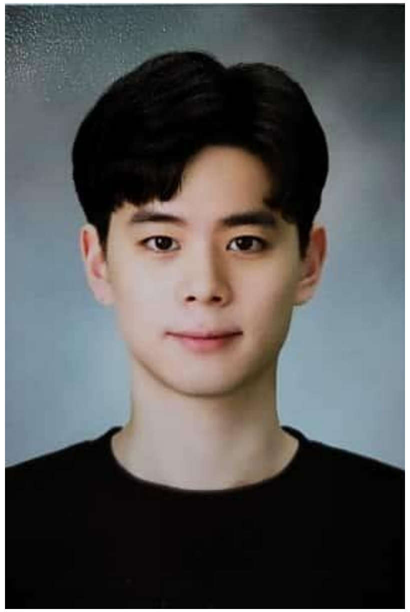
Self-Supervised Anomaly Detection

목충협

2022.08.19

발표자



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  - ✓ 고려대학교 산업경영공학
  - ✓ Data Mining & Quality Analytics Lab.
  - ✓ 석박통합과정(2019.03 ~)

- 관심분야
  - ✓ Anomaly Detection
  - ✓ Self-Supervised Learning
  - ✓ Multi-task learning

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Contents

Anomaly Detection

Introduction

Anomaly detection is the task of identifying samples that differs significantly from the majority of data and often signals an irregular, fake, rare, or fraudulent observation

다수의 데이터와 다른 이상한 샘플을 찾아내는 작업

Chandola, V., Banerjee, A., & Kumar, V. (2007). Outlier detection: A survey. ACM Computing Surveys, 14, 15.

Anomaly Detection

Introduction

❖ Anomaly Detection

- 정상 데이터의 분포와 다른 분포를 갖는 샘플들을 찾아내는 것

  예시) 강아지 / 고양이

❖ Outlier Detection

- 정상 데이터의 분포 내에서 자주 발생하지 않는 샘플들을 찾아내는 것

  예시) 강아지 / 희귀종 강아지

❖ Novelty Detection

- 정상 데이터의 분포 내에서 새로운 비정상 영역을 찾아내는 것

  예시) 강아지 / 새로운 종의 강아지

❖ Out-of-Distribution Detection

- 학습 클래스들에 속하지 않는 샘플들을 찾아내는 것

  예시) 강아지 / 식물

L. Ruff, J. R. Kauffmann, R. A. Vandermeulen, G. Montavon, W. Samek, M. Kloft, T. G. Dietterich, and K.-R. Muller, “A unifying ¨ review of deep and shallow anomaly detection,” Proceedings of the IEEE, 2021.

Anomaly Detection

Introduction

❖ 심각한 데이터 불균형

- 많은 양의 정상 데이터와 극소수의 이상 데이터로 구성됨
- 실제 현실 문제와 유사한 설정

❖ 이상 데이터의 분포를 정의할 수 없음

- 하나의 클래스로 정의할 수 없음
- 학습 단계에 없었던 새로운 타입의 이상 데이터가 나타날 수 있음

일반적으로 정상 데이터만 사용하며, 레이블 정보가 필요 없는 태스크으로 모델 학습

L. Ruff, J. R. Kauffmann, R. A. Vandermeulen, G. Montavon, W. Samek, M. Kloft, T. G. Dietterich, and K.-R. Muller, "A unifying ¨ review of deep and shallow anomaly detection," Proceedings of the IEEE, 2021.

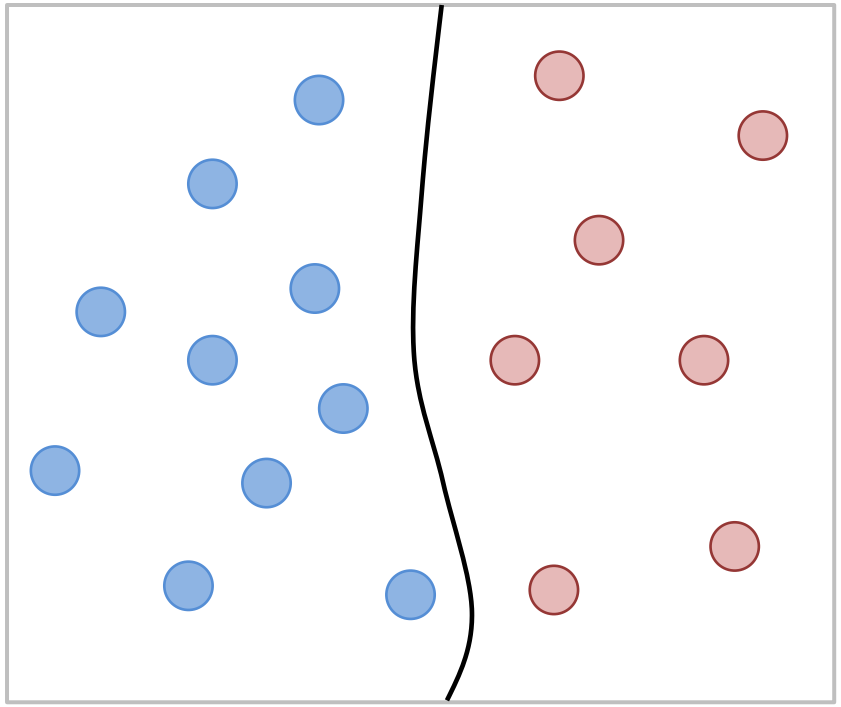
Anomaly Detection

Introduction

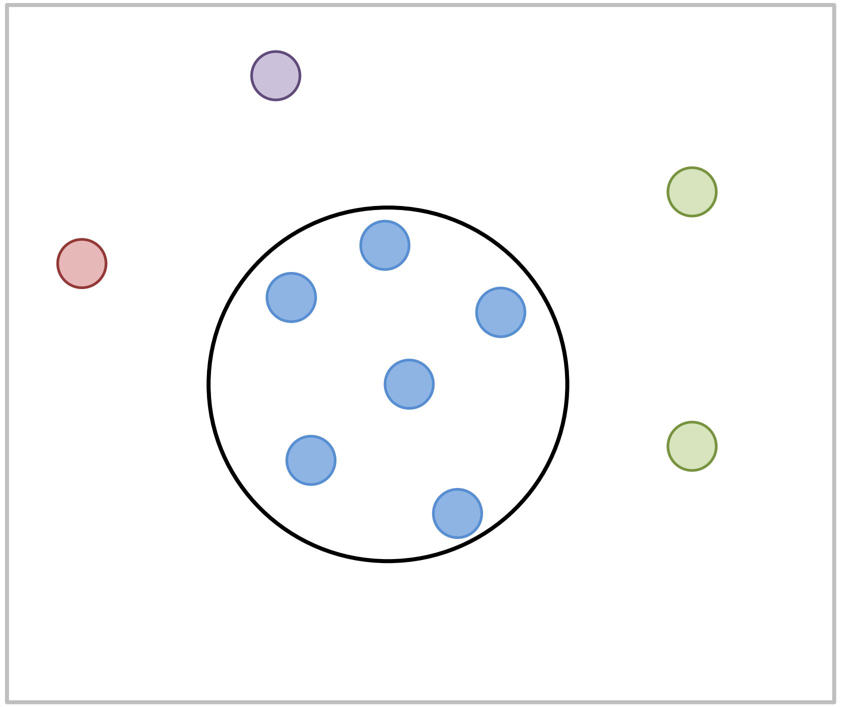
❖ Classification vs Anomaly Detection

- Classification : 입력 데이터가 어떤 클래스에 속하는지 분류
- Anomaly detection : 입력 데이터가 정상인지 아닌지 판단

Classification



Anomaly Detection



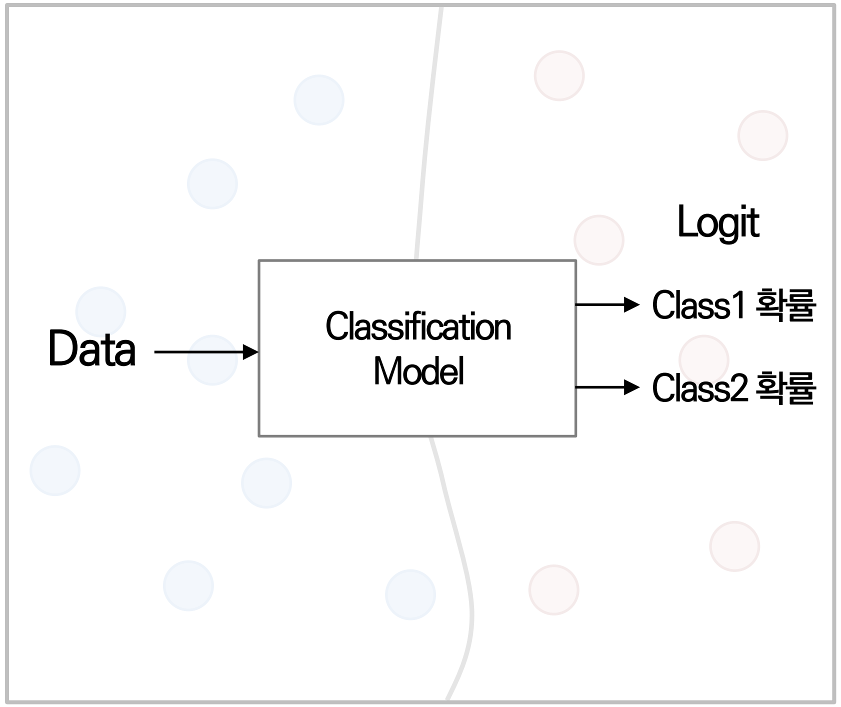
Anomaly Detection

Introduction

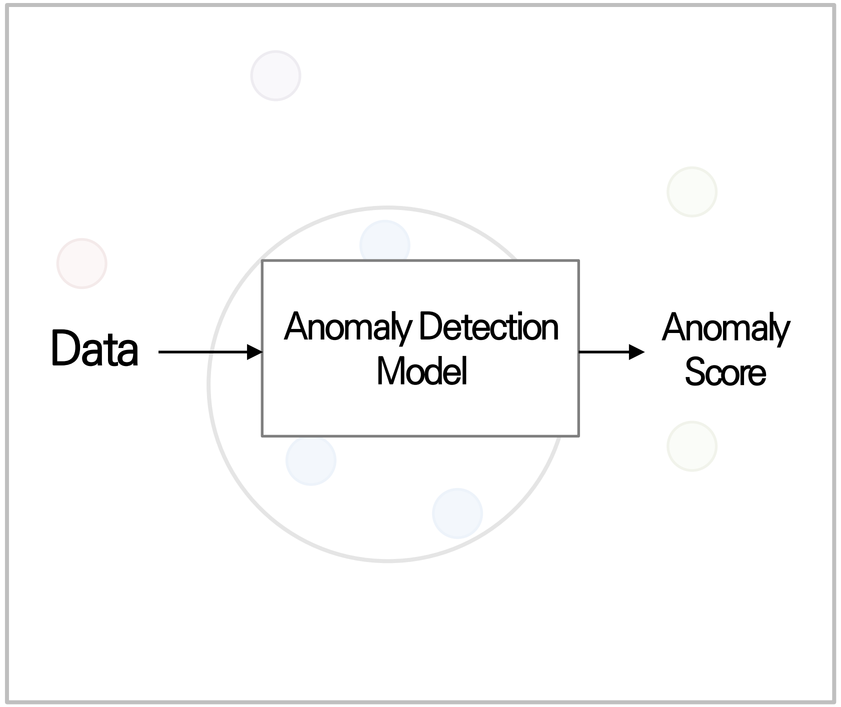
❖ Classification vs Anomaly Detection

- Classification: 각 클래스에 속할 확률 중 가장 큰 값 기준으로 예측
- Anomaly detection: anomaly score를 계산하여 임계치(threshold)기준으로 정상/이상 판단

Classification



Anomaly Detection



Anomaly Detection

Machine Learning Models

❖ Anomaly score

- Distance / similarity / density–based
  - ✓ Kernel density estimation
  - ✓ Local outlier factor
  - ✓ K–nearest neighbor
- Model–based
  - ✓ One–class support vector machine
  - ✓ Isolation forest
- Reconstruction–based
  - ✓ PCA

Anomaly Detection

Machine Learning Models

❖ Anomaly score

- Distance / similarity / density–based
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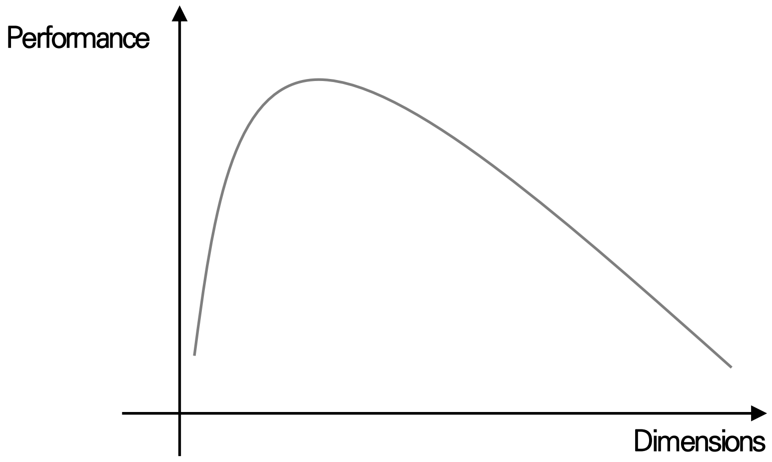
- Reconstruction–based
  - ✓ PCA

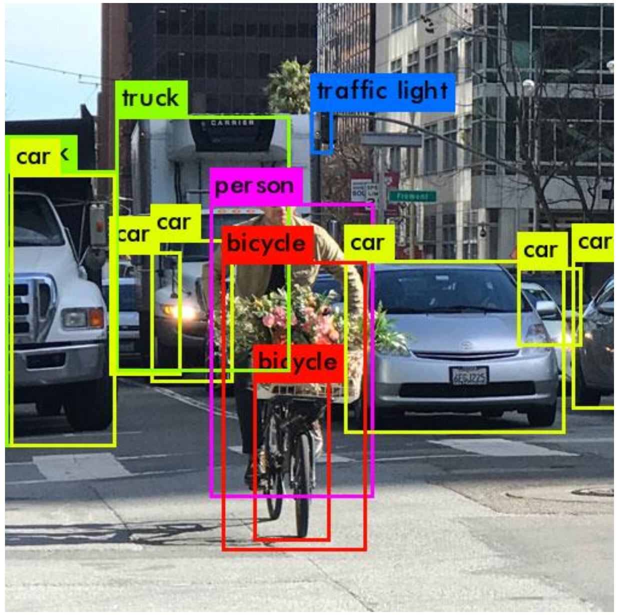
고차원 데이터에서는
좋지 않은 성능을 보임
(Curse of dimensionality)



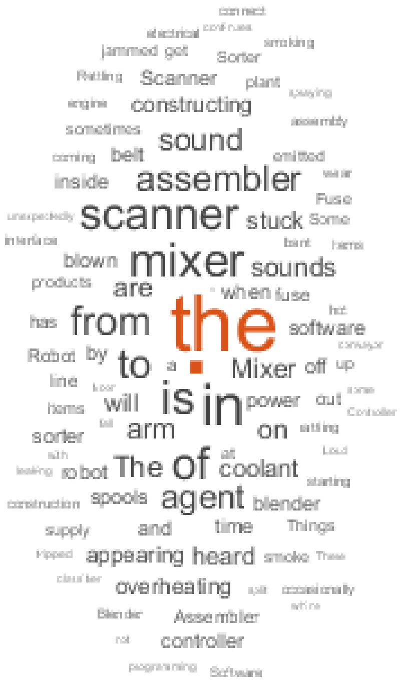
Anomaly Detection

Deep-Learning based Models for Anomaly Detection

이미지



텍스트



센서 데이터

	V_1	V_2	V_3	…	V_{89}
1	1.5	3.1	1.3	…	3.4
2	3.2	7.1	2.5	…	9.3
3	5.7	8.9	1.4	…	6.6
4	1.1	4.9	1.4	…	7.6
5	2.9	0.6	4.8	…	4.2
…	…	…	…	…	…

머신 러닝 방법론들은 고차원의 현실 데이터에는 적용하기 어려움

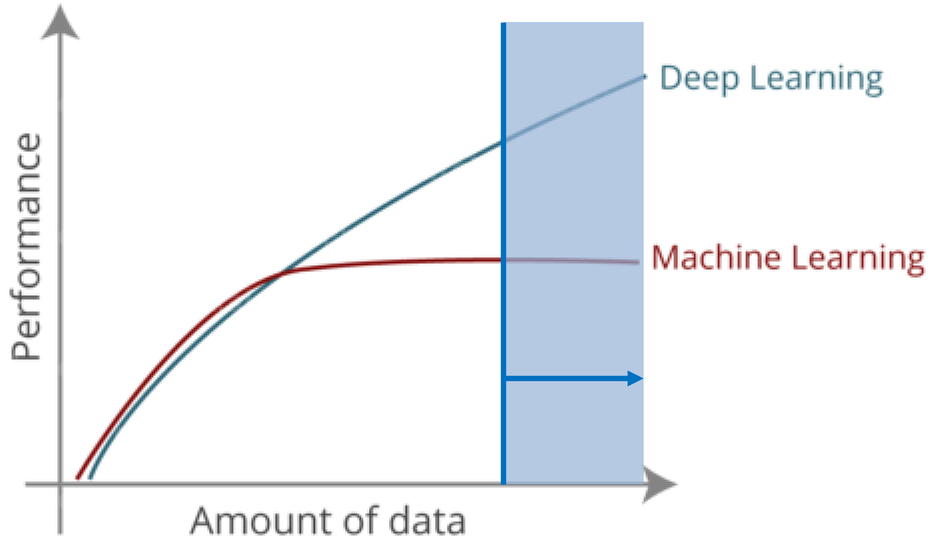
출처 : https://brunch.co.kr/@gdhan/7
https://kr.mathworks.com/help/textanalytics/ug/prepare-text-data-for-analysis.html

Anomaly Detection

Deep-Learning based Models for Anomaly Detection

❖ Deep Learning

- 충분한 양의 데이터를 학습시키면 좋은 성능을 기대할 수 있음

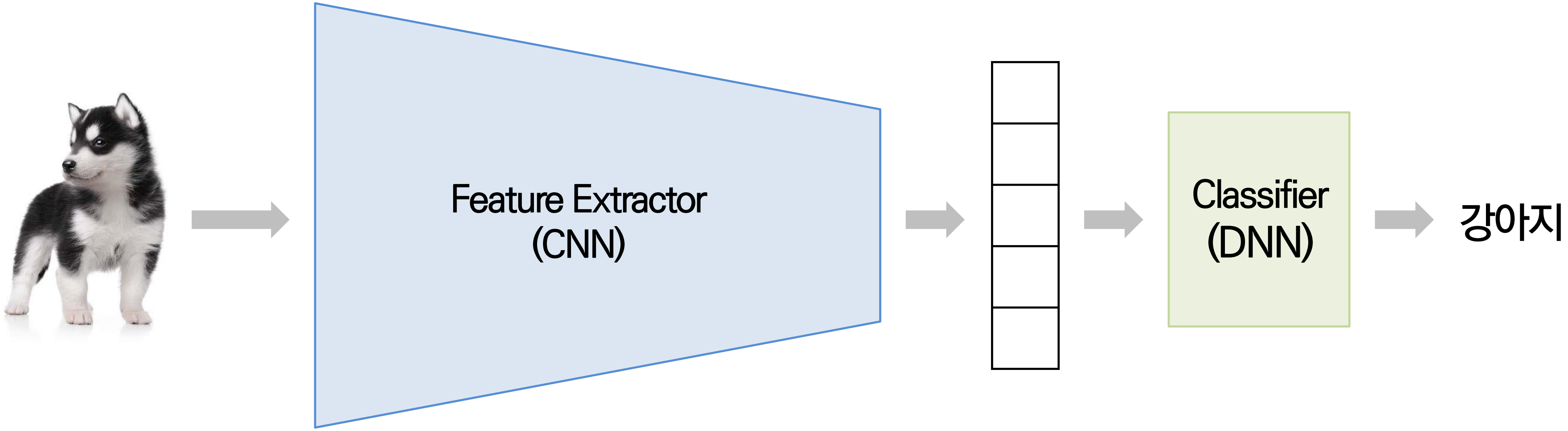


Anomaly Detection

Deep-Learning based Models for Anomaly Detection

❖ Deep Learning

- 예시) 이미지 분류 모델
  - ✓ Feature extractor : 이미지를 저차원 벡터로 표현하는 부분
  - ✓ Classifier : 저차원 벡터로 클래스를 예측하는 부분



Anomaly Detection

Deep-Learning based Models for Anomaly Detection

❖ Deep Learning

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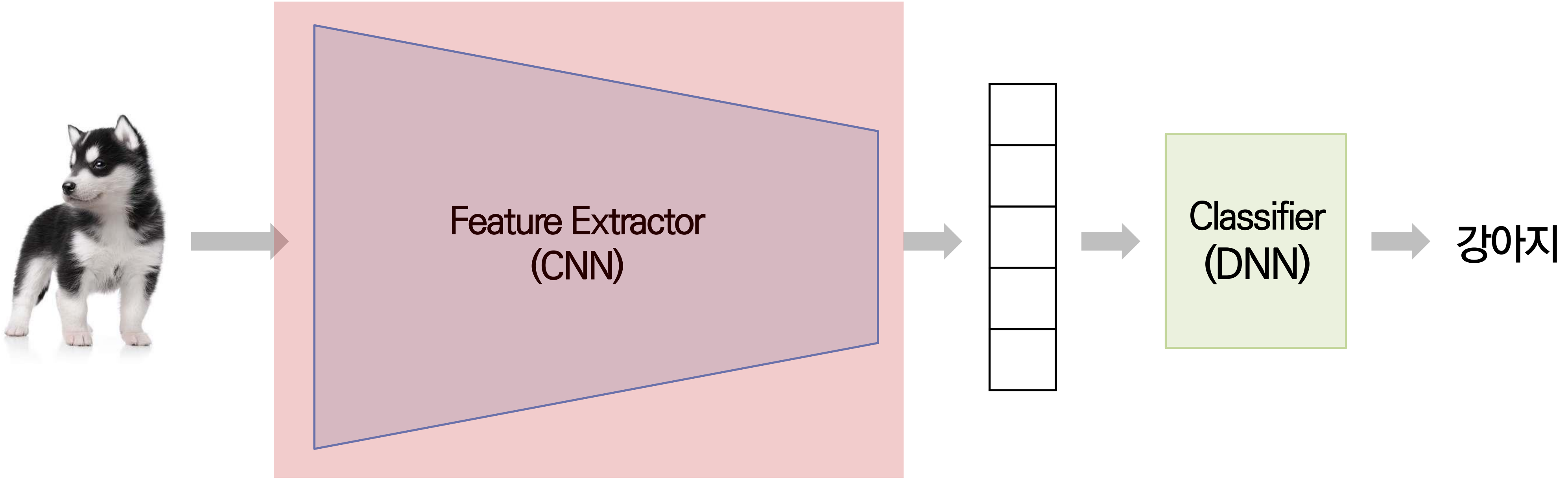


Anomaly Detection

Deep-Learning based Models for Anomaly Detection

❖ 차원 축소 기반 이상 탐지

- 딥러닝 모델을 이용하여 고차원 데이터를 저차원으로 축소 (representation learning)
- 축소된 데이터로 기존의 이상 탐지 모델을 학습

❖ Reconstruction 기반 이상 탐지

- Autoencoder, GAN 등의 딥러닝 모델로 정상 데이터 분포를 학습
- Reconstruction error 기반으로 이상 탐지

❖ End-to-end 이상 탐지

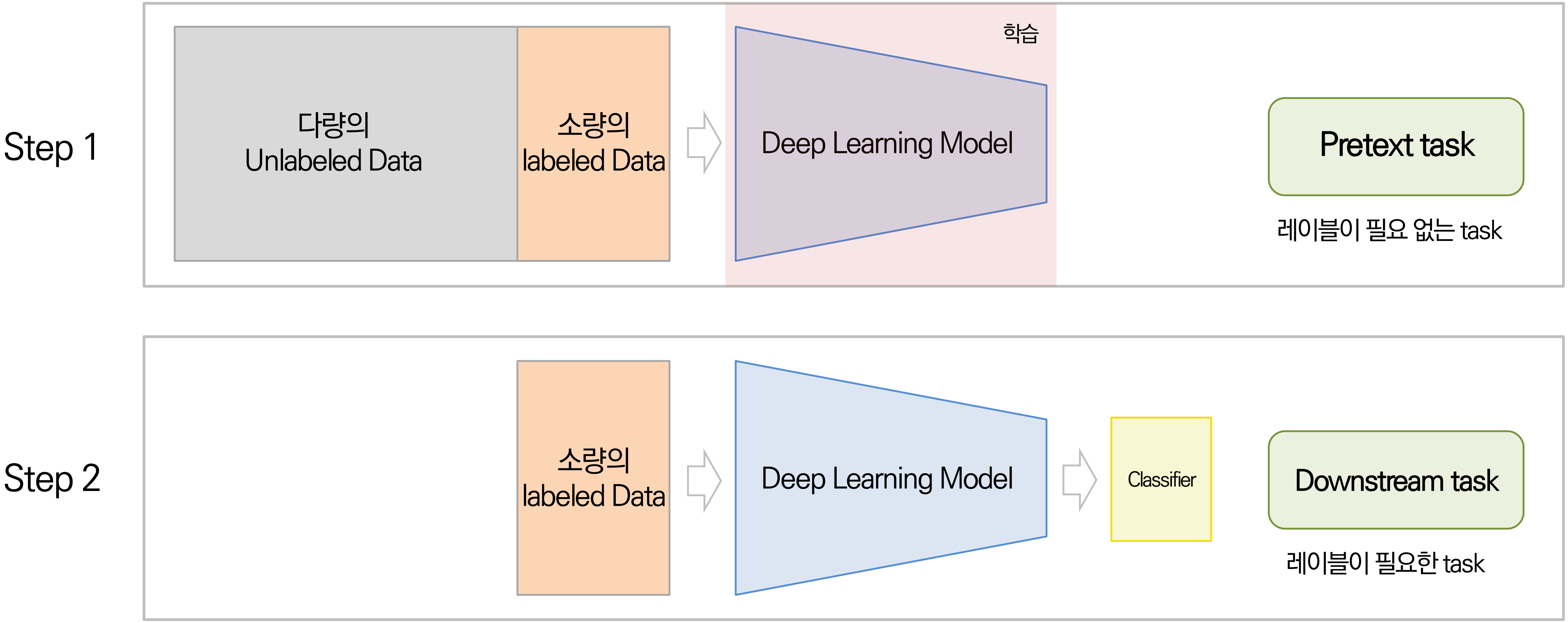
- 차원 축소 및 이상 탐지를 동시에 학습
- 이상 탐지 모델을 gradient descent를 이용하는 학습하는 방식으로 변형

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

Self-Supervised Learning

Self-Supervised Learning for Supervised Learning

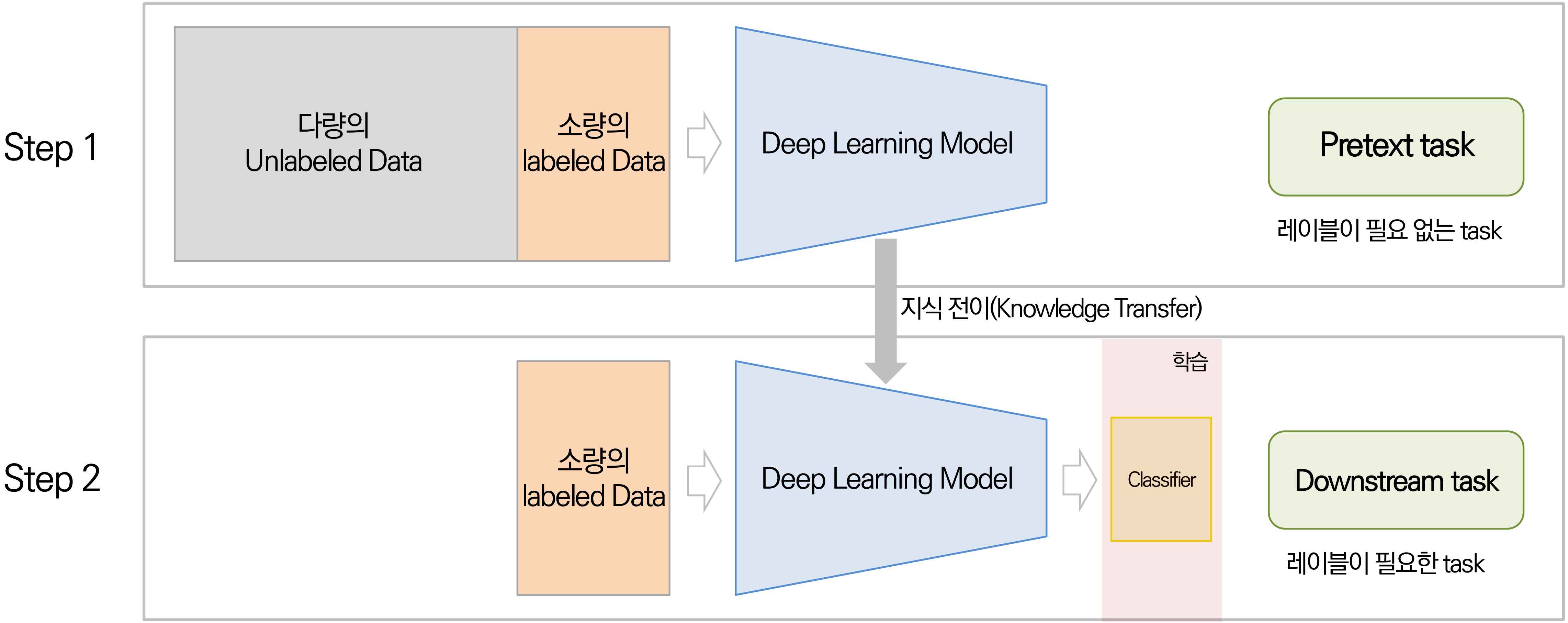
❖ Self-Supervised Learning Framework



Self-Supervised Learning

Self-Supervised Learning for Supervised Learning

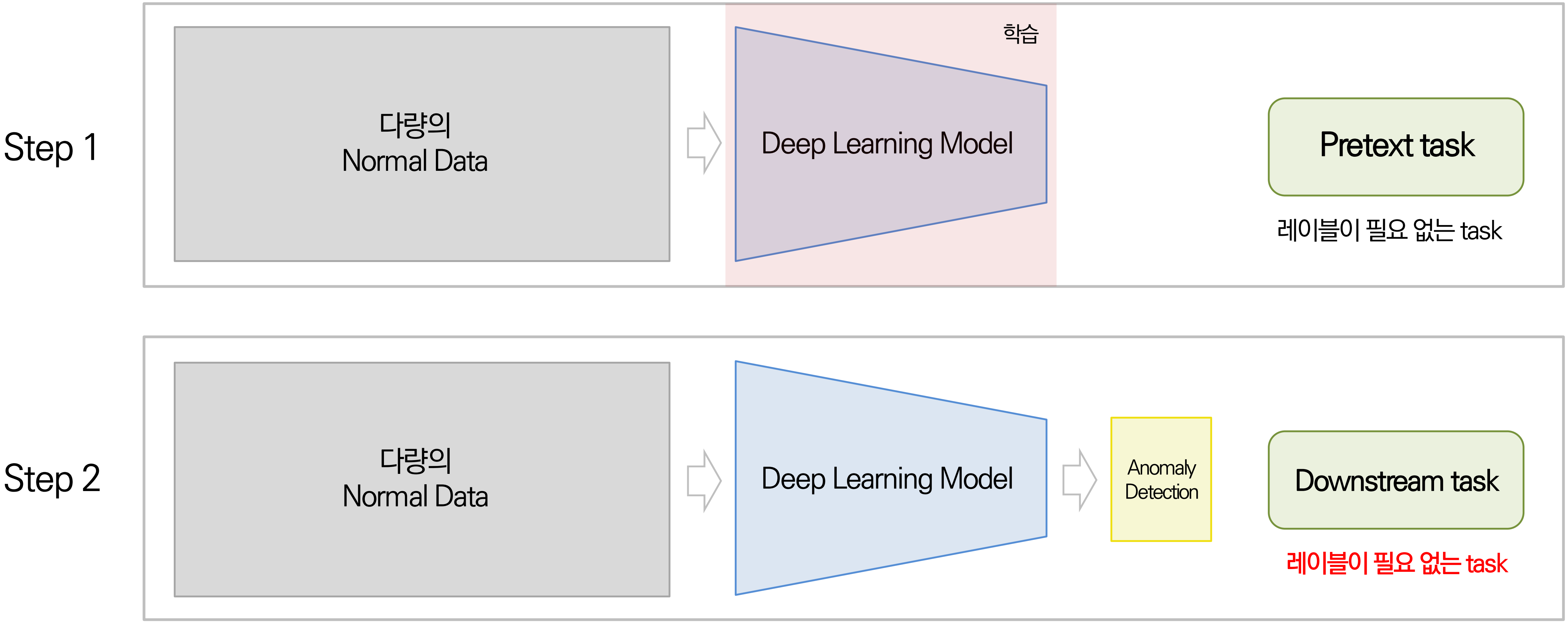
❖ Self-Supervised Learning Framework



Self-Supervised Learning

Self-Supervised Learning for Anomaly Detection

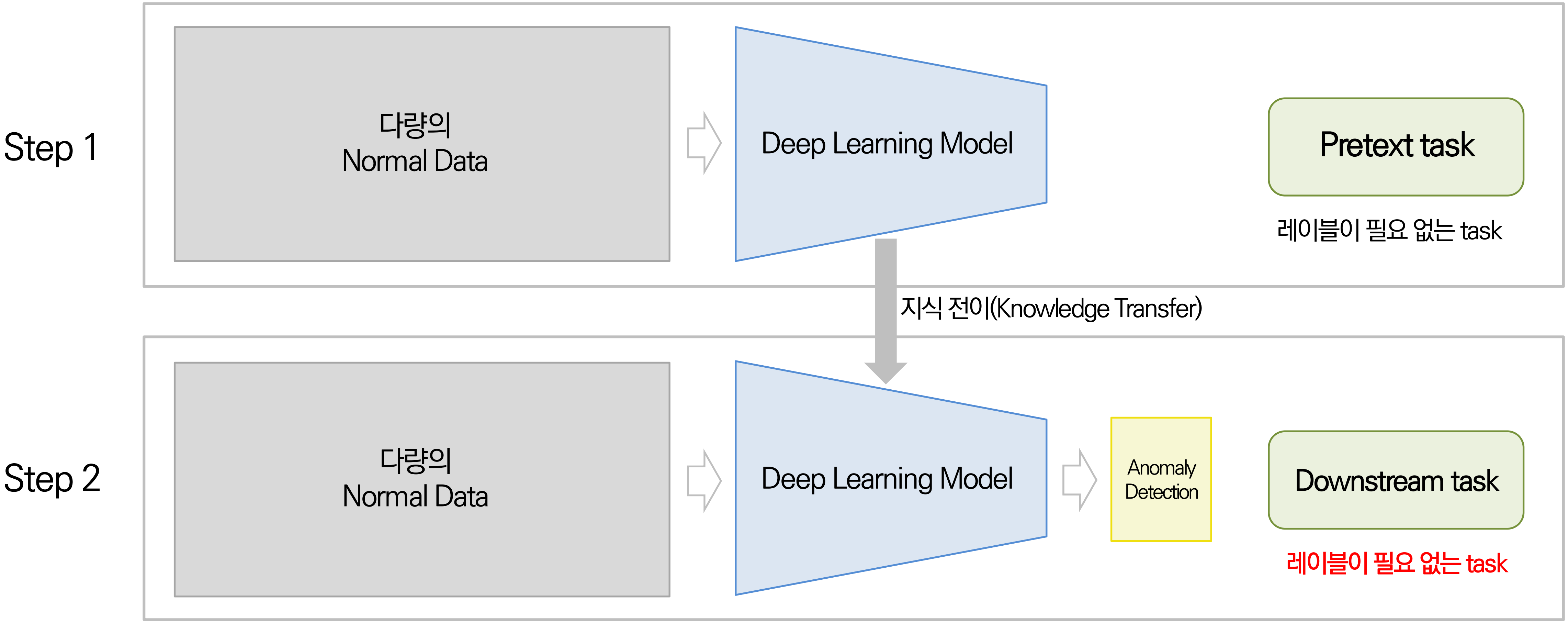
❖ Self-Supervised Learning Framework



Self-Supervised Learning

Self-Supervised Learning for Anomaly Detection

❖ Self-Supervised Learning Framework

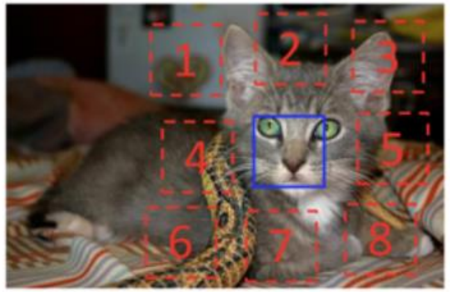


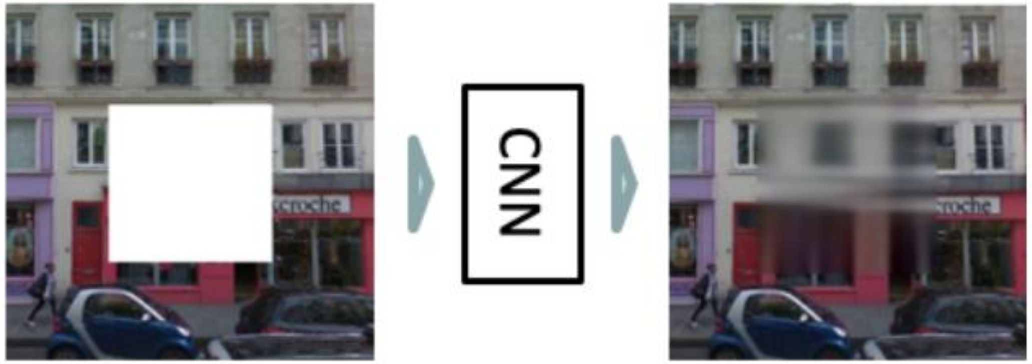
Self-Supervised Anomaly Detection

Self-Supervised Learning for Anomaly Detection

❖ Self-Predictive Methods

- 입력 데이터에 변형을 주어 변형 방법을 예측하거나, 기존 입력 데이터로 복원하는 방식





Doersch, C., Gupta, A., & Efros, A. A. (2015). Unsupervised visual representation learning by context prediction. In *Proceedings of the IEEE international conference on computer vision* (pp. 1422-1430).

Self-Supervised Anomaly Detection

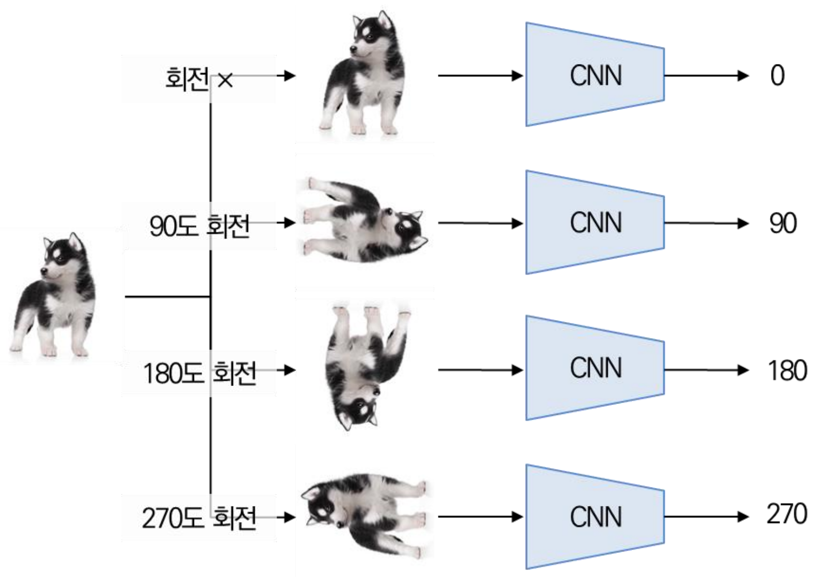
Self-Supervised Learning for Anomaly Detection

❖ Self-Predictive Methods

- Deep anomaly detection using geometric transformations – GEOM (NeurIPS 2018)

Pretext task

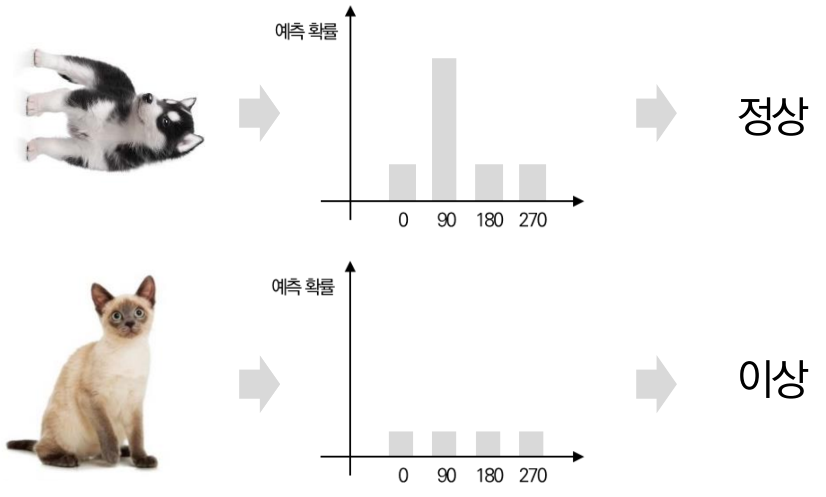
Multi-Class Classification



이미지의 변형 방법을 예측하는 문제

Downstream task

Anomaly detection
(Dirichlet Normality Score)



클래스 별 예측 확률(Softmax)을 이용하여 이상 탐지

Self-Supervised Anomaly Detection

Self-Supervised Learning for Anomaly Detection

❖ Self-Predictive Methods

- Classification-based anomaly detection for general data – GOAD (ICLR 2020)

Pretext task

Metric Learning (Triplet)

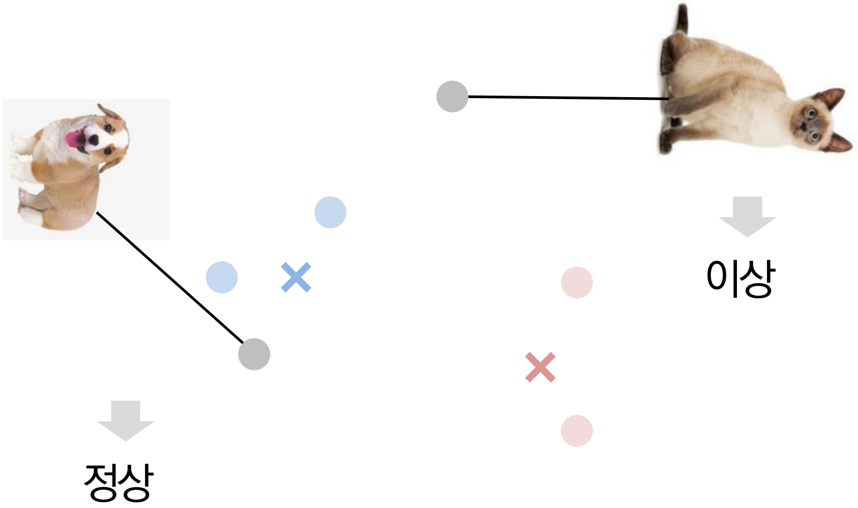
$$\begin{bmatrix} a_{11} & a_{12} & a_{tx} \\ a_{21} & a_{22} & a_{ty} \\ 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} a_{11}\times x + a_{12}\times y + a_{tx}\times 1 \\ a_{21}\times x + a_{22}\times y + a_{ty}\times 1 \\ 0\times x + 0\times y + 1\times 1 \end{bmatrix}$$

2D affine transformation 예시

데이터의 변형 방법을 affine transformation으로 정의
→ 이미지 외 다양한 데이터에 사용 가능(테이블 데이터 등)

Downstream task

Anomaly detection (Softmax Probability)



변형 클래스별 중심과의 거리를 기준으로 이상 탐지

Bergman, L., & Hoshen, Y. (2020). Classification-based anomaly detection for general data. *arXiv preprint arXiv:2005.02359*.

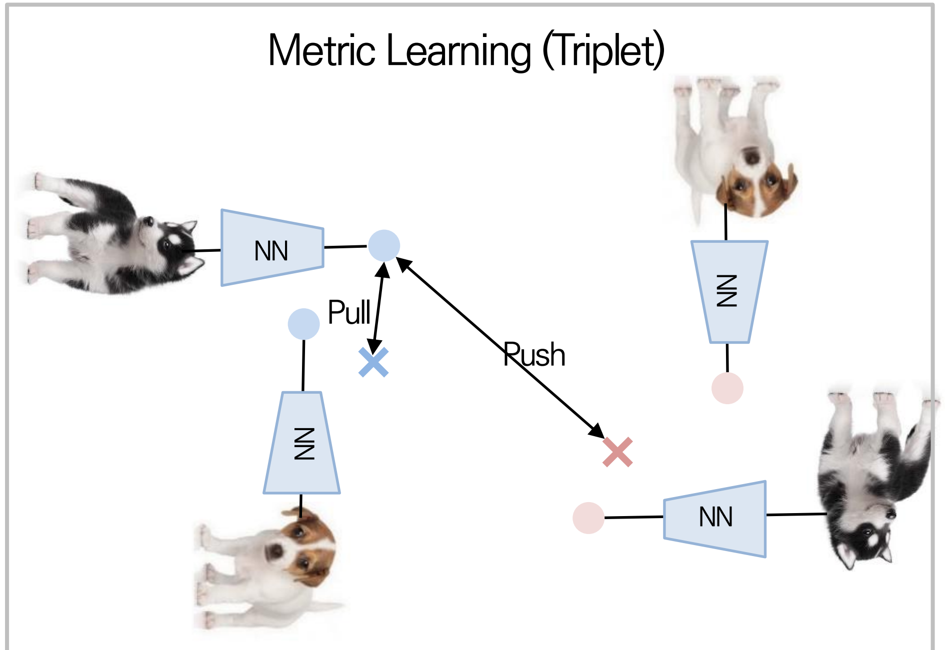
Self-Supervised Anomaly Detection

Self-Supervised Learning for Anomaly Detection

❖ Self-Predictive Methods

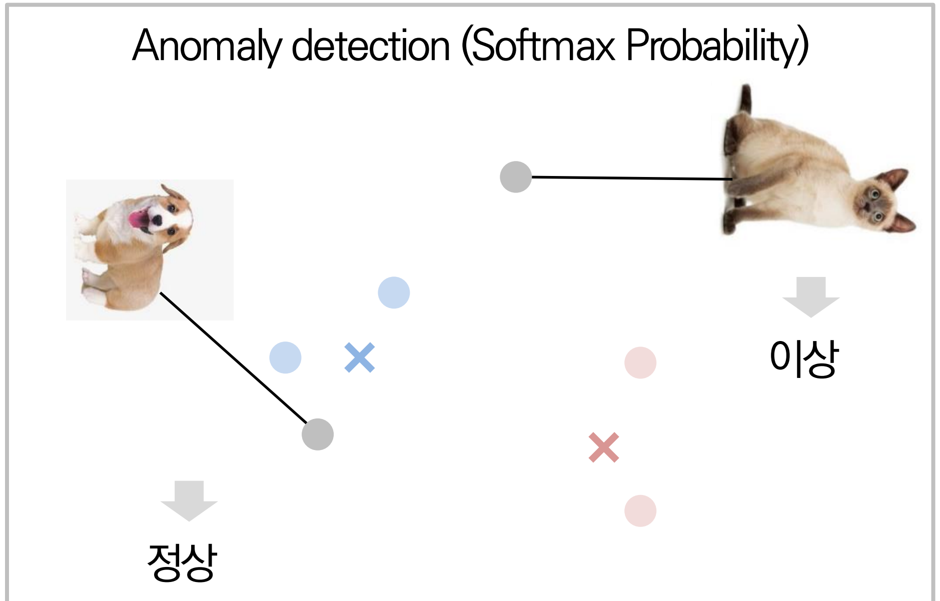
- Classification-based anomaly detection for general data – GOAD (ICLR 2020)

Pretext task



변형 클래스별로 중심을 정의하여 metric learning

Downstream task



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Self-Supervised Anomaly Detection

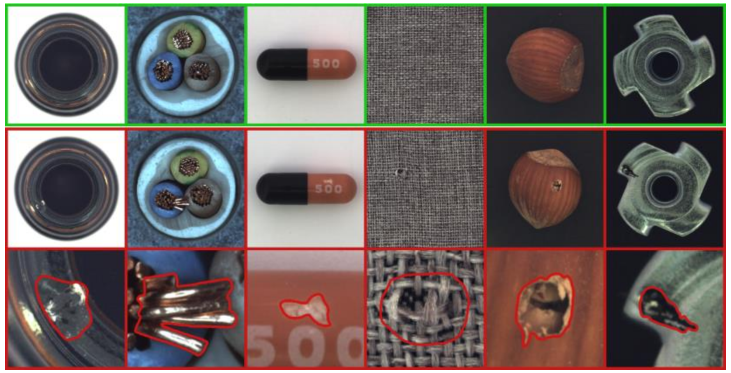
Self-Supervised Learning for Anomaly Detection

❖ Self-Predictive Methods

- Deep anomaly detection using geometric transformations – GEOM (NeurIPS 2018)
- Classification-based anomaly detection for general data – GOAD (ICLR 2020)

이미지/데이터 전체를 변형하기 때문에 sensory anomalies(low-level)에 취약함

Semantic anomaly



Sensory anomaly
(Mvtec dataset)

Self-Supervised Anomaly Detection

Definition

❖ Types of Anomaly

- Point anomalies : 각 샘플이 일반적인 패턴과 다른 이상치 (개 -> 고양이)
- Contextual anomalies : 특정 관점 기준으로 이상치 (과속 차량)
- Collective anomalies : 샘플 각각은 정상이지만 모아서 봤을 때 패턴과 다른 이상치 (도난 카드)
- Sensory anomalies : 샘플 내의 일부(low-level)가 일반적인 패턴과 다른 이상치 (mvtec / 센서)
- Semantic anomalies : 샘플 전체적으로 (high-level)

V. Chandola, A. Banerjee, and V. Kumar, “Outlier detection: A survey,” ACM Computing Surveys, vol. 14, p. 15, 2009
G. Pang, C. Shen, L. Cao, and A. V. D. Hengel, “Deep learning for anomaly detection: A review,” ACM Comput. Surv., vol. 54, no. 2, mar 2021.
L. Ruff, J. R. Kauffmann, R. A. Vandermeulen, G. Montavon, W. Samek, M. Kloft, T. G. Dietterich, and K.-R. Muller, “A unifying review of deep and shallow anomaly detection,” Proceedings of the IEEE, 2021

Self-Supervised Anomaly Detection

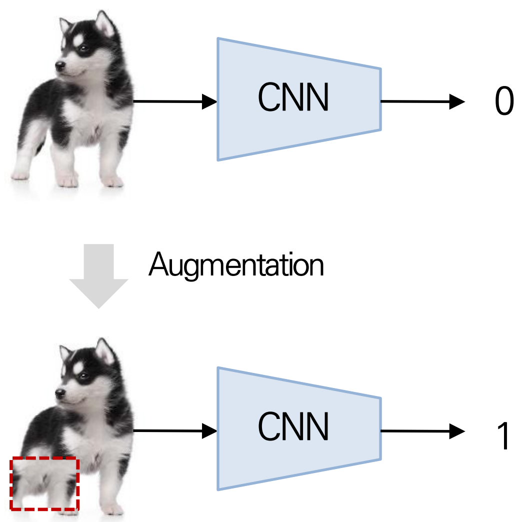
Self-Supervised Learning for Anomaly Detection

❖ Self-Predictive Methods

- CutPaste: self-supervised learning for anomaly detection and localization (CVPR 2021)

Pretext task

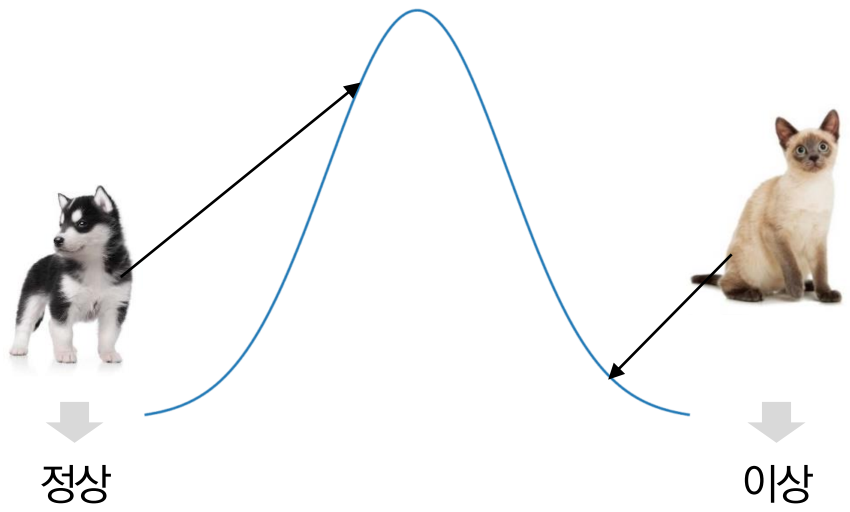
Two-Class Classification (Softmax)



이미지의 일부를 다른 위치에 붙여넣는 방식으로 변형
원본 데이터와 변형된 데이터를 구분하도록 학습

Downstream task

Anomaly detection (Gaussian Density Estimator)



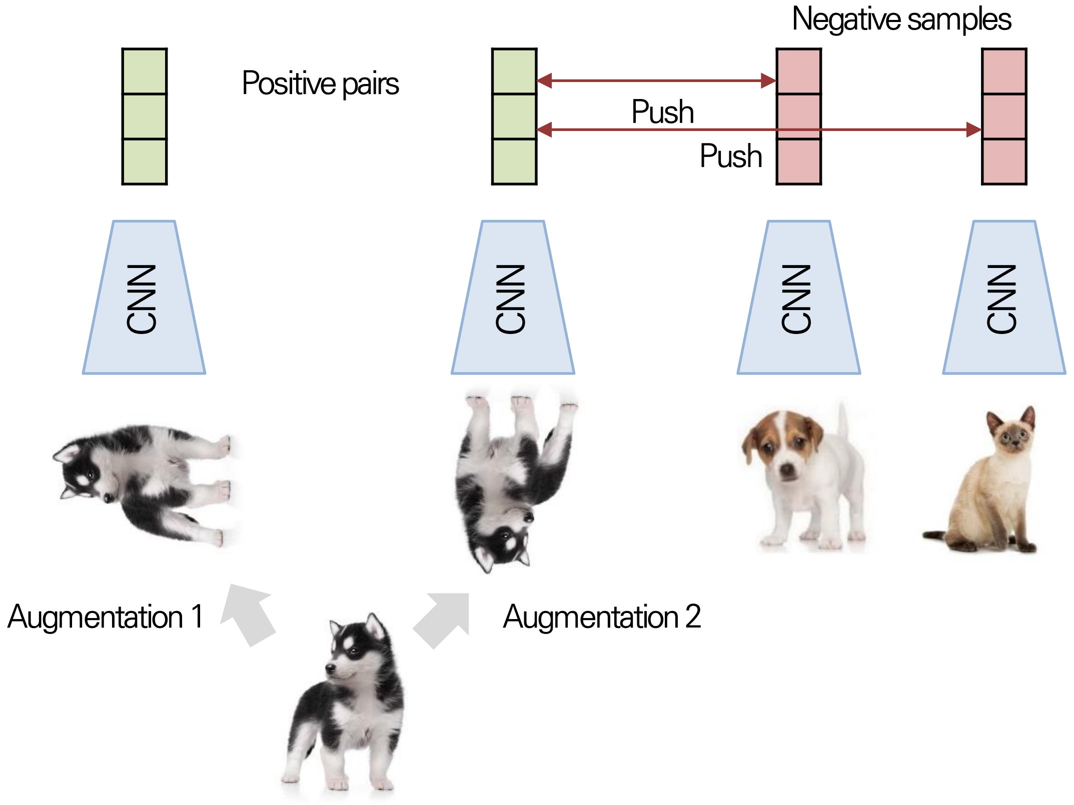
Gaussian Density Estimator로 이상 탐지 및 score 도출
Score기반 grad-CAM을 이용하여 원인 분석

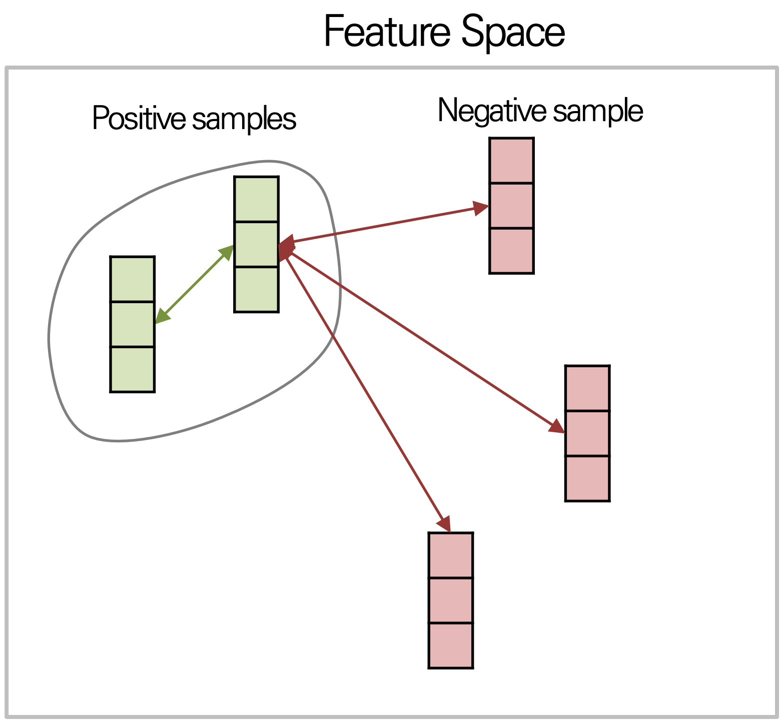
Self-Supervised Anomaly Detection

Self-Supervised Learning for Anomaly Detection

❖ Contrastive Methods (SimCLR)

- 샘플들의 관계를 정의
- Positive 샘플들은 가깝게, negative 샘플들은 멀어지도록 학습





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Self-Supervised Learning for Anomaly Detection

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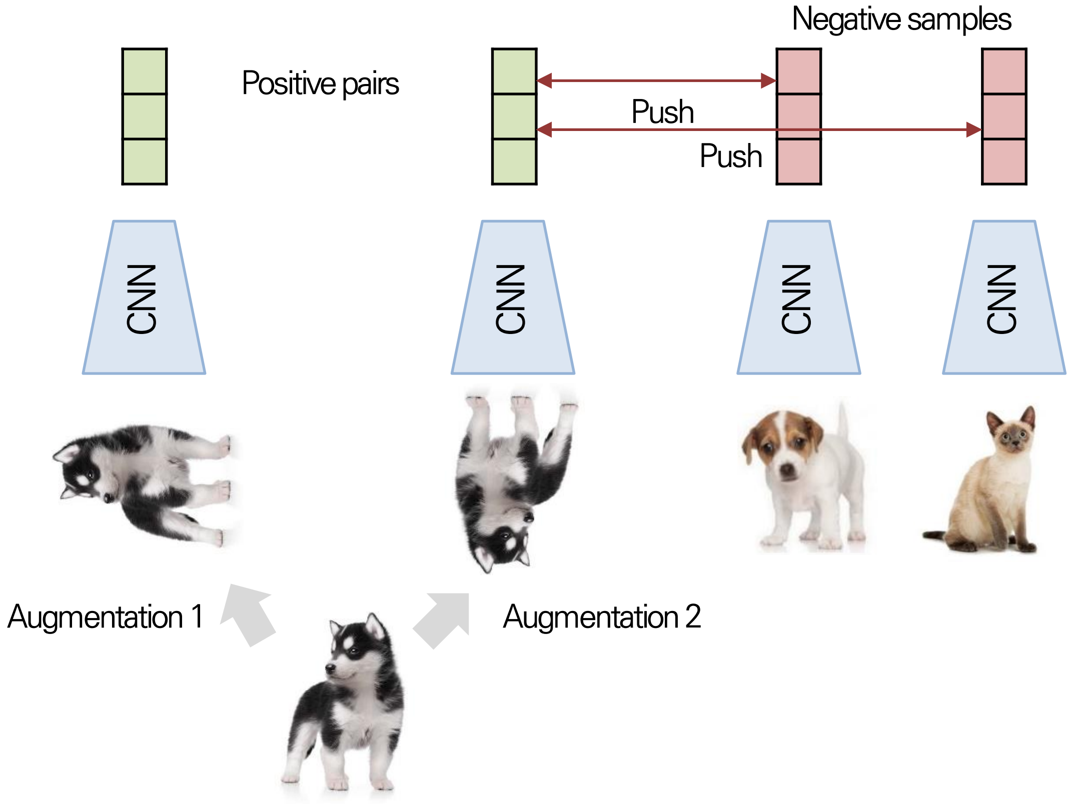
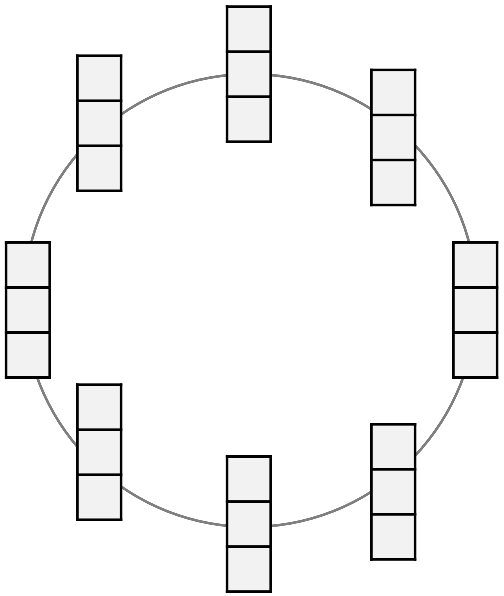


Feature Space



Self-Supervised Anomaly Detection

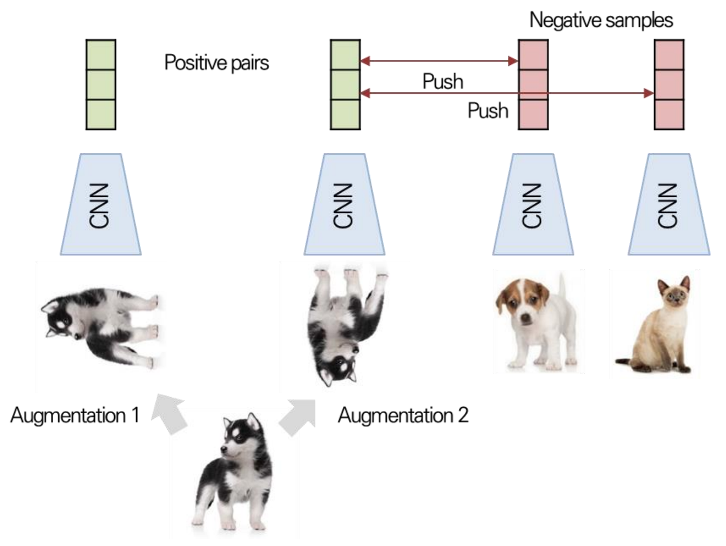
Self-Supervised Learning for Anomaly Detection

❖ Contrastive Methods (Unsupervised)

- SSD: a feature detector and cluster-conditioned detection (ICLR 2021)

Pretext task

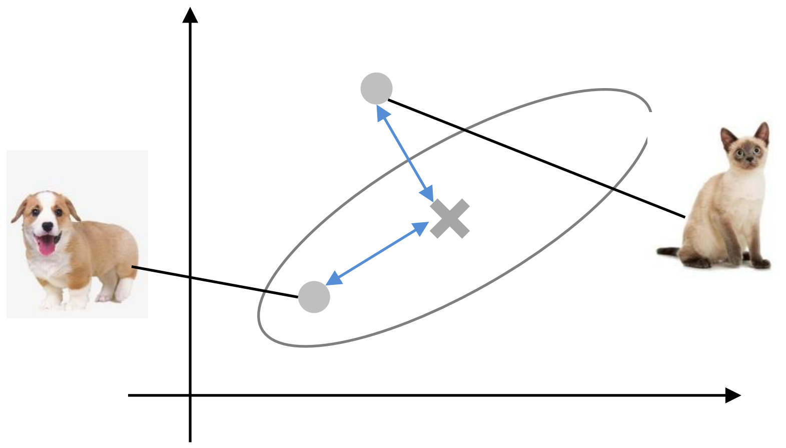
Contrastive Learning + Clustering



SimCLR와 동일한 contrastive learning 사용

Downstream task

Anomaly detection (Mahalanobis Distance)



특징 벡터의 Mahalanobis distance가 클수록 이상

Sehwag, V., Chiang, M., & Mittal, P. (2021). Ssd: A unified framework for self-supervised outlier detection. *arXiv preprint arXiv:2103.12051*.

Self-Supervised Anomaly Detection

Self-Supervised Learning for Anomaly Detection

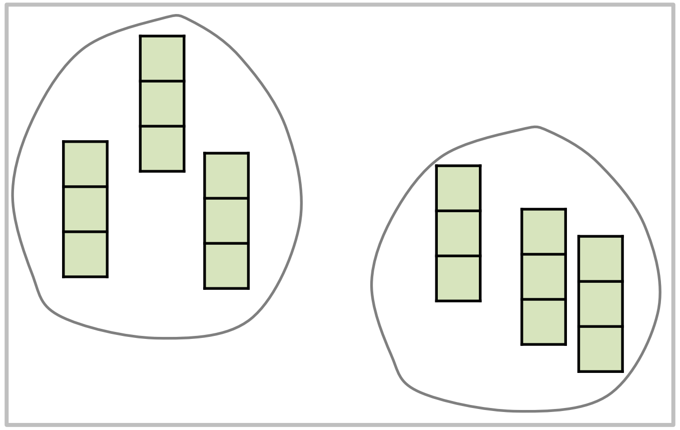
❖ Contrastive Methods (Unsupervised)

- SSD: a feature detector and cluster-conditioned detection (ICLR 2021)

Pretext task

Contrastive Learning + Clustering

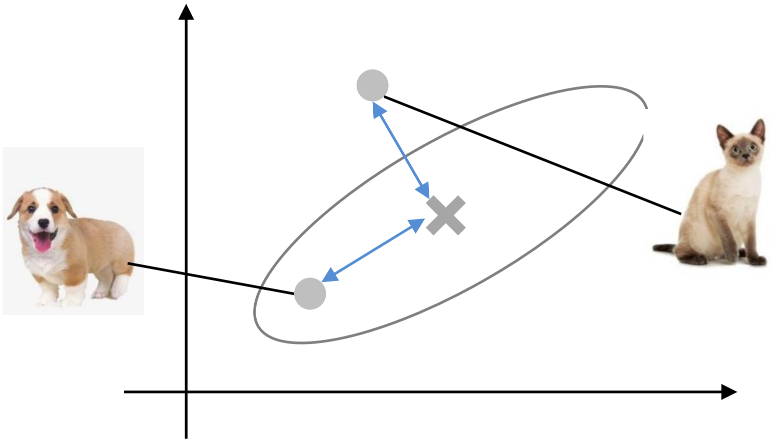
Feature Space



학습된 특징 벡터들로 k-means clustering 진행

Downstream task

Anomaly detection (Mahalanobis Distance)



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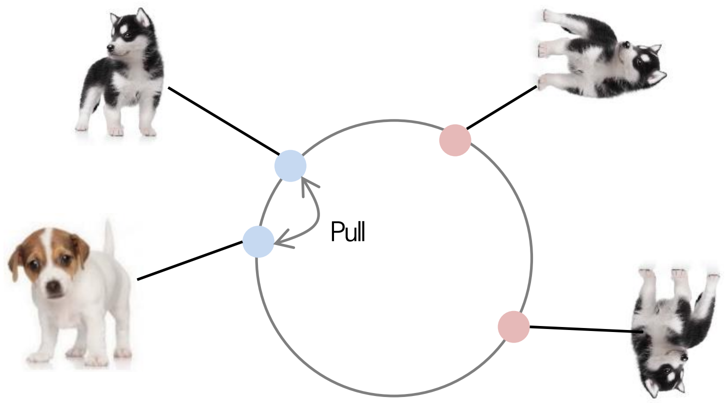
Self-Supervised Learning

❖ Contrastive Methods Methods (Unsupervised 기준)

- CSI: Novelty Detection via Contrastive Learning on Distributionally Shifted Instances (NeurIPS 2020)

Pretext task

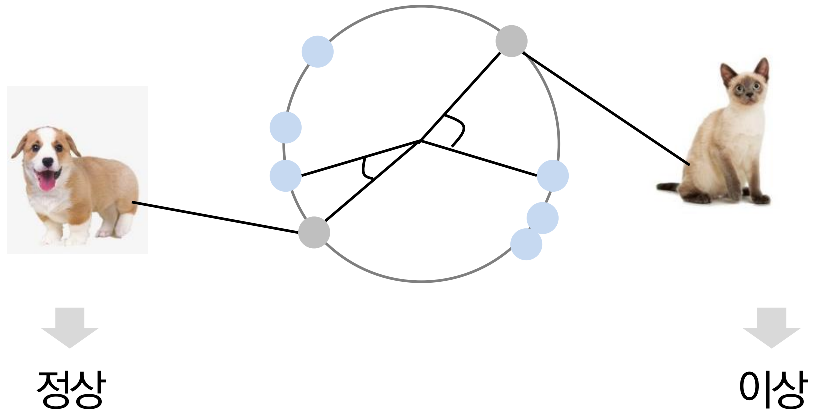
Contrastive Learning + Multi-Class Classification



Augmented data를 negative sample로 정의
다른 샘플들을 positive sample로 정의

Downstream task

Anomaly detection (Cosine Similarity&Norm)



제일 가까운 샘플과의 cosine similarity 계산
각도가 클수록 이상

Tack, J., Mo, S., Jeong, J., & Shin, J. (2020). Csi: Novelty detection via contrastive learning on distributionally shifted instances. Advances in neural information processing systems, 33, 11839-11852.

Self-Supervised Learning

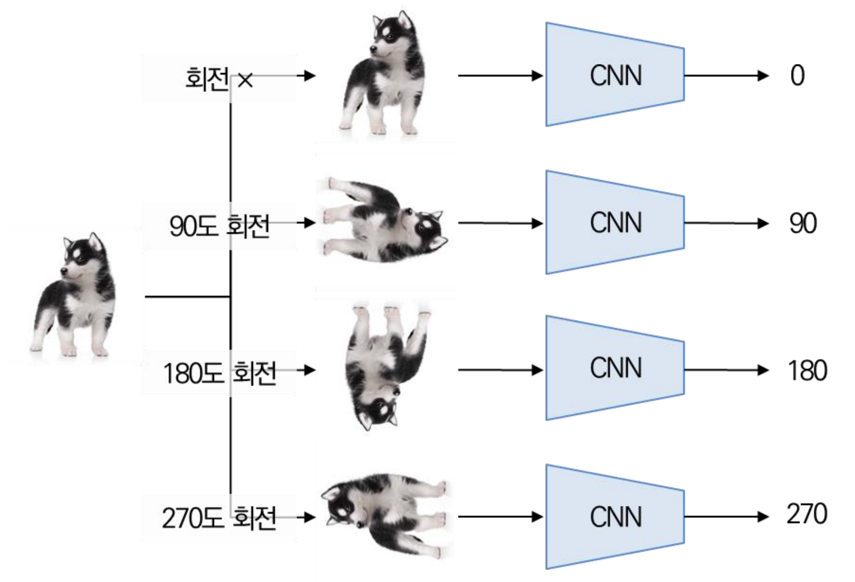
Self-Supervised Learning for Anomaly Detection

❖ Contrastive Methods Methods (Unsupervised 기준)

- CSI: Novelty Detection via Contrastive Learning on Distributionally Shifted Instances (NeurIPS 2020)

Pretext task

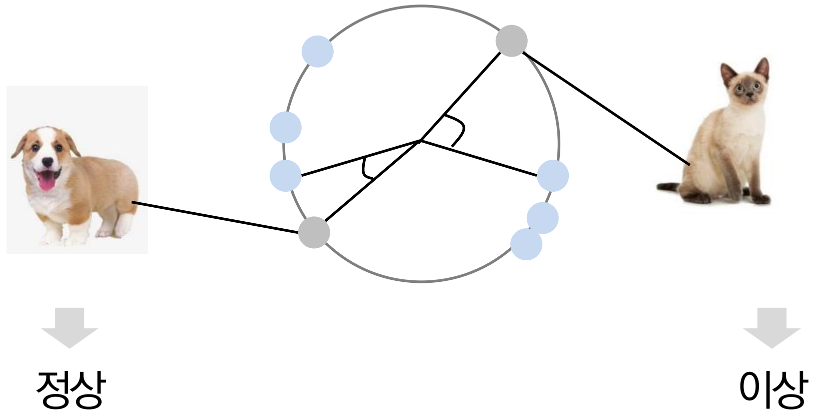
Contrastive Learning + Multi-Class Classification



또한 augmentation 방법도 예측

Downstream task

Anomaly detection (Cosine Similarity&Norm)



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Self-Supervised Learning

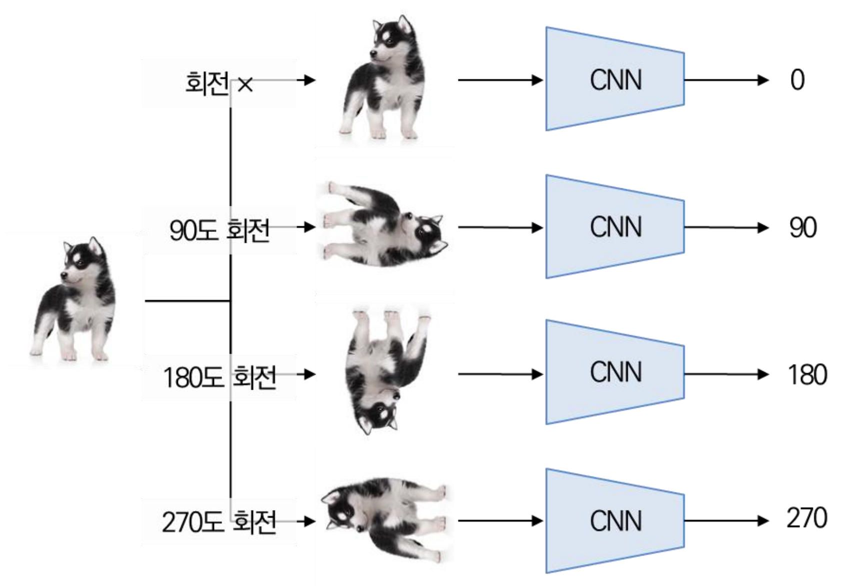
Self-Supervised Learning for Anomaly Detection

❖ Contrastive Methods Methods (Unsupervised 기준)

- CSI: Novelty Detection via Contrastive Learning on Distributionally Shifted Instances (NeurIPS 2020)

Pretext task

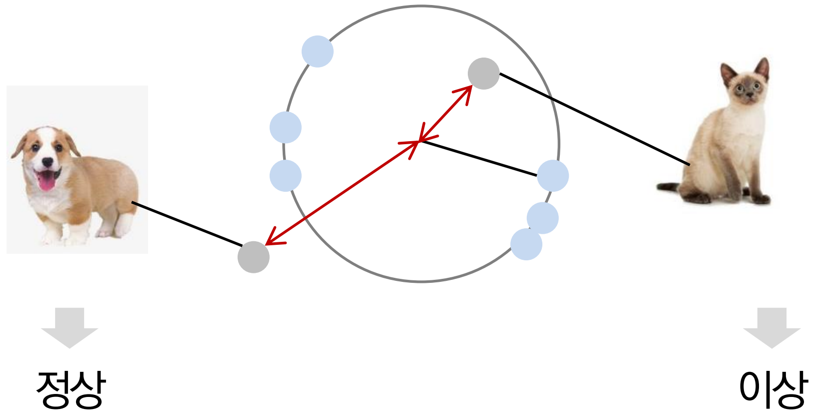
Multi-Class Classification + Contrastive Learning



또한 augmentation 방법도 예측

Downstream task

Anomaly detection (Cosine Similarity&Norm)



특징벡터의 길이(Norm)이 작을수록 이상

Tack, J., Mo, S., Jeong, J., & Shin, J. (2020). Csi: Novelty detection via contrastive learning on distributionally shifted instances. Advances in neural information processing systems, 33, 11839-11852.

Conclusions

Anomaly Detection

↓

Deep Learning–based Anomaly Detection

↓

Self-Supervised Anomaly Detection

Conclusions

❖ Self-Supervised Anomaly Detection

- Pretext task model (representation learning) → 고도화
- Downstream model (anomaly detection) → 간소화

❖ Contrastive Learning

- Negative sample 정의 방법

❖ Data Dependency

- Data 종류/ 정상/이상 타입에 따라 방법론이 달라짐

Thank you