Transfer learning and Domain adaptation

Vision & Language

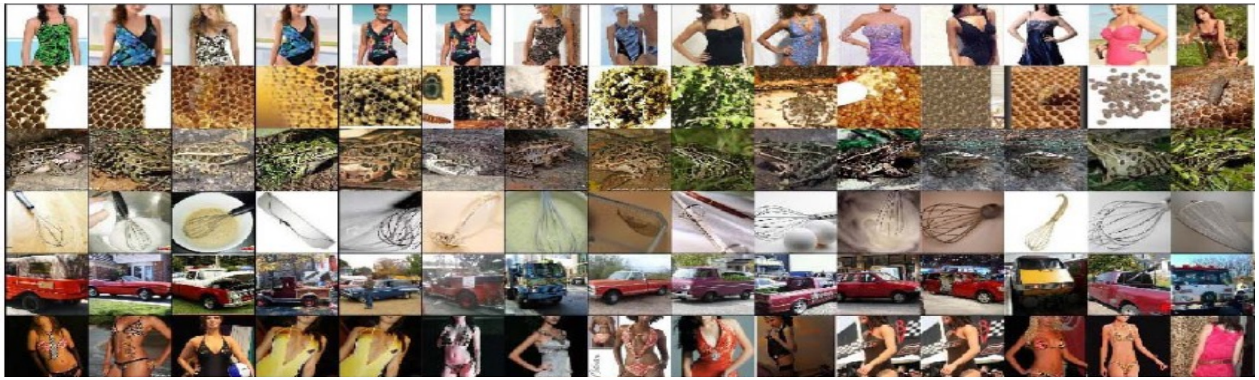
Transfer from ImageNet (source)

Transfer as **generic features**

Brut Deep features (learned from ImageNet)

(== a learned embedding from Image to vector representation)

Retrieval



Transfer learning (from source to target)

Frozen features + SVM => solution to small datasets

Frozen features + Deep

Fine tuning not easy in that case (small datasets)

Transfer from source(=ImageNet task) to target task

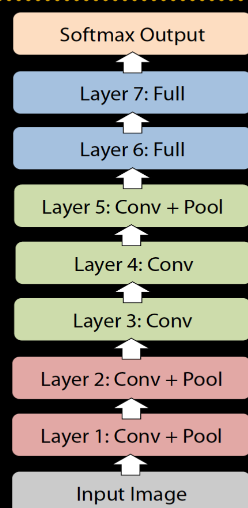
Source: ImageNet (dataset + 100 classes) => AlexNet trained

Target: new dataset Cal-101 and new classification task with 101 classes =>Chopped

AlexNet (layer i) + SVM trained on

Architecture of Krizhevsky et al.

- 8 layers total
- Trained on Imagenet dataset [Deng et al. CVPR'09]
- 18.2% top-5 error
- Our reimplementation:
  18.1% top-5 error



Tapping off Features at each Layer

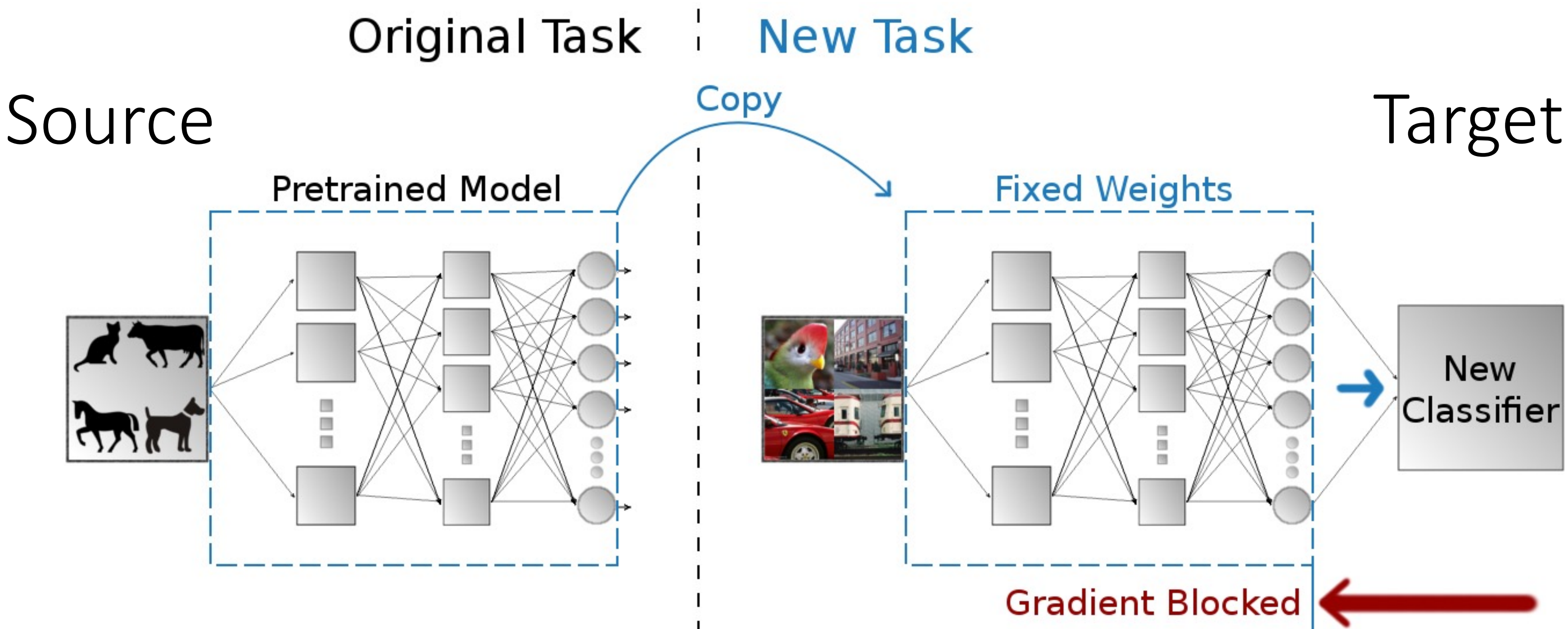
Plug features from each layer into linear SVM or soft-max

	Cal-101 (30/class)	Cal-256 (60/class)
SVM (1)	44.8 ± 0.7	24.6 ± 0.4
SVM (2)	66.2 ± 0.5	39.6 ± 0.3
SVM (3)	72.3 ± 0.4	46.0 ± 0.3
SVM (4)	76.6 ± 0.4	51.3 ± 0.1
SVM (5)	$\mathbf{86.2 \pm 0.8}$	65.6 ± 0.3
SVM (7)	$\mathbf{85.5 \pm 0.4}$	$\mathbf{71.7 \pm 0.2}$
Softmax (5)	82.9 ± 0.4	65.7 ± 0.5
Softmax (7)	$\mathbf{85.4 \pm 0.4}$	$\mathbf{72.6 \pm 0.1}$

=> Results better than SoA CV methods on Cal-101!

Transfer: fine-tuning of a deep model on target task

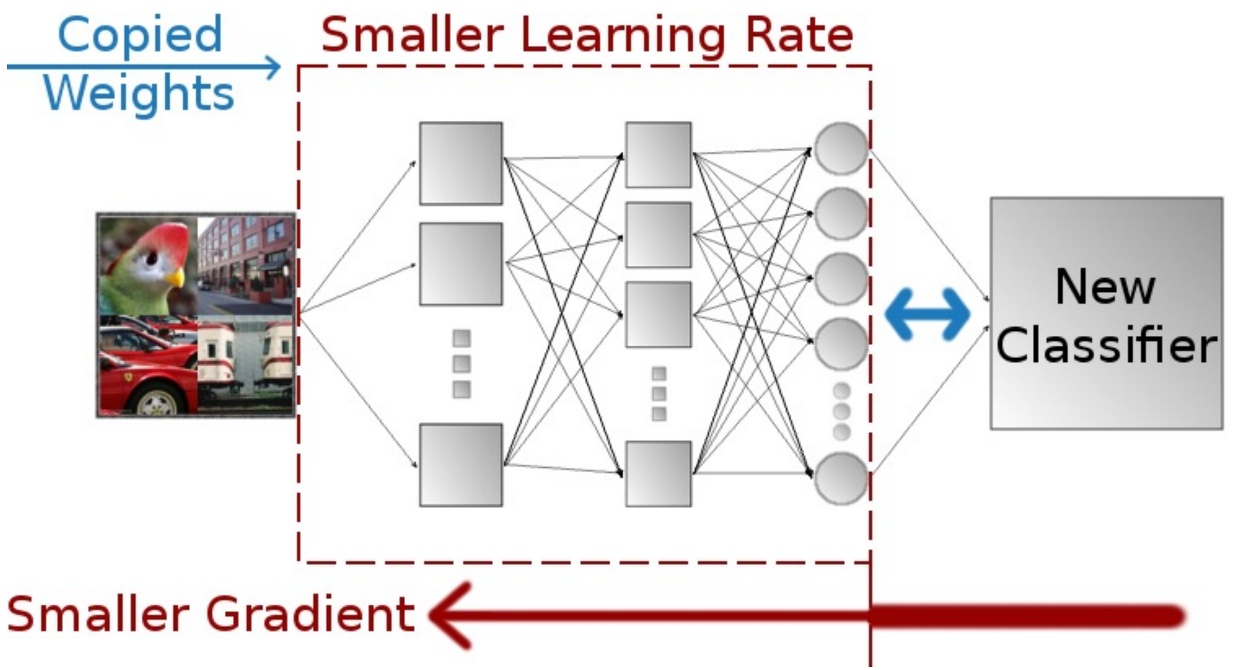
Train a deep (AlexNet) on source (ImageNet)
Keep the deep params. for target and complete with a small deep on top (fully trained on target task)
Fine-tune the whole model on target data
    Challenge: only limited target data, careful about overfitting
    Solution: Freeze the gradient's update for AlexNet part



Transfer: fine-tuning of a deep model on target task

Train a deep (AlexNet) on source (ImageNet)
Keep the deep params. for target and complete with a small deep on top (fully trained on target task)
Fine-tune the whole model on target data

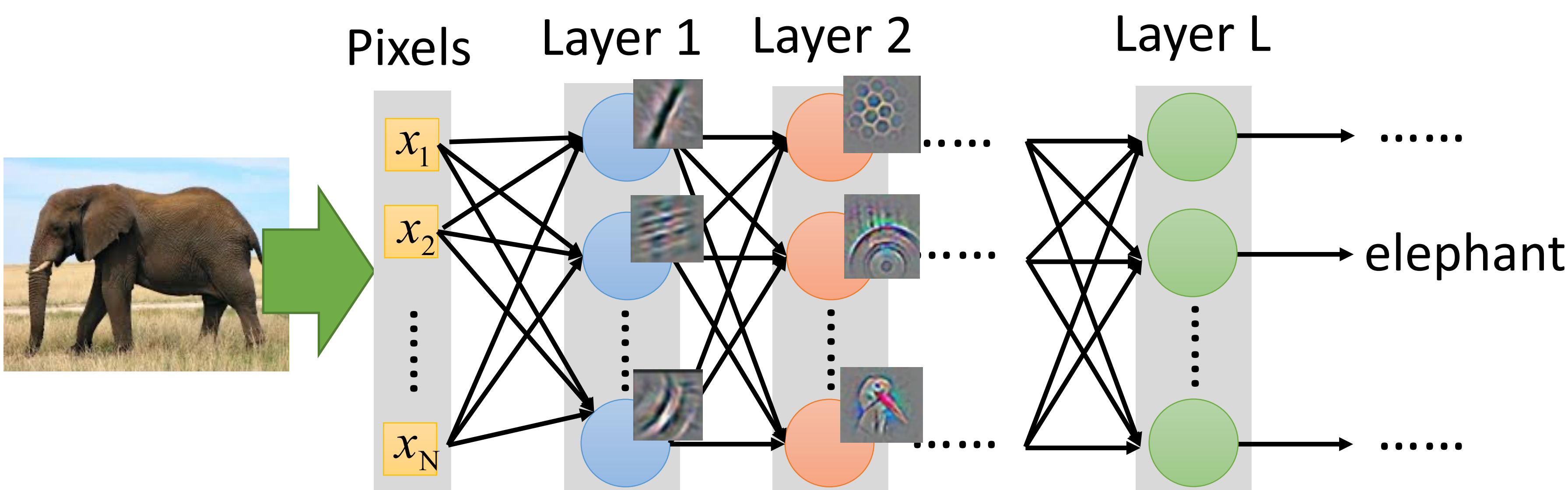
- Challenge: only limited target data, careful about overfitting
- Solution: Freeze the gradient's update for AlexNet part
- Other solution: use smaller gradient's update for AlexNet part



Transfer: which parts of the deep?

Which layer(s) can be transferred (copied)?

- Speech: usually copy the last few layers
- Image: usually copy the first few layers



Transfer: which supervision?

- Task description
  - Source data: (x^s, y^s) ⇐ A large amount
  - Target data: (x^t, y^t) ⇐ *(Very)* little

Rq: Few/One-shot learning: only a few/one examples in target domain

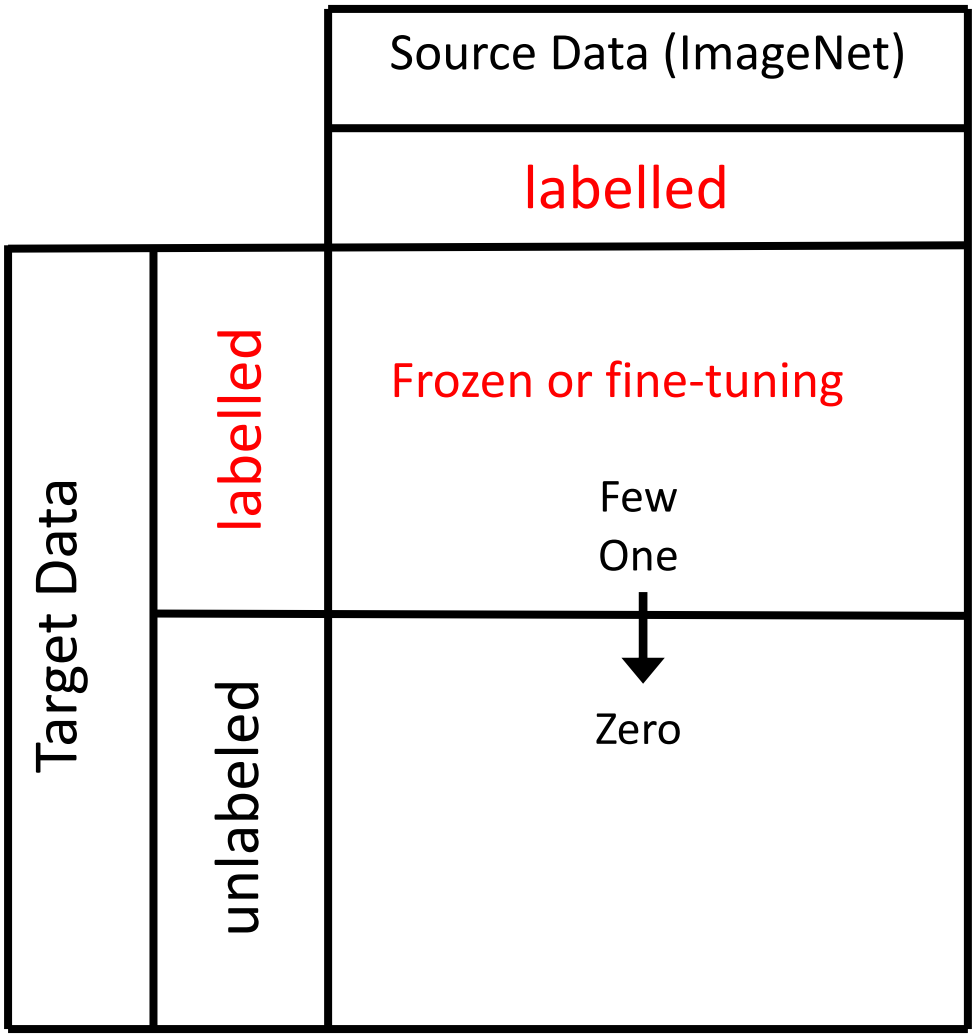
Many different contexts:

In vision: from large dataset (ImageNet) to small datasets (VOC2007)

In speech: (supervised) speaker adaption

- Source data: audio data and transcriptions from many speakers
- Target data: audio data and its transcriptions of specific user

More on transfer framework



Main purposes:

Similar visual domain?

Same tasks (ie class)?

Similar domain: ImageNet task => Dog/Cat task

Target: Dog/Cat Classifier

cat

dog

Data ***not directly related to*** the task considered

ImageNet: Similar domain,
different task (1000 classes but NOT Dog and Cat classes)

General Framework for Transfer Learning

Target:
Dog/Cat
Classifier

cat

dog

Data ***not directly related to*** the task considered

elephant

tiger

Similar domain, completely different tasks

dog

cat

Different domains, same task

General Framework for Transfer Learning

		Source Data (not directly related to the task)	
		labelled	unlabeled
Target Data	labelled	Fine-tuning *Multitask Learning*	Self-supervised Self-taught learning
	unlabeled	Domain-adversarial training *Zero-shot learning*	Self-taught Clustering

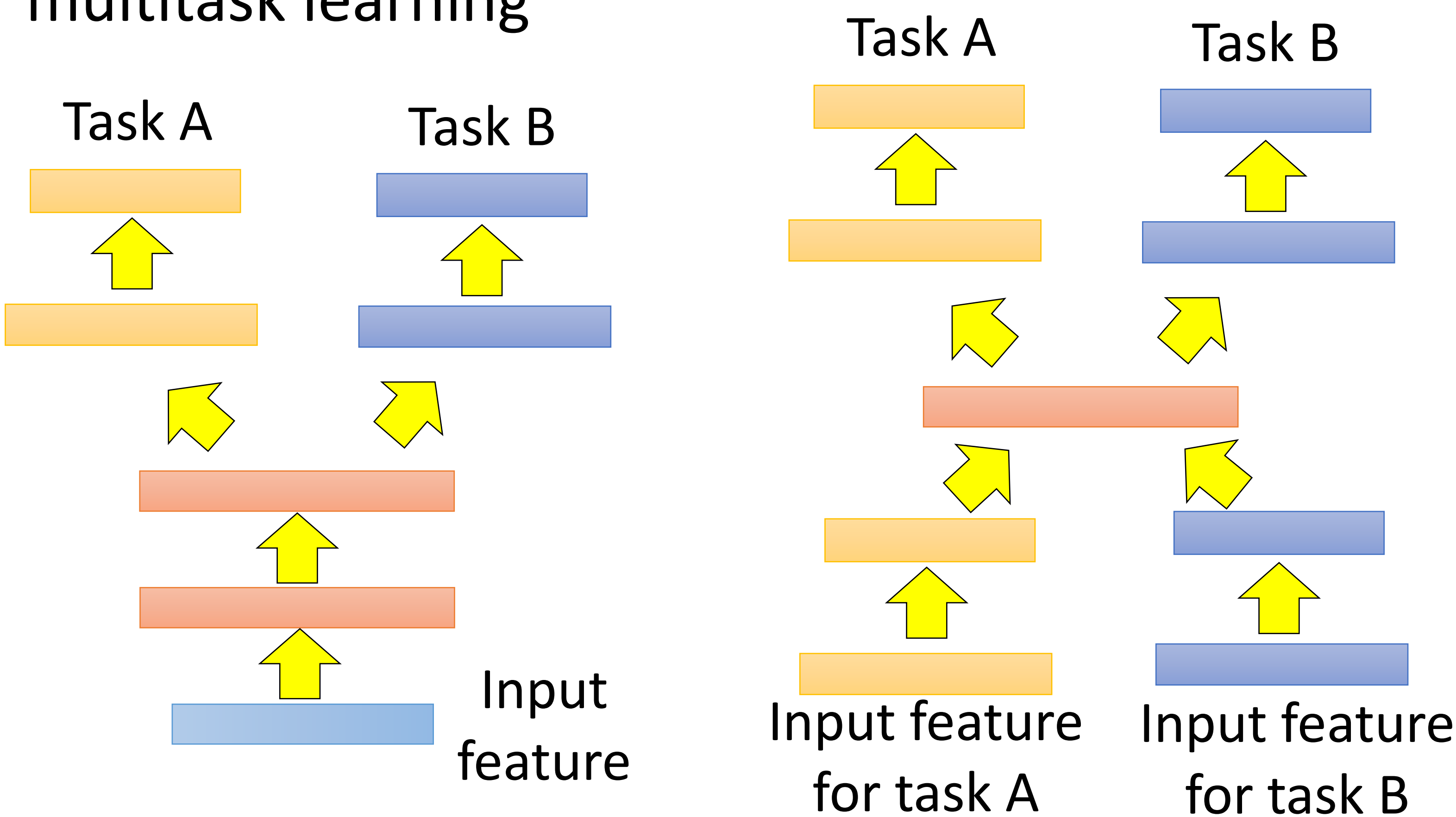
Not considered here

General Framework for Transfer Learning

		Source Data (not directly related to the task): labelled	Source Data (not directly related to the task): unlabeled
Target Data	labelled	Fine-tuning ***Multitask Learning***	Not considered here
Target Data	unlabeled		Not considered here

Multitask Learning

- The multi-layer structure makes NN suitable for multitask learning



Transfer Learning - Overview

		Source Data (not directly related to the task)	
		labelled	unlabeled
Target Data	labelled	Fine-tuning *Multitask Learning*	Not considered here
	unlabeled	**Domain adaptation-adversarial training**	Not considered here

Unsupervised Domain Adaptation (UDA)

Source data: (x^s, y^s) → Training data

Target data: (x^t) → Training data

Same task, domain mismatch

MNIST

SOURCE

with labels

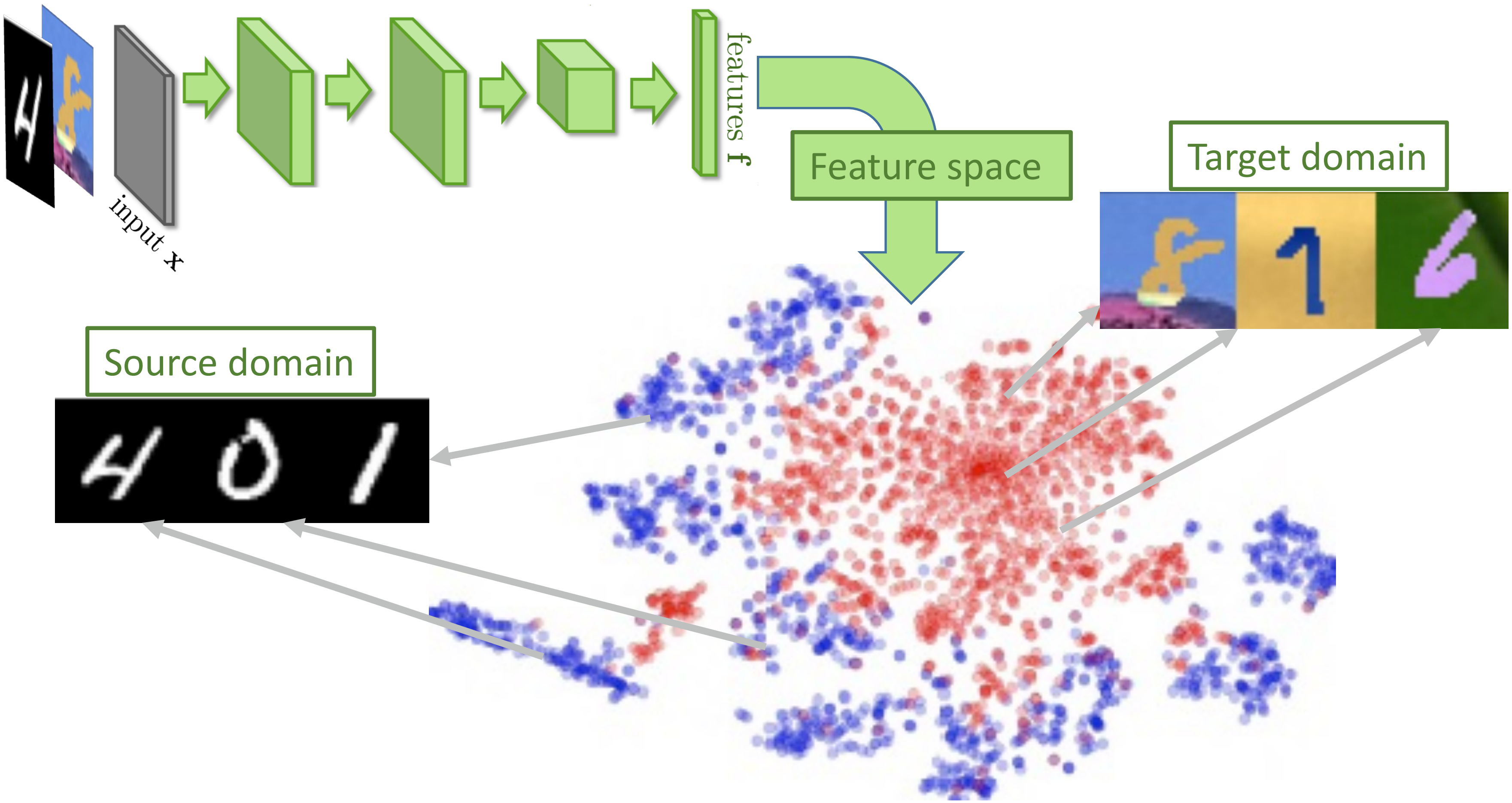
TARGET

without labels

MNIST-M

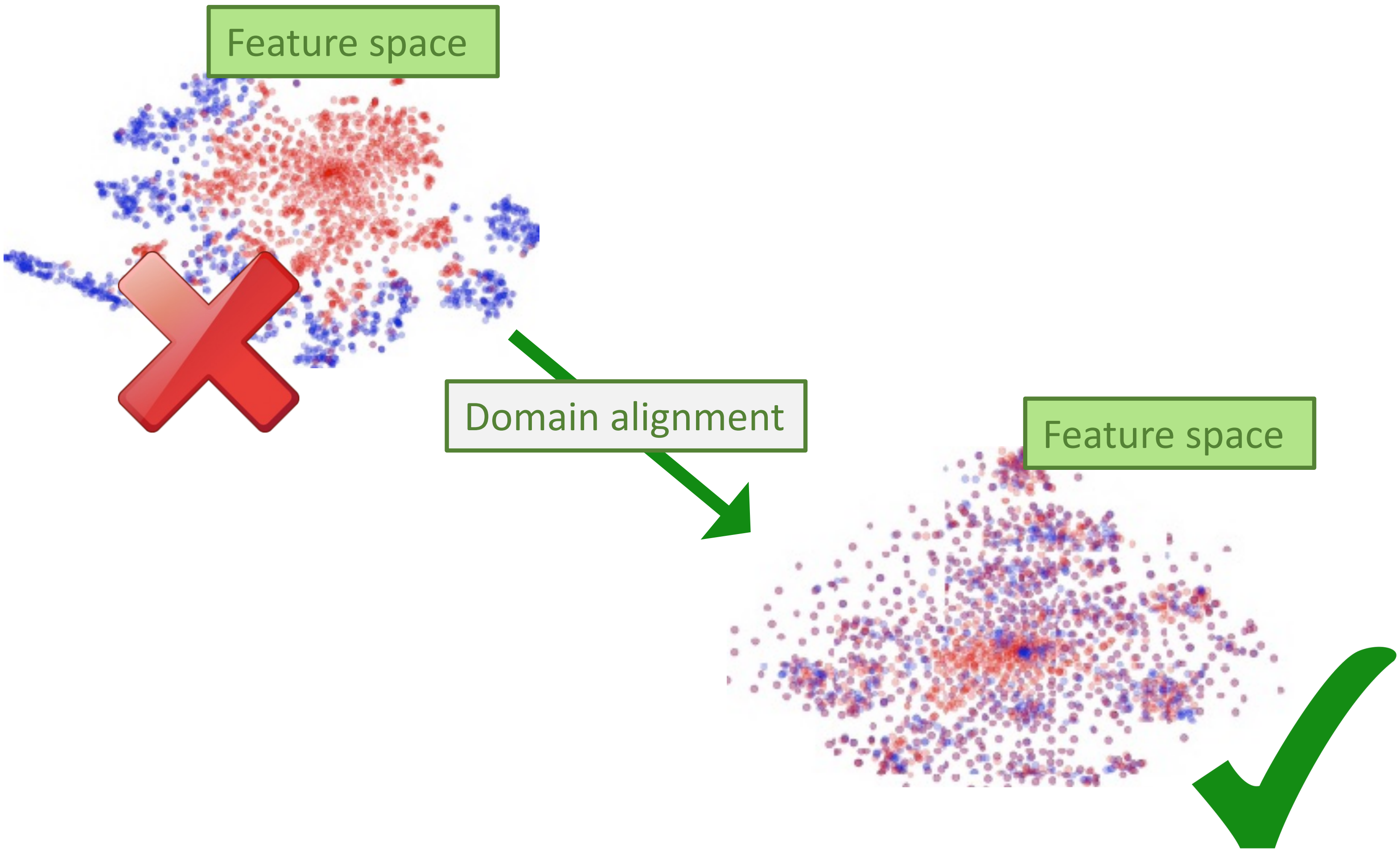
Final test on target domain!

Unsupervised Domain adaptation (UDA): objectives



Main principle: diminish the domain shift in the learned features, encourage domain confusion

UDA strategy: align both domains



UDA strategy: 1/ domain-adversarial training

Add to the feature generator (G) a domain classifier (discriminant D) for which labels are available!

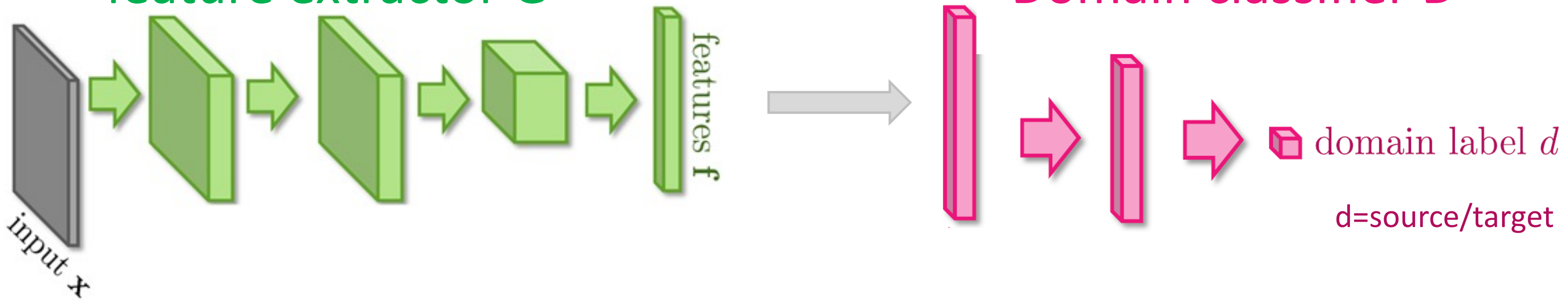
Learn G and D:

G tries to align domains

D tries to identify domains

feature extractor G

Domain classifier D

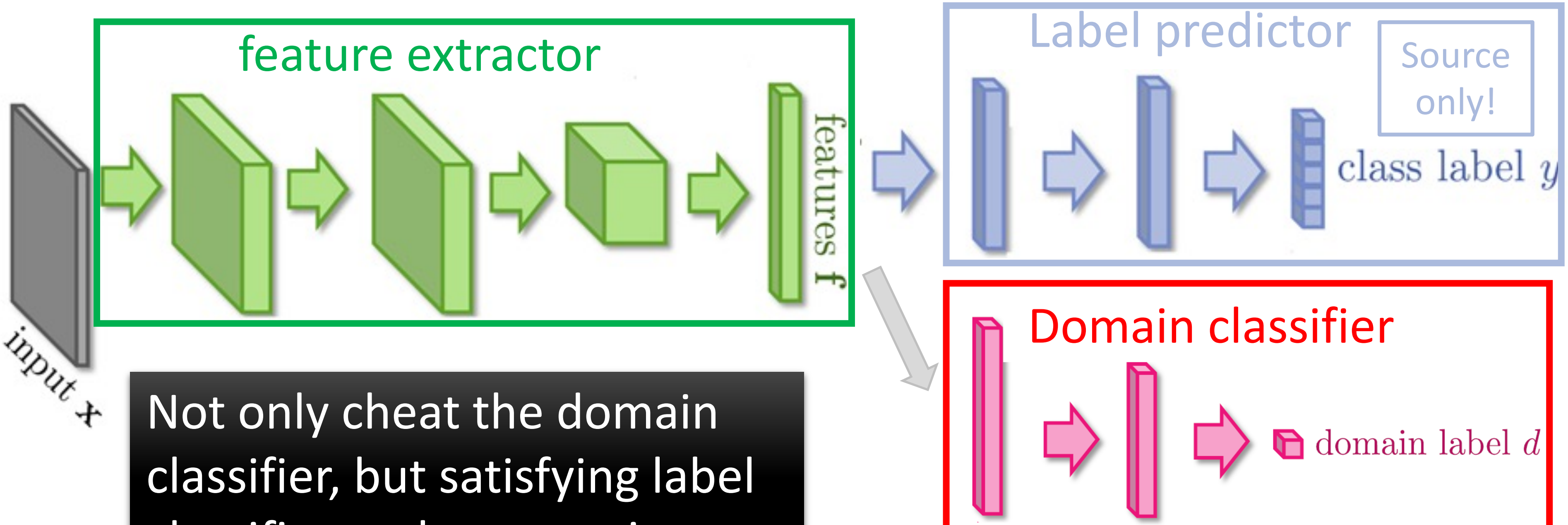


Rq: Similar to GAN (coming soon)

UDA strategy: 1/ domain-adversarial training
2/ classification task (same for source and target here)

Maximize label classification accuracy + minimize domain classification accuracy

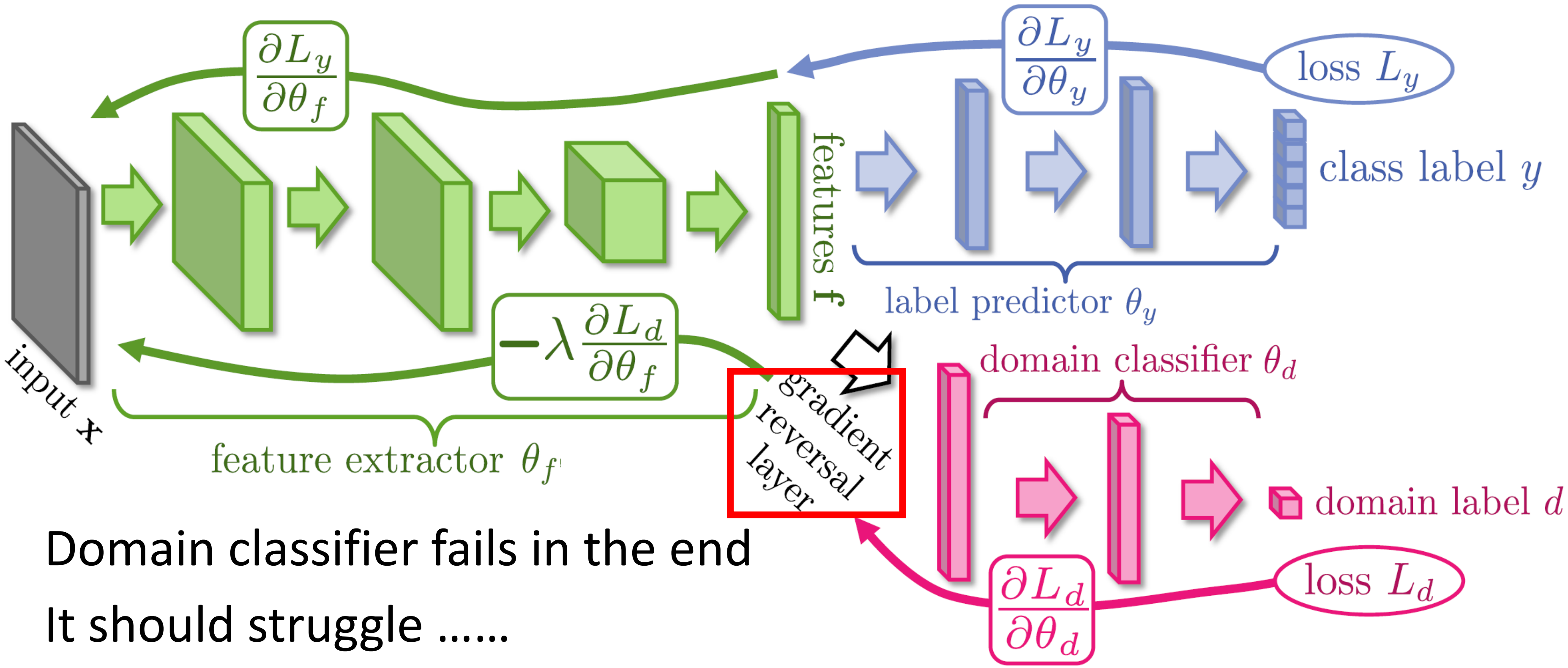
Maximize label classification accuracy



Not only cheat the domain classifier, but satisfying label classifier at the same time

Maximize domain classification accuracy

UDA strategy: joint learning



Domain classifier fails in the end

It should struggle ……

Yaroslav Ganin, Victor Lempitsky, Unsupervised Domain Adaptation by Backpropagation, ICML, 2015

Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, Mario Marchand, Domain-Adversarial Training of Neural Networks, JMLR, 2016

Domain-adversarial training

Method (Source / Target)	MNIST / MNIST-M	Syn Numbers / SVHN	SVHN / MNIST	Syn Signs / GTSRB
Source only	.5749	.8665	.5919	.7400
SA (Fernando et al., 2013)	.6078 (7.9%)	.8672 (1.3%)	.6157 (5.9%)	.7635 (9.1%)
Proposed approach	**.8149** (57.9%)	**.9048** (66.1%)	**.7107** (29.3%)	**.8866** (56.7%)
Train on target	.9891	.9244	.9951	.9987

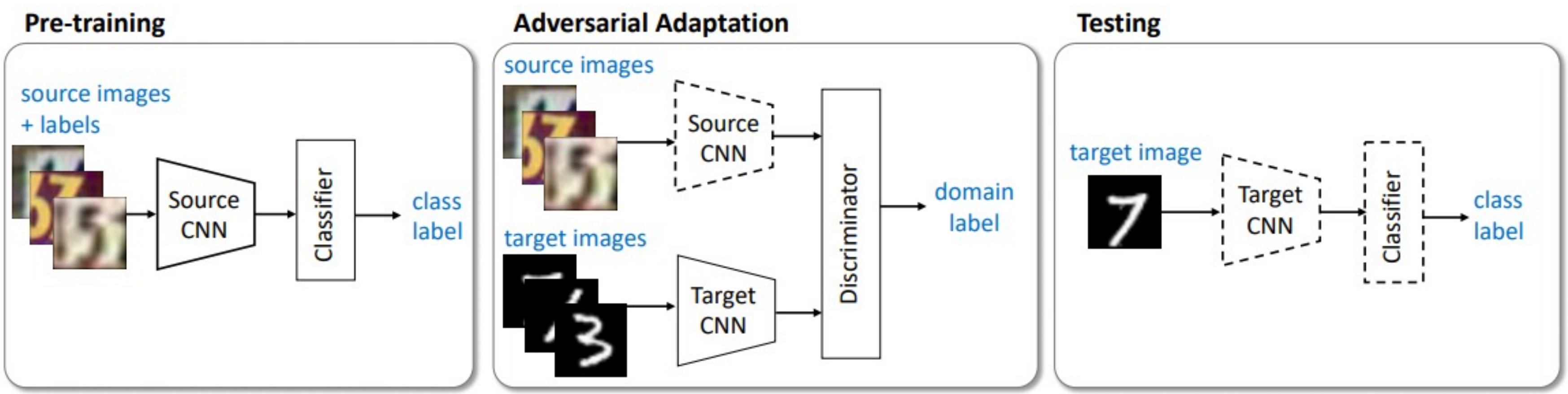
Yaroslav Ganin, Victor Lempitsky, Unsupervised Domain Adaptation by Backpropagation, ICML, 2015

Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, Mario Marchand, Domain-Adversarial Training of Neural Networks, JMLR, 2016

Domain adaptation

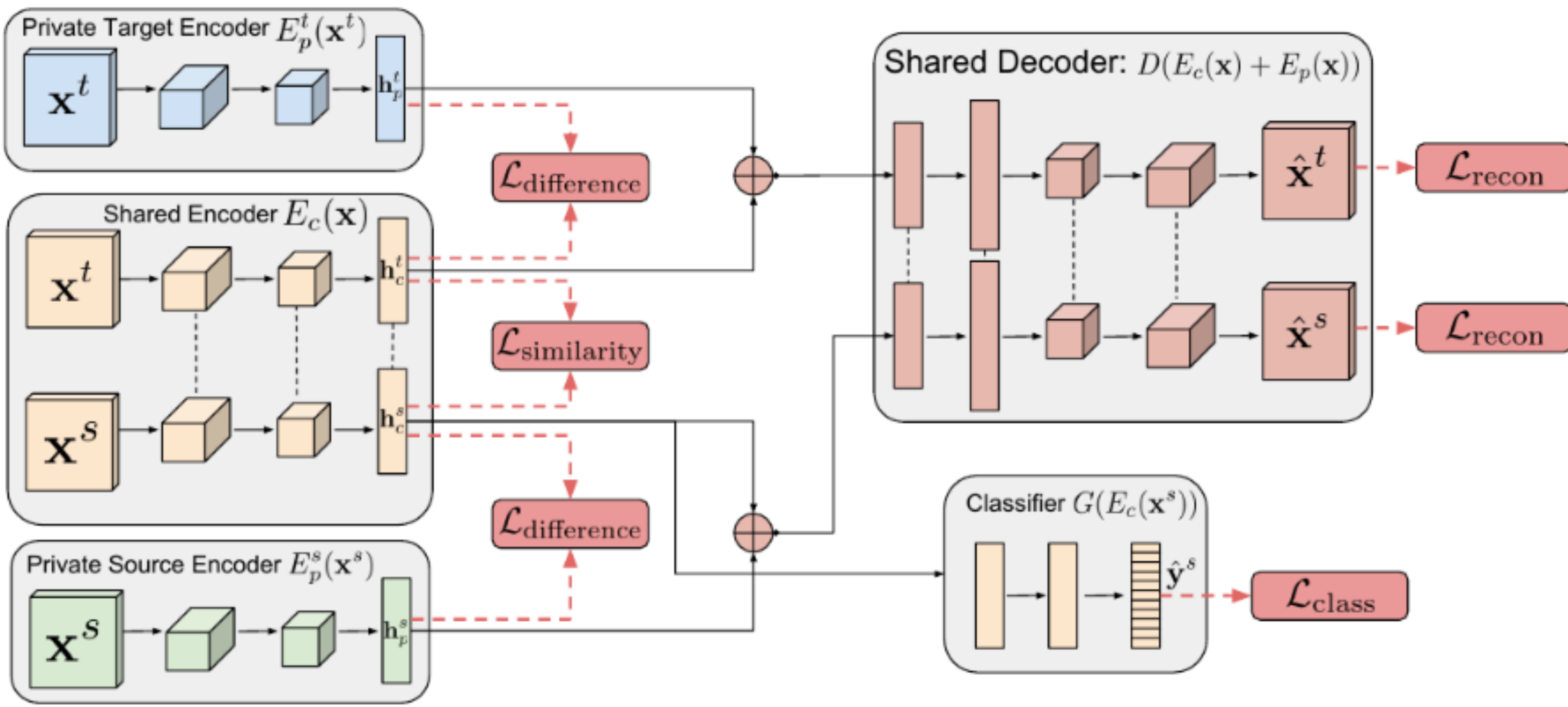
Main principle: diminish the domain shift in the learned features, encourage domain confusion

Another example: Adversarial Discriminative Domain Adaptation [Tzeng et al. 2017]



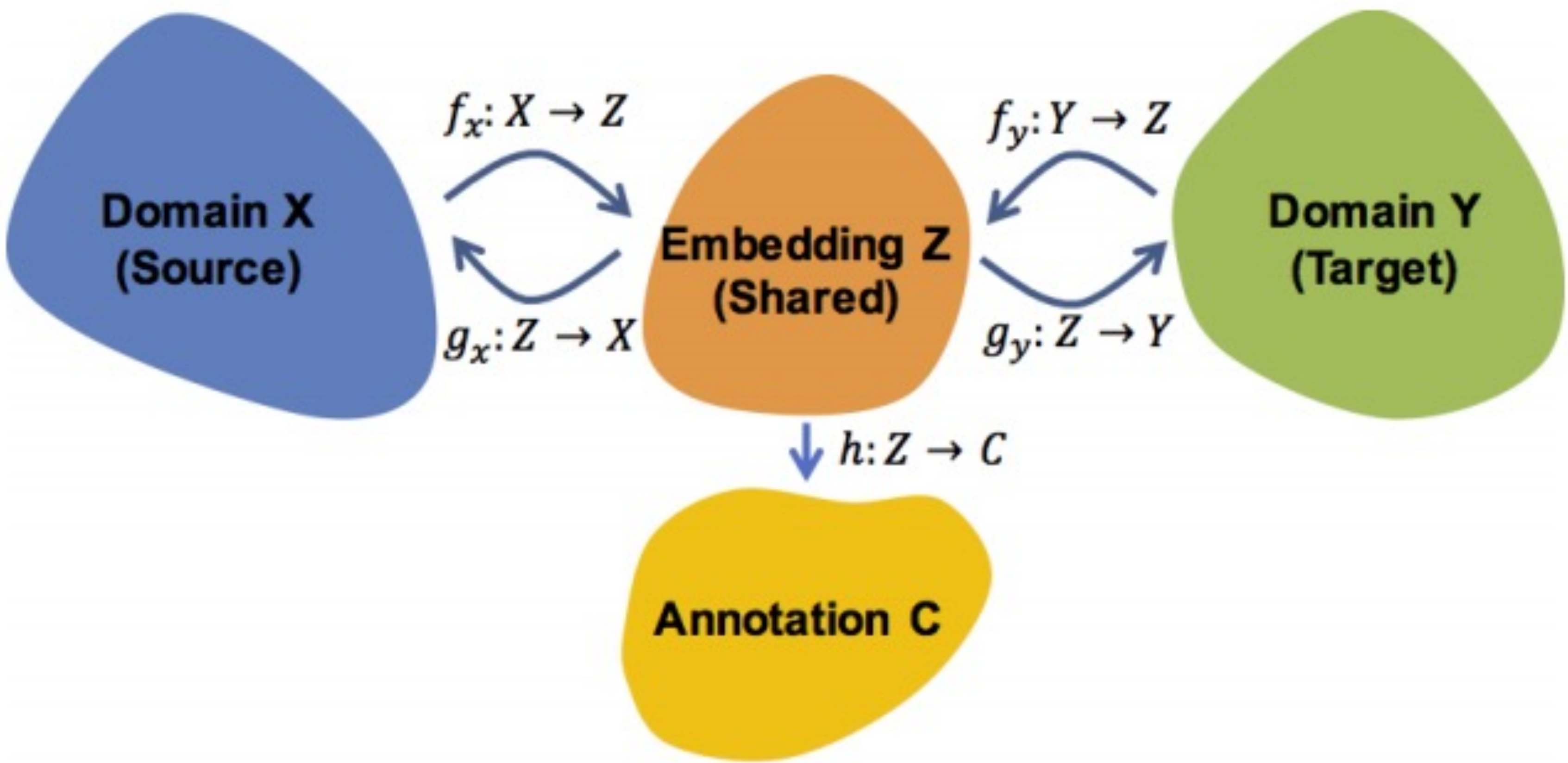
Domain adaptation

Other architecture



Domain adaptation

Other architecture: Image translation for Domain adaptation [Murez 2017]



Domain adaptation

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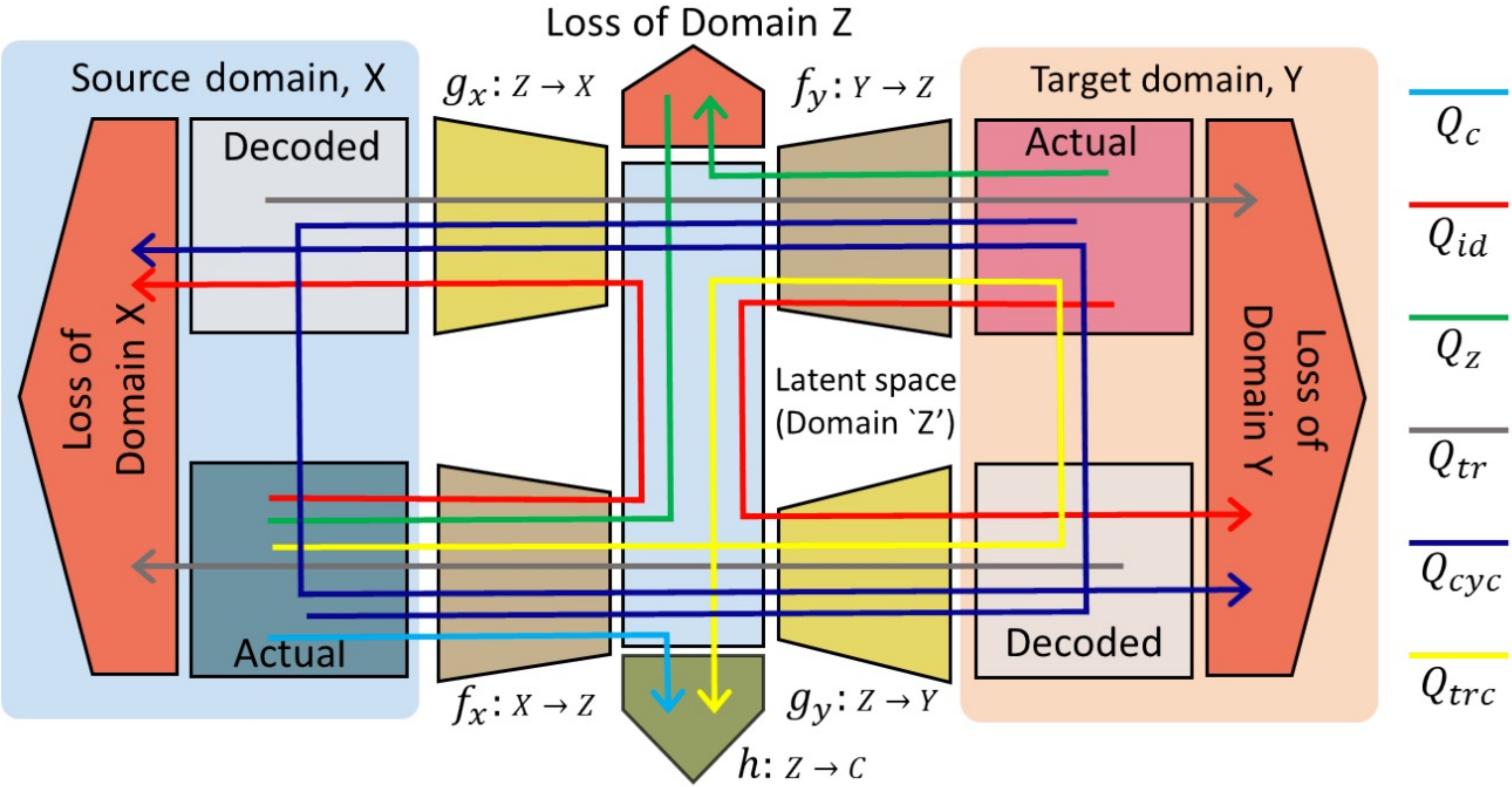
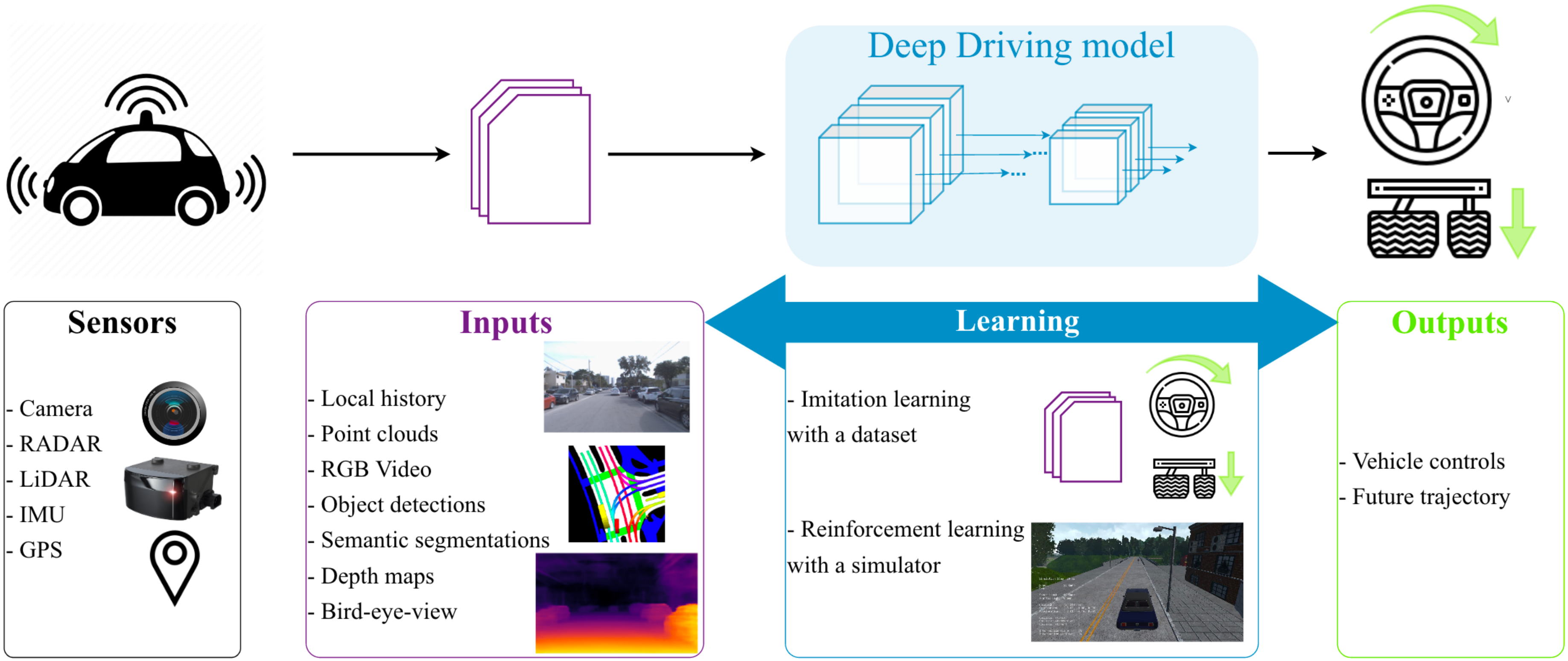


Use-Case: Domain adaptation for Autonomous driving

Context: Neural network-based autonomous driving system framework



Challenges for perception

Multi-sensor perception

- Sensor fusion; Camera, radar and Lidar

3D dynamic understanding

- 3D object detection; Motion forecast; Intention prediction

Frugal learning

- Training with limited data or supervision; Domain adaptation

Reliability

- Robustness; Uncertainty estimation; Failure prediction

Explainability

- Decision interpretation; Post-hoc or by-design

Domain gap

Different, though *related* input data distributions

Source domain → Target domain

- Different weather, light, location, sensor’s spec/setup

Domain gap

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Domain gap

Different, though *related* input data distributions

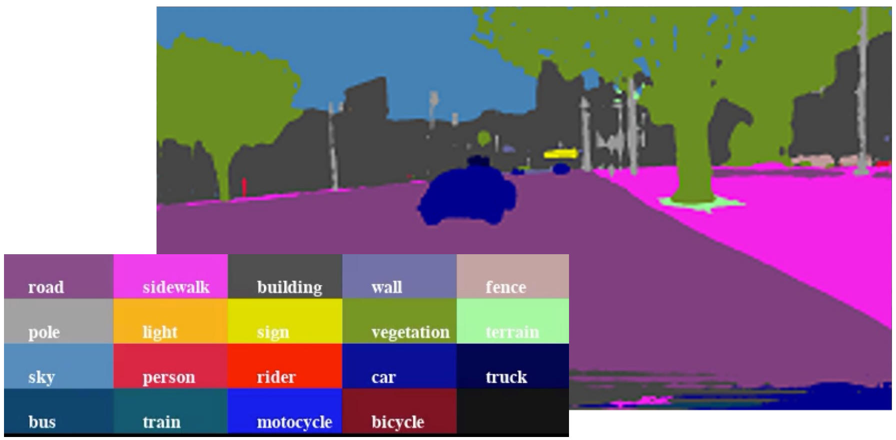
Source domain → Target domain

- Synthetic vs. real

Domain gap for VISUAL SEGMENTATION

Different, though *related* input data distributions

Source domain → Target domain

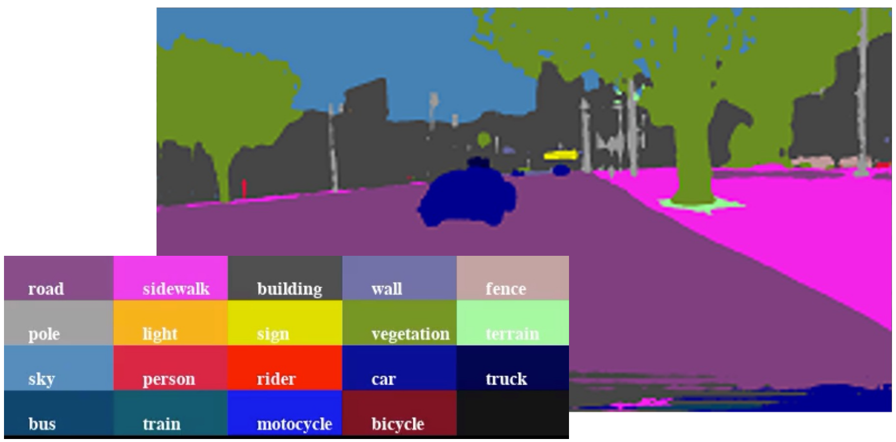


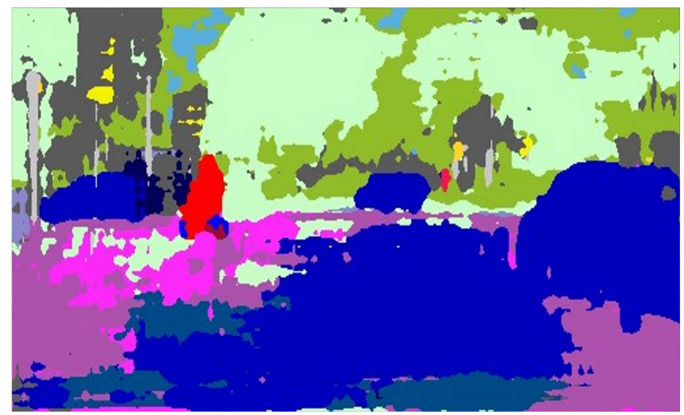
- Synthetic vs. real

Domain gap

Different, though *related* input data distributions

Source domain → Target domain

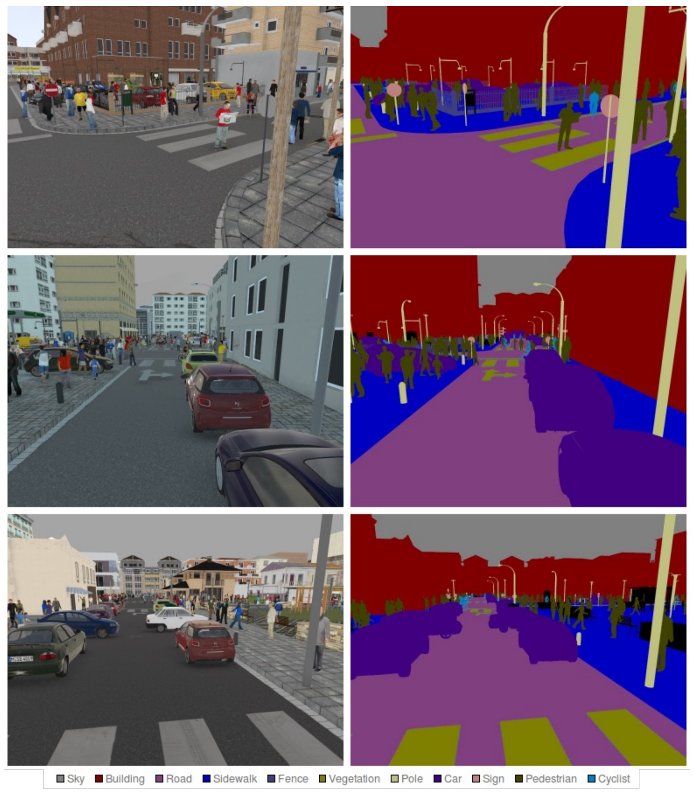




- Synthetic vs. real

Unsupervised Domain Adaptation (UDA)

Labelled source domain data

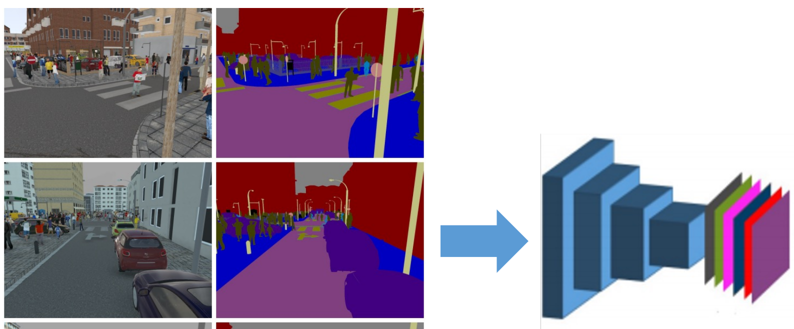


Unlabelled target domain data

Unsupervised Domain Adaptation (UDA)

TRAIN

Source labelled data

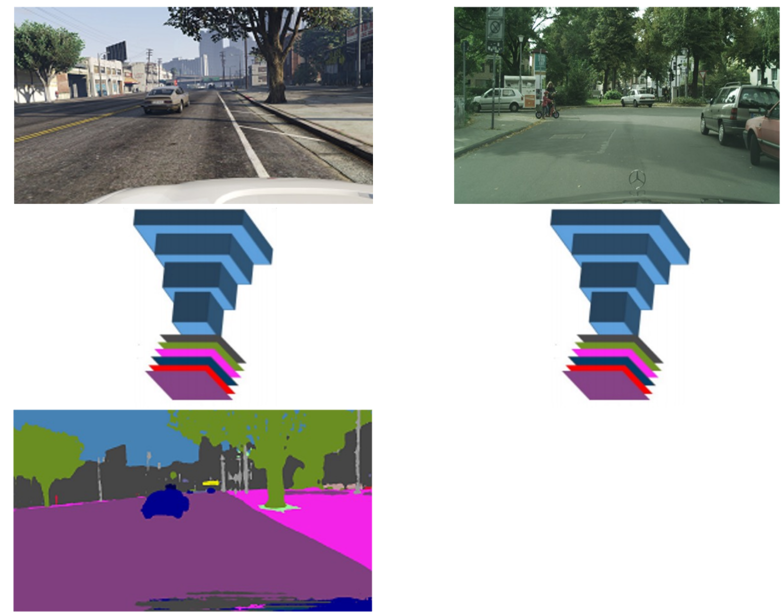


learned segmentation model

TEST

Source

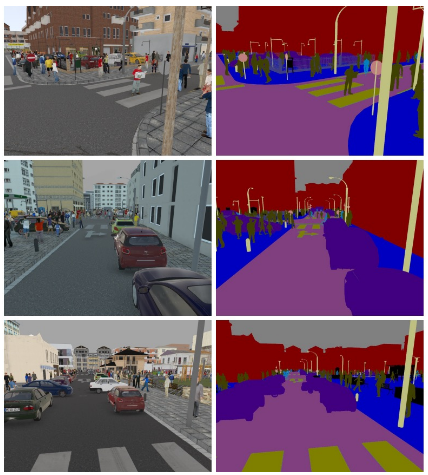
Target

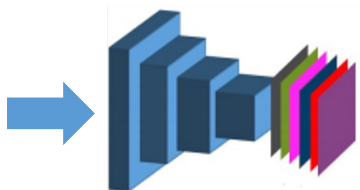


Unsupervised Domain Adaptation (UDA)

TRAIN

Source labelled data





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segmentation
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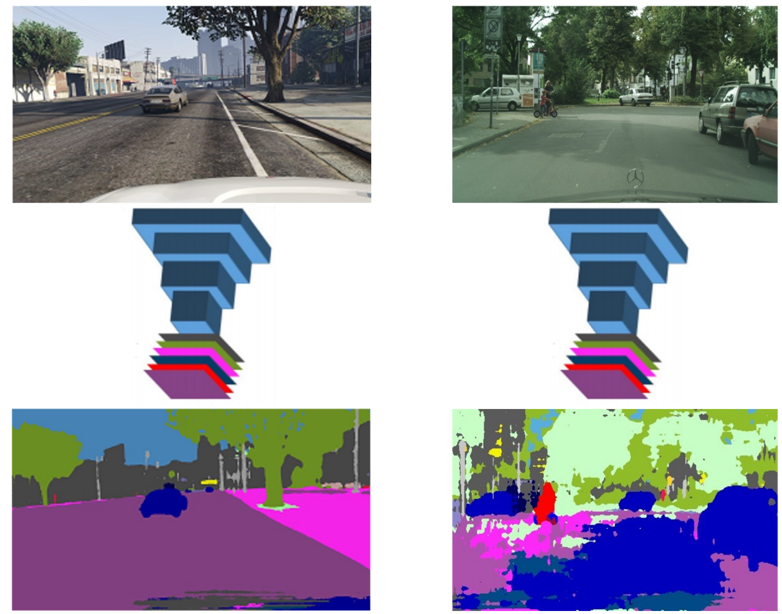

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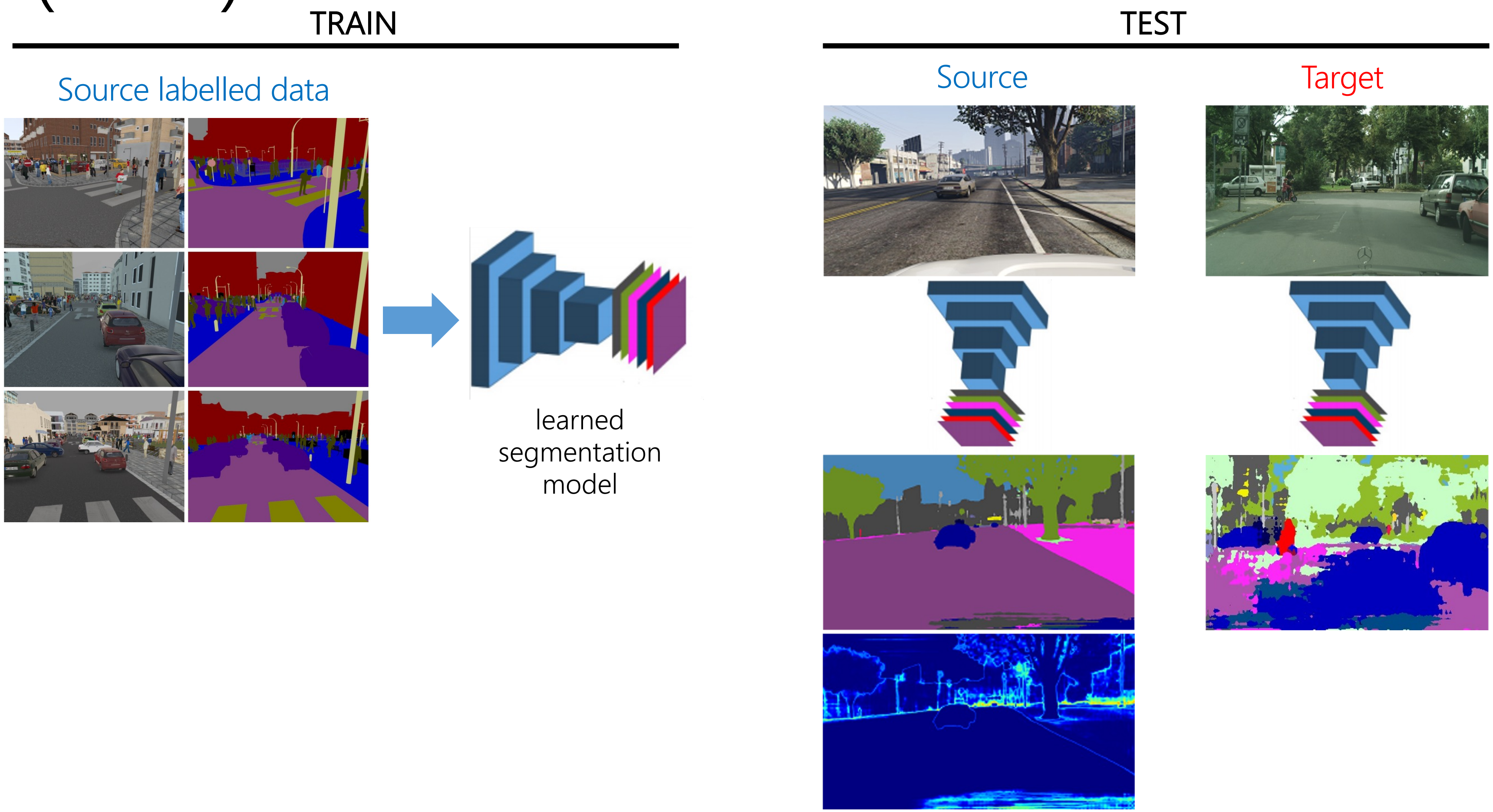
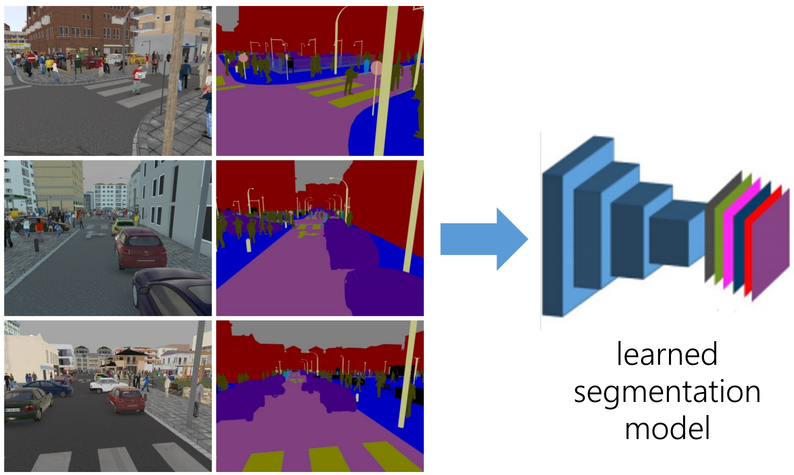


Unsupervised Domain Adaptation (UDA)

TRAIN

Source labelled data



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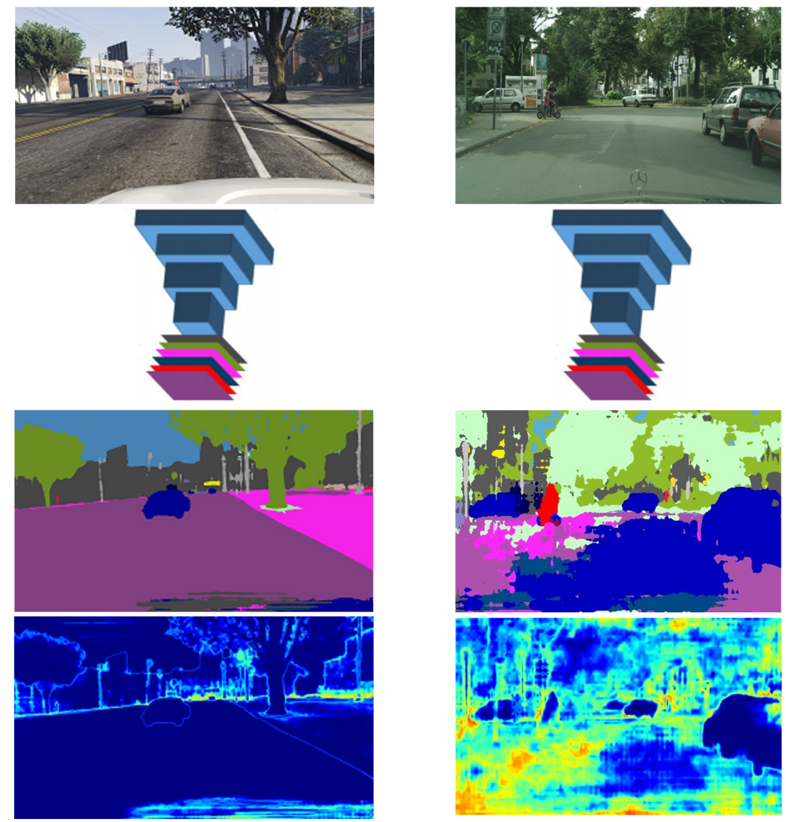
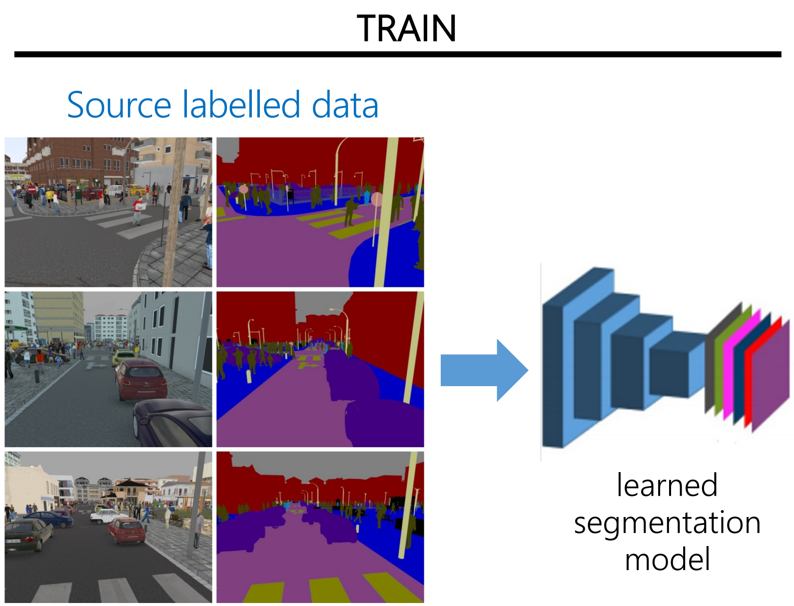
TEST

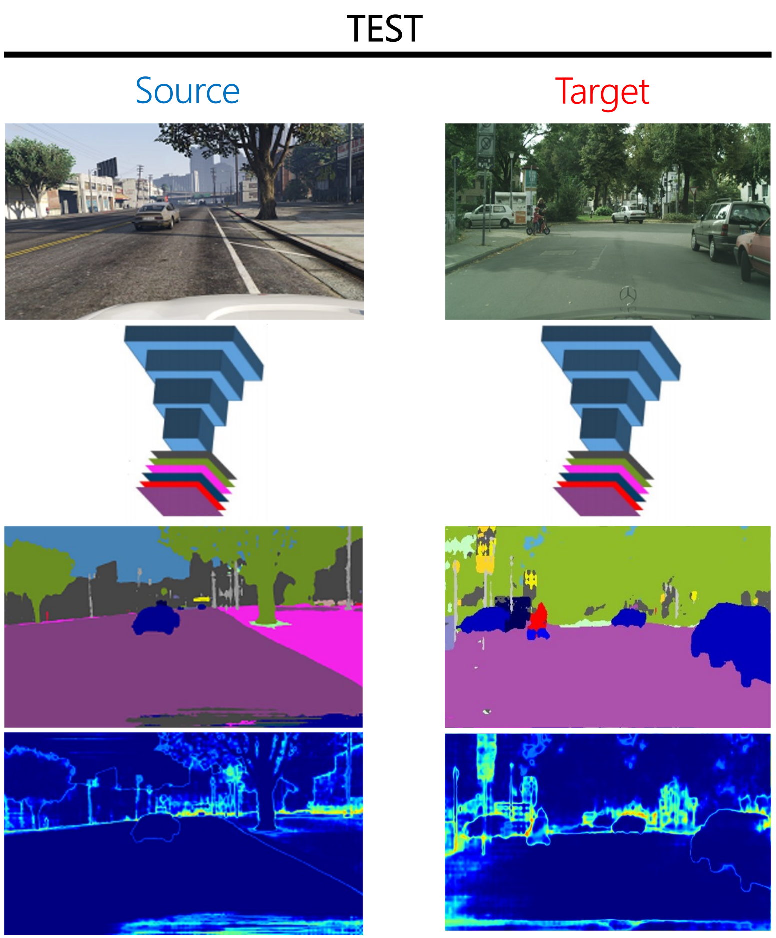
Source

Target

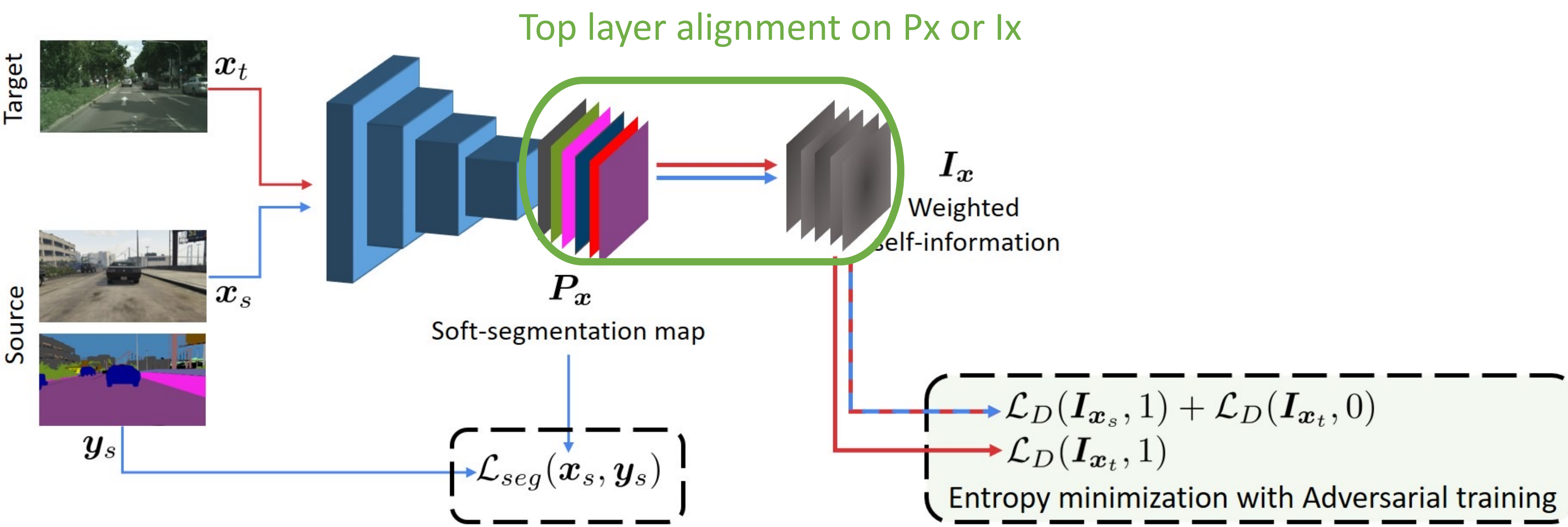


Expected results with UDA training



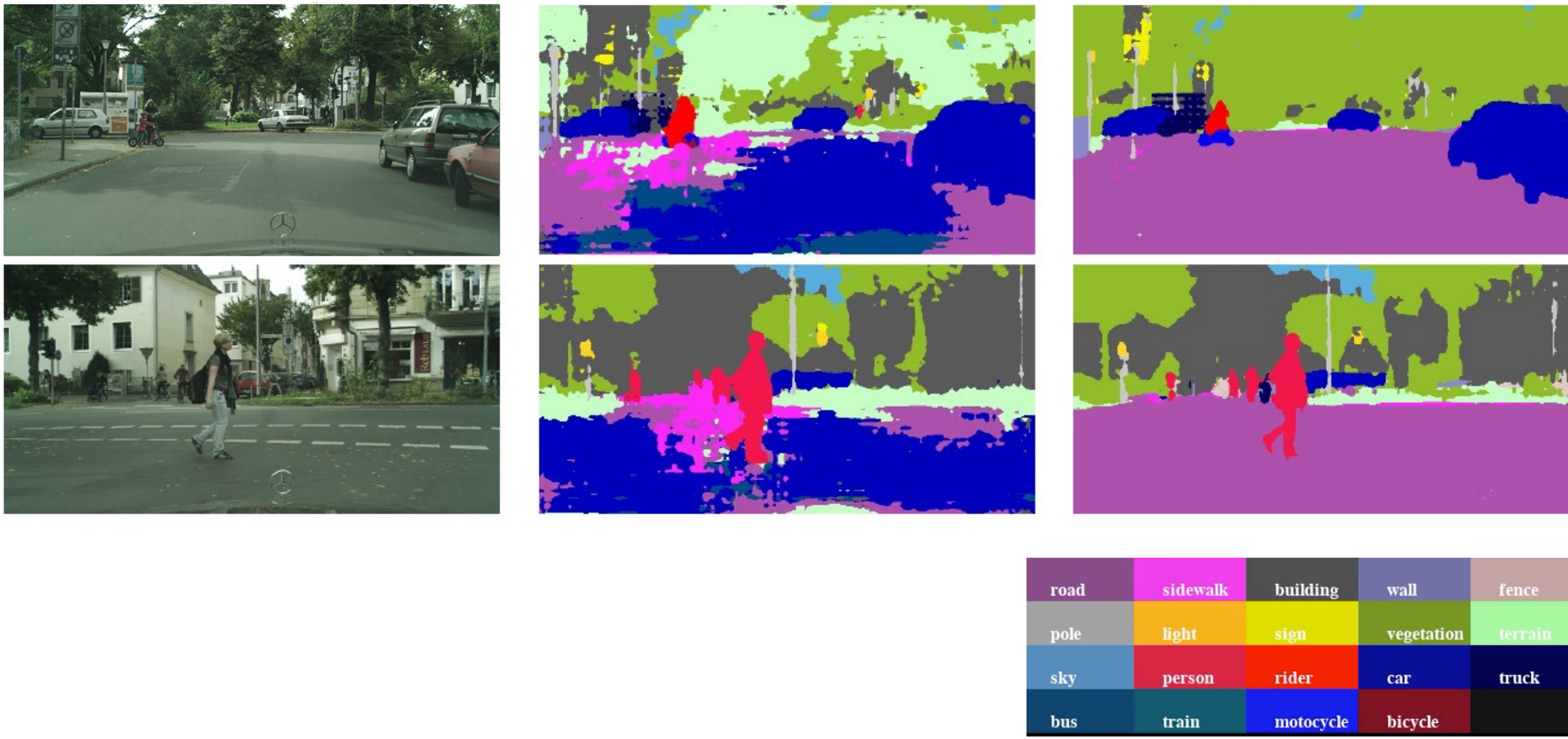


Unsupervised Domain Adaptation (UDA)

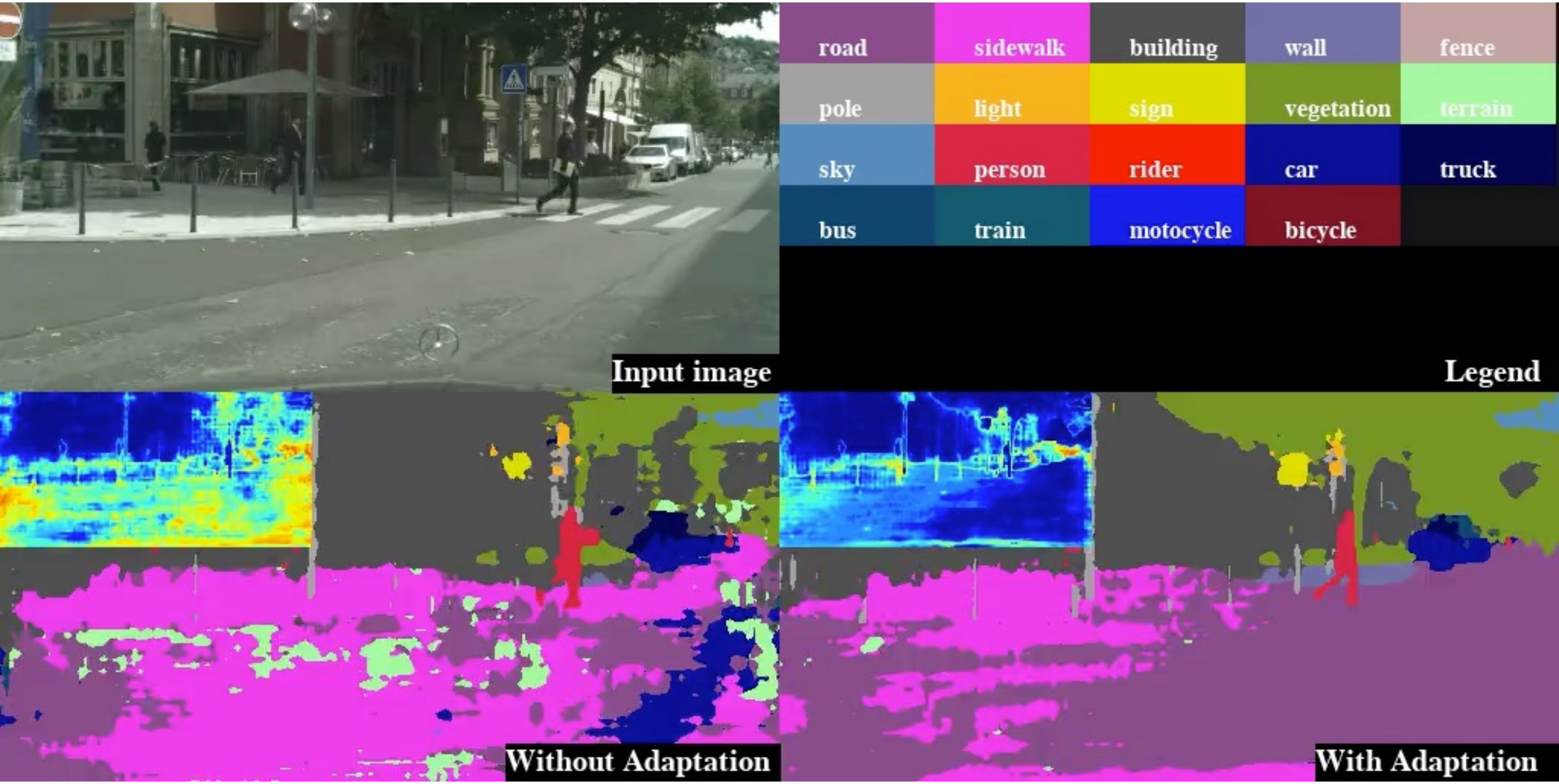


Qualitative results

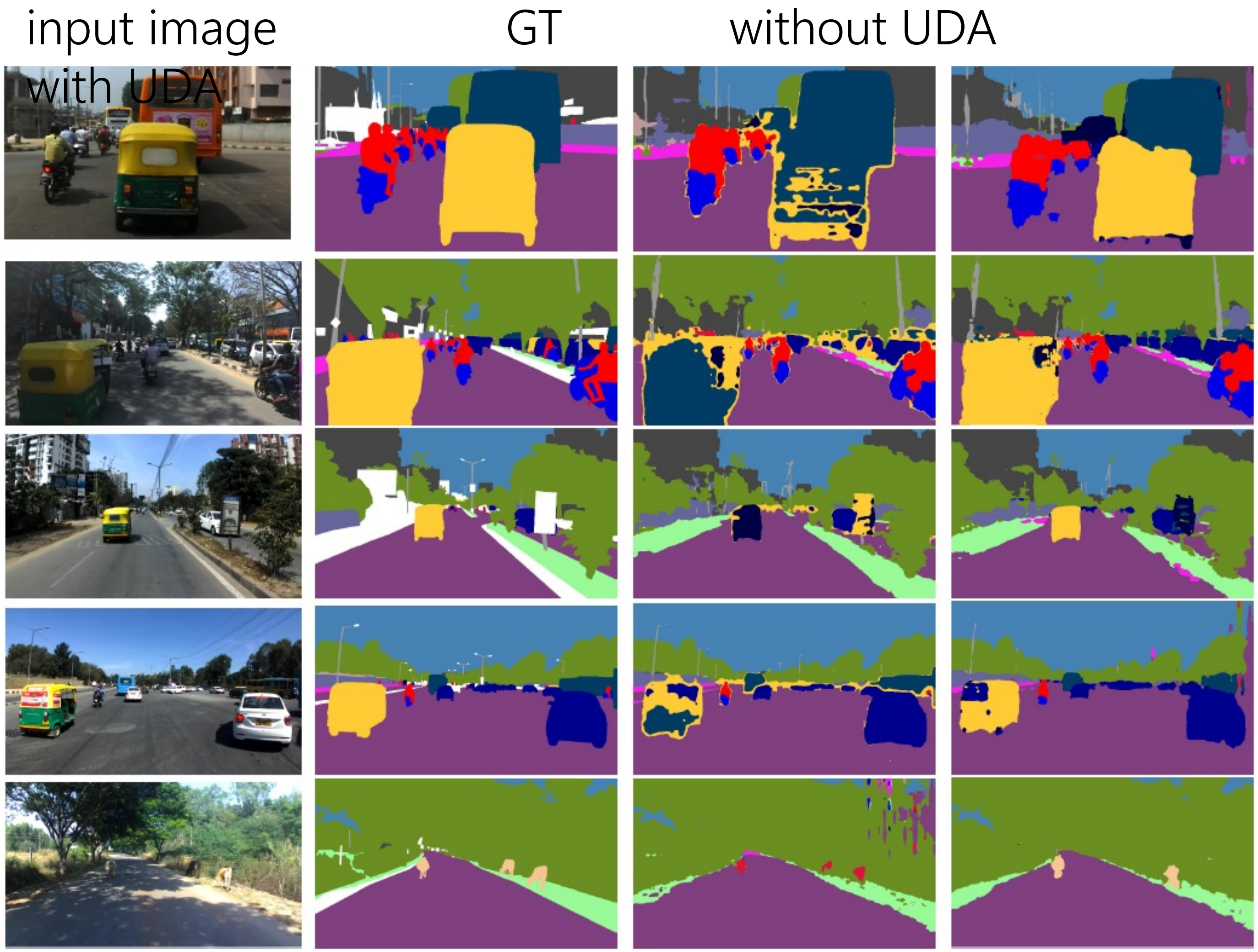
input image without UDA with UDA



UDA Results (with Adversarial Entropy)



Extension: Zero shot + Domain adaptation



Private target classes: tuk-tuk, animal. Some shared classes: truck, road, side walk, car, person, motorbike, tree, building.

Transfer Learning - Overview

		Source Data (not directly related to the task): labelled	Source Data (not directly related to the task): unlabeled
Target Data	labelled	Fine-tuning *Multitask Learning*	Not considered here
Target Data	unlabeled	Domain adaptation-adversarial training ***Zero-shot learning***	Not considered here

Zero-shot Learning

- Source data: (x^s, y^s) ➡ Training data
- Target data: $(\emptyset)$ usually same domain

Different tasks

Training time :

x^s:   …

y^s: cat dog …

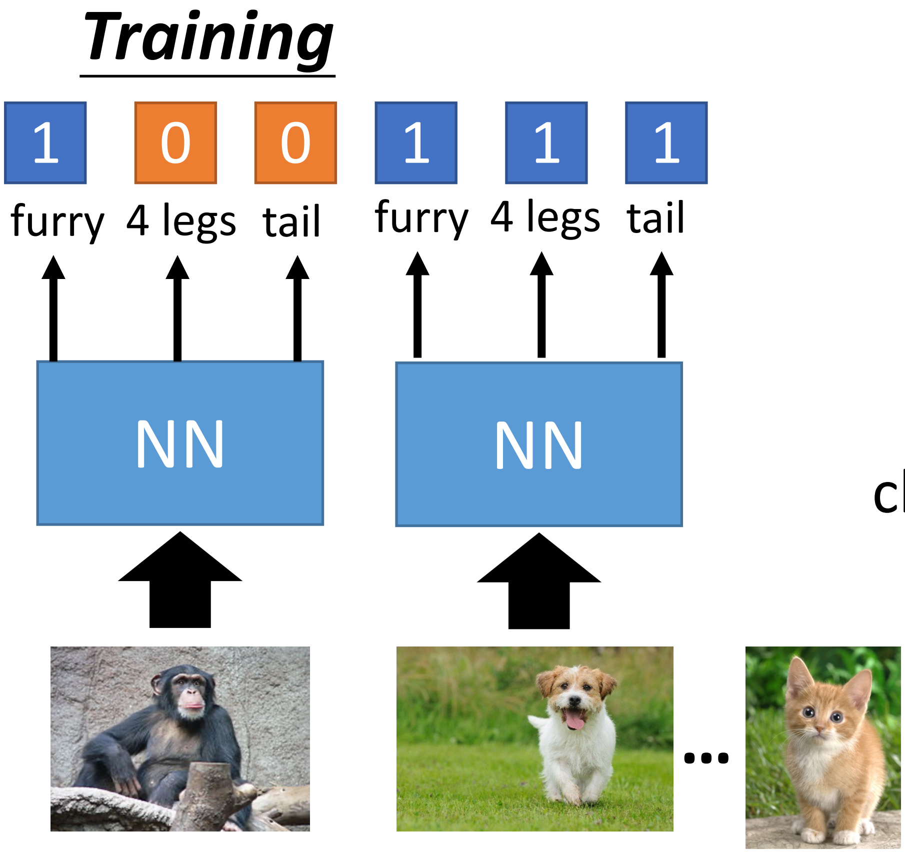
+ Class Information

Test time x^t: 

=> Fish class!

Zero-shot Learning

- Representing each class by its attributes



+
Database attributes

class

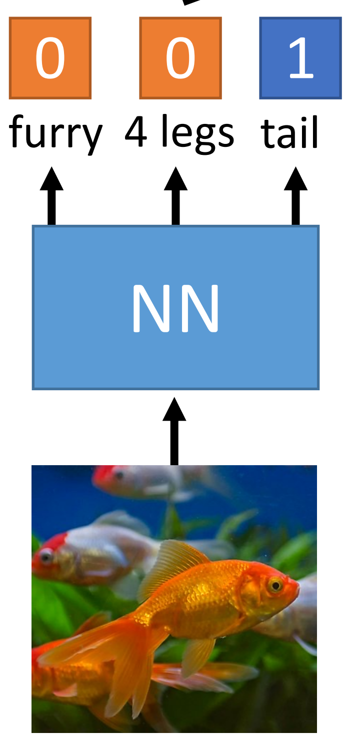
	furry	4 legs	tail	…
Dog	O	O	O	
Fish	X	X	O	
Chimp	O	X	X	
…				

sufficient attributes for one to one mapping

Zero-shot Learning

- Representing each class by its attributes

Testing



Find the class with the most similar attributes

class

attributes

	furry	4 legs	tail	…
Dog	O	O	O	
Fish	X	X	O	
Chimp	O	X	X	
…				

sufficient attributes for one to one mapping

Zero-shot Learning

What if we don't have attribute database

- Attribute embedding + class (word name) embedding

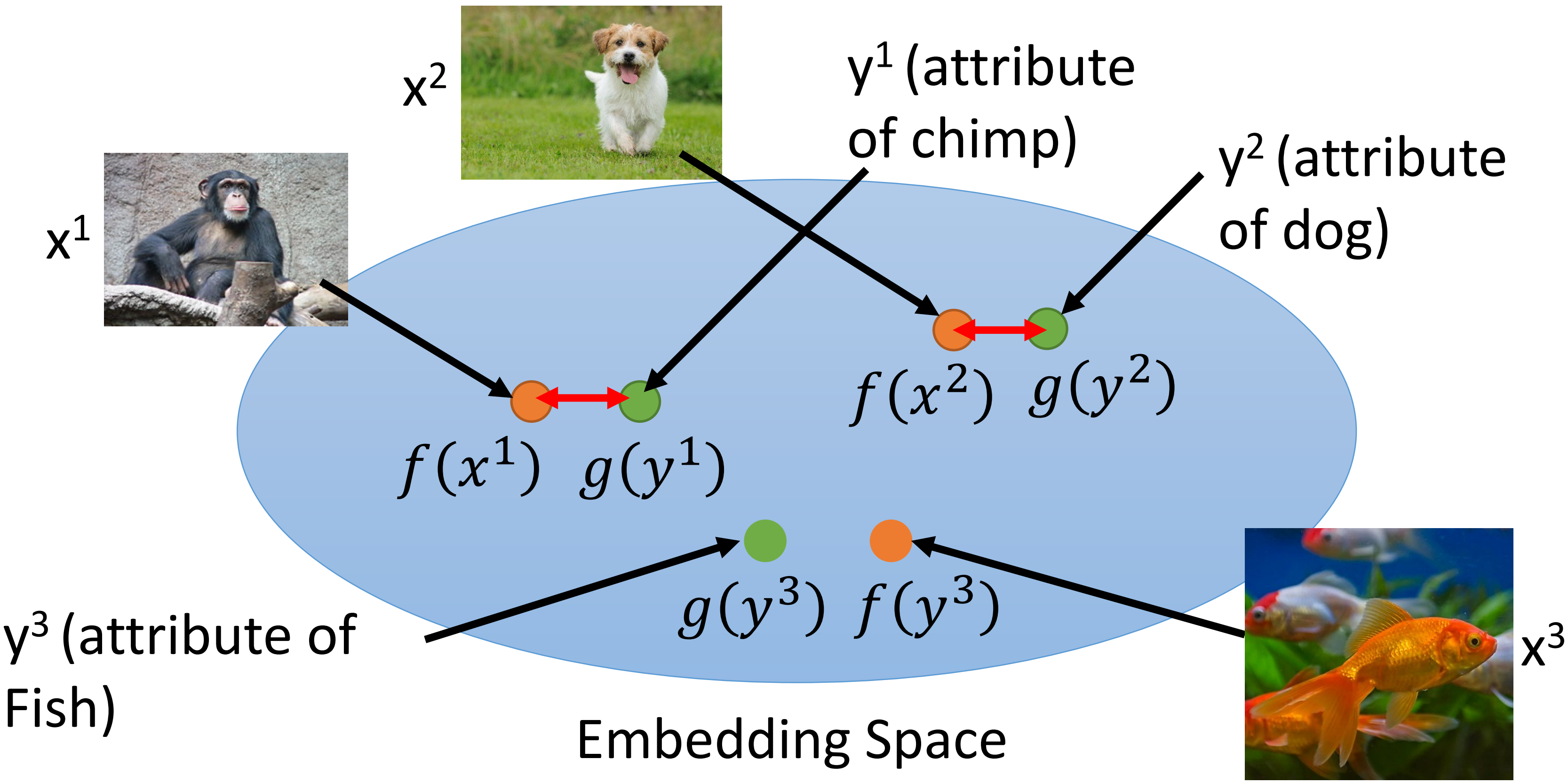
Zero-shot Learning

$f(*)$ and $\mathrm{g}(*)$ can be NN.

Training target:

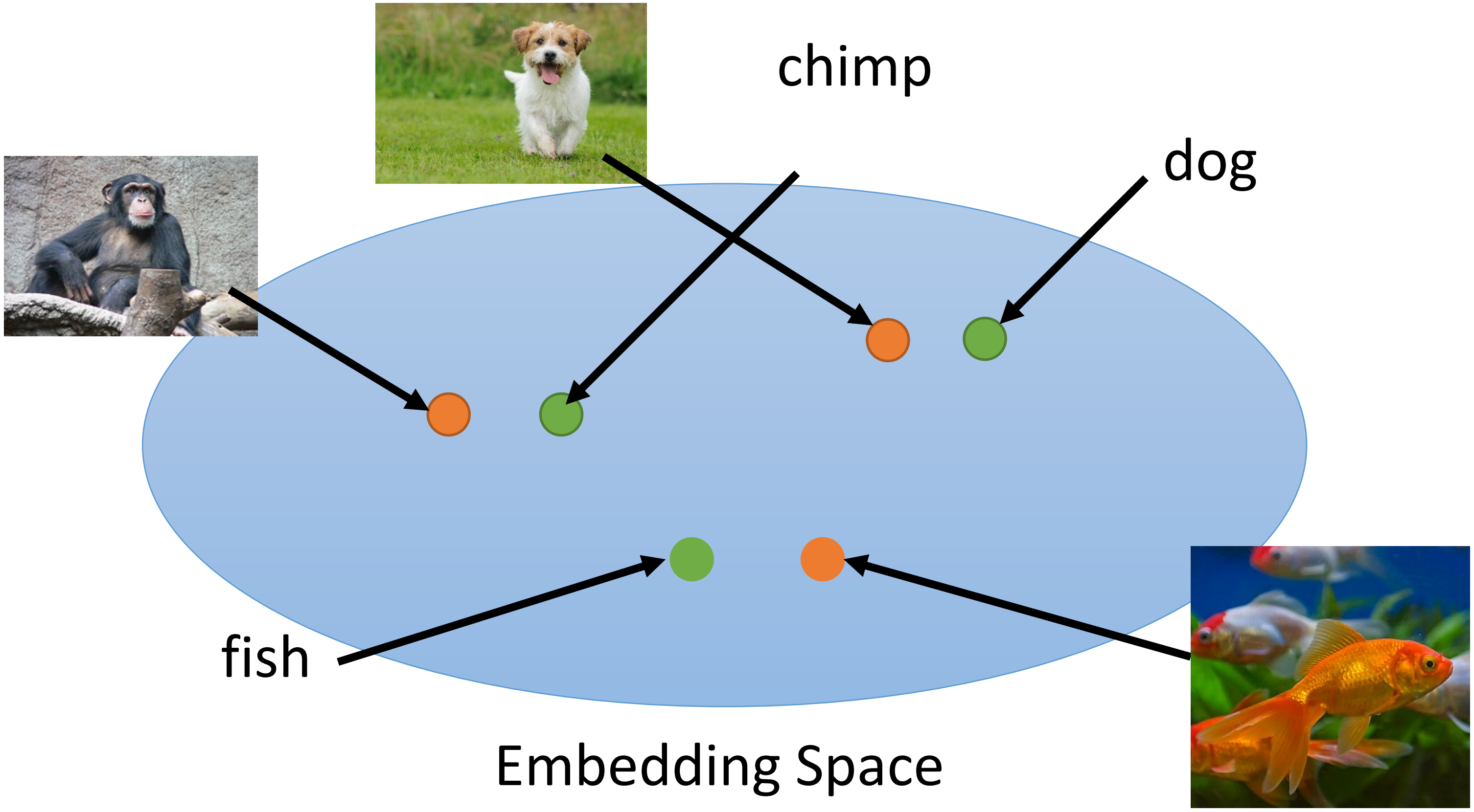
$f(x^n)$ and $g(y^n)$ as close as possible

- Attribute embedding



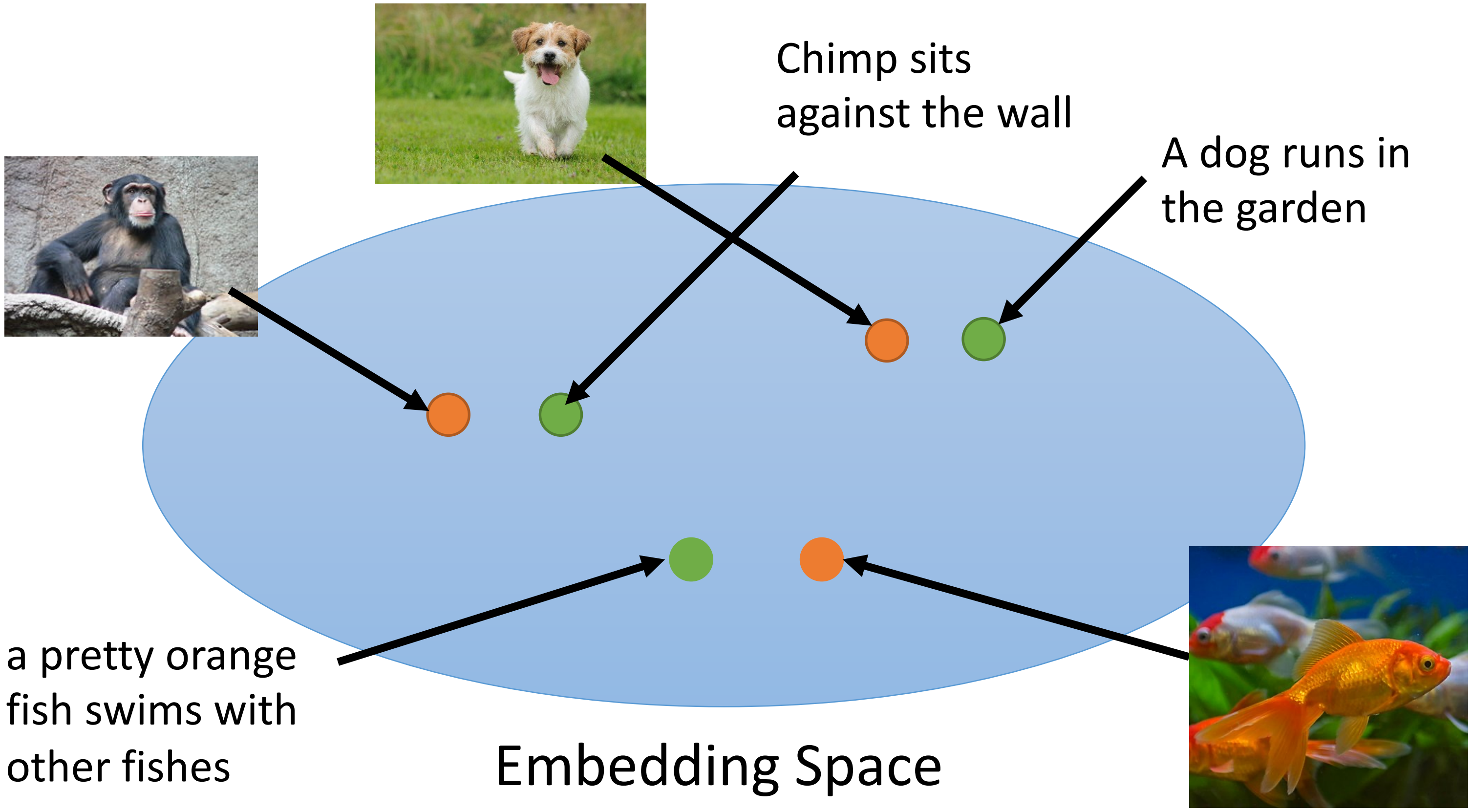
y^i are linked together by a class relationship (e.g. class name embedding as W2v)

More on Vision-Language



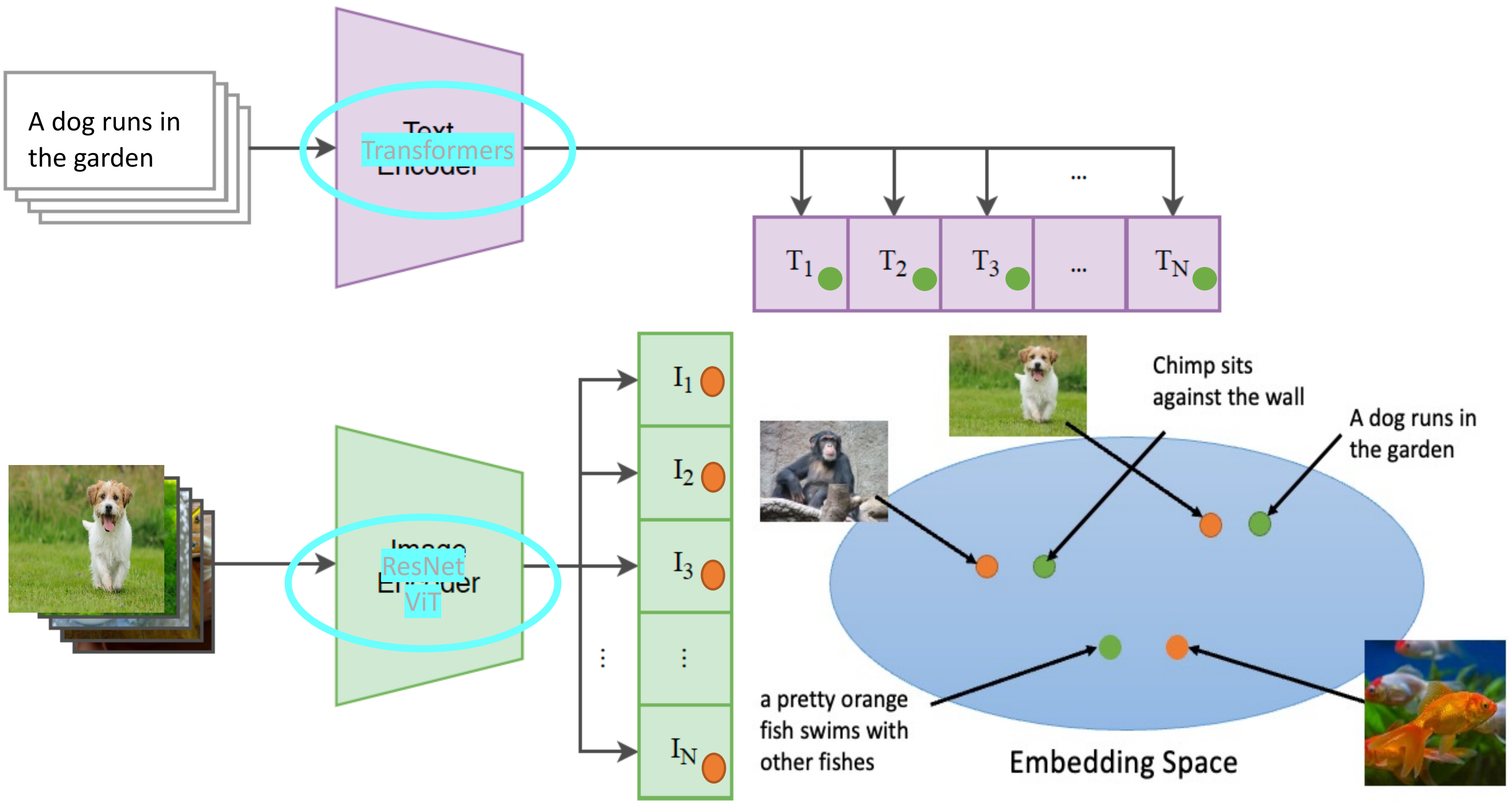
CLIP: Vision + Language Models (VLM)

[Learning transferable visual models from natural language supervision. Radford/Sutskever ICML, 2021]



CLIP: Vision + Language Models (VLM)

Dual architecture: Text encoder + Image encoder



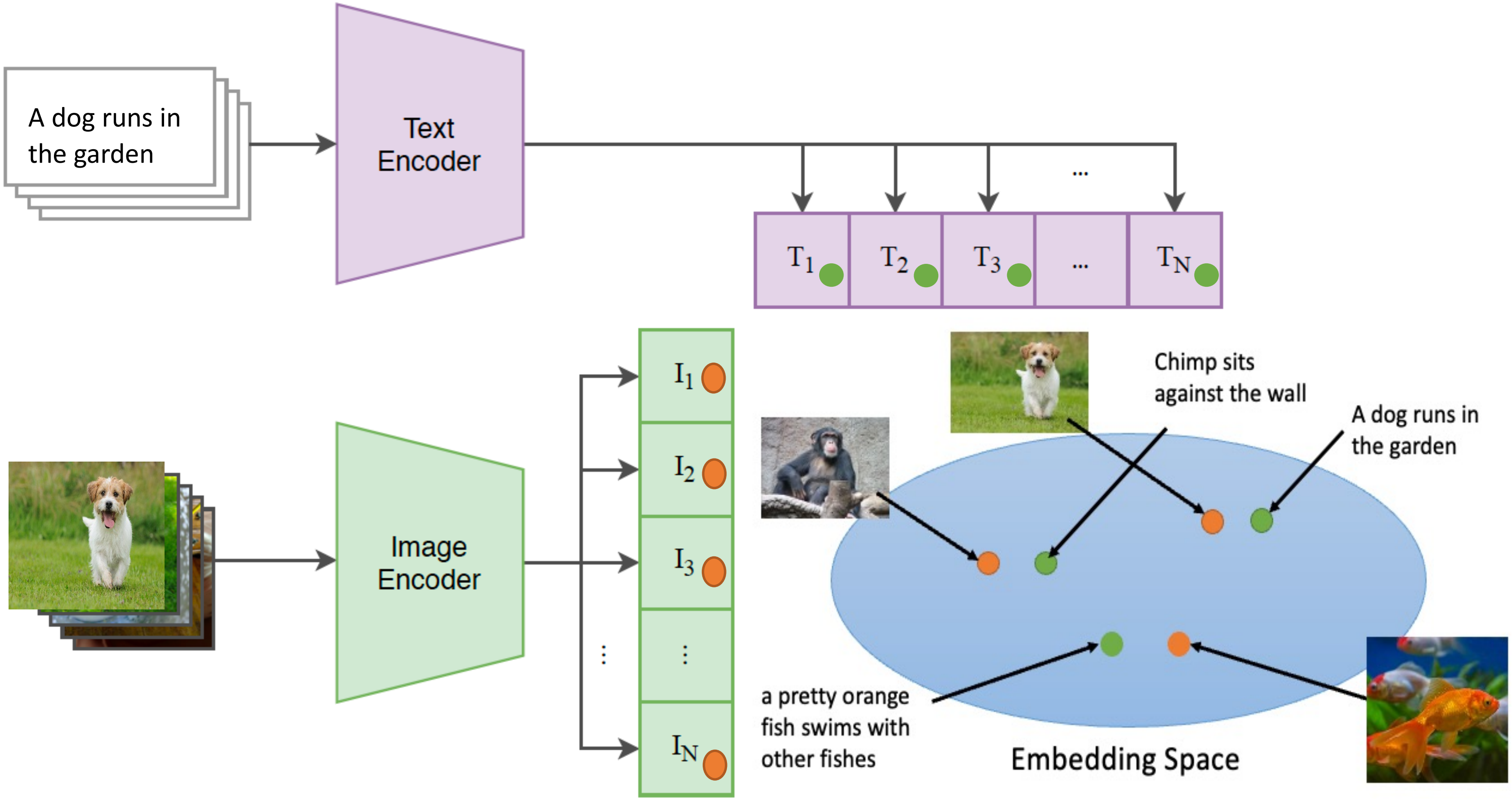
CLIP: Vision + Language Models (VLM)

Learning strategy

Training set: $A = \{(\mathbf{I}_n, \mathbf{T}_n)\}_n$ of image/caption pairs (coherent!)

Massive Text+Image =**400M pairs** to train the model (from the Internet)

Contrastive loss for training: positive pair vs negative one or set



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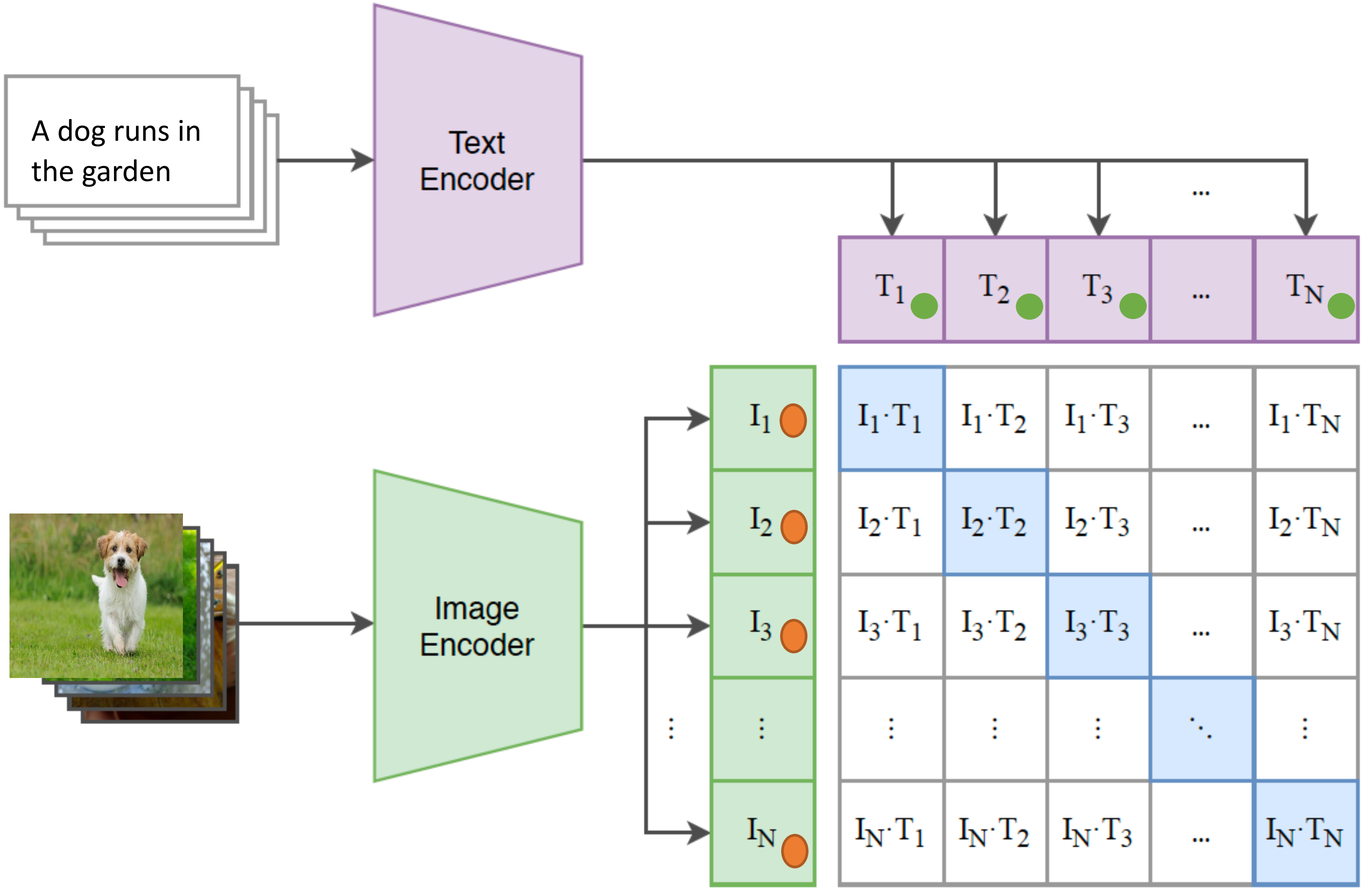

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Contrastive loss for training: positive pair vs negative pair or more

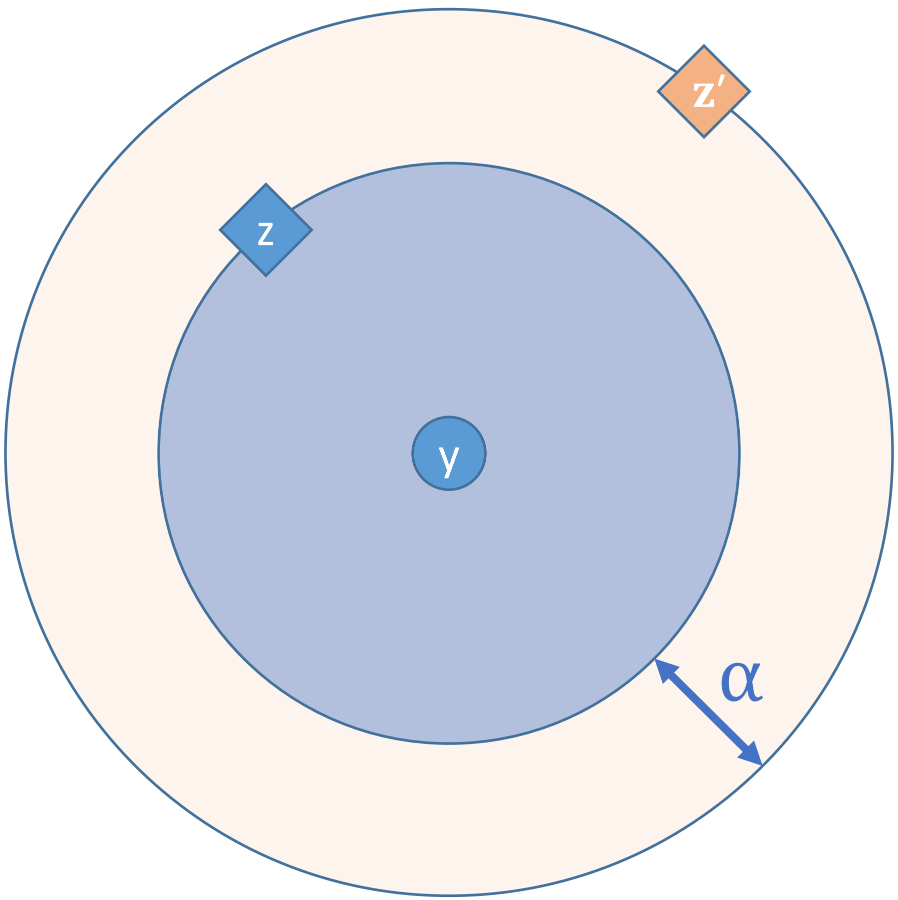
(contrastive) Triplet loss: A variant of the standard margin based loss (SVM)

- Triplet $(\mathbf{y}, \mathbf{z}, \mathbf{z}')$
- Anchor: $\mathbf{y}$ (E.g image representation)
- Positive: $\mathbf{z}$ (E.g associated caption representation)
- Negative: $\mathbf{z}'$ (E.g contrastive caption representation)
- Margin parameter α

$$\boxed{\mathrm{loss}(\mathbf{y}, \mathbf{z}, \mathbf{z}') = \max\{0, \alpha - < \mathbf{y}, \mathbf{z} > + < \mathbf{y}, \mathbf{z}' >\}}$$

Learning strategy: triplet loss

$$\mathrm{loss}(\mathbf{y},\mathbf{z},\mathbf{z}') = \max\{0, \alpha + \mathrm{d}(\mathbf{y},\mathbf{z}) - \mathrm{d}(\mathbf{y},\mathbf{z}')\}$$



Learning strategy: triplet loss

Hard negative margin-based loss:

Loss for a **batch** $\mathcal{B} = \{(\mathbf{I}_n, \mathbf{T}_n)\}_{n \in B}$ of image/sentence pairs:

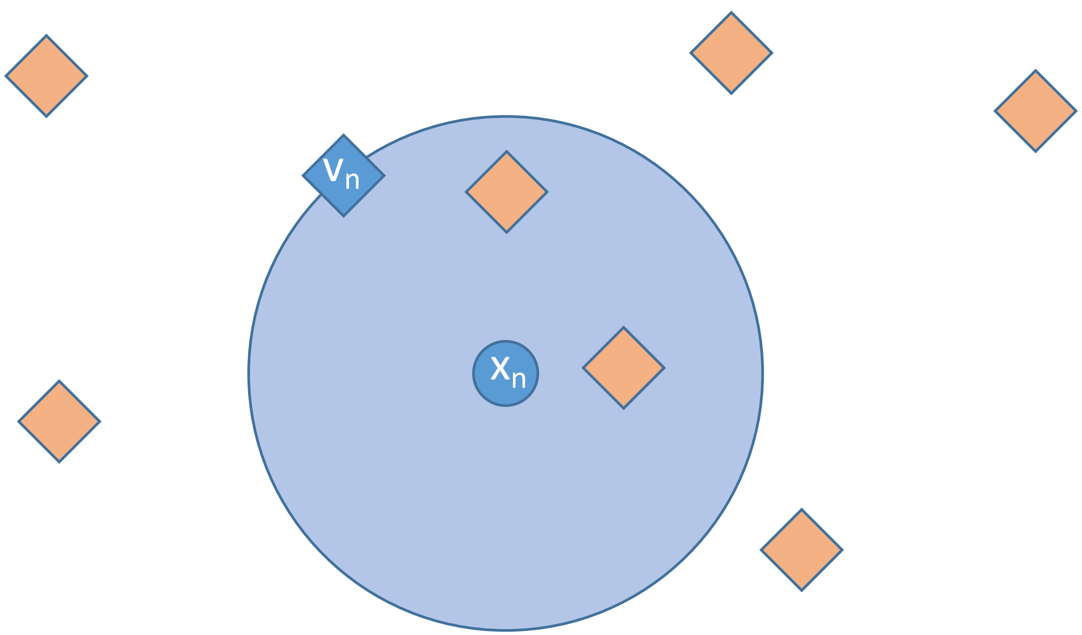
$$\boxed{\mathcal{L}(\mathbf{\Theta}; \mathcal{B}) = \frac{1}{|B|} \sum_{n \in B} \left(\begin{array}{l} \max\limits_{m \in C_n \cap B} \text{loss}\,(\mathbf{x}_n, \mathbf{v}_n, \mathbf{v}_m) \\ + \max\limits_{m \in D_n \cap B} \text{loss}\,(\mathbf{v}_n, \mathbf{x}_n, \mathbf{x}_m) \end{array} \right)}$$

With C_n (resp. D_n) set of indices of caption (resp. image) unrelated to n-th element

Learning strategy: hard negative triplet loss

Mining hard negative contrastive example:

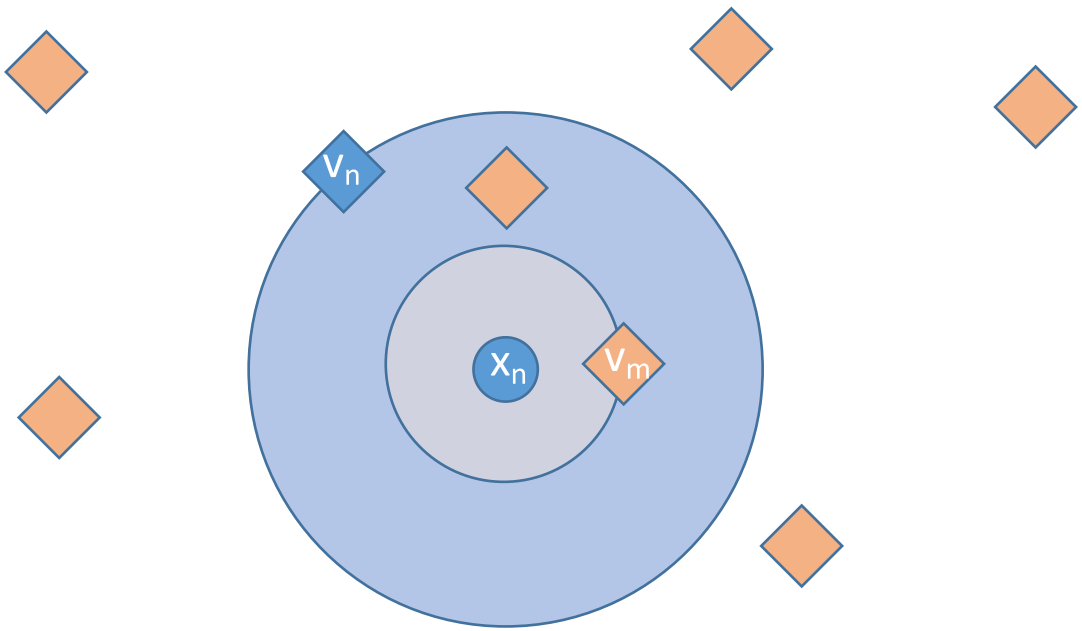
$$\boxed{\mathcal{L}(\boldsymbol{\Theta};\mathcal{B}) = \frac{1}{|B|}\sum_{n\in B}\left(\begin{array}{l}\max\limits_{m\in C_n\cap B} \operatorname{loss}(\mathbf{x}_n,\mathbf{v}_n,\mathbf{v}_m)\\ +\max\limits_{m\in D_n\cap B} \operatorname{loss}(\mathbf{v}_n,\mathbf{x}_n,\mathbf{x}_m)\end{array}\right)}$$



Learning strategy: hard negative triplet loss

Mining hard negative contrastive example:

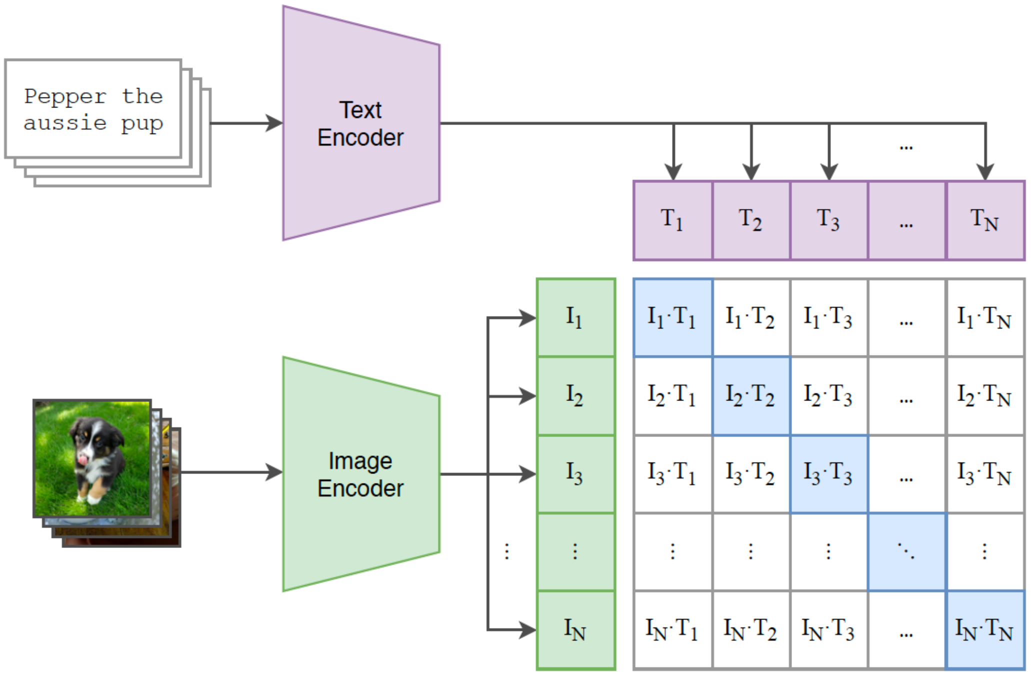
$$\mathcal{L}(\boldsymbol{\Theta};\mathcal{B}) = \frac{1}{|B|}\sum_{n\in B}\left(\max_{m\in C_n\cap B} \operatorname{loss}(\mathbf{x}_n,\mathbf{v}_n,\mathbf{v}_m) + \max_{m\in D_n\cap B} \operatorname{loss}(\mathbf{v}_n,\mathbf{x}_n,\mathbf{x}_m)\right)$$



CLIP: Vision + Language Models (VLM)

Massive Text+Image =**400M pairs** to train the model (from the Internet)

Contrastive loss for training

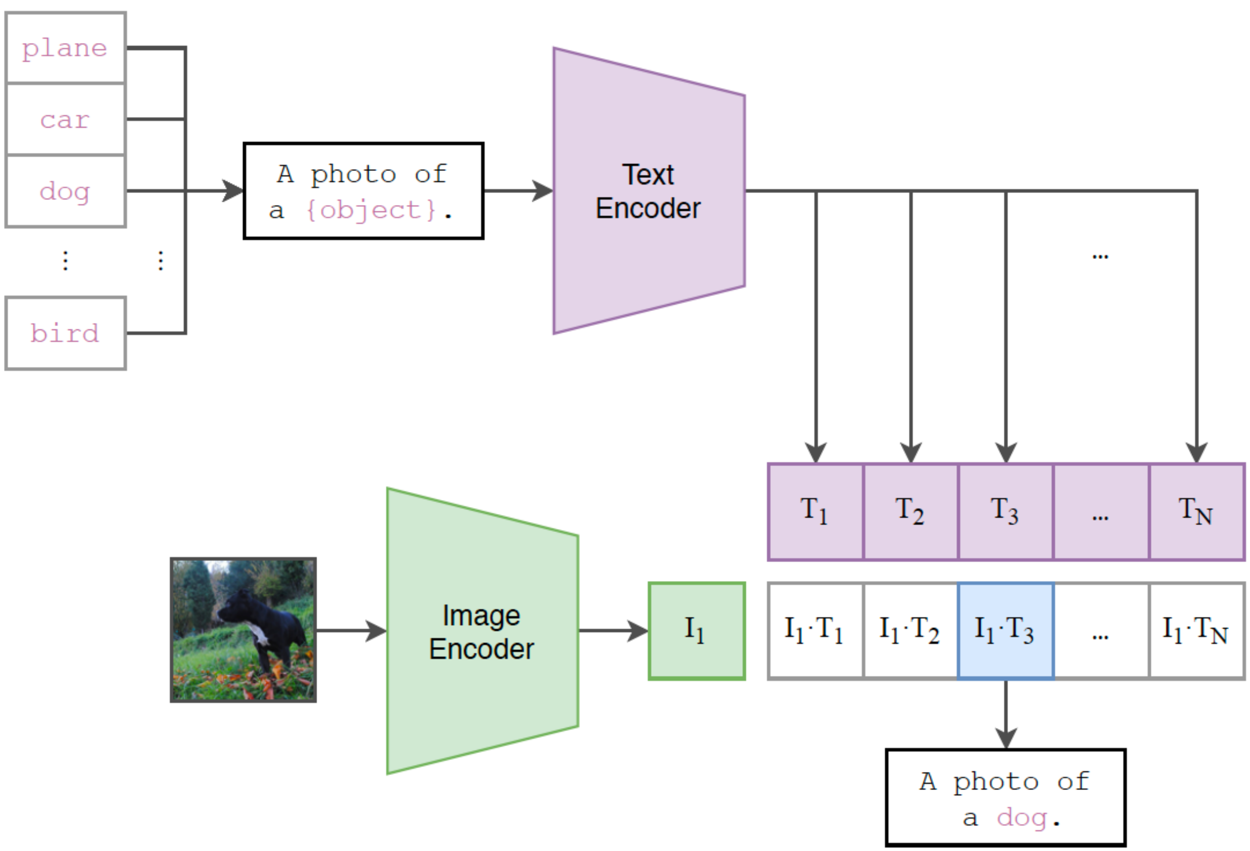


$$\mathcal{L}_{InfoNCE_{CLIP}} = -\sum_i \log\left(\frac{exp(\frac{sim(I_i, T_i)}{\tau})}{\sum_{k=1}^{N} exp(\frac{sim(I_i, T_k)}{\tau})}\right)$$

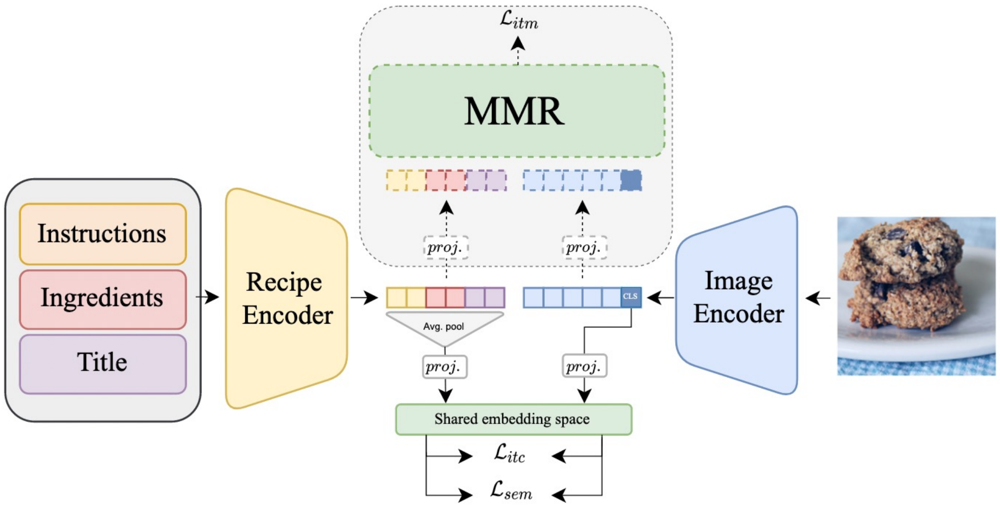
CLIP: Vision + Language Models (VLM)

Pre-trained encoders = **dual encoders** (Text/Image)

used for Zero-shot classifier, and other downstream tasks



A lot of variants ….



Title query	Ingredient query	Instruction query	Top 5 retrieved images
Mint Chocolate Chip Frosting.	1 cup Unsalted Butter, 2 Tablespoons Heavy Cream, 2 drops Green Food Coloring, .. Chocolate..	Add sugar, cream, peppermint, and food coloring... ...scoop the frosting and place on top of your cupcakes Source: Chocolate Cupcakes with Mint Chocolate Chip ...	
Honey-Grilled Chicken.	1 broiler-fryer chicken, halved, 34 cup butter, melted, 14 cup honey..	Place the halved chicken in a large, shallow container... ...Combine the remaining ingredients, stirring sauce well Grill chicken, skin side up..	
The Best Kale Ever.	1/2 cup Kale, 1 teaspoon Olive Oil, 1/4 teaspoons Red Pepper Flakes..	Wash and cut kale off the stems... Heat olive oil on medium heat and add garlic Add in kale and red pepper flakes..