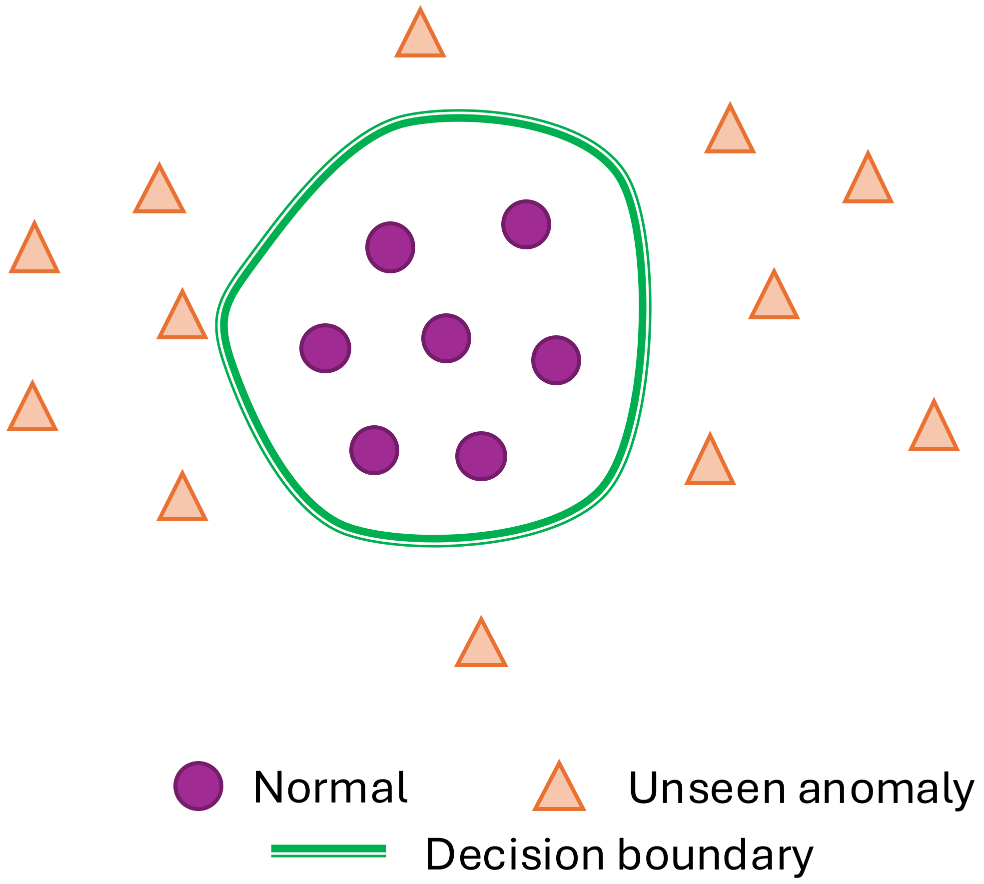
- Training with only normal data



AD method: one-class: model

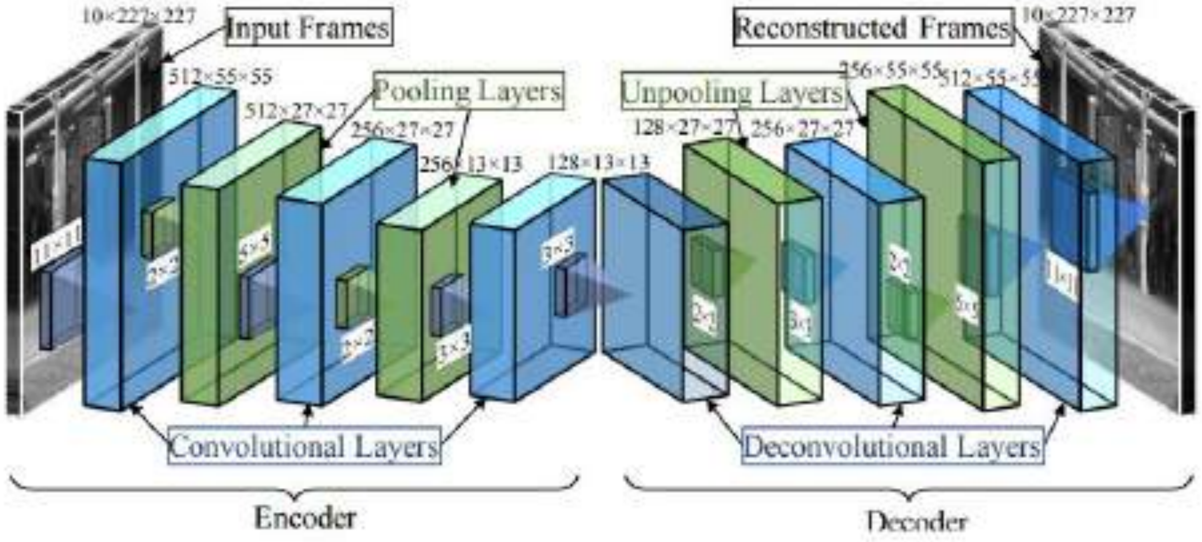
- Training with only normal data

At test,



AD method: one-class: model

- Example #1: Autoencoder (AE) trained to reconstruct normal data



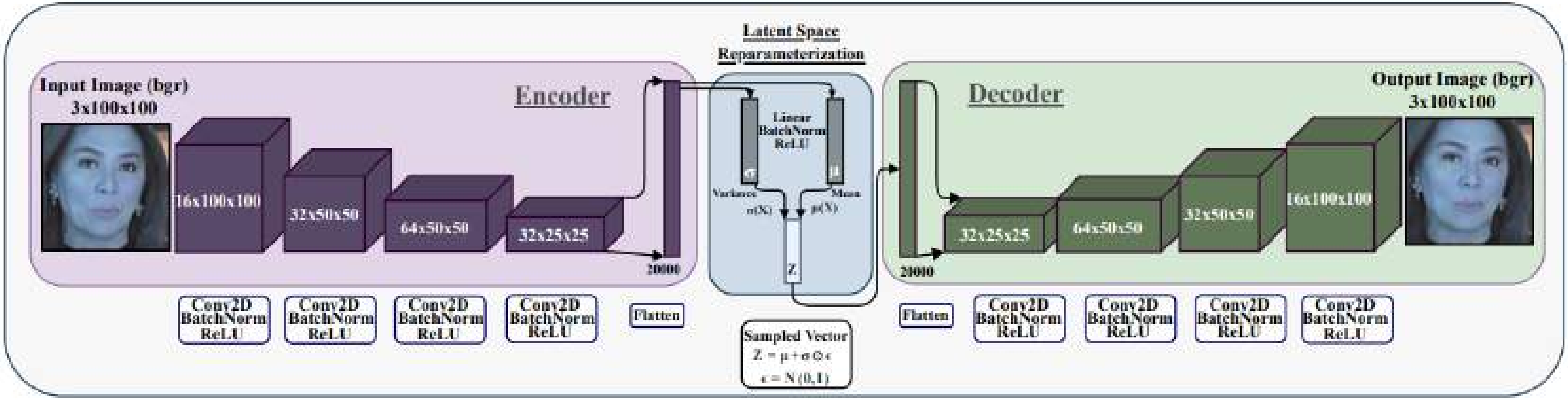
Expectation during test
Normal: low reconstruction loss
Anomaly: high reconstruction loss

Problem: AE can reconstruct too well, including anomaly that was not seen during training
→ Need constrain

Source: Hasan, M., Choi, J., Neumann, J., Roy-Chowdhury, A.K. and Davis, L.S., 2016. Learning temporal regularity in video sequences. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 733-742).

AD method: one-class: model

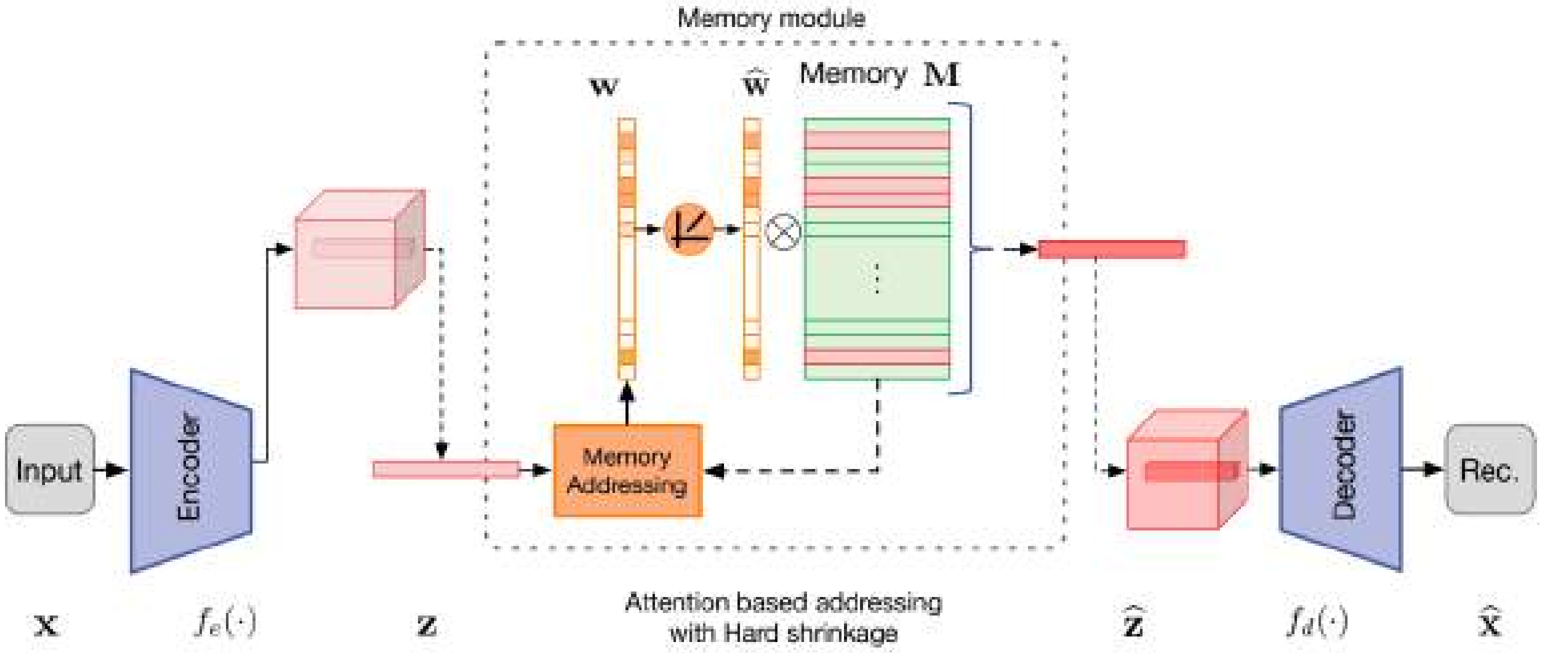
- Example #2: Variational AE (AE but the latent is constrained to Gaussian distribution)



Source: Khalid, H. and Woo, S.S., 2020. Oc-fakedect: Classifying deepfakes using one-class variational autoencoder. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition workshops* (pp. 656-657).

AD method: one-class: model

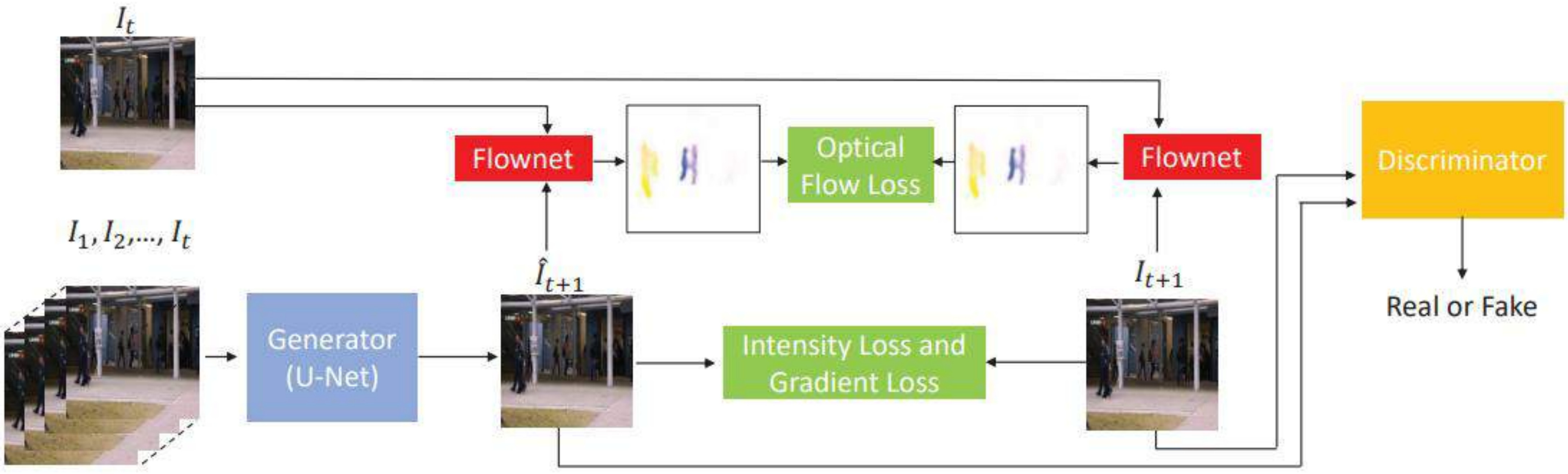
- Example #3: AE + memory module
  - Forcing the decoder to reconstruct only based on limited normal memory



Source: Gong, D., Liu, L., Le, V., Saha, B., Mansour, M.R., Venkatesh, S. and Hengel, A.V.D., 2019. Memorizing normality to detect anomaly: Memory-augmented deep autoencoder for unsupervised anomaly detection. In *Proceedings of the IEEE/CVF international conference on computer vision* (pp. 1705-1714).

AD method: one-class: model

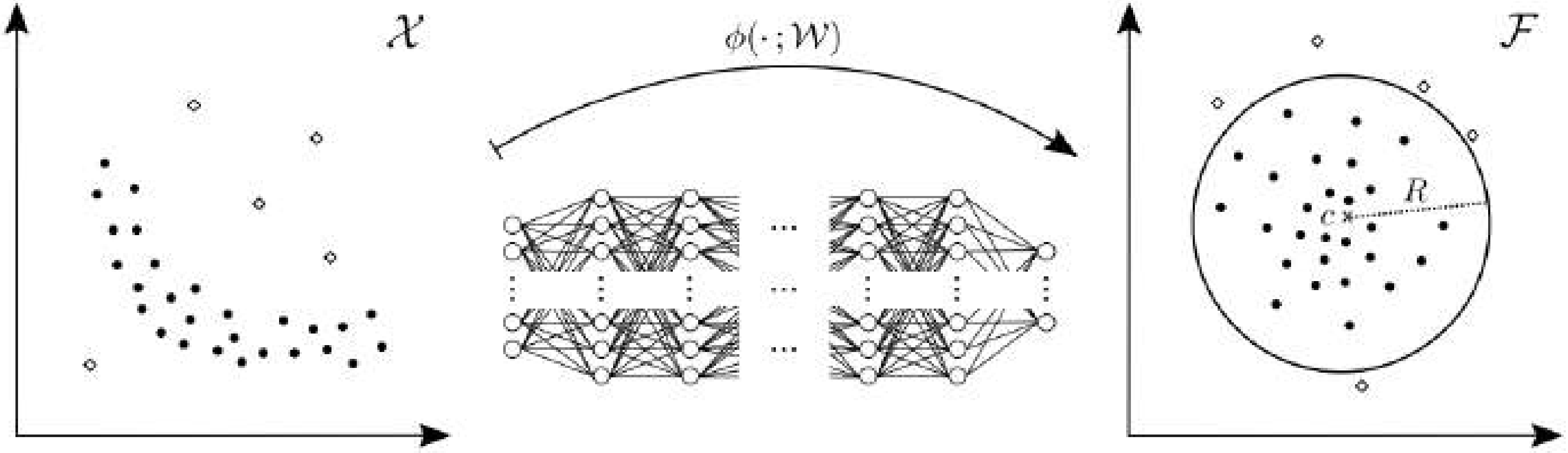
- Example #4: predicting next frame (more difficult task than reconstruction)
  - During test, if the next frame can't be predicted well → anomaly



Source: Liu, W., Luo, W., Lian, D. and Gao, S., 2018. Future frame prediction for anomaly detection–a new baseline. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 6536-6545).

AD method: one-class: model

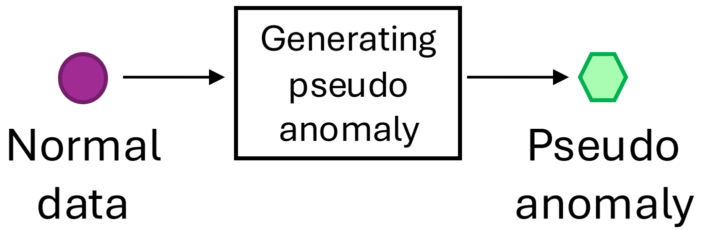
- Example #5: Deep SVDD (Deep Support Vector Data Description)
  - Forcing normal data to be inside a hypersphere
  - During test time → data outside hypersphere = anomaly

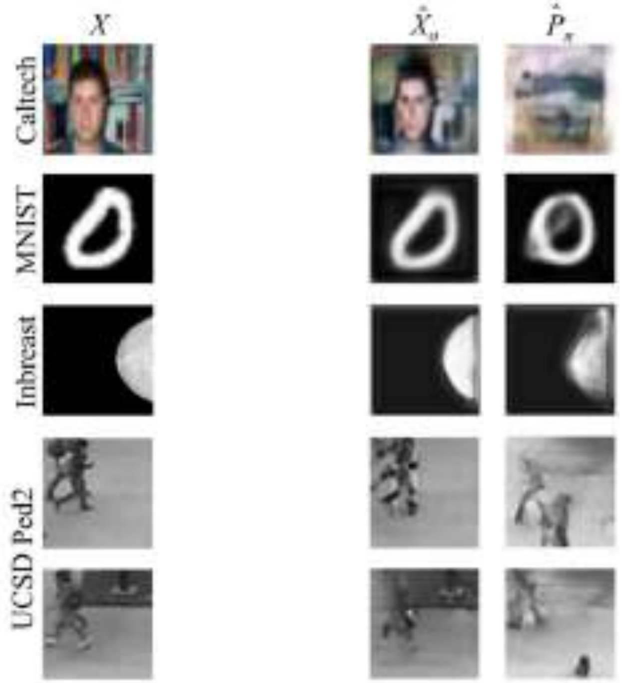


Source: Ruff, L., Vandermeulen, R., Goernitz, N., Deecke, L., Siddiqui, S.A., Binder, A., Müller, E. and Kloft, M., 2018, July. Deep one-class classification. In *International conference on machine learning* (pp. 4393-4402). PMLR.

AD method: one-class: data augmentation

- Pseudo anomaly
  - Difficult to **obtain** anomalies? → **create** them!





Normal data Pseudo anomalies

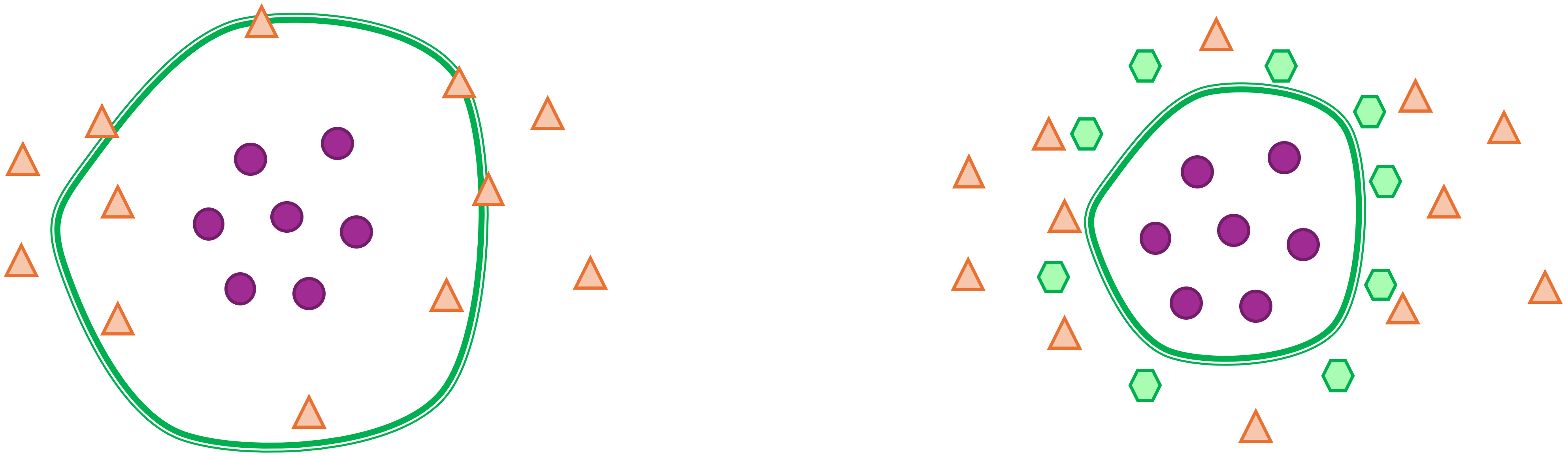
Image source: Zaheer, M.Z., Lee, J.H., Mahmood, A., **Astrid, M.** and Lee, S.I., 2022. Stabilizing adversarially learned one-class novelty detection using pseudo anomalies. IEEE Transactions on Image Processing, 31, pp.5963-5975.

AD method: one-class: data augmentation

- Pseudo anomaly
  - Benefit to one-class model → tightening decision boundary

Without pseudo anomaly

With pseudo anomaly



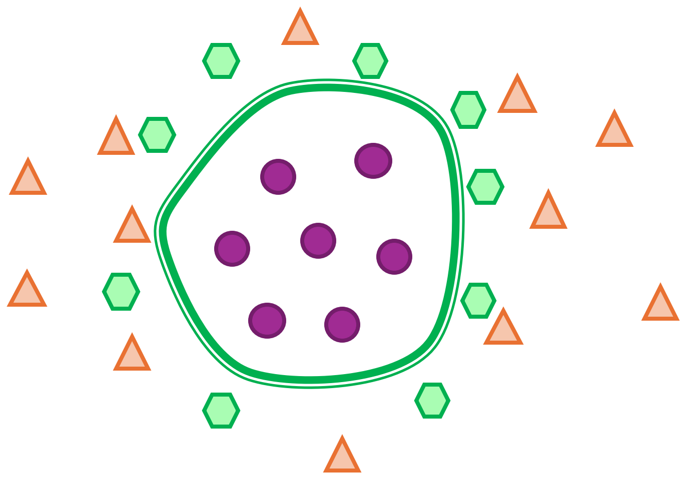
Problem: Nothing limiting the decision boundary

Normal   Unseen anomaly   Pseudo anomaly   Decision boundary

AD method: one-class: data augmentation

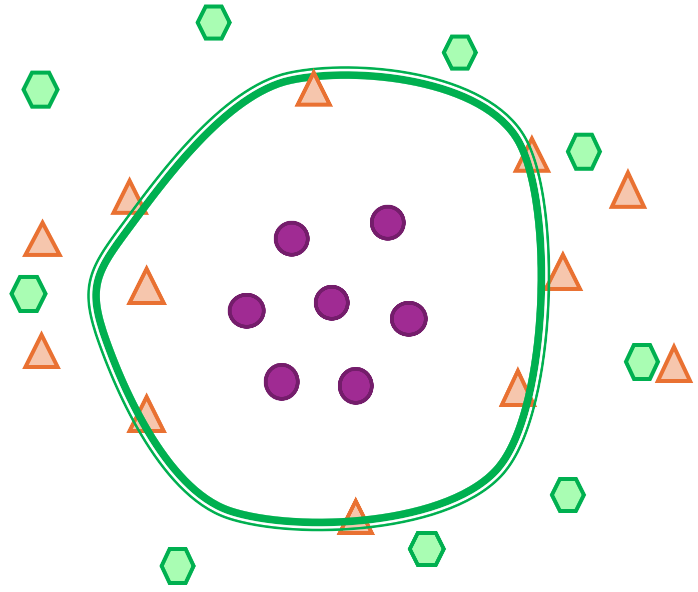
- Pseudo anomaly
  - Better pseudo-anomaly should be closer to normal data

Better pseudo anomalies



Tight to the normal data

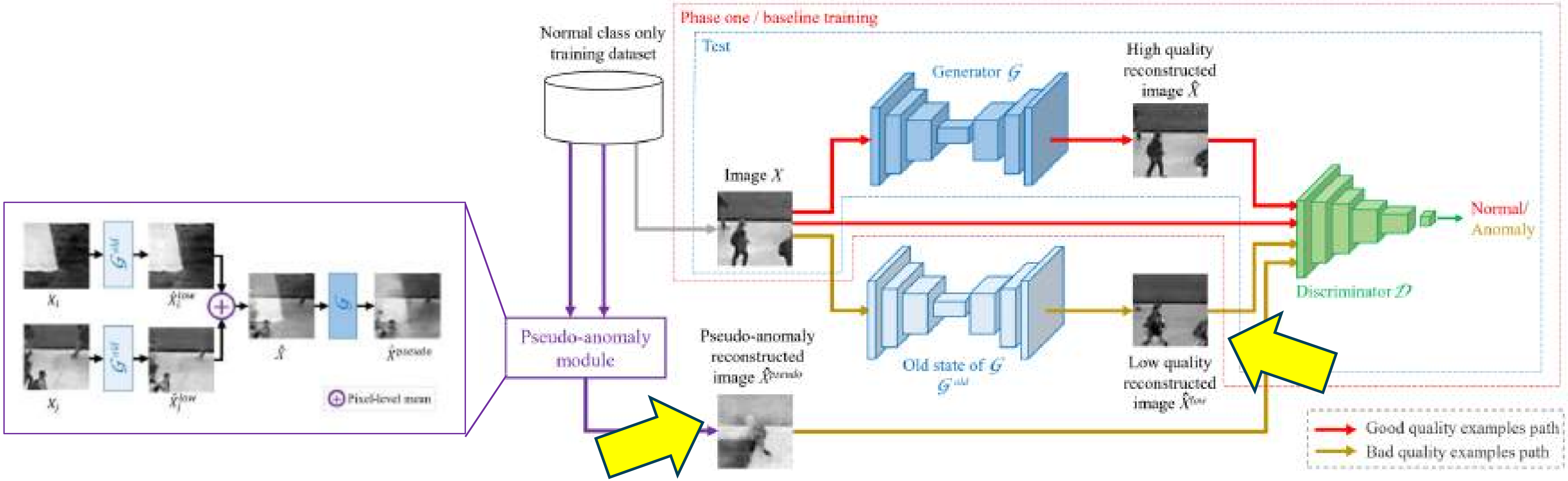
Not-so-good pseudo anomalies



Normal　Unseen anomaly　Pseudo anomaly　Decision boundary

AD method: one-class: data augmentation

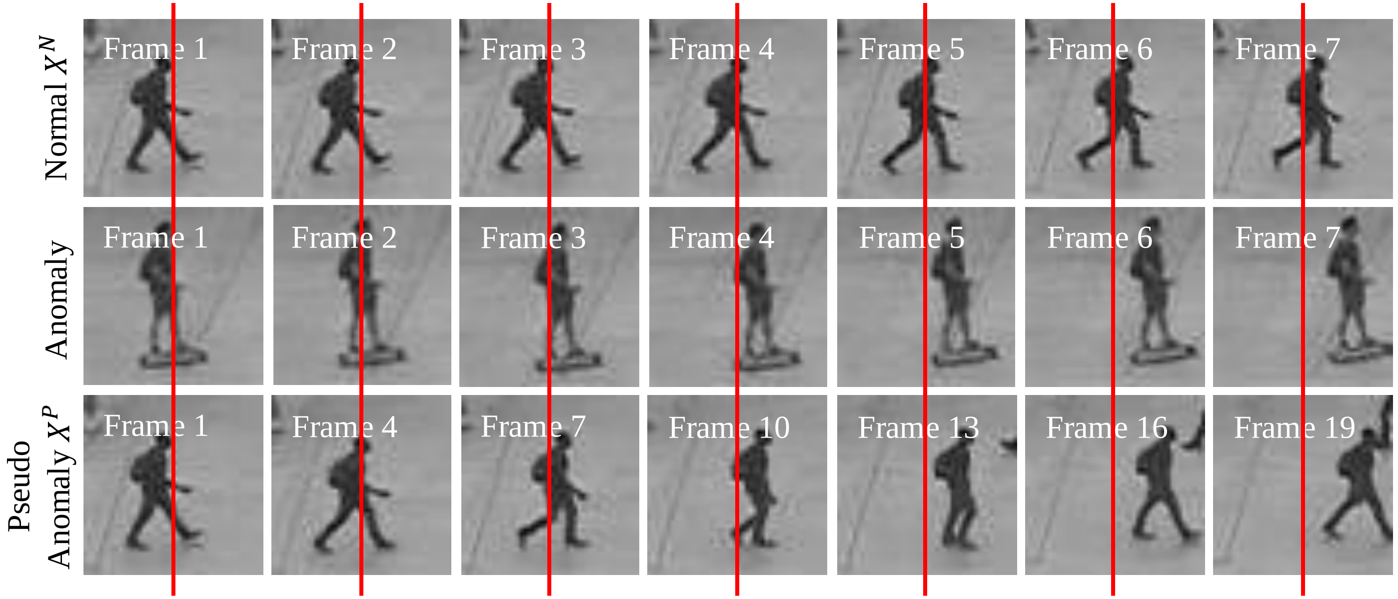
- Pseudo anomaly generation
  - Example #1: Undertrained autoencoder/generator + fusion



Source: Muhammad Zaigham Zaheer, Jin-ha Lee, **Marcella Astrid**, and Seung-Ik Lee. "Old is Gold: Redening the adversarially learned one-class classier training paradigm". In: Proceedings of the *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).* June 14-19, 2020.

AD method: one-class: data augmentation

- Pseudo anomaly generation
  - Example #2: Skipping frames
    - Using prior knowledge, e.g., anomalies in surveillance are related to speed



Source: **Marcella Astrid**, Muhammad Zaigham Zaheer, and Seung-Ik Lee. "Synthetic Temporal Anomaly Guided End-to-End Video Anomaly Detection". In: *International Conference on Computer Vision (ICCV 2021) Workshop* (Virtual). Oct. 11–17, 2021.

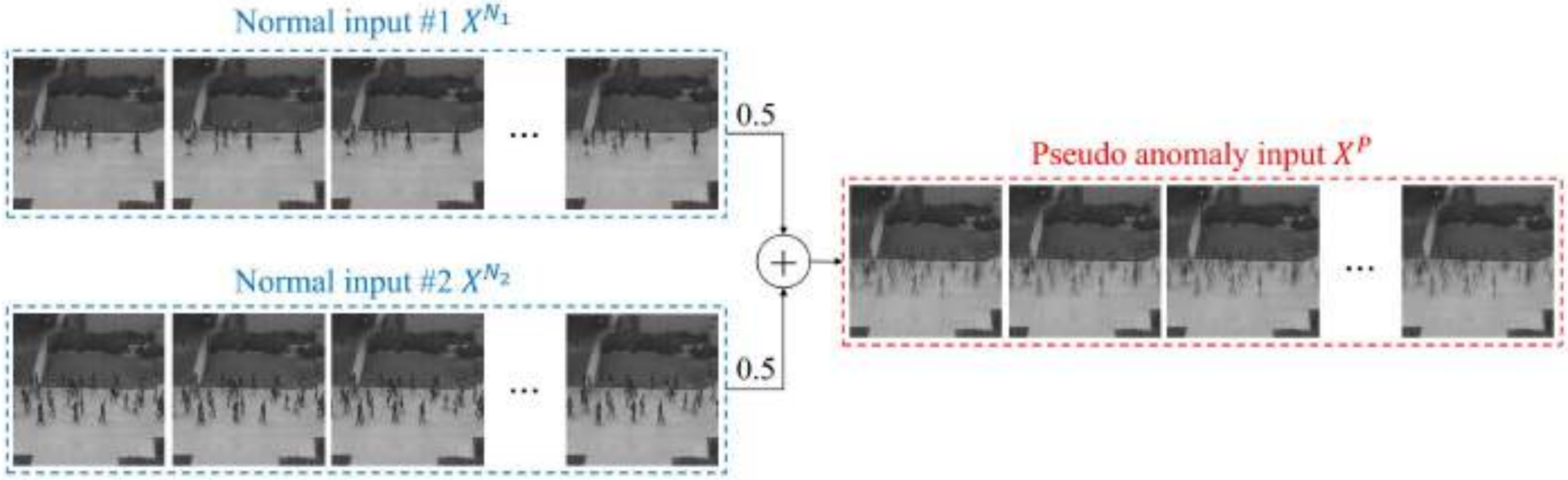
AD method: one-class: data augmentation

- Pseudo anomaly generation
  - Example #3: creating patch from another dataset
    - Using prior knowledge, e.g., anomalous objects

Source: **Marcella Astrid**, Muhammad Zaigham Zaheer, Jae-Yeong Lee, and Seung-Ik Lee. "Learning Not to Reconstruct Anomalies". In: *British Machine Vision Conference 2021 (BMVC2021)* (Virtual). Nov. 22–25, 2021.

AD method: one-class: data augmentation

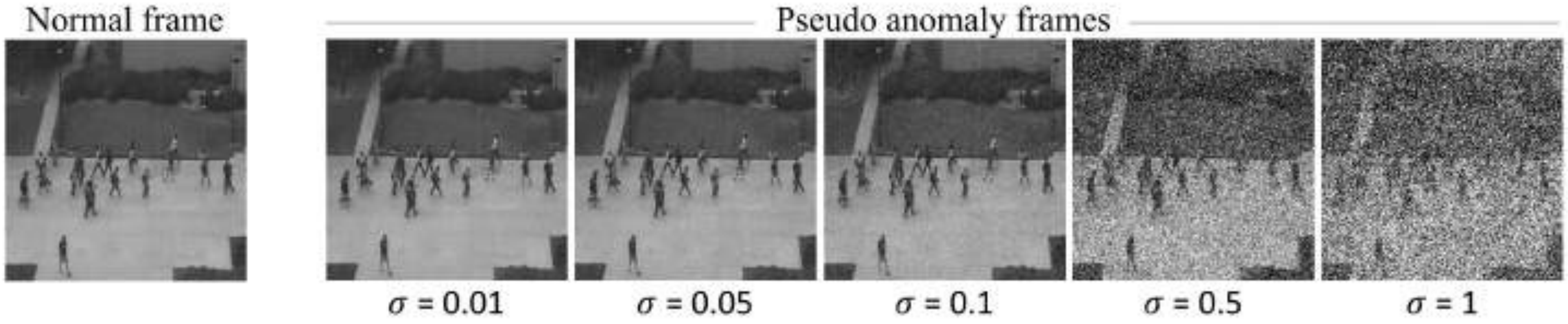
- Pseudo anomaly generation
  - Example #4: fuse 2 normal to create anomalous shape



Source: **Marcella Astrid**, Muhammad Zaigham Zaheer, and Seung-Ik Lee. "PseudoBound: Limiting the anomaly reconstruction capability of one-class classifiers using pseudo anomalies". *Neurocomputing* 534 (2023):147-160.

AD method: one-class: data augmentation

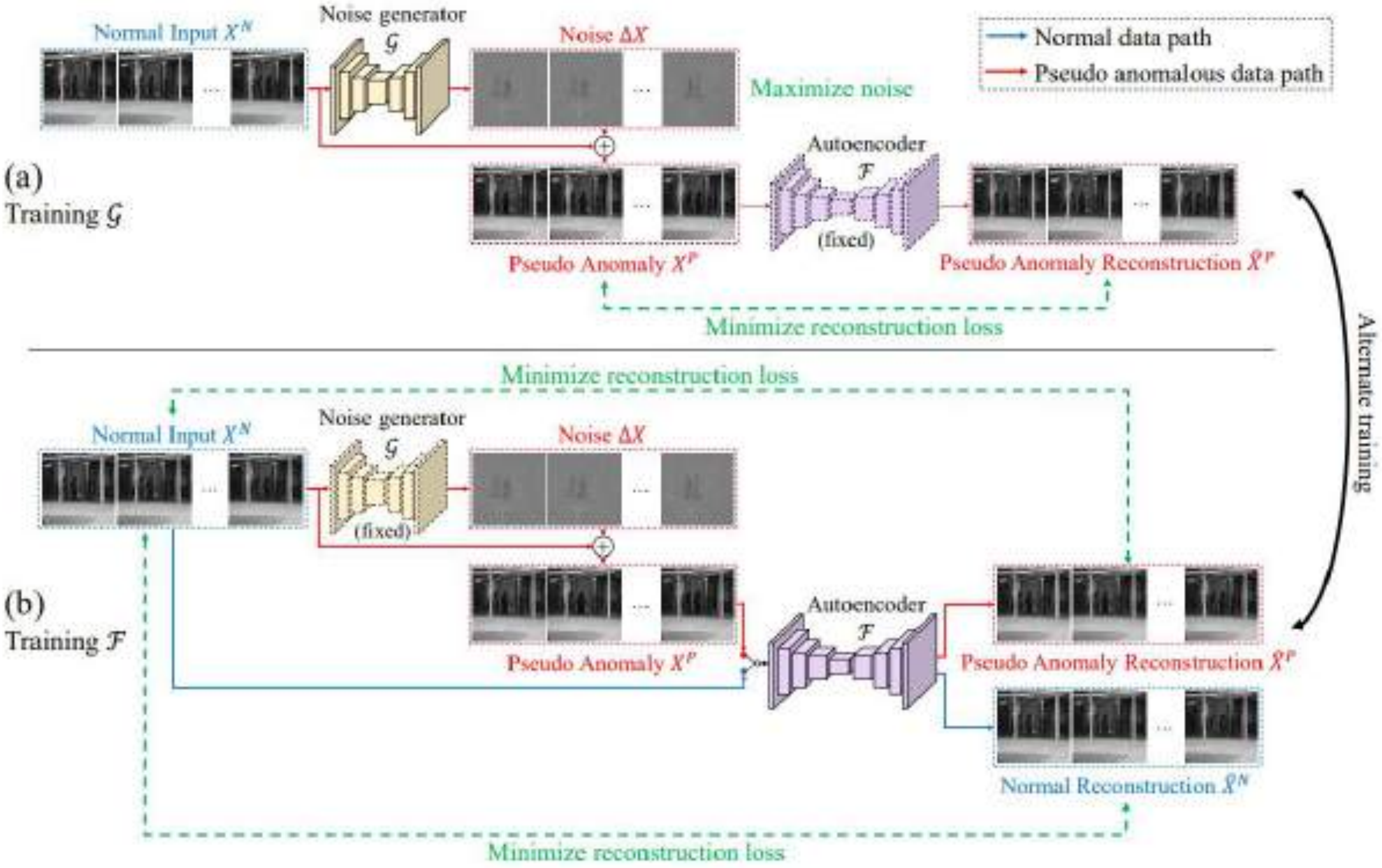
- Pseudo anomaly generation
  - Example #5: Adding noise
    - Potential problem: noisy normal input



Source: **Marcella Astrid**, Muhammad Zaigham Zaheer, and Seung-Ik Lee. "PseudoBound: Limiting the anomaly reconstruction capability of one-class classifiers using pseudo anomalies". *Neurocomputing* 534 (2023):147-160.

AD method: one-class: data augmentation

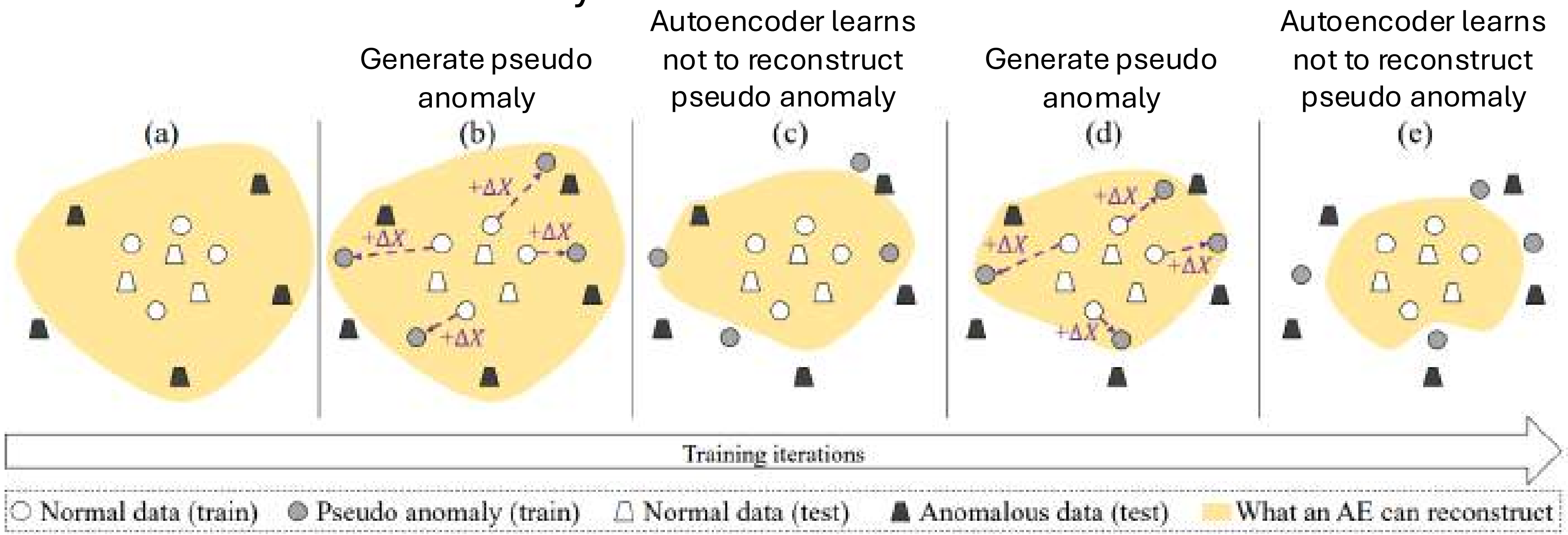
- Pseudo anomaly generation
  - Example #6: Learnable noise – exploiting autoencoder's weakness, i.e., reconstruct anomalies too well



Source: **Marcella Astrid**, Muhammad Zaigham Zaheer, and Seung-Ik Lee. " Exploiting autoencoder's weakness to generate pseudo anomalies". *Neural Computing and Applications,* 36(23), pp.14075-14091.

AD method: one-class: data augmentation

- Pseudo anomaly generation
  - Example #6: Learnable noise – exploiting autoencoder's weakness, i.e., reconstruct anomalies too well
    - How it works intuitively



Source: **Marcella Astrid**, Muhammad Zaigham Zaheer, and Seung-Ik Lee. " Exploiting autoencoder's weakness to generate pseudo anomalies". *Neural Computing and Applications,* 36(23), pp.14075-14091.

AD method: one-class: data augmentation

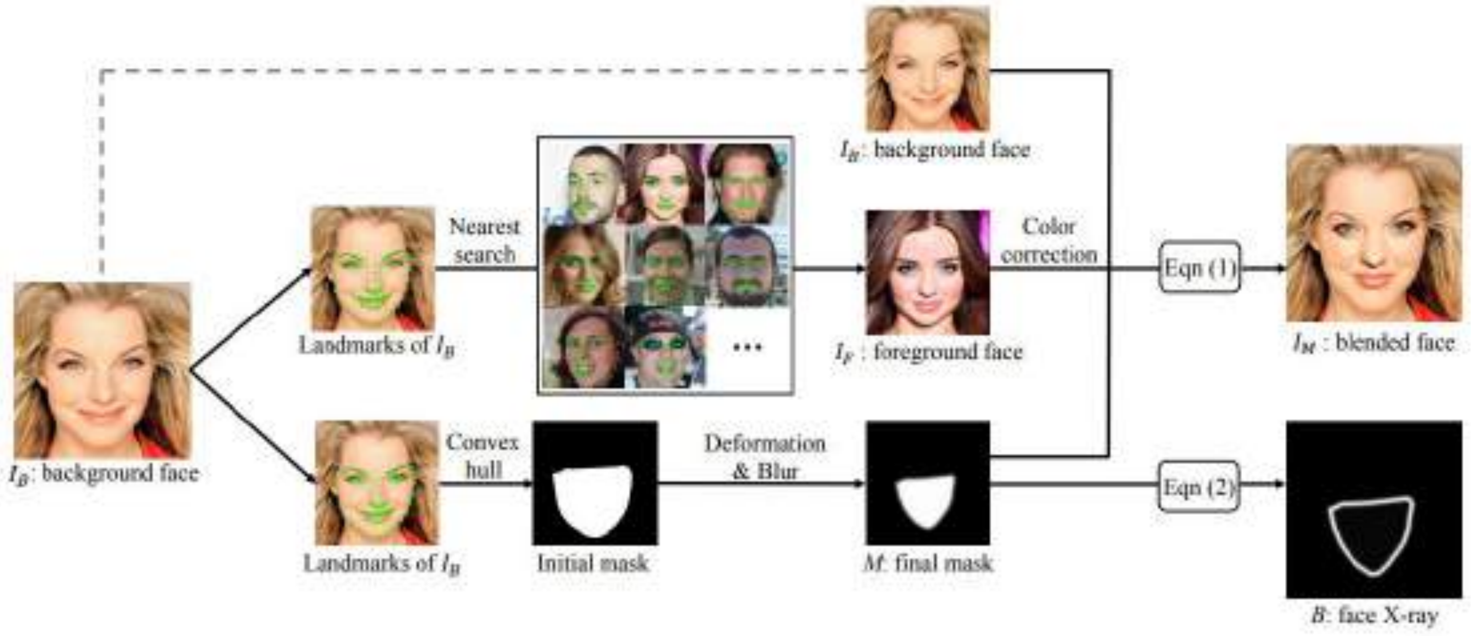
- Pseudo anomaly generation
  - Example #6: Learnable noise – exploiting autoencoder's weakness, i.e., reconstruct anomalies too well
    - Better than non-learnable noise → Higher quality pseudo-anomalies (closer to normal) are better

	Pseudo anomaly	Ped2 AUC	Avenue AUC	ShanghaiTech AUC	CIFAR-10 AUC	KDDCUP F1	KDDCUP Precision	KDDCUP Recall
	None (baseline)	92.49	81.47	71.28	60.10	94.53	93.94	95.13
non-learnable noise	Gaussian noise $\sigma = 0.1$	93.32	81.56	71.24	63.20	94.52	93.78	95.28
non-learnable noise	Gaussian noise $\sigma = 0.5$	93.12	82.10	71.73	61.80	94.78	94.04	95.53
non-learnable noise	Gaussian noise $\sigma = 1$	93.03	82.09	71.92	61.91	95.52	94.78	96.27
	Learnable noise (ours)	**94.57**	**83.23**	**73.23**	**67.76**	**95.58**	**94.84**	**96.34**

Source: **Marcella Astrid**, Muhammad Zaigham Zaheer, and Seung-Ik Lee. " Exploiting autoencoder's weakness to generate pseudo anomalies". *Neural Computing and Applications,* 36(23), pp.14075-14091.

AD method: one-class: data augmentation

- Pseudo anomaly generation
  - Example #7: Blended Image (BI) - Combining 2 *normal* data
    - Prior knowledge: face swap to create deepfake

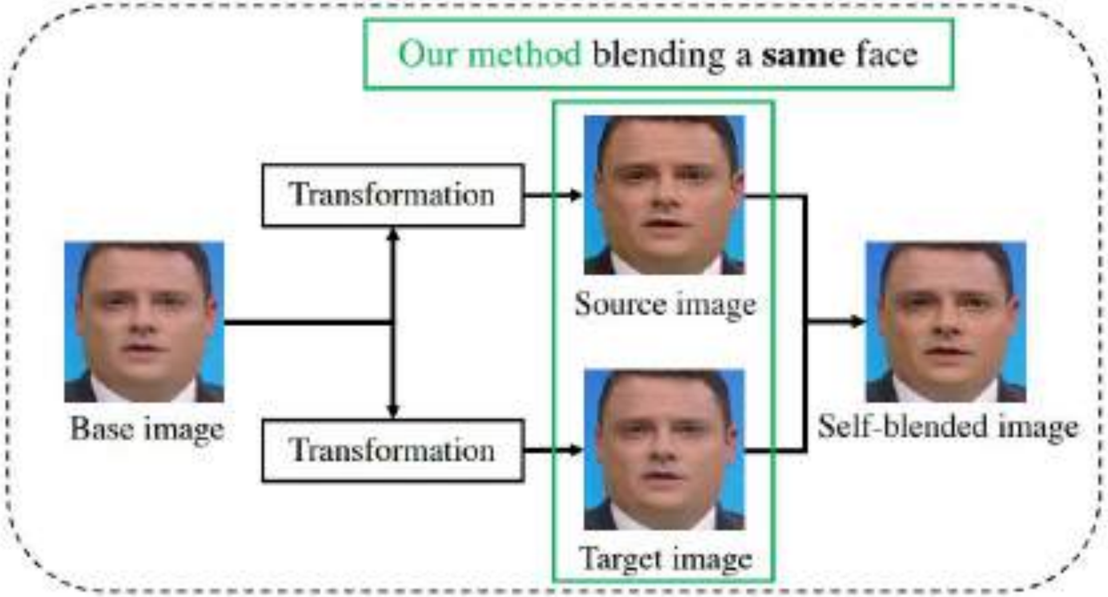


Pseudo anomaly

Source: Li, L., Bao, J., Zhang, T., Yang, H., Chen, D., Wen, F. and Guo, B., 2020. Face x-ray for more general face forgery detection. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition* (pp. 5001-5010).

AD method: one-class: data augmentation

- Pseudo anomaly generation
  - Example #8: Self-Blended Image (SBI) - combining 2 same *normal* data



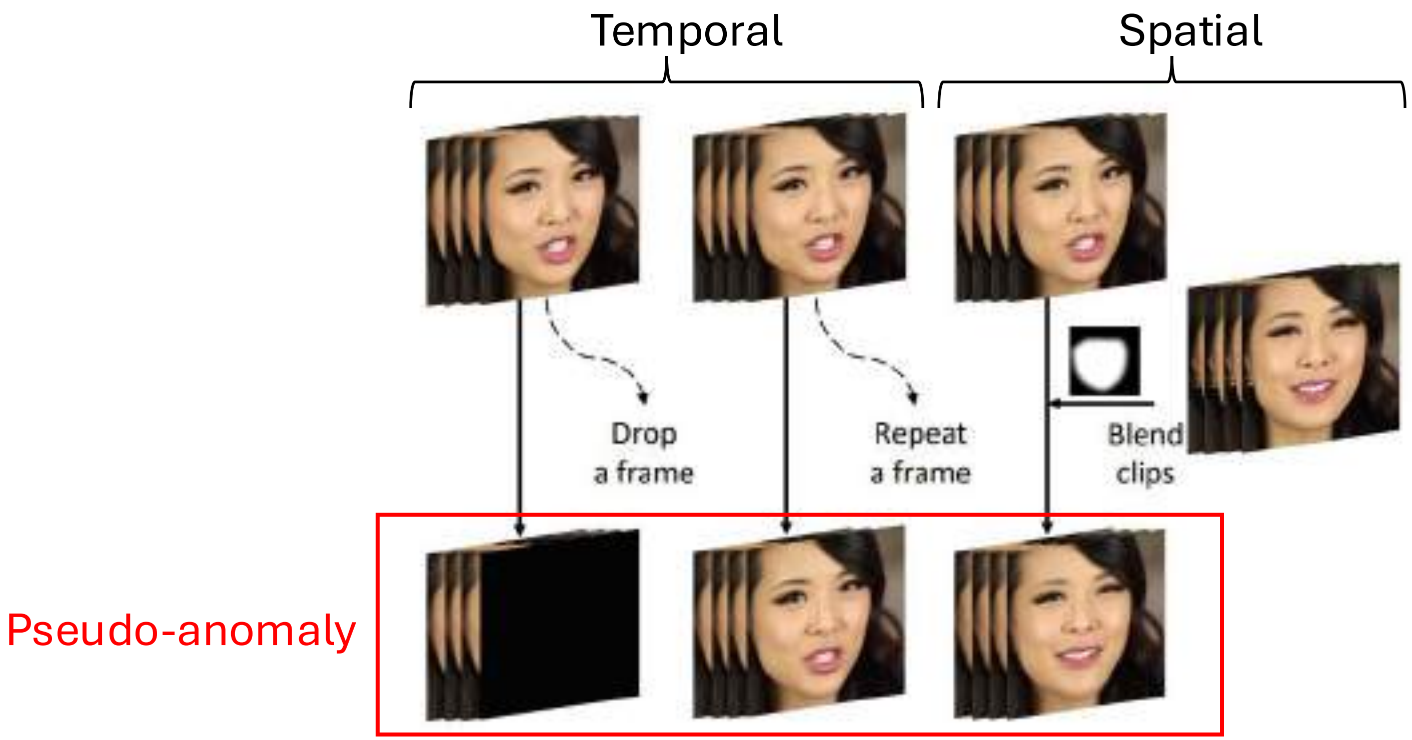
Higher quality pseudo-anomalies (closer to normal) are better:

Method	Test Set AUC (%)				
	DF	F2F	FS	NT	FF++
Xception + BI [39]	98.95	97.86	89.29	97.29	95.85
Xception + SBIs (Ours)	**99.99**	**99.90**	**98.79**	**98.20**	**99.22**

Source: Shiohara, K. and Yamasaki, T., 2022. Detecting deepfakes with self-blended images. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 18720-18729).

AD method: one-class: data augmentation

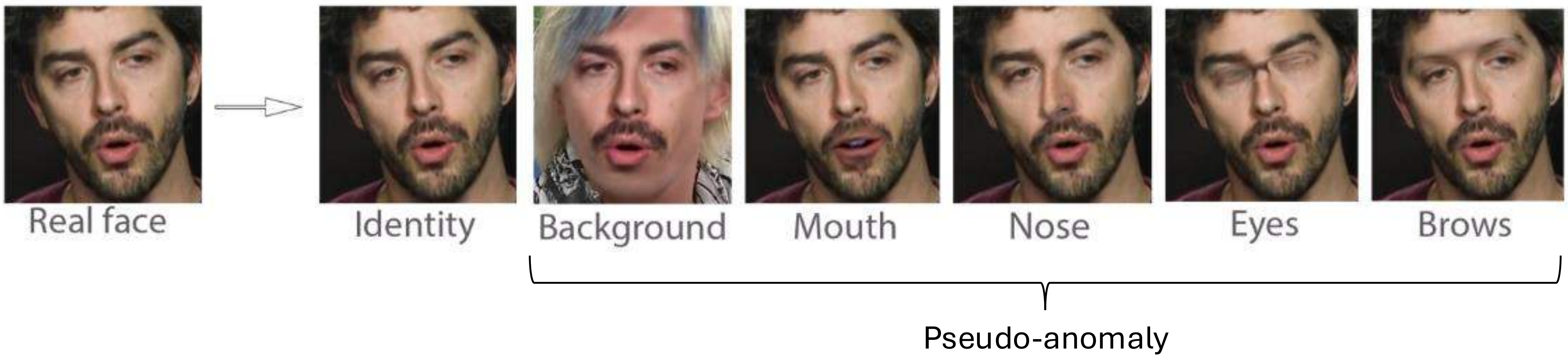
- Pseudo anomaly generation
  - Example #9: Create temporal and spatial inconsistencies, mimicking video deepfakes



Source: Wang, Z., Bao, J., Zhou, W., Wang, W. and Li, H., 2023. AltFreezing for More General Video Face Forgery Detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 4129-4138).

AD method: one-class: data augmentation

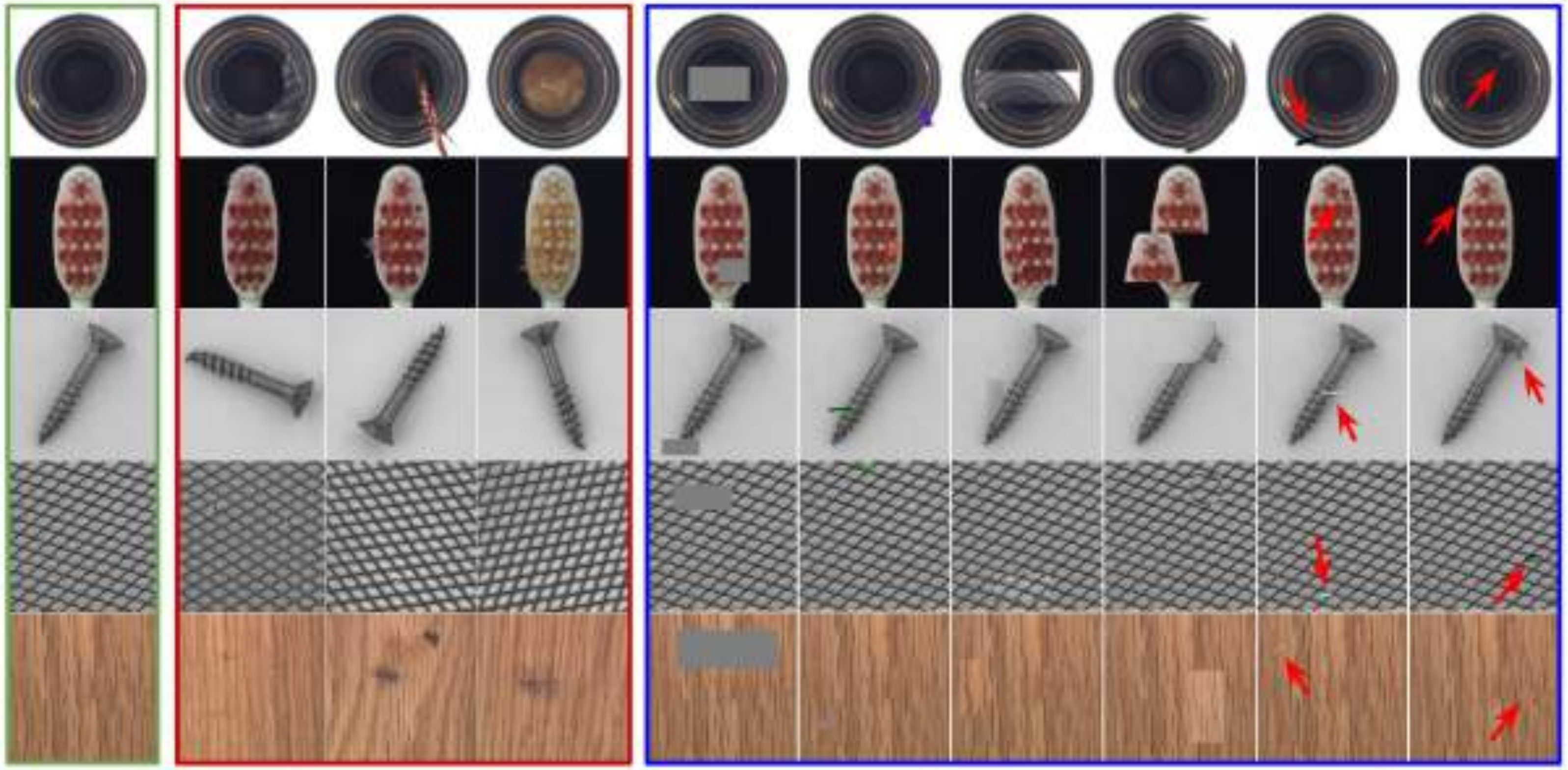
- Pseudo anomaly generation
  - Example #10: modify only part of face, instead of whole face



Source: Mejri, N., Ghorbel, E. and Aouada, D., 2023, June. UNTAG: Learning Generic Features for Unsupervised Type-Agnostic Deepfake Detection. In *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* (pp. 1-5). IEEE.

AD method: one-class: data augmentation

- Pseudo anomaly generation
  - Example #11:

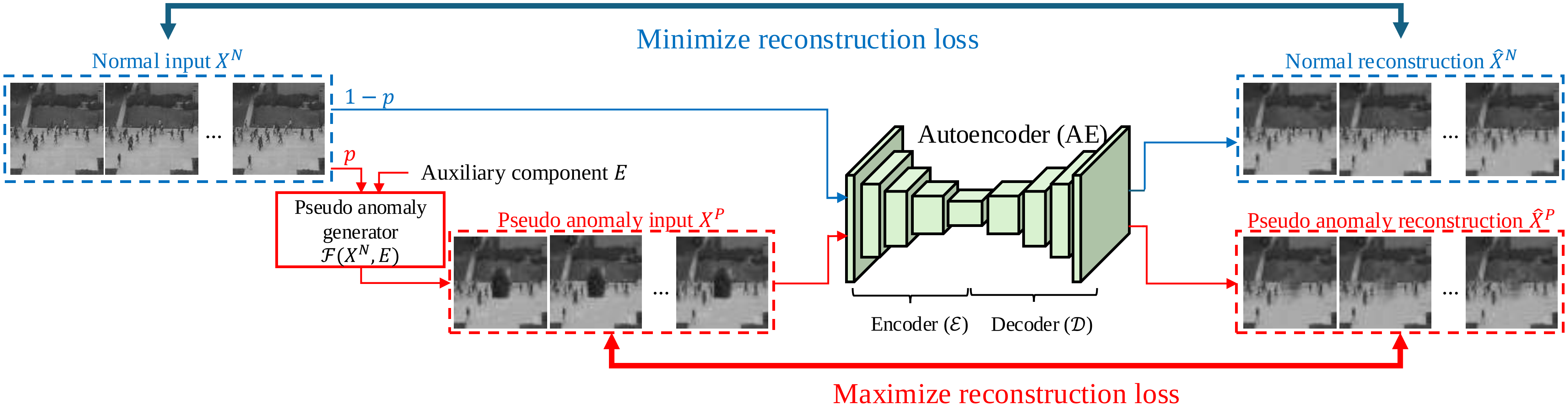


(a) Normal (b) Anomaly (c) Cutout (d) Scar (e) CutPaste (f) CutPaste (Scar)

Source: Li, C.L., Sohn, K., Yoon, J. and Pfister, T., 2021. Cutpaste: Self-supervised learning for anomaly detection and localization. In Proceedings of the *IEEE/CVF conference on computer vision and pattern recognition* (pp. 9664-9674).

AD method: one-class: framework

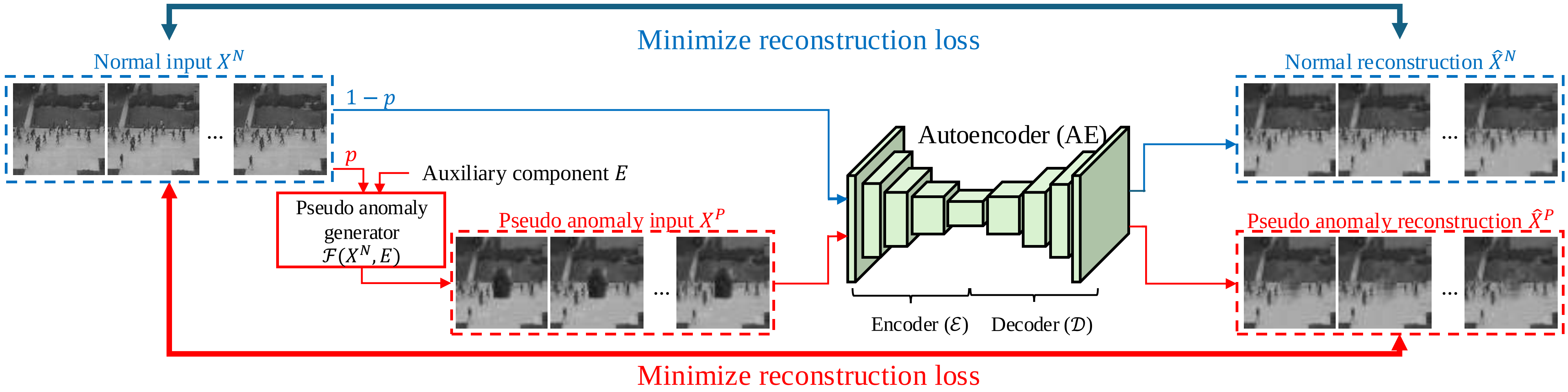
- Example #1: well-reconstruct normal, poorly-reconstruct pseudo anomaly



Source: **Marcella Astrid**, Muhammad Zaigham Zaheer, and Seung-Ik Lee. "Synthetic Temporal Anomaly Guided End-to-End Video Anomaly Detection". In: *International Conference on Computer Vision (ICCV 2021) Workshop* (Virtual). Oct. 11–17, 2021.

AD method: one-class: framework

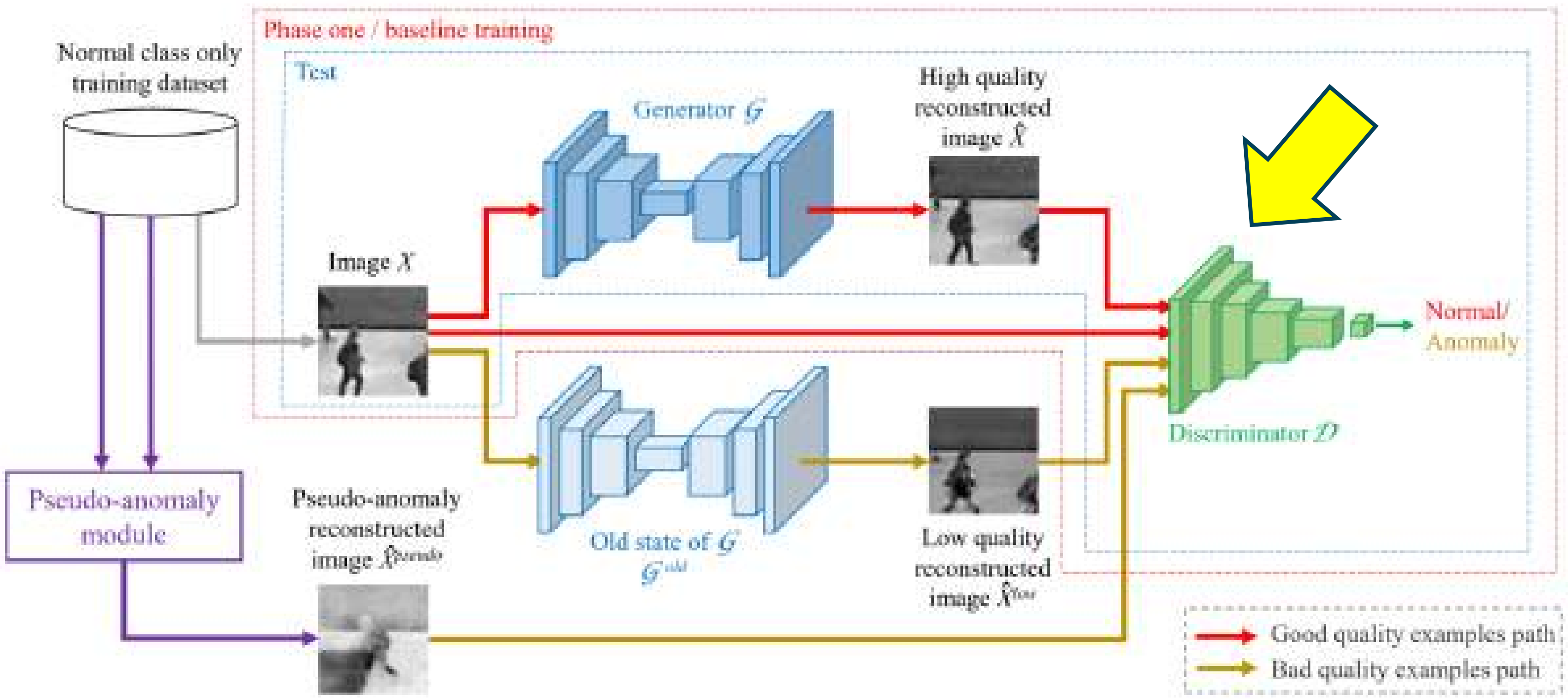
- Example #2: Learn to reconstruct only normal regardless the input (normal & pseudo anomaly)



Source: **Marcella Astrid**, Muhammad Zaigham Zaheer, Jae-Yeong Lee, and Seung-Ik Lee. "Learning Not to Reconstruct Anomalies". In: *British Machine Vision Conference 2021 (BMVC2021)* (Virtual). Nov. 22–25, 2021.

AD method: one-class: framework

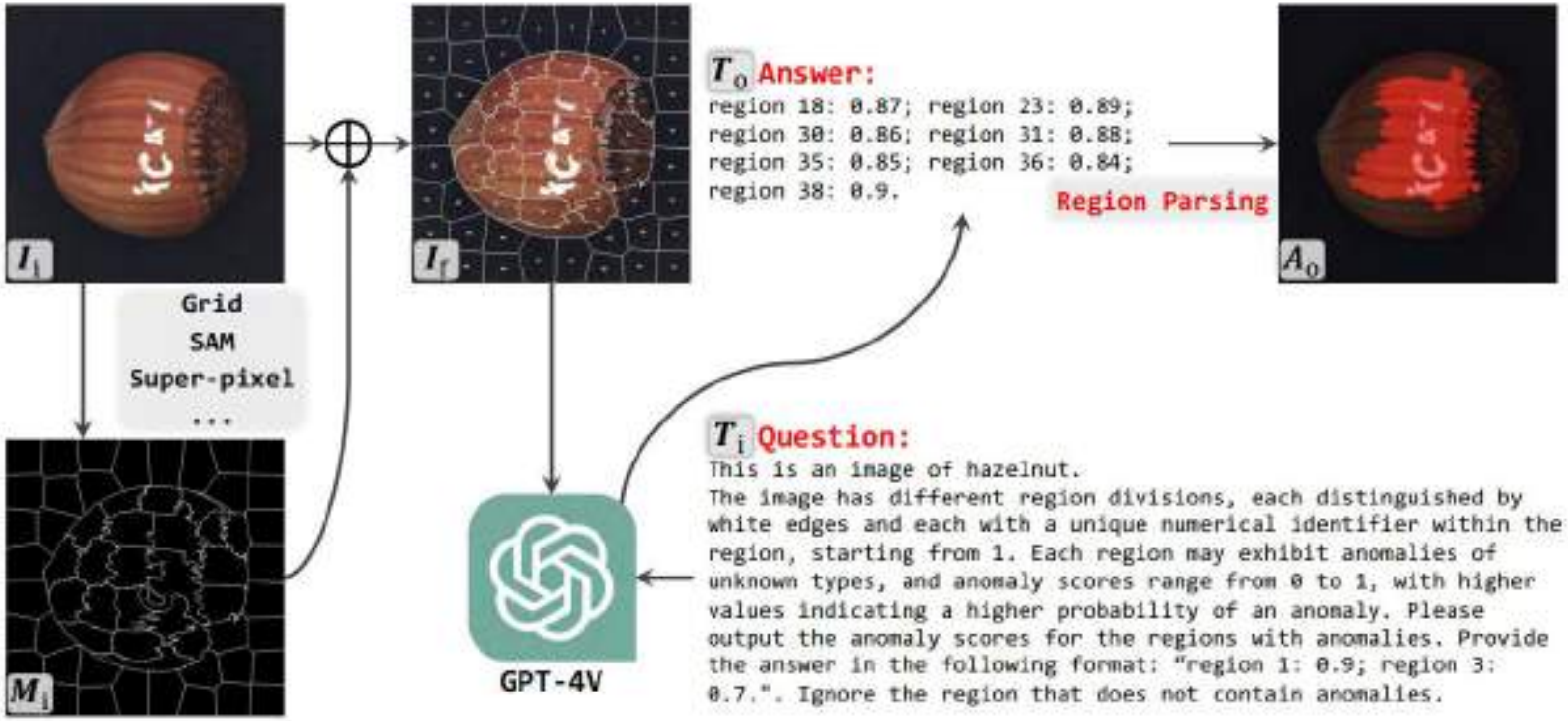
- Example #3: binary classifier between normal and pseudo-anomaly



Source: Muhammad Zaigham Zaheer, Jin-ha Lee, **Marcella Astrid**, and Seung-Ik Lee. "Old is Gold: Redening the adversarially learned one-class classier training paradigm". In: Proceedings of the *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).* June 14-19, 2020.

AD method: zero-shot

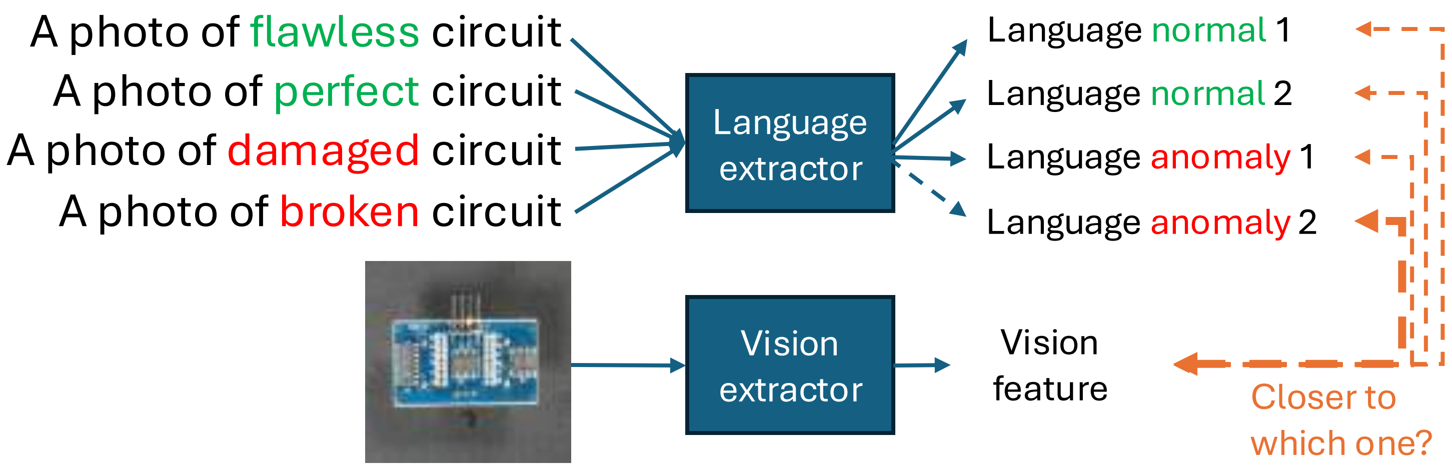
- Example #1: using Visual-Question-Answering (VQA) model



Source: Zhang, J., He, H., Chen, X., Xue, Z., Wang, Y., Wang, C., Xie, L. and Liu, Y., 2024, August. Gpt-4v-ad: Exploring grounding potential of vqa-oriented gpt-4v for zero-shot anomaly detection. In *International Joint Conference on Artificial Intelligence* (pp. 3-16). Singapore: Springer Nature Singapore.

AD method: zero-shot

- Example #2: using CLIP



Source: Jeong, J., Zou, Y., Kim, T., Zhang, D., Ravichandran, A. and Dabeer, O., 2023. Winclip: Zero-/few-shot anomaly classification and segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 19606-19616).

Overview

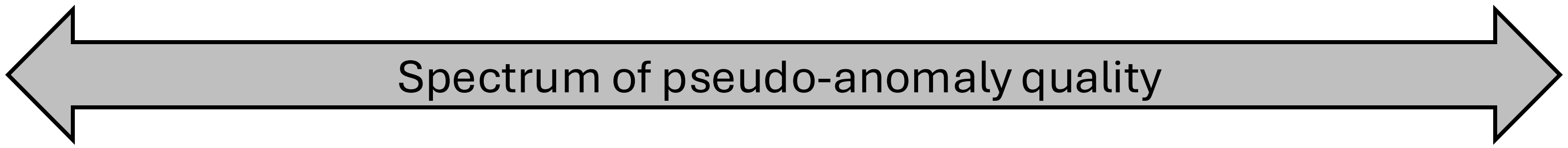
- Part 2: Introduction to Anomaly Detection
  - Anomalies
  - Anomaly Detection (AD)
  - Application of AD
  - Challenges of AD
  - AD method
    - One-class
      - Model-based
      - Data augmentation-based
      - Framework (model + data augmentation)
    - Zero-shot
  - Summary and food for thought

Summary

- Anomalies are difficult to collect
  - Rare
  - Unlimited possibilities
- Method
  - One class
    - Model: AE, VAE, …
    - Data: pseudo anomaly
      - Near normal data should be better
    - Hybrid
  - Zero-shot

Food for thought

- How much closer to normal data should be the pseudo anomaly?
  - TOO close to normal data → more false positives (normal data detected as anomaly)
  - TOO far from normal data → not that helpful



Good

When is it TOO good or bad?

Bad

Normal

Anomaly

Food for thought

- Unseen normal
  - The analogy

Food for thought

- Unseen normal
  - The analogy

I don’t know this is normal?!

Me who just moved to Korea from Indonesia

Food for thought

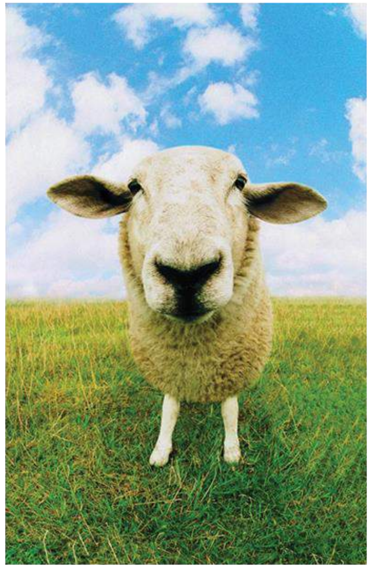
- Unseen normal
  - Applications: new environment

Vehicles are normal on the street

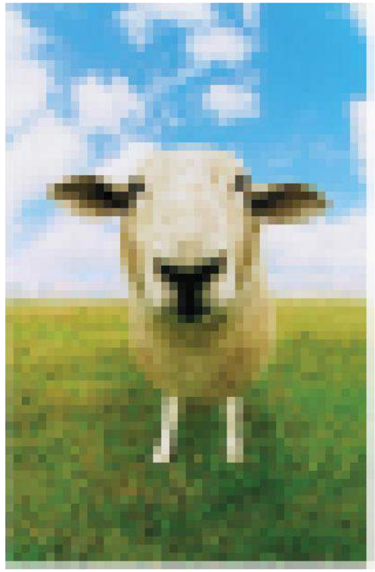
Vehicles are anomalous in the house

Food for thought

- Unseen normal
  - Applications: compressed/noisy data



High Resolution



Low Resolution

Food for thought

- What is anomaly/normal anyway?
  - New normal, the analogy

Normal before covid
Anomalous during covid

Normal during covid

Food for thought

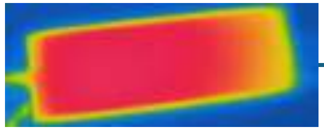
- What is anomaly/normal anyway?
    - Rare normal, the analogy

Overview

- Part 3: Anomaly Detection for Battery Monitoring System
  - AD for thermal image battery
  - Challenges
  - One-shot method
  - Zero-shot method
  - Ongoing challenges

AD for BMS

- AD for battery monitoring system (BMS) with thermal image
  - For safe battery usage
  - Even though, in reality, currently we don’t have a way how to put thermal camera in the BMS system 🤌🤌

 → AD model → Normal/anomaly

Challenges in AD for thermal image battery

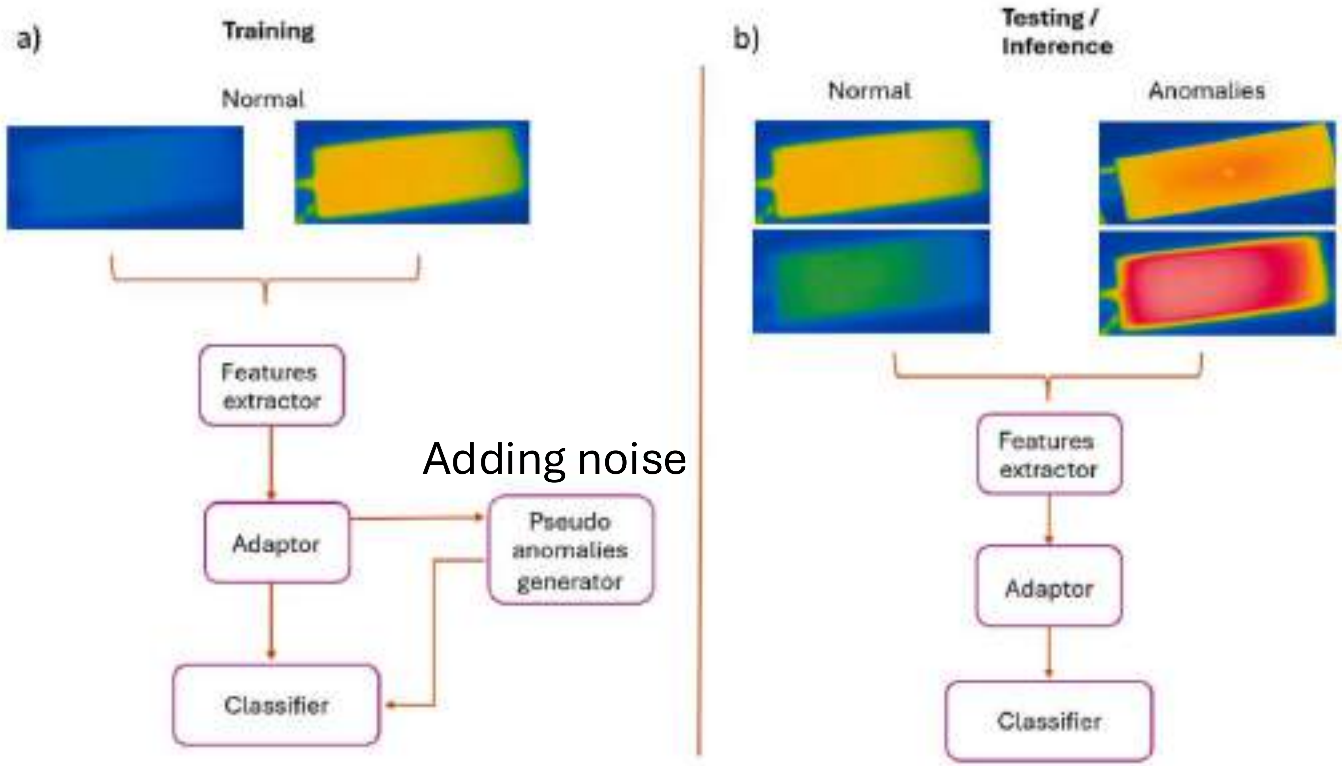
- (Same problem as AD) Anomalous data is difficult to get
  - Safety reason

Overview

- Part 3: Anomaly Detection for Battery Monitoring System
  - AD for thermal image battery
  - Challenges
  - One-shot method
  - Zero-shot method
  - Ongoing challenges

One-class + pseudo anomaly AD for thermal image battery

- Binary classifier + feature-level pseudo-anomaly
  - Method



Source: Shabayek, A., Rathinam, A., Ruthven, M., Aouada, D. and Amietszajew, T., 2025. AI-enabled thermal monitoring of commercial (PHEV) Li-ion pouch cells with Feature-Adapted Unsupervised Anomaly Detection. *Journal of Power Sources*, *629*, p.235982.

One-class + pseudo anomaly AD for thermal image battery

- Binary classifier + feature-level pseudo-anomaly
  - Results (one-class)

Technique	AUROC (**clean normal data**)
FAUAD	**1**
SimpleNet [22]	**1**
DRAEM [39]	0.991
CFA [40]	0.942
STFPM [41]	0.961
PaDiM [42]	0.996
EfficientAD [43]	**1**
DFM [44]	0.996
FastFlow [37]	**1**
PatchCore [21]	0.990
CFLOW-AD [36]	0.873

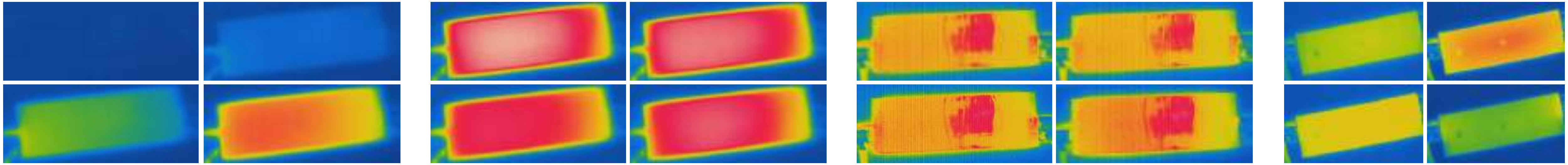
Too many perfect results from many methods.

- Is the dataset too easy?
- Do complicated method necessary?

Source: Shabayek, A., Rathinam, A., Ruthven, M., Aouada, D. and Amietszajew, T., 2025. AI-enabled thermal monitoring of commercial (PHEV) Li-ion pouch cells with Feature-Adapted Unsupervised Anomaly Detection. *Journal of Power Sources*, *629*, p.235982.

One-class + pseudo anomaly AD for thermal image battery

- Binary classifier + feature-level pseudo-anomaly
  - Dataset
    - Test dataset is representative enough for real anomalies?
      - There can be more anomalies that are more subtle than anomalies in this test data
      - Normal in this dataset can be anomaly depending on context (e.g. in time domain)



(a) Normal

Training: 160 images
Test: 27 images

(b) Overheating

Test: 13 images

(c) Reflection

Test: 12 images

(d) Spatial tape

Test: 8 images

Source: Shabayek, A., Rathinam, A., Ruthven, M., Aouada, D. and Amietszajew, T., 2025. AI-enabled thermal monitoring of commercial (PHEV) Li-ion pouch cells with Feature-Adapted Unsupervised Anomaly Detection. *Journal of Power Sources*, *629*, p.235982.

One-class + pseudo anomaly AD for thermal image battery

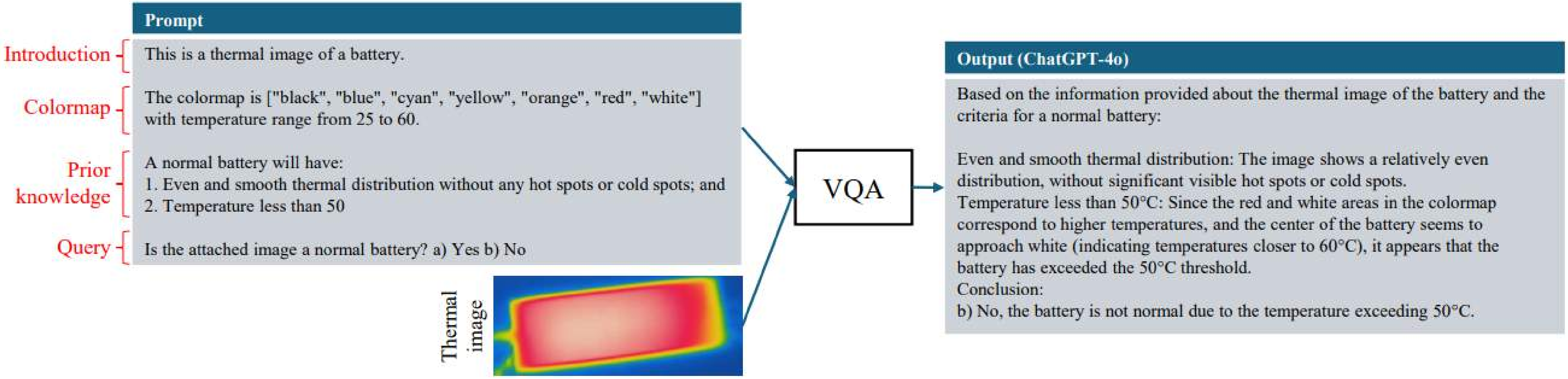
- Binary classifier + feature-level pseudo-anomaly
  - Results (unsupervised)
    - But the method is not specifically built for noisy data
      (Why does the model robust to noisy data?)

Technique	AUROC (normal data contaminated with 10 % anomalies)
FAUAD	**0.990**
SimpleNet [22]	0.977
DRAEM [39]	0.922
CFA [40]	0.878
STFPM [41]	0.871
PaDiM [42]	0.863
EfficientAD [43]	0.810
DFM [44]	0.803
FastFlow [37]	0.793
PatchCore [21]	0.774
CFLOW-AD [36]	0.769

Source: Shabayek, A., Rathinam, A., Ruthven, M., Aouada, D. and Amietszajew, T., 2025. AI-enabled thermal monitoring of commercial (PHEV) Li-ion pouch cells with Feature-Adapted Unsupervised Anomaly Detection. *Journal of Power Sources*, *629*, p.235982.

Zero-shot AD for thermal image battery

- Using VQA model with prior knowledge of normal battery
  - Method



Source: **Marcella Astrid**, Abdelrahman Shabayek, and Djamila Aouada. "Zero-Shot Anomaly Detection in Battery Thermal Images Using Visual Question Answering with Prior Knowledge". In: The 33rd European Signal Processing Conference (EUSIPCO 2025). September 8-12, 2025.

Zero-shot AD for thermal image battery

- Using VQA model with prior knowledge of normal battery
  - Results

Method	AUC (%) clean train	AUC (%) noisy train	Method	AUC (%) clean train	AUC (%) noisy train
CFLOW-AD [19]	87.3	76.9	STFPM [20]	96.1	87.1
PatchCore [21]	99.0	77.4	CFA [22]	94.2	99.0
FastFlow [23]	100.0	79.3	DRAEM [24]	99.1	92.2
DFM [25]	99.6	80.3	SimpleNet [26]	100.0	97.7
EfficientAD [27]	100.0	81.0	FAUAD [8]	100.0	99.0
PaDiM [28]	99.6	86.3	Ours (zero-shot)	86.6	

86.6 only using ChatGPT without any training.
Not so bad, huh?

Source: **Marcella Astrid**, Abdelrahman Shabayek, and Djamila Aouada. "Zero-Shot Anomaly Detection in Battery Thermal Images Using Visual Question Answering with Prior Knowledge". In: The 33rd European Signal Processing Conference (EUSIPCO 2025). September 8-12, 2025.

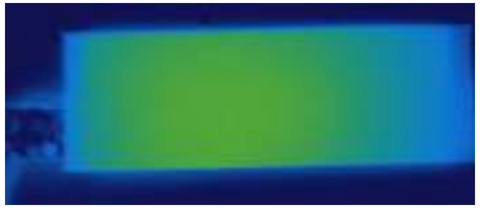
Overview

- Part 3: Anomaly Detection for Battery Monitoring System
  - AD for thermal image battery
  - Challenges
  - One-shot method
  - Zero-shot method
  - Ongoing challenges

Ongoing challenges

- Obtaining representative anomalous data → at least, for test.
  - Possible solutions:
    - Synthetic but realistic data
    - Almost-anomaly as “anomaly”
    - Really try exploding batteries, e.g., inside explosion-proof room
    - ???

Real data (normal)



Synthetic data (normal)

The heat propagation is not same
→ can we trust the synthetic data?

Thank You!

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