Approaches for Domain Adaptive Object Detection in Production Environments

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Master of Science in Data Science and Engineering

April 4, 2022

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Introduction

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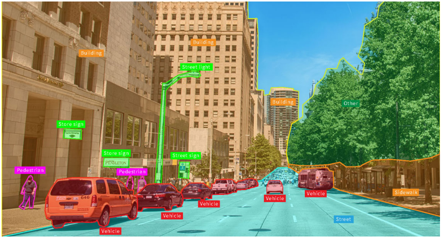
Deep learning methods are extremely effective on computer vision tasks



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- **Domain adaptation** methods transfer knowledge between domains

Introduction

Context

- Thesis conducted at Neovision[1], engineering company based in Grenoble, France, and specialized in artificial intelligence

  - Lack of annotated data is a big obstacle for *machine learning* projects
  - Domain adaptation methods depend on specific network architectures, with deep modifications

$\Rightarrow$ Domain adaptation can raise performances, but is complicated to set up in industrial projects

[1] https://neovision.fr/en/

Introduction

Method

- Focus on object detection task and *sim2real* transfer
  - Car detection
  - Synthetic dataset: *Sim10k*
  - Real dataset: *CityScapes*
- Research of "simple" approaches for domain adaptation
  - Domain randomization through data augmentation
  - Matching image statistics between domains
- Analysis of popular domain adaptation methods and of their issues
  - One and two stage object detectors: Faster R-CNN[2] and RetinaNet[3]

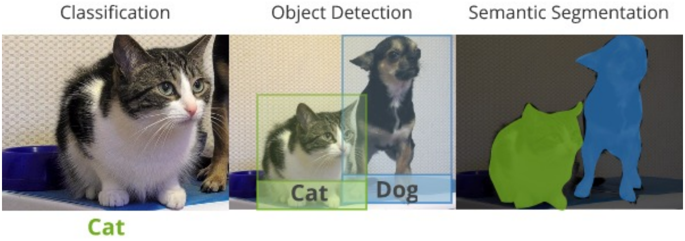
[2] Shaoqing Ren et al. *Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks*. 2016.

[3] Tsung-Yi Lin et al. *Focal Loss for Dense Object Detection*. 2018.

Domain adaptation

Computer vision

- Convolutional Neural Networks (CNNs) extract features from images
- Three main tasks:
  - Image classification: class of an image
  - Object detection: position and class for all object in an image
  - Semantic segmentation: class of each pixel in an image



Domain adaptation

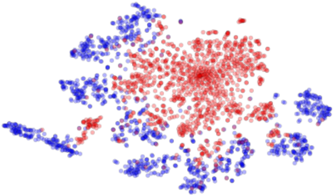
Domain adaptation

- Special case of transfer learning
- Goal to transfer knowledge acquired on a source domain (synthetic images) to a target domain (real images), without training a new model from scratch
- Source domain is annotated, while target domain is not: unsupervised domain adaptation

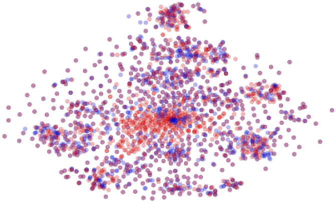
Domain adaptation

Domain adaptation approaches

- ***Domain invariant feature learning***
  - Goal of aligning feature distributions
  - After alignment, it is impossible to determine from which domain features are extracted
  - *Adversarial* approach: feature extractor evolves with the aim of fooling a domain classifier



(a) Non-adapted



(b) Adapted

Domain adaptation

Domain adaptation approaches

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  - *Adversarial* approach: feature extractor evolves with the aim of fooling a domain classifier
- ***Domain mapping***
  - Images from source domain are transformed to look like the target domain
  - Annotations are not altered by the style transfer

Method

Data augmentation for domain randomization

- Data augmentation:
  - Standard technique to ease the training of deep neural networks
  - Training images are randomly modified to introduce new data and increase variability
  - Geometric or color-based

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⇒ **Domain randomization**:
  - Network is "overwhelmed" with widely different versions of the same training images
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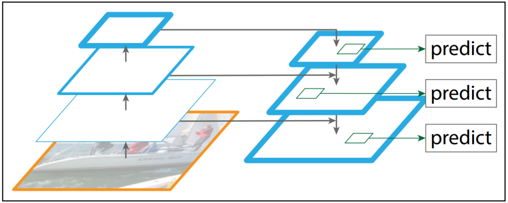
- Experiments confirm the hypothesis:
  - Detection results are improved on *RetinaNet* and *Faster R-CNN*
  - Color operators contribute the most

Method

Adapting the Feature Pyramid Network

- FPN[4] is widely used for object detection:
  - Extract feature maps at multiple levels from a single image
  - Sequence of convolutional layers, size divided by two at consecutive stages, with top-down connections
  - Increases detection performances, but adversarial domain alignment is non-trivial



[4] Tsung-Yi Lin et al. *Feature Pyramid Networks for Object Detection*. 2017.

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- Tested approaches:
  - Align levels of extracted feature pyramid
  - Align layers of the ResNet feature extractor, input for FPN
- Extracted representation is meaningful and independent of input domain

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- Method is effective on *RetinaNet*, but not on *Faster R-CNN*

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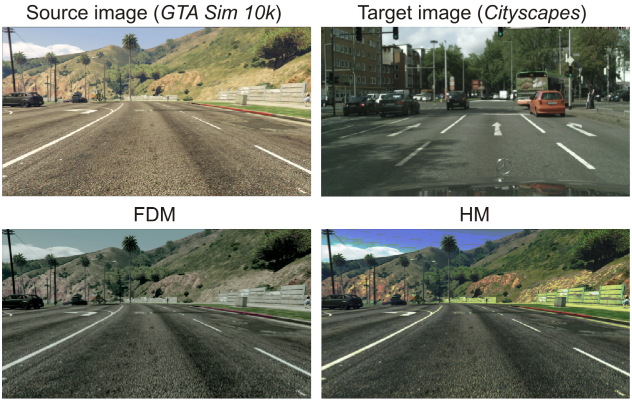
Method

Image statistics matching

- Domain mapping approach that updates source image statistics to match the target domain[5]



[5] Alexey Abramov, Christopher Bayer, and Claudio Heller. *Keep it Simple: Image Statistics Matching for Domain Adaptation*. 2020.

Results

Domain randomization

Transformations						Detector	
Horizontal flip	Rotation	Translation	Color jitter	Solarization	Equalization	mAP@0.5 RetinaNet	mAP@0.5 Faster R-CNN w/ FPN
✓						30.4	46.3
✓	✓	✓				37.6	48.8
✓	✓	✓	✓			49.4	**57.9**
✓	✓	✓	✓	✓	✓	**52.7**	**57.9**
Oracle						68.7	76.3

- FPN drives *Faster R-CNN* to better detection performances than *RetinaNet*

Results

RetinaNet

Method	Transformations				mAP@0.5
	Horizontal flip	Rotation	Translation	Color jitter	
Baseline	✓				30.4
Image statistics matching	✓				48.2
	✓	✓	✓		52.0
	✓	✓	✓	✓	**62.7**
Adversarial adaptation	✓				52.8
	✓	✓	✓		54.2
	✓	✓	✓	✓	54.8
Oracle	✓				68.7

Results

Faster R-CNN

Method	FPN	Transformations				mAP@0.5
		Horizontal flip	Rotation	Translation	Color jitter	
Baseline		✓				33.7
	✓	✓				46.3
Image statistics matching	✓	✓				55.0
	✓	✓	✓	✓		62.0
	✓	✓	✓	✓	✓	**62.5**
Adversarial adaptation		✓				36.3
	Aligned	✓				45.0
	ResNet aligned	✓				46.8
Oracle	✓	✓				76.3

Conclusions

- Performance gap due to the domain shift between cheap synthetic images and expensive real images

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- 👎 Popular methods for domain adaptive object detection depend on architecture-specific components
- 👎 Adversarial alignment may be unstable
- 👍 Domain mapping methods are effective with low training and implementation cost: suitable for production environments

Conclusions

- Performance gap due to the domain shift between cheap synthetic images and expensive real images

- Popular methods for domain adaptive object detection depend on architecture-specific components
- Adversarial alignment may be unstable
- Domain mapping methods are effective with low training and implementation cost: suitable for production environments

- Domain randomization through data augmentation can be enough
- ...and can support more advanced domain adaptation methods

Thank you for your attention!

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