Mitigating Spurious Correlations in Weakly Supervised Semantic Segmentation via Cross-architecture Consistency Regularization

Industrial Exhaust Smoke emission-Oriented Pseudo label Refinement Method

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Outline

Background

Goal

- Task: Industrial exhaust smoke segmentation.
- Challenge: Scarcity of pixel-level annotations.
- Approach: Multi-stage weakly supervised semantic segmentation based on image-level labels.

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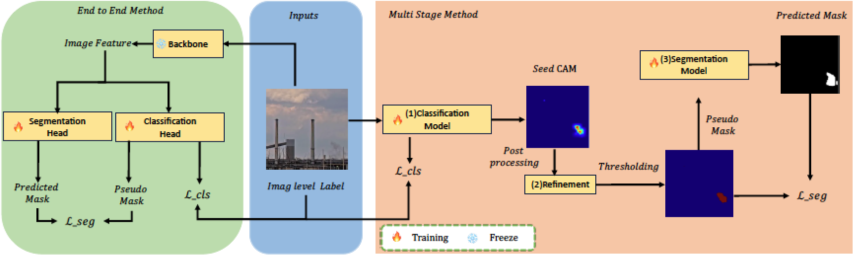
The pipeline of weakly supervised semantic segmentation

1. Train a Classifier using image-level labels.
2. Using class activation map to generate pseudo labels.
3. Train a segmentation model using pseudo labels.



Challenges

Observation: The classifier achieves very high accuracy, but the CAM is inaccurate or even fails to localize the foreground.

How to Address These Issues?

Post-processing

- Applied **after** CAM generation to improve pseudo mask quality.
- Encourages spatial consistency
  Limitations:
  - May amplify existing errors.
  - Effectiveness is bounded by the initial CAM quality.

Optimizing CAM Generation

- Improve the quality of Class Activation Maps **at the source**.
- Leads to better semantic localization and more accurate masks.

Previous Work: Addressing Spurious Correlations

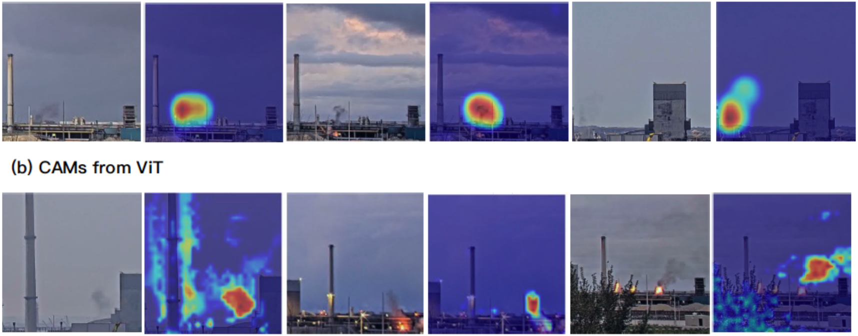
- **Data Augmentation**: Breaking object co-occurrence
  - **Image decomposition**: Separate foreground and background.
  - **Supplemental images**: Introduce diverse contexts.
- **Human Priors**:
  - **Human-in-the-loop**: Human feedback.
  - **Causality chain modeling**: Incorporate causal reasoning into training.
- **External Supervision / Additional Knowledge**:
  - **Saliency map**: Use saliency maps as guidance for pseudo label refinement.
  - **CLIP**: Leverage natural language supervision.

Key Observation

Biased knowledge extracted from both sides.

(a) CAMs from ResNet

(b) CAMs from ViT



Motivation

Intuition: CNNs and ViTs offer complementary strengths.

- **CNNs** leverage local convolutions and strong inductive biases, making them effective at precisely localizing foreground objects.
- **ViTs** utilize global self-attention mechanisms, enabling them to capture rich semantic context.

Table: Key architectural differences between ResNet and ViT

Aspect	**ResNet (CNN)**	**ViT (Transformer)**
Receptive Field	**Local**	**Global**
Inductive Bias	**Strong spatial priors**: • Locality • Spatial invariance	**Weak spatial priors**: • Learn from data • Global context modeling
CAM	**Precise localization**	**Semantic rich but diffused**

Outline

Research question

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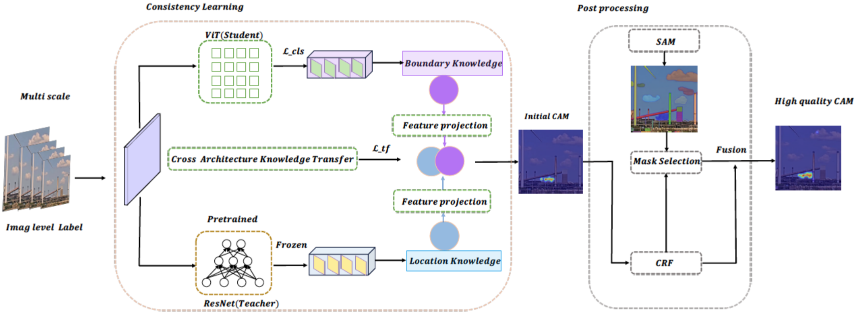
Question 2: Is it possible to address co-occurrence issue without external supervision or additional knowledge?

Question 3: Can we collaboratively aggregate heterogeneous features from CNN based and Transformer based models to address co-occurrence issue?

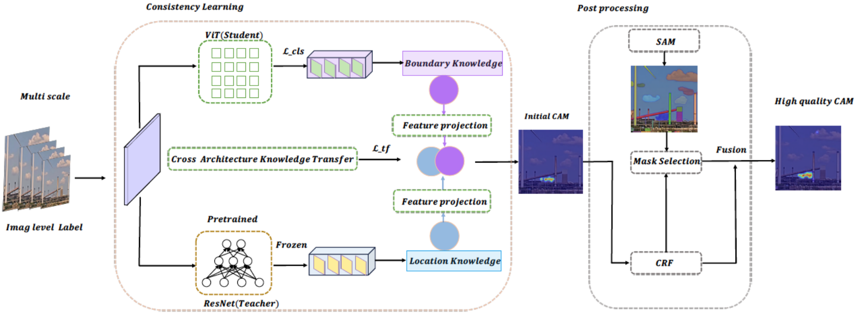
Outline

Framework



Consistency Learning
Post processing
ViT(Student)
£_cls
Boundary Knowledge
Multi scale
Feature projection
Initial CAM
SAM
High quality CAM
Cross Architecture Knowledge Transfer
£_tf
Mask Selection
Fusion
Feature projection
Imag level Label
Pretrained
Frozen
Location Knowledge
CRF
ResNet(Teacher)

Framework

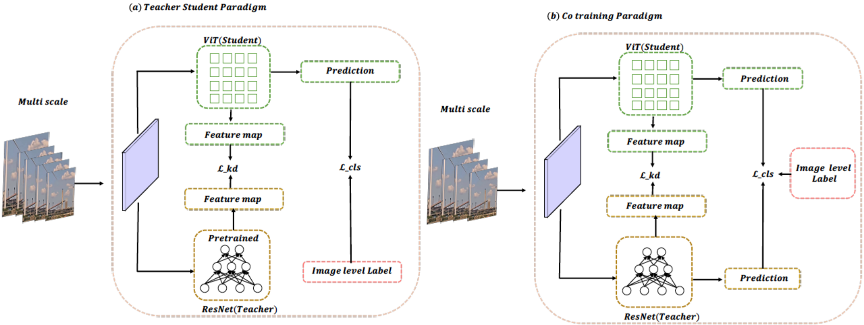


$$\mathcal{L} = \mathcal{L}_{\text{cls}} + \lambda\mathcal{L}_{\text{tf}}$$

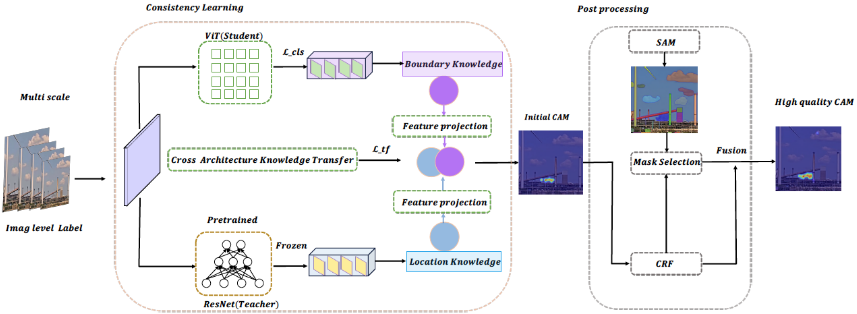
Cross-Architecture Feature

Challenge: Transferring knowledge between fundamentally different architectures—such as Transformers and CNNs—is more difficult. Their distinct design principles lead to divergent feature representations, making compact and effective knowledge transfer non-trivial.

Knowledge transfer training scheme



Framework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ResNet(Teacher)

Which part provides a more informative knowledge source?

The knowledge transfer performance is sensitive to how the knowledge is defined.

Logit-Based

- Uses the teacher's softmax predictions as pseudo labels for the student.
- Not suitable for our task, as it loses the spatial information and ignores how the internal representations are formed.

Feature-Based

- Minimizes the difference between the intermediate feature representations of the student and the teacher.
- Preserves semantic and spatial information.

How to align the mismatched representations

Spatial Map: Aggregates channel information into a 2D spatial map.

$$F : \mathbb{R}^{C\times H\times W} \rightarrow \mathbb{R}^{H\times W}$$

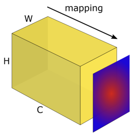

Figure: Spatial map: loses channel idms semantic information.

Inner Product: Computes pairwise channel relations to preserve semantic structure.

$$F : \mathbb{R}^{C\times H\times W} \rightarrow \mathbb{R}^{C\times C}$$

Cross-Architecture Feature Alignment Strategies

Table: Comparison of Feature Shapes and Their Properties

Shape	Keeps Channel Info?	Keeps Spatial Info?	Semantically Rich?
$[B, C, H \times W]$	✓ Yes	✓ Yes	✓ Yes
$[B, H \times W]$	No	✓ Yes	No
$[B, C, C]$	✓ Yes	No	No

[B, C, H×W] :flatten spatial layout while keeping semantic channels. Then use a learnable feature projection layer to align the feature.

Cross-Architecture Feature Alignment Strategies

Comparison Strategies:

- **Global Alignment:** Enforces consistency in holistic feature representations.
- **Channel-Wise Alignment:** Aligns feature responses along the channel dimension, helping match semantic filters between models.
- **Spatial Alignment:** precise pixel-to-pixel correspondence.

Various Post-processing Techniques

Problem: The initially generated CAMs are often redundant and incomplete.

- **Multi-scale Inference:** Aggregates CAMs from multiple input resolutions to improve robustness and capture multi-level semantics.
- **CRF (Conditional Random Field):** Models pixel-level relationships to enforce spatial consistency and sharpen object boundaries.
- **AffinityNet:** Learns pairwise pixel affinities and propagates CAMs to refine segmentation masks.
- **CAM Fusion:** Combines CAMs from different layers to increase coverage and completeness.

Emerging Trends

- **SAM-Enhanced** Leverage SAM for zero-shot pseudo masks generation, enhancing spatial consistency and boundary quality.
- **CLIP-Aided** Incorporate vision-language priors by using CLIP's text encoder to generate class-specific weights for CAM generation. The effectiveness relies heavily on well-crafted textual prompts, especially for abstract concepts like smoke.

Outline

Dataset description

Dataset

Source	Examples	Supervision Type	Class
IJmond	train	image-level	Smoke&non-smoke
IJmond	test	pixel-level	Smoke
Smoke5K	train	image-level	Smoke
RISE	train	image-level	Smoke&non-smoke

Comparison with baseline models

Table: Evaluate mIOU of pseudo masks with different backbones. T_1:Train dataset. T_2:Part of the test dataset. Gray rows indicate ours method.

Supervision	**Source**	**Backbone**	**mIOU**
image-level	T_1	ResNet50	26.10
image-level	T_1	ResNet101	21.29
image-level	T_1	ViT-S	13.18
image-level	T_1	Ours	47.37
image-level	$T_1 + T_2$	ViT-B	47.99
image-level+limited pixel-level	$T_1 + T_2$	ViT-B	✗

Fully supervised model vs Weakly supervised model

Table: Comparison of semantic segmentation methods. Fully supervised learning methods are trained with ground truth labels without any post-processing.

Method	**Backbone**	**mIOU**
Fully Supervised		
SERT[?]	Transformer	68.27
SAM-fine-tuning	ViT-B	54.68
Multi stage WSSS		
Ours+post-processing	ViT-S+ResNet50	52.93

Comparison with previous methods

Table: Comparison with previous methods.

Method	**backbone**	**mIOU**
TransCAM	Conformer	15.02
AffinityNet	ResNet50	24.28
PCM	ResNet50	33.56
Ours	ViT-S+ResNet50	47.37
Ours+post-processing	ViT-S+ResNet50	52.93

Post-processing

Table: Evaluation of pseudo labels with different post-processing techniques.

Method	mIoU
w/o post-processsing	37.42
+Multi scale	38.49
+AffinityNet[?]	34.00
+SAM-enhanced[?]	43.20
+CLIP[?]	✗
+CRF	43.27
+CAM fusion	46.91
+CRF+CAM fusion	37.81
+CRF+AffinityNet[?]	38.51
Optimal threshold	53.92

(a) CAMs generated by ours (Worse seed)

Method	mIoU
w/o post-processsing	46.25
+Multi scale	47.37
+CAM fusion	45.27
+CRF+AffinityNet[?]	49.16
+SAM-enhanced[?]	51.00
+CLIP[?]	✗
+CRF	52.52
+CRF+SAM-enhanced	52.93
Optimal threshold	57.15

(b) CAMs generated by ours (Best seed)

Ablation Studies

Table: Comparison of different knowledge transfer strategies

Paradigm	Teacher	Student	Metric	Level	mIOU
Teacher-Student	ResNet(Pre-trained)	ViT	Cosine	Global	47.37
Teacher-Student	ResNet(Pre-trained)	ViT	L_1	Global	38.39
Teacher-Student	ResNet(Pre-trained)	ViT	L_2	Global	33.74
Teacher-Student	ResNet(Pre-trained)	ViT	Cosine	Spatial	43.70
Teacher-Student	ResNet(Pre-trained)	ViT	Cosine	Channel	46.85
Co-training	ViT + ResNet(From scratch)	ViT+ResNet	Cosine	Global	45.93
Co-training	ViT + ResNet(From scratch)	ViT+ResNet	L_1	Global	18.51
Co-training	ViT + ResNet(From scratch)	ViT+ResNet	L_2	Global	0.27
Co-training	ViT + ResNet(From scratch)	ViT+ResNet	Cosine	Spatial	45.11
Co-training	ViT + ResNet(From scratch)	ViT+ResNet	Cosine	Channel	42.75

Table: The impact of the knowledge transfer Loss coefficient

λ	**mIOU**
0.3	38.55 $\uparrow$ 4.99
0.5	43.81 $\uparrow$ 10.25
0.8	45.04 $\uparrow$ 11.48
1.0	47.37 $\uparrow$ 13.81
1.3	46.62 $\uparrow$ 13.06
1.5	41.90 $\uparrow$ 8.34

Outline

Conclusion

- We propose a simple yet effective **knowledge transfer** method based on **cross-architecture consistency**, aimed at mitigating spurious correlations without relying on human priors or external supervision.
- Our approach successfully transfers **complementary knowledge** from the teacher model while preserving the strengths of the student model, thereby **reducing classifier bias**.
- In addition, we explore and evaluate various post-processing techniques to further enhance the quality of pseudo labels.

Limitations and Future Work

- Explore additional feature alignment strategies for better cross-architecture knowledge transfer.
- Investigate more effective integration of post-processing techniques.
- Extend the approach from binary to multi-class classification.
- Evaluate the generalization of the method on other datasets.
- Validate the effectiveness in a end-to-end WSSS setting.

End

Thanks for listening!