Domain Adaptation for Unknown Image Distortions

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Training of Instance Segmentation

Labeled Training Data → Instance Segmentation → Learn

Training Data

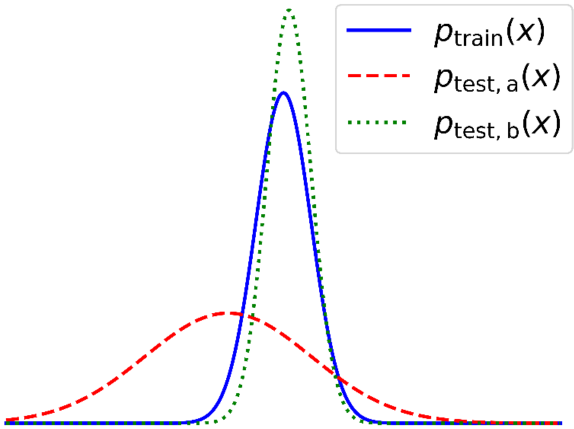
Source: cityscapes-dataset.com

Annotations

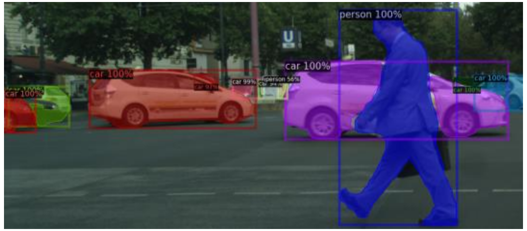
Source: cityscapes-dataset.com

Application of Instance Segmentation

Test Data → Instance Segmentation → Predict Labels



Domain Shift



Outline

- Motivation
- Domain Adaptation
- State-of-the Art
- Unpaired Learning of Unknown Image Distortions
- Evaluation
- Conclusion

Domain Adaptation

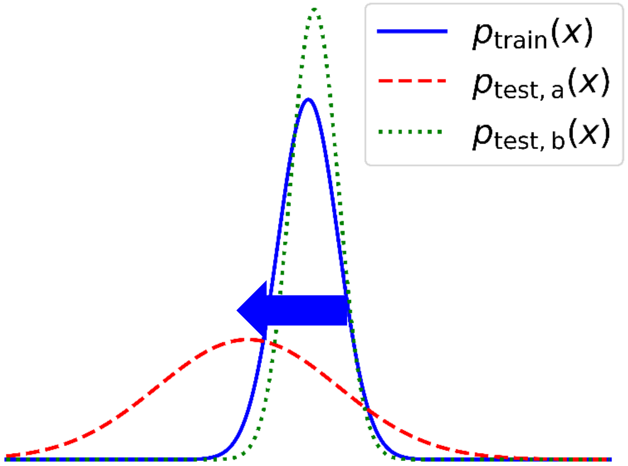
Problem:

- Instance segmentation not directly applicable to new domains
- Annotated data required for each domain
- Data annotation expensive

→ Domain Adaptation **[1]**:

– Collect data from new domain

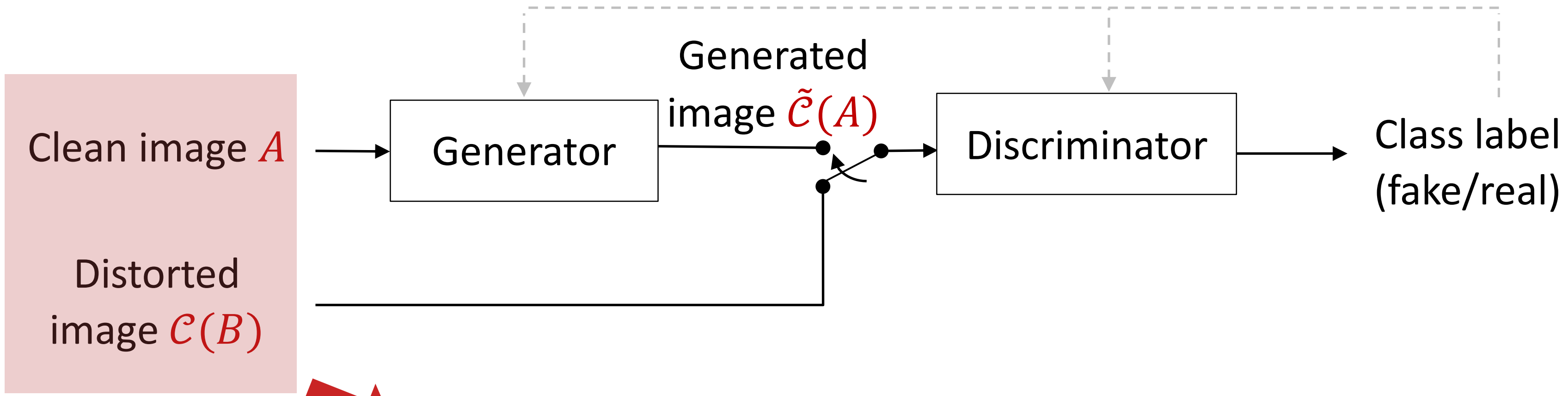
– Adapt annotated data sets to new domain



[1] G. Csurka, "A Comprehensive Survey on Domain Adaptation for Visual Applications." Springer, 2017, ch. 1, pp. 135.

Adversarial Learning for Domain Adaptation

Adversarial training: Train function $\tilde{\mathcal{C}}$, which approximates the true pristine-to-distortion mapping function $\mathcal{C}$



Paired: Image $A = B$ **[2]**

Unpaired: Image $A \neq B$ **[3]**

[2] P. Isola, et al., “Image-to-Image Translation with Conditional Adversarial Networks,” in Proc. Conference on Computer Vision and Pattern Recognition (CVPR), 2017.
[3] J. Zhu, et al., “Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks,” in Proc. International Conference on Computer Vision (ICCV), 2017.

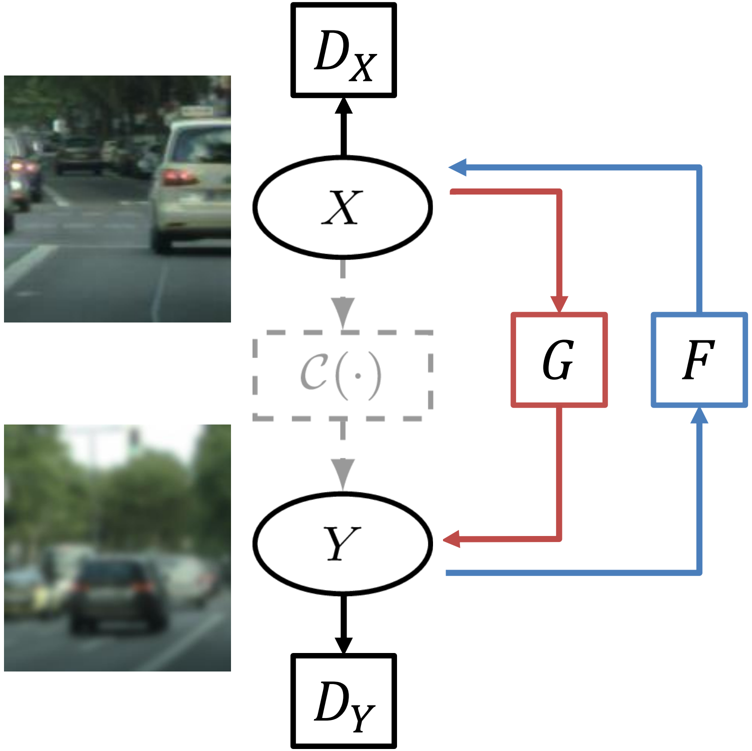
Paired Learning of Image Distortions

Paired learning of image distortions **[4]**

- White noise, pink noise, JPEG2000, JPEG
- Based on pix2pix framework **[2]**
- Evaluation in terms of image quality
- No application to machine vision tasks

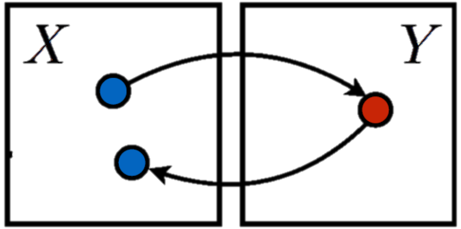
[4] L.-H. Chen, et al., "Learning to Distort Images Using Generative Adversarial Networks," IEEE Signal Processing Letters, vol. 27, pp. 2144–2148, 2020.

Unpaired Learning of Unknown Distortions



CycleGAN **[2]**:

- Generators G, F
- Discriminators D_X, D_Y
- GAN loss: least-squares
- Cycle-consistency loss



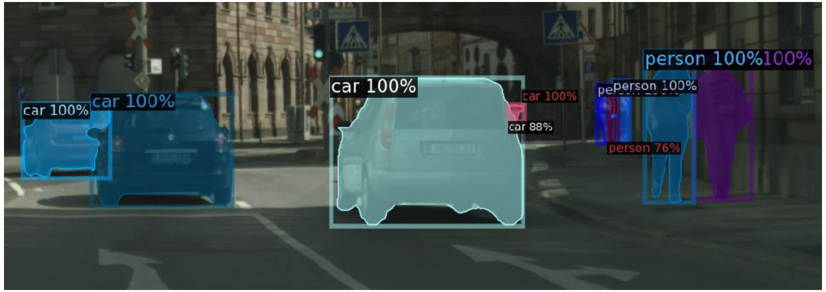
Unpaired Learning of Unknown Distortions

Pristine	Blur	White noise	JPEG2000	JPEG	HEIF
	$\sigma_{\text{blur}} = 3$	$\sigma_{\text{AWGN}} = 20$	$\text{PSNR} = 32\text{dB}$	$\text{CL} = 18$	$\text{QP} = 42$

Instance Segmentation with Mask R-CNN

Task:

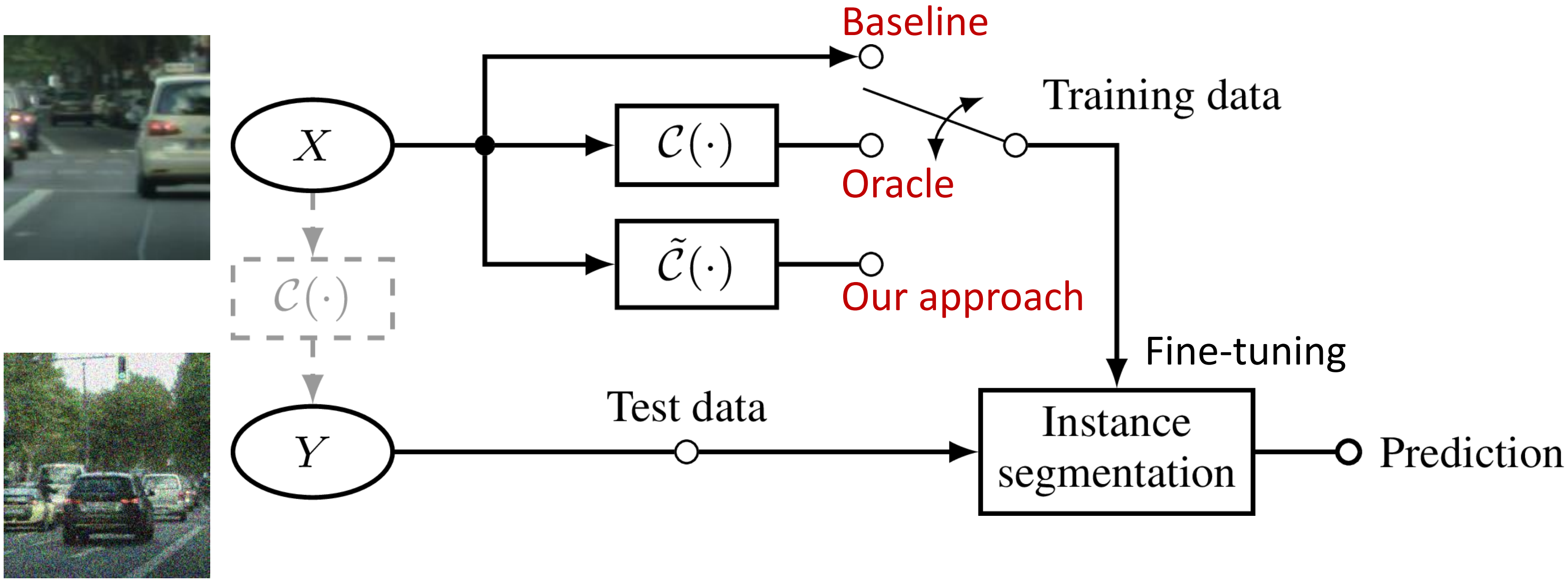
- Localization of all objects
- Distinguishing between instances
- Pixel-wise segmentation of all instances



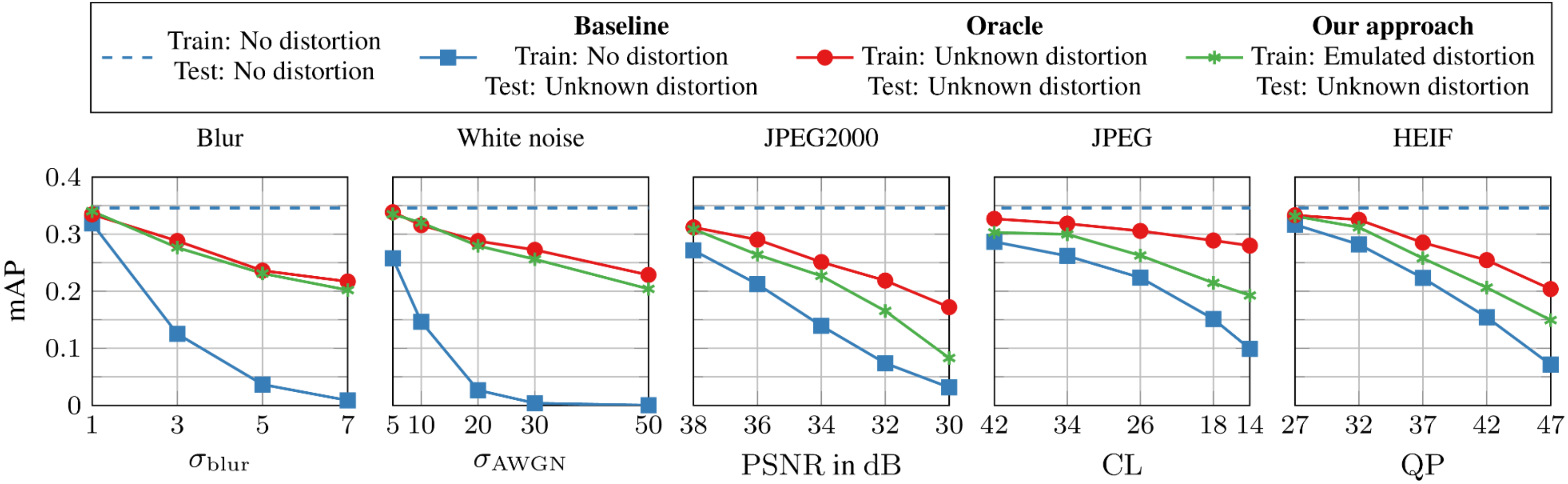
Evaluation:

- Average Precision (AP) per class
  - Averaged across range of overlap thresholds
- Mean Average Precision (mAP)
  - Averaged over all classes

Evaluation Setup



Results: Instance Segmentation



Average mAP Gains Over Baseline Model

Distortion	Oracle	Our approach	Difference
Blur	0.15	0.14	-0.01
White noise	0.20	0.19	-0.01
JPEG2000	0.10	0.06	-0.04
JPEG	0.10	0.05	-0.05
HEIF	0.07	0.04	-0.03

Conclusion

Goal: Overcome domain shift for unknown distortions

1. Learn distortion from test data
2. Emulate distortion on training data
3. Fine-tune Instance segmentation

Average gains of 0.04 up to 0.19 in mAP

Distortion not present in training data

Distortion emulated in training data