Anomaly Detection

2023년도 하계 세미나

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Outline

- Background
  - Anomaly detection methods and approach

- A Simple Network for Image Anomaly Detection and Localization
  - CVPR 2023

- Explicit Boundary Guided Semi-Push-Pull Contrastive Learning for Supervised Anomaly Detection
  - CVPR 2023

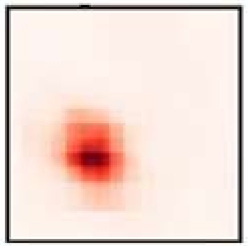
Background

- Anomaly detection
  - Binary classification problem
    - Input 이미지의 anomaly 포함 여부를 판단
      - Abnormal 샘플은 normal 샘플 수 대비 소수이기 때문에 적절한 distribution을 학습하기 어려워 normal 샘플만 학습하는 one-class classification 방식이 주를 이룸
- Anomaly localization
  - 이미지 데이터에서 검출된 anomaly는 localize 할 수 있으며, anomaly segmentation은 anomaly를 pixel level에서 localize 시키는 것임

normal
abnormal

input 이미지 내 이상치 포함 여부를 판단

[Anomaly Detection]



input 이미지 내 pixel-level 비정상 여부를 탐지

[Anomaly Segmentation]

Background

- Supervised and unsupervised approaches
  - Supervised AD
    - 학습 데이터 셋에 normal과 abnormal sample의 data와 label이 모두 존재하는 경우
      - Abnormal sample을 다양하게 보유할수록 더 높은 성능 달성 가능
    - 산업 현장에서는 normal 대비 abnormal sample의 발생 빈도가 현저히 적기 때문에 class-imbalance 문제 발생
      - 특히, unseen anomaly 대상으로 현저히 낮은 성능을 보임
  - Unsupervised AD
    - 대부분의 데이터가 normal sample이라고 가정하고 label 없이 학습시키는 방법
      - 데이터 중 어떤 것이 normal sample 인지 알기 위해서는 normal sample에 대한 label 확보가 필요
      - Unsupervised AD의 대표적인 예로 Autoencoder 기반 AD가 있음

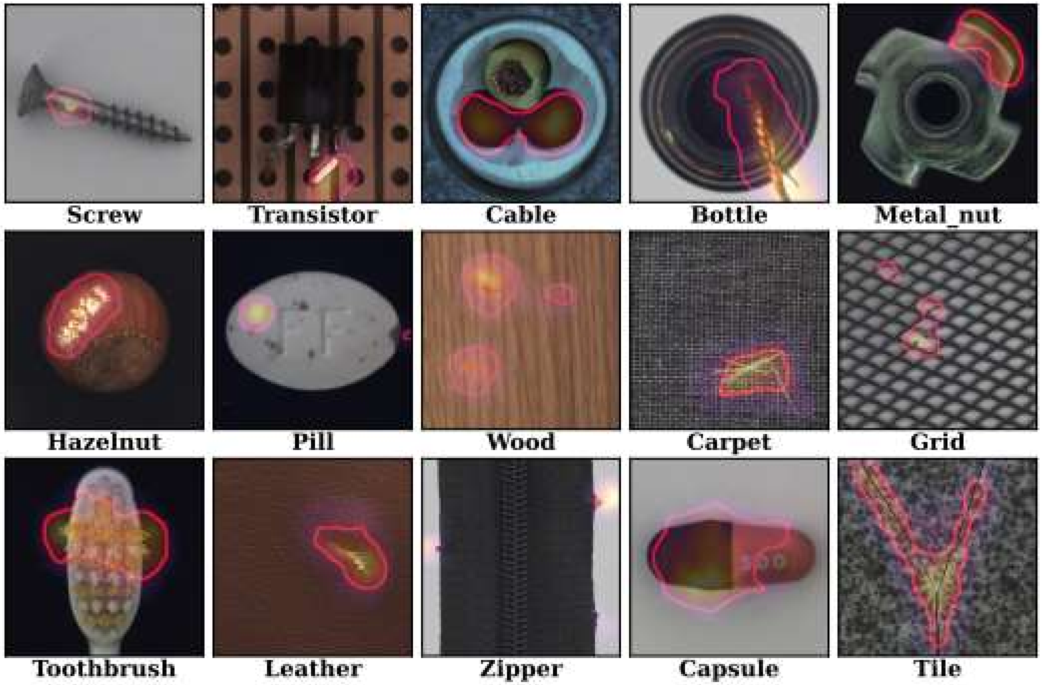
Background

- 기존 AD 방법들의 한계점
  - Reconstruction based anomaly detection
    - Normal 데이터만으로 학습 시 anomal region을 정확하게 reconstruct 할 수 없음
      - Pixel-wise reconstruction error는 anomaly localization 위한 anomaly score로 간주
      - 때로는 anomal region도 잘 reconstruct 할 수 있어 misdetection으로 이어짐
  - Synthesizing based anomaly detection
    - Normal 이미지에 생성된 합성 anomaly를 학습하여 normal과 abnormal 사이의 decision boundary를 estimate 함
      - 합성 anomaly는 충분히 사실적이지 않아서 normal feature에서 멀리 벗어날 수 있음
      - 이러한 defect 샘플을 학습 시 normal feature space가 loosely bounded 될 수 있음
  - Embedding based anomaly detection (최근 SOTA 성능을 내고 있는 방법)
    - ImageNet pre-trained CNN을 활용하여 normal feature를 추출 후 distribution을 embed 함
      - 산업용 이미지는 일반적으로 ImageNet과 분포가 달라, ImageNet-specific feature를 직접 사용하면 mismatch 문제가 발생할 수 있음
      - Statistical algorithm은 높은 계산 복잡성과 높은 메모리 소비 문제가 존재함

- **SimpleNet: A Simple Network for Image Anomaly Detection and Localization**
  - Unsupervised anomaly detection
  - CVPR 2023

Introduction

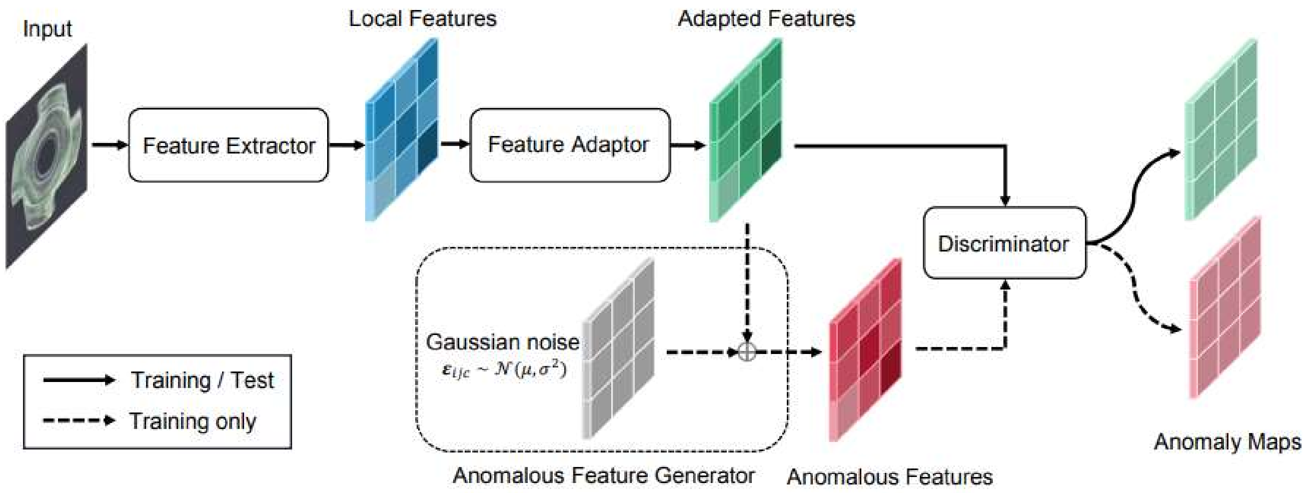
- Synthesizing-based and embedding-based 방법을 적용
  - Feature adaptor를 사용하여 target oriented feature를 생성
  - Image에 직접적으로 anomaly를 생성하는 대신 feature space 상에서 normal feature에 noise를 추가
  - Simple discriminator 학습을 통해 anomaly detection procedure를 단순화시킴



[Anomaly localization result of MVTec AD]

Methods

- Network architecture
  - Feature extractor
    - Pre-trained ResNet backbone에서 feature를 추출
  - Feature Adaptor
    - Training feature를 target domain으로 transfer 시킴
  - Anomalous Feature Generator & discriminator
    - Normal feature에 Gaussian noise를 추가하여 defect feature를 생성
    - Discriminator를 통해 normality score 예측



[Overview of the SimpleNet]

Methods

- Feature extractor
  - Pretrained network를 사용하여 추출한 patch feature에 adaptive average pooling을 적용
    - Patch feature를 그대로 사용할 시 patch 각각이 서로 겹치지 않고 서로 본인 정보만 가지고 있어 locally aware하지 않음
  - High level feature가 아닌 mid level feature [2, 3] 를 사용
    - High level feature는 ImageNet classification을 위해 특화된 정보 (ImageNet specific 해짐)
    - High level로 올라갈 수록 pooling을 거치며 위치 정보가 사라짐

Model	I-AUROC%	P-AUROC%
ResNet18	98.3	95.7
ResNet50	99.6	98.0
ResNet101	99.2	97.6
WideResNet50	**99.6**	**98.1**

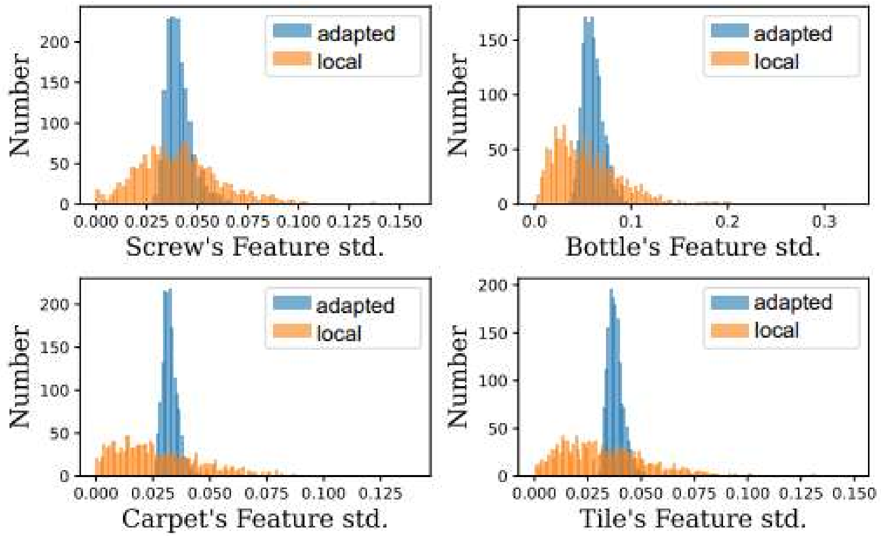
[Performance under different backbones]

level1	level2	level3	I-AUROC%	P-AUROC%
✓			93.0	94.2
	✓		98.4	96.7
		✓	99.2	97.5
✓	✓		96.7	96.7
	✓	✓	**99.6**	**98.1**
✓	✓	✓	99.1	**98.1**

[Performance under different combinations of hierarchy levels of WideResNet50]

Methods

- Feature adaptor
  - Industrial 이미지(ex. MVTec)는 backbone pre-training에 사용된 데이터 세트와 분포가 다름
    - Feature adapter를 통해 training feature를 target domain으로 보냄
    - Feature adaptor로 single fully-connected layer를 사용함
- Anomalous feature generator
  - Normal feature에 gaussian noise를 random하게 더해주어 anomalous feature를 생성
    - 생성된 anomalous feature와 학습 시 adapted feature space가 compact해지는 효과가 나타남



[Histogram of std. along each dimension of local feature and adapted feature]

Methods

- Discriminator
  - Discriminator는 normal score를 측정하며 이미지의 normality를 예측
    - Normal feature와 함께 생성된 negative feature도 discriminator 학습 시 포함
    - 일반적인 classifier 처럼 2-layer multi-layer perceptron (MLP) structure 적용
- Loss function
  - Simple truncated l1 loss 사용

$$l^i_{h,w} = \max(0, th^+ - D_\psi(q^i_{h,w})) + \max(0, -th^- + D_\psi(q^{i-}_{h,w}))$$

    - Overfitting 방지를 위해 truncation term(th)을 적용

Algorithm 1 SimpleNet training pseudo-code, Pytorch-like

```
# F: Feature Extractor
# G: Feature Adaptor
# N: i.i.d Gaussian noise
# D: Discriminator
pretrain_init(F)
random_init(G, D)
for x in data_loader:
    o = F(x)  # normal features
    q = G(o)  # adapted features
    q_ = q + random(N) # anomalous features

    loss = loss_func(D(q), D(q_)).mean()
    loss.backward() # back-propagate

    F = F.detach() # stop gradient
    update(G, D) # Adam

# loss function
def loss_func(s, s_):
    th_ = -th = 0.5
    return max(0, th-s) + max(0, th_+s_)
```

[Pseudo-code of training procedure]

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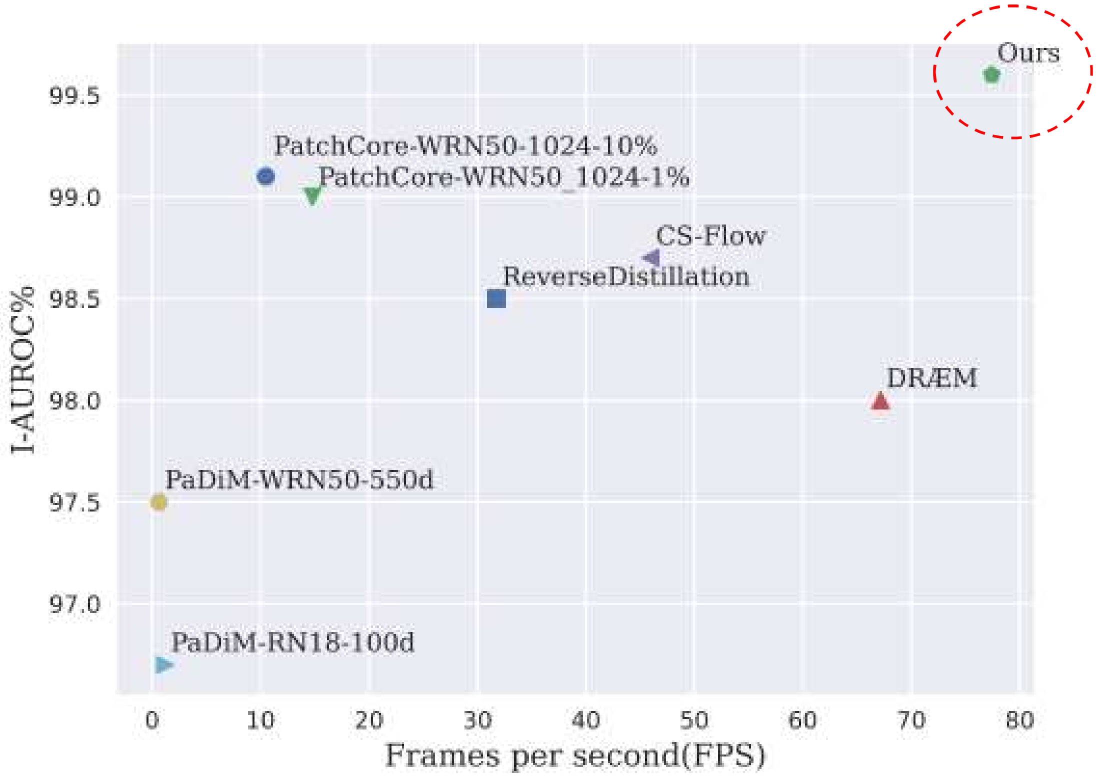
Experimental results

- Baseline 대비 높은 성능과 빠른 inference speed를 보임
  - PatchCore 대비 inference speed가 약 8배 빠름



[Inference speed (FPS) versus I-AUROC on MVTec AD benchmark]

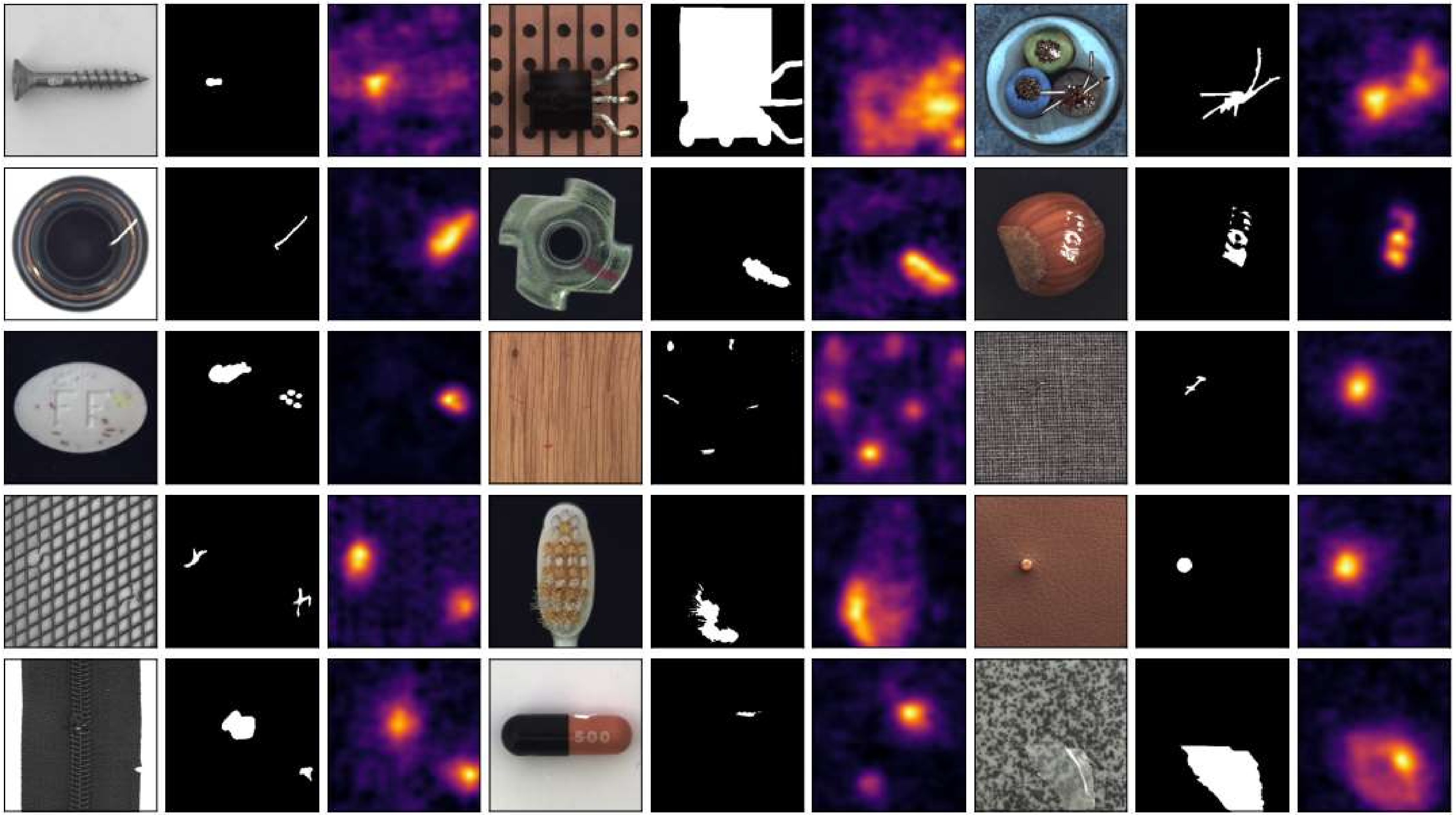
Experimental results

- Comparison with state-of-the-arts works on MVTec AD
  - 15개 class 중 9개 class에서 가장 높은 성능을 보임

Type	Reconstruction-based		Synthesizing-based		Embedding-based				Ours
Model	AE-SSIM	RIAD	DRÆM	CutPaste	CS-Flow	PaDiM	RevDist	PatchCore	SimpleNet
Carpet	87/64.7	84.2/96.3	97.0/95.5	93.9/98.3	**100**/-	99.8/99.1	98.9/98.9	98.7/**99.0**	99.7/98.2
Grid	94/84.9	99.6/98.8	99.9/99.7	**100**/97.5	99.0/-	96.7/97.3	**100/99.3**	98.2/98.7	99.7/98.8
Leather	78/56.1	**100**/99.4	**100**/98.6	**100/99.5**	**100**/-	**100**/99.2	**100**/99.4	**100**/99.3	**100**/99.2
Tile	59/17.5	98.7/89.1	99.6/**99.2**	94.6/90.5	**100**/-	98.1/94.1	99.3/95.6	98.7/95.6	99.8/97.0
Wood	73/60.3	93.0/85.8	99.1/**96.4**	99.1/95.5	**100**/-	99.2/94.9	99.2/95.3	99.2/95.0	**100**/94.5
Avg. Text.	78/56.7	95.1/93.9	99.1/**97.9**	97.5/96.3	**99.8**/-	95.5/96.9	99.5/97.7	99.0/97.5	**99.8**/97.5
Bottle	93/83.4	99.9/98.4	99.2/**99.1**	98.2/97.6	99.8/-	99.1/98.3	**100**/98.7	**100**/98.6	**100**/98.0
Cable	82/47.8	81.9/84.2	91.8/94.7	81.2/90.0	99.1/-	97.1/96.7	95.0/97.4	99.5/**98.4**	**99.9**/97.6
Capsule	94/86.0	88.4/92.8	**98.5**/94.3	98.2/97.4	97.1/-	87.5/98.5	96.3/98.7	98.1/98.8	97.7/**98.9**
Hazelhut	97/91.6	83.3/96.1	**100/99.7**	98.3/97.3	99.6/-	99.4/98.2	99.9/98.9	**100**/98.7	**100**/97.9
Metal Nut	89/60.3	88.5/92.5	98.7/**99.5**	99.9/93.1	99.1/-	96.2/97.2	**100**/97.3	**100**/98.4	**100**/98.8
Pill	91/83.0	83.8/95.7	98.9/97.6	94.9/95.7	98.6/-	90.1/95.7	96.6/98.2	96.6/97.4	**99.0/98.6**
Screw	96/88.7	84.5/98.8	93.9/97.6	88.7/96.7	97.6/-	97.5/98.5	97.0/**99.6**	98.1/99.4	**98.2**/99.3
Toothbrush	92/78.4	**100**/98.9	**100**/98.1	99.4/98.1	91.9/-	**100**/98.8	99.5/**99.1**	**100**/98.7	99.7/98.5
Transistor	90/72.5	90.9/87.7	93.1/90.9	96.1/93.0	99.3/-	94.4/97.5	96.7/92.5	**100**/96.3	**100/97.6**
Zipper	88/66.5	98.1/97.8	**100**/98.8	99.9/99.3	99.7/-	98.6/98.5	98.5/98.2	99.4/98.8	99.9/**98.9**
Avg. Obj.	91/75.8	89.9/94.3	97.4/97.0	95.5/95.8	98.2/-	96.0/97.8	98/97.9	99.2/**98.4**	**99.5/98.4**
Average	87/69.4	91.7/94.2	98.0/97.3	96.1/96.0	98.7/-	95.8/97.5	98.5/97.8	99.1/**98.1**	**99.6/98.1**

Experimental results

- Qualitative results for each class in MVTec AD



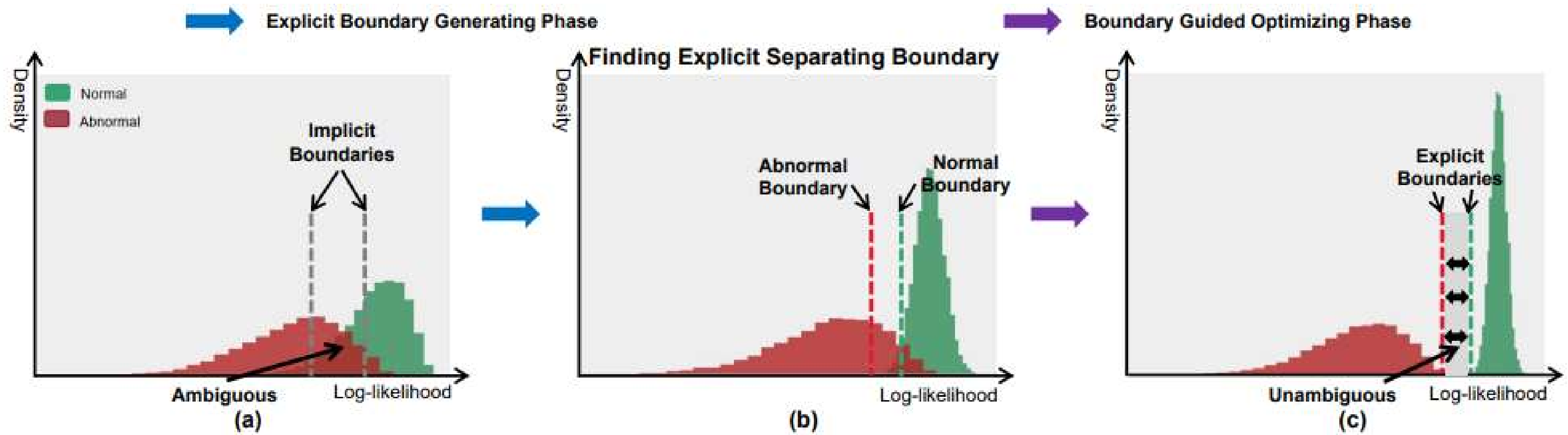
Conclusion

- Simple하면서도 efficient한 unsupervised anomaly detection 방법 제안
  - 실제 산업 환경에 맞게 여러 개의 simple한 neural network module로만 구성
  - Simple하지만 기존 SOTA 방법론 대비 성능과 inference speed를 능가함
  - Anomaly detection task에 있어 academic research와 industrial application 사이의 gap을 줄이는데 기여함

- **Explicit Boundary Guided Semi-Push-Pull Contrastive Learning for Supervised Anomaly Detection**
  - Supervised anomaly detection
  - CVPR 2023

Introduction

- Unsupervised AD는 decision boundary가 implicit하며 충분히 discriminative 하지 않음
  - Normal 샘플에서만 학습 시 AD model의 discriminability가 제한될 수 있음
    - Anomaly score distribution usually has ambiguous regions
- Semi-supervised AD는 소수의 anomaly를 활용하여 detection 성능을 향상시킴
  - 모든 anomaly를 represent 할 수 없고, known anomaly에 의해 biased 될 수 있음
- Supervised AD 방식으로 discriminability와 generalizability 모두를 향상시킬 수 있음

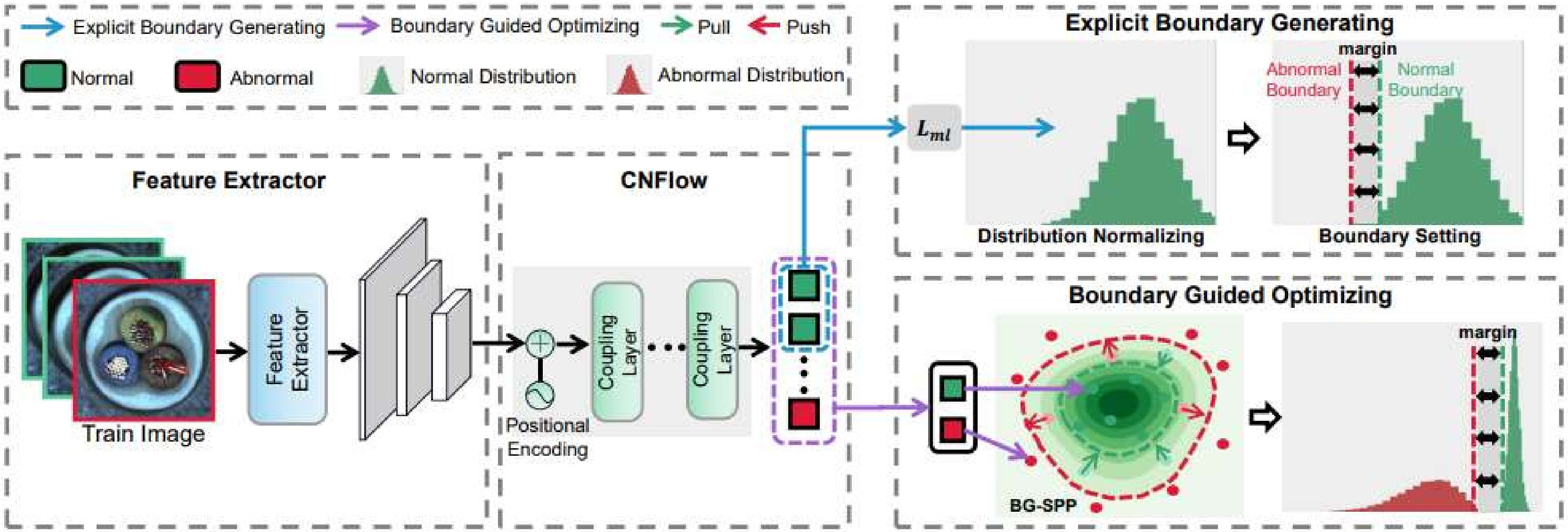


b) Normalized normal feature distribution
c) BG-SPP loss를 통해 normal과 abnormal distribution gap을 생성

[Conceptual illustration of BG-SPP method]

Method

- Network architecture
  - Feature extractor
    - Efficientnet b6 적용
  - Conditional normalizing flow (CNFlow)
    - Normalizing flow를 통해 normal feature distribution 학습
  - Explicit boundary generating and boundary guided optimizing



[Model overview]

Method

- Learning normal feature distribution by normalizing flow
  - Feature extractor에서 추출된 feature는 CNFlow의 input feature로 사용
  - Normalizing flow의 coupling layer에 2D-aware position embedding을 추가
    - Coupling layer는 일반적으로 fully connected layer로 구성됨
      - 이는 2D feature map을 1D로 flatten 시키므로 spatial position relationship을 destroy시킴
    - Positional information을 보존하기 위해 2D-aware position embedding을 추가
      - Sine & cosine positional encoding을 적용
  - Normalizing flow를 적용하여 maximum likelihood optimization을 통해 normal feature distribution 학습
    - Normal feature 학습 시 latent variable distribution은 multivariate gaussian distribution을 따름
      - Anomaly-independent separating boundary를 찾기 위해 normal feature distribution이 선행 학습되어야 함 (0 epoch에서는 normal sample만 학습)

$$\mathcal{L}_{ml} = \mathbb{E}_{x \in \mathcal{X}^n}\left[\frac{d}{2}\log(2\pi) + \frac{1}{2}\varphi_\theta(x)^T\varphi_\theta(x) - \sum_{l=1}^{L}\log\left|\det J_{\varphi_l}(y_{l-1})\right|\right]$$

[Maximum likelihood loss function for learning normal feature distribution]

Method

- Finding an explicit and compact separating boundary
  - 학습된 normal feature distribution으로부터 separating boundary를 찾을 수 있음
    - 하지만, feature의 high dimensional characteristic 때문에 anomal score distribution을 활용
    - CNFlow를 통해 생성된 log-likelihood distribution을 anomaly score로 변환하여 boundary 선택
      - Normalizing flow는 각각의 input feature 대상 exact log-likelihood logp(x) 예측이 가능

$$\log p(x) = -\frac{d}{2}\log(2\pi) - \frac{1}{2}\varphi_\theta(x)^T\varphi_\theta(x) + \sum_{l=1}^{L}\log\left|\det J_{\varphi_l}(y_{l-1})\right|$$

      - Estimated된 log-likelihood logp(x)는 exponential function을 통해 likelihood로 변환하여 normality를 measure 할 수 있음

$$s(x) = 1 - \exp(\log p(x))$$

→ s(x)는 anomaly score of x

      - 결론적으로, separating boundary in log-likelihood distribution은 boundary in anomaly score distribution과 동일함

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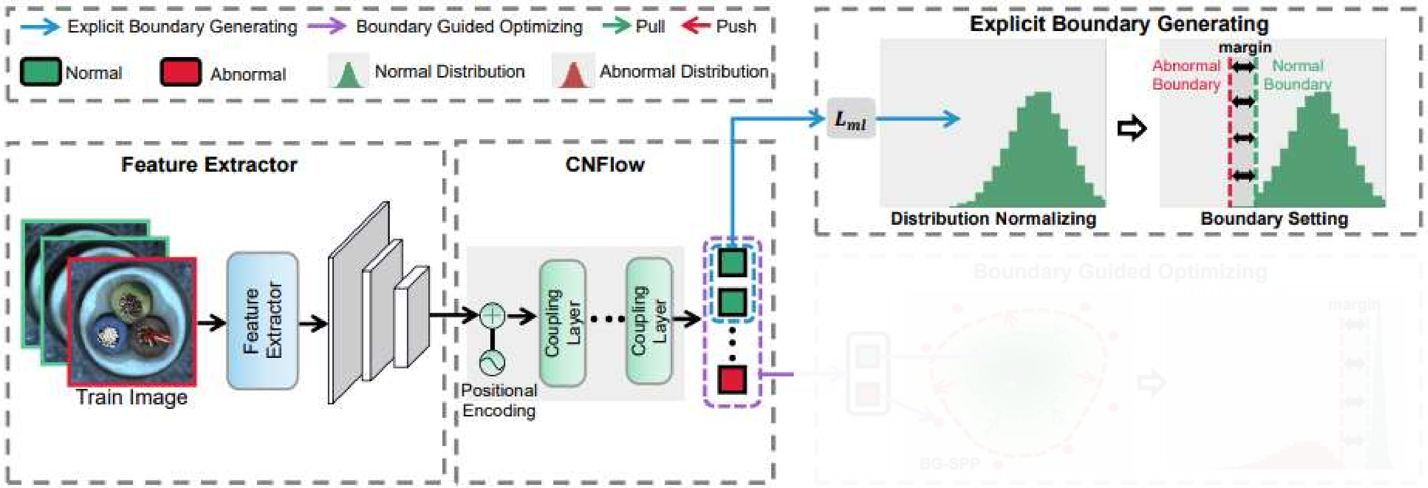
Method

- Finding an explicit and compact separating boundary
  - 적절한 boundary를 찾는 것은 dilemma임
    - Boundary를 distribution 중앙에 두면 normal distribution tail에 있는 샘플을 anomaly로 오분류 됨
    - Boundary를 distribution 중앙에서 멀리 두면 anomaly 샘플들이 normal로 오분류 됨
  - 이를 해결하기 위해 position hyperparameter(β)와 margin hyperparameter(τ)를 적용
    - Beta : control the distance from the distribution center
      - β-th percentile of sorted normal log-likelihood distribution as the normal boundary, b_n
    - Abnormal boundary : $b_a = b_n - \tau$

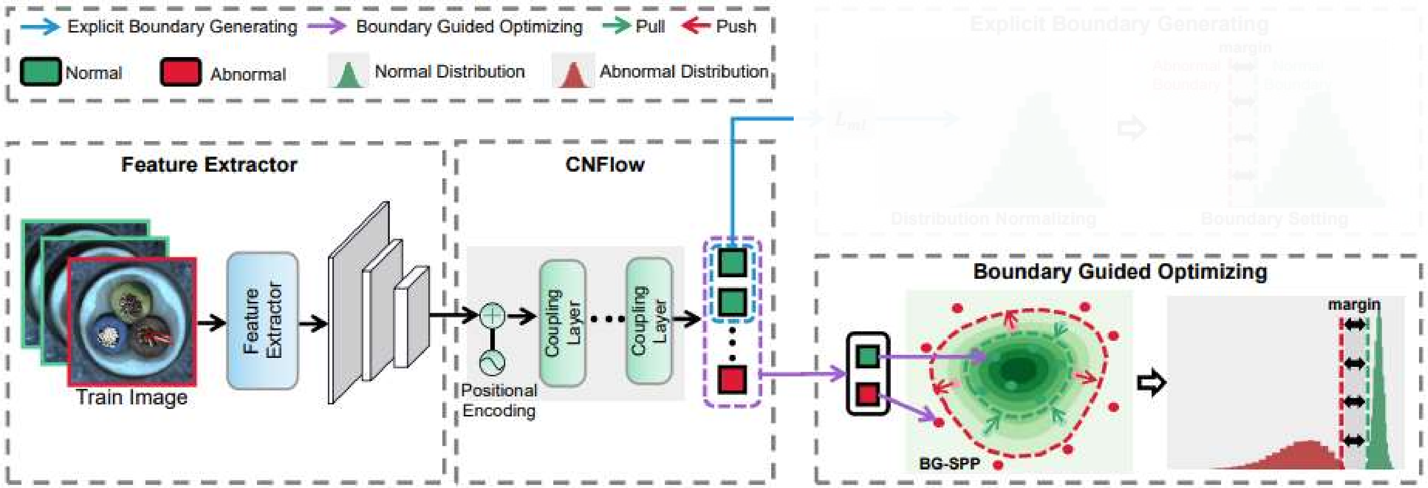


[Finding explicit normal and abnormal boundary]

Method

- Learning More Discriminative Features by Boundary Guided Semi-Push-Pull
  - Discriminative feature learning을 위해 boundary guided semi-push-pull (BG-SPP) loss 적용
    - Boundary bn을 contrastive target으로 활용하여 log-likelihood가 bn 보다 작은 normal feature는 pull하고 (semi-pull), log-likelihood가 ba 보다 큰 abnormal feature는 margin tau(τ) 밖으로 push 함 (semi-push)

$$\mathcal{L}_{bg-spp} = \sum_{i=1}^{N} |\min((\log p_i - b_n), 0)| + \sum_{j=1}^{M} |\max((\log p_j - b_n + \tau), 0)|$$



[Boundary guided semi-push-pull]

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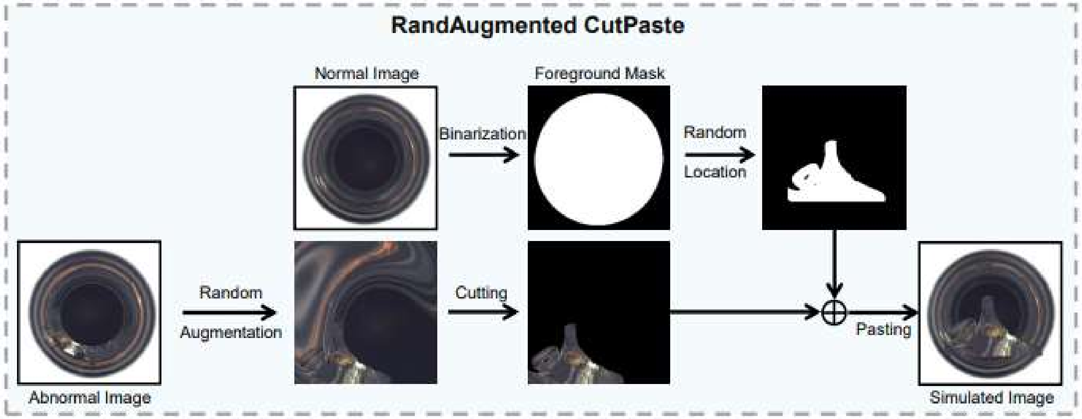
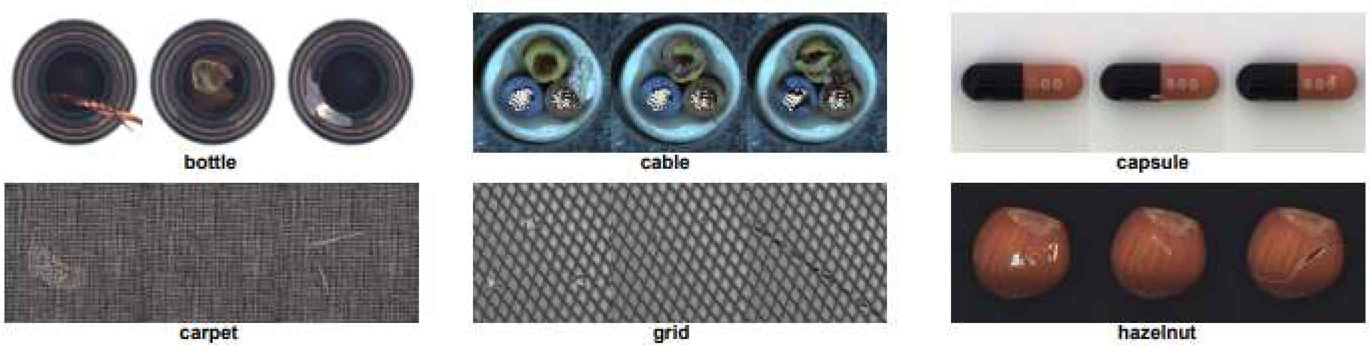
Method

- RandAugment-based Pseudo Anomaly Generation
  - 랜덤하게 local irregularity를 생성하여 irregular pattern의 수와 다양성을 향상시킴



[RPAG process]



[Generated abnormal samples by RPAG]

Experimental results

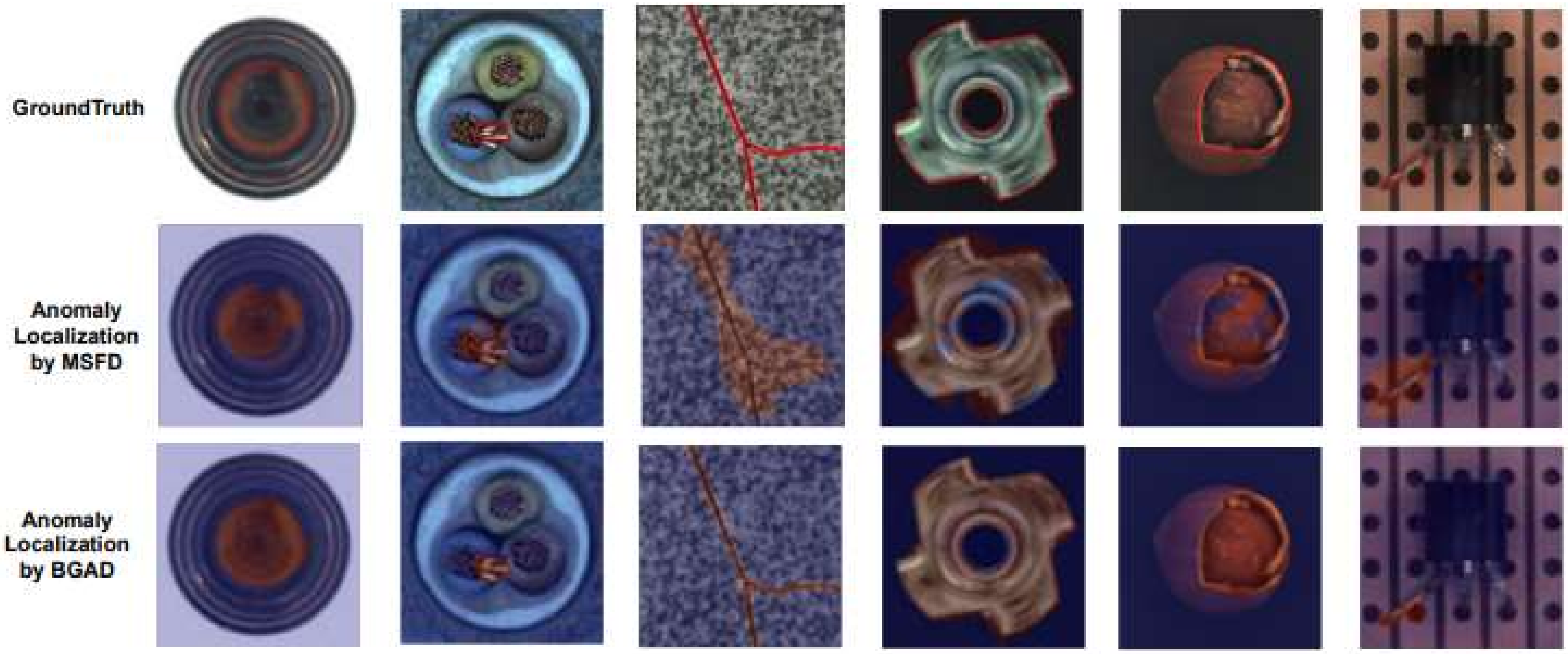
- Quantitative results on MVTec AD compared to unsupervised and supervised methods

Category		Unsupervised AD Methods							Supervised AD Method
		DRAEM* [52]	PaDiM* [10]	MSFD* [47]	PatchCore* [32]	CFA* [20]	NFAD‡	BGAD$^{w/o}$ (Ours)	BGAD (Ours)
Textures	Carpet	0.954/0.947	0.983/0.946	0.990/0.958	0.985/0.959	0.989/0.943	0.994/0.983	0.994/0.982	**0.996**±0.0002/**0.989**±0.0004
	Grid	0.997/0.984	0.963/0.894	0.986/0.937	0.974/0.891	0.977/0.932	0.993/0.980	0.994/0.980	**0.995**±0.0002/**0.986**±0.0001
	Leather	0.992/0.981	0.984/0.966	0.978/0.924	0.992/0.974	0.991/0.958	0.997/0.994	0.997/0.994	**0.998**±0.0001/**0.994**±0.0003
	Tile	0.994/0.949	0.958/0.884	0.952/0.841	0.960/0.939	0.960/0.860	0.969/0.929	0.968/0.927	**0.994**±0.0077/**0.978**±0.0021
	Wood	0.962/0.935	0.963/0.891	0.953/0.925	0.968/0.857	0.948/0.882	0.969/0.957	0.970/0.957	**0.982**±0.0053/**0.970**±0.0007
Objects	Bottle	0.993/0.955	0.978/0.936	0.985/0.940	0.986/0.956	0.987/0.944	0.988/0.965	0.989/0.964	**0.994**±0.0009/**0.971**±0.0011
	Cable	0.961/0.910	0.979/0.973	0.972/0.922	0.986/**0.980**	**0.987**/0.931	0.975/0.944	0.980/0.968	0.986±0.0010/0.977±0.0030
	Capsule	0.869/0.901	0.980/0.924	0.979/0.878	0.990/0.946	0.989/0.943	0.989/0.952	0.992/0.959	**0.992**±0.0021/**0.964**±0.0033
	Hazelnut	0.997/0.985	0.980/0.951	0.982/0.968	0.988/0.924	0.986/0.953	0.984/0.976	0.985/0.976	**0.995**±0.0040/**0.982**±0.0028
	Metal nut	0.992/0.935	0.979/0.929	0.972/0.985	0.986/0.935	0.987/0.918	0.971/0.942	0.976/0.948	**0.996**±0.0003/**0.970**±0.0012
	Pill	0.979/0.959	0.978/0.957	0.971/0.929	0.983/0.947	0.986/0.965	0.976/0.978	0.980/0.980	**0.996**±0.0002/**0.988**±0.0005
	Screw	0.992/0.965	0.974/0.923	0.983/0.924	0.984/0.928	0.985/0.944	0.988/0.945	0.992/0.960	**0.993**±0.0003/**0.968**±0.0010
	Toothbrush	0.970/0.940	0.980/0.894	0.986/0.877	0.987/0.939	0.989/0.894	0.983/0.904	0.986/0.938	**0.995**±0.0003/**0.961**±0.0026
	Transistor	0.970/0.935	0.983/0.967	0.886/0.781	0.964/0.967	**0.985**/0.960	0.923/0.788	0.940/0.830	0.983±0.0005/**0.972**±0.0015
	Zipper	0.984/0.966	0.978/0.948	0.981/0.935	0.986/0.963	0.988/0.944	0.986/0.957	0.987/0.957	**0.993**±0.0003/**0.977**±0.0002
Mean		0.969/0.947	0.976/0.932	0.970/0.915	0.981/0.940	0.982/0.931	0.979/0.946	0.982/0.955	**0.992**±0.0007/**0.976**±0.0006
Image-level Mean		0.978	0.975	0.964	0.988	0.989	0.968	0.974	**0.993**±0.0012

Category	Supervised AD Methods (Ten Abnormal Samples)			
	FCDD* [24]	DevNet* [27]	DRA* [12]	BGAD (Ours)
Carpet	0.981/0.952	-/-	-/-	**0.996**±0.0002/**0.989**±0.0004
Grid	0.949/0.897	-/-	-/-	**0.995**±0.0002/**0.986**±0.0001
Leather	0.984/0.973	-/-	-/-	**0.998**±0.0001/**0.994**±0.0003
Tile	0.977/0.938	-/-	-/-	**0.994**±0.0077/**0.978**±0.0021
Wood	0.950/0.901	-/-	-/-	**0.982**±0.0053/**0.970**±0.0007
Bottle	0.966/0.939	-/-	-/-	**0.994**±0.0009/**0.971**±0.0011
Cable	0.963/0.980	-/-	-/-	0.986±0.0010/0.977±0.0030
Capsule	0.970/0.922	-/-	-/-	**0.992**±0.0021/**0.964**±0.0033
Hazelnut	0.970/0.958	-/-	-/-	**0.995**±0.0040/**0.982**±0.0028
Metal nut	0.966/0.934	-/-	-/-	**0.996**±0.0003/**0.970**±0.0012
Pill	0.975/0.960	-/-	-/-	**0.996**±0.0002/**0.988**±0.0005
Screw	0.963/0.925	-/-	-/-	**0.993**±0.0003/**0.968**±0.0010
Toothbrush	0.967/0.907	-/-	-/-	**0.995**±0.0003/**0.961**±0.0026
Transistor	0.942/0.935	-/-	-/-	0.983±0.0005/**0.972**±0.0015
Zipper	0.968/0.948	-/-	-/-	**0.993**±0.0003/**0.977**±0.0002
Mean	0.966/0.938	-/-	-/-	**0.992**±0.0007/**0.976**±0.0006
Image-level Mean	0.965	0.948	0.961	**0.993**±0.0012

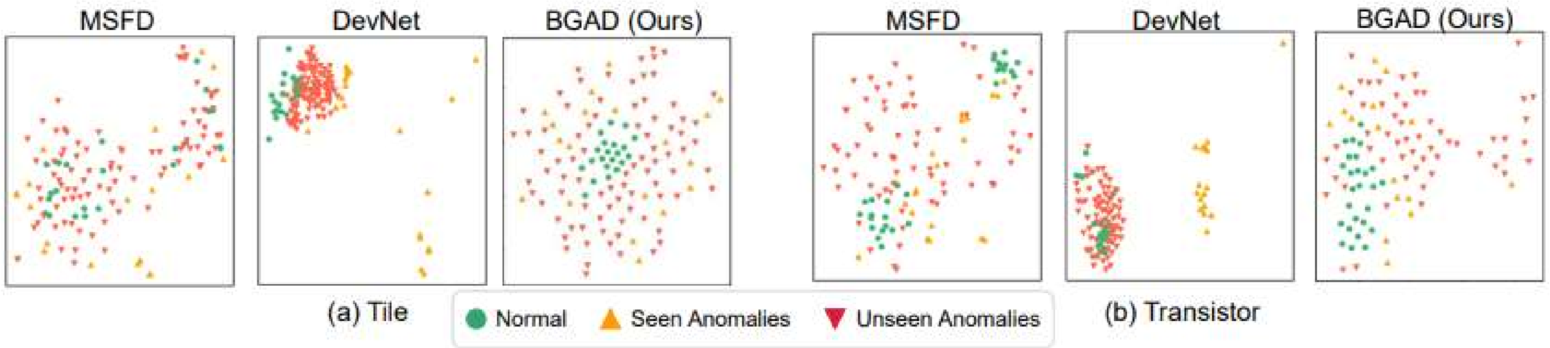
Experimental results

- Qualitative results on MVTec AD compared to unsupervised and supervised methods

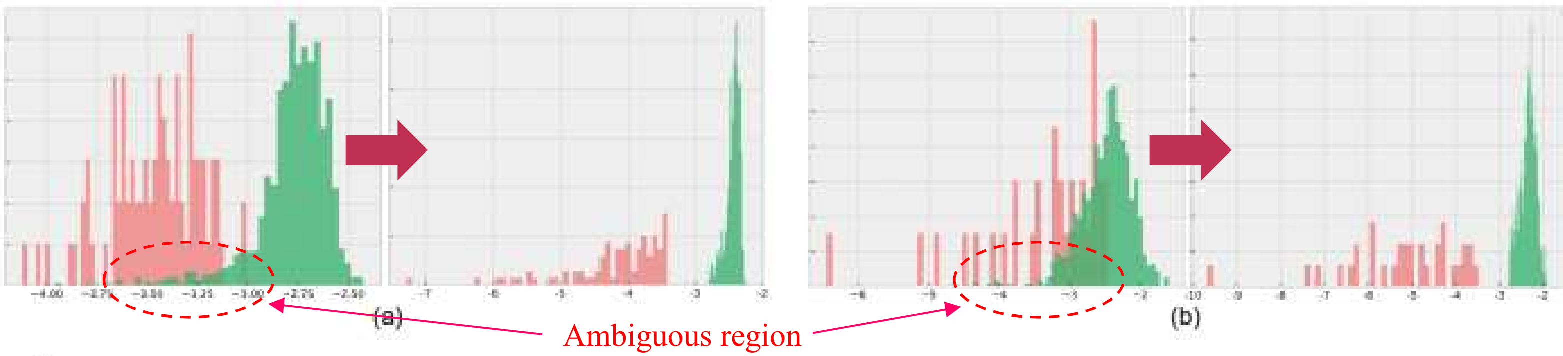


Experimental results

- Feature distributions learned by comparable methods
  - Supervised DevNet은 known anomalies에 biased 되어 unseen anomalies를 구분하는데 실패
  - 반면, proposed method는 unsupervised MSFD 방법 보다 더 discriminative한 feature를 생성



- Log-likelihood histograms
  - Ambiguous log-likelihood region은 RPAG를 통해 생성한 anomaly sample과 학습 후 개선됨



Conclusion

- Boundary guided AD를 제안
  - Few anomaly를 효과적으로 적용함으로써 anomaly를 구분하는데 있어 unsupervised model 보다 discriminative feature를 더 잘 학습할 수 있음
  - Explicit separating boundary and semi-push-pull mechanism 적용을 통해 supervised AD 방식에서 known anomaly에 biased 되는 부분을 해결할 수 있음

감사합니다.