Carnegie Mellon
School of Computer Science

Deep Reinforcement Learning and Control

# SIM2Real Transfer

Katerina Fragkiadaki

# Paradox

The requirement of large number of samples for model-free RL, **only possible in simulation**, renders model-free RL a **model-based** framework: we can't do without the simulator.

We want to learn manipulation and locomotion policies, what do we do?

# Choices

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1. We use a Physics simulator, where Physics rules between objects and/or particles have been hand coded by engineers. We train our policies there with trial-and-error and/or demonstations in simulation. We then **transfer** them in the real world.

2. We directly learn policies in the real world. Because we cannot afford many samples, model-based RL isusually a better choice than model-free RL.

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3. We build better simulators to better model the real world, e.g., food: object deformation, fluids, etc.. Then, GOTO 1.

# In the course so far

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# This lecture

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# Pros of Simulation

- We can afford many more samples
- Safe: we do not want to deploy partially trained policies in the real world
- Avoids wear and tear of the robot
- We can explore creative robot configurations

# Cons of Simulation

- Under-modeling: It is hard to exactly replicate the real world and its uncertainty
- Large engineering effort into building the environment which we care to manipulate
- Wrong parameters. Even if our physical equations were correct, we would need to estimate the right parameters, e.g., inertia, frictions (system identification).
- Systematic discrepancy w.r.t. the real world regarding:

  1. observations

  2. dynamics

policies learnt in simulation may not directly transfer to the real world

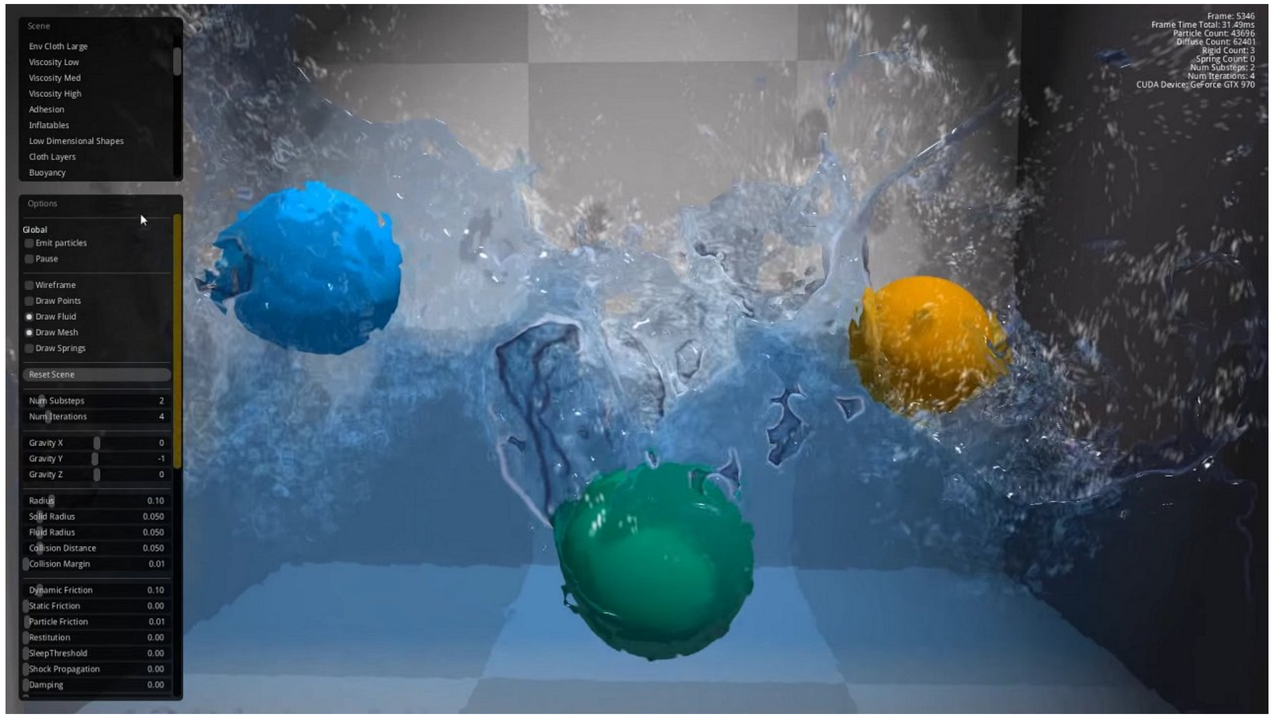
# Mostly rigid body simulators

Mujoco


http://www.mujoco.org/image/home/mujocodemo.mp4

# Particle based physics simulator

FLEX: Real-time simulator on a GPU for both rigid and soft bodies, fluids and gas.




https://www.youtube.com/watch?v=1o0Nuq71gI4

# What has shown to work

- Domain randomization (dynamics, visuals)
- Learning to adapt the textures of the simulator to match the real domain
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- Learning from label (as opposed to pixel) maps-> semantic maps between simulation and real world are closer than textures
- Learning higher level policies, not low-level controllers, as the low level dynamics are very different between Sim and REAL

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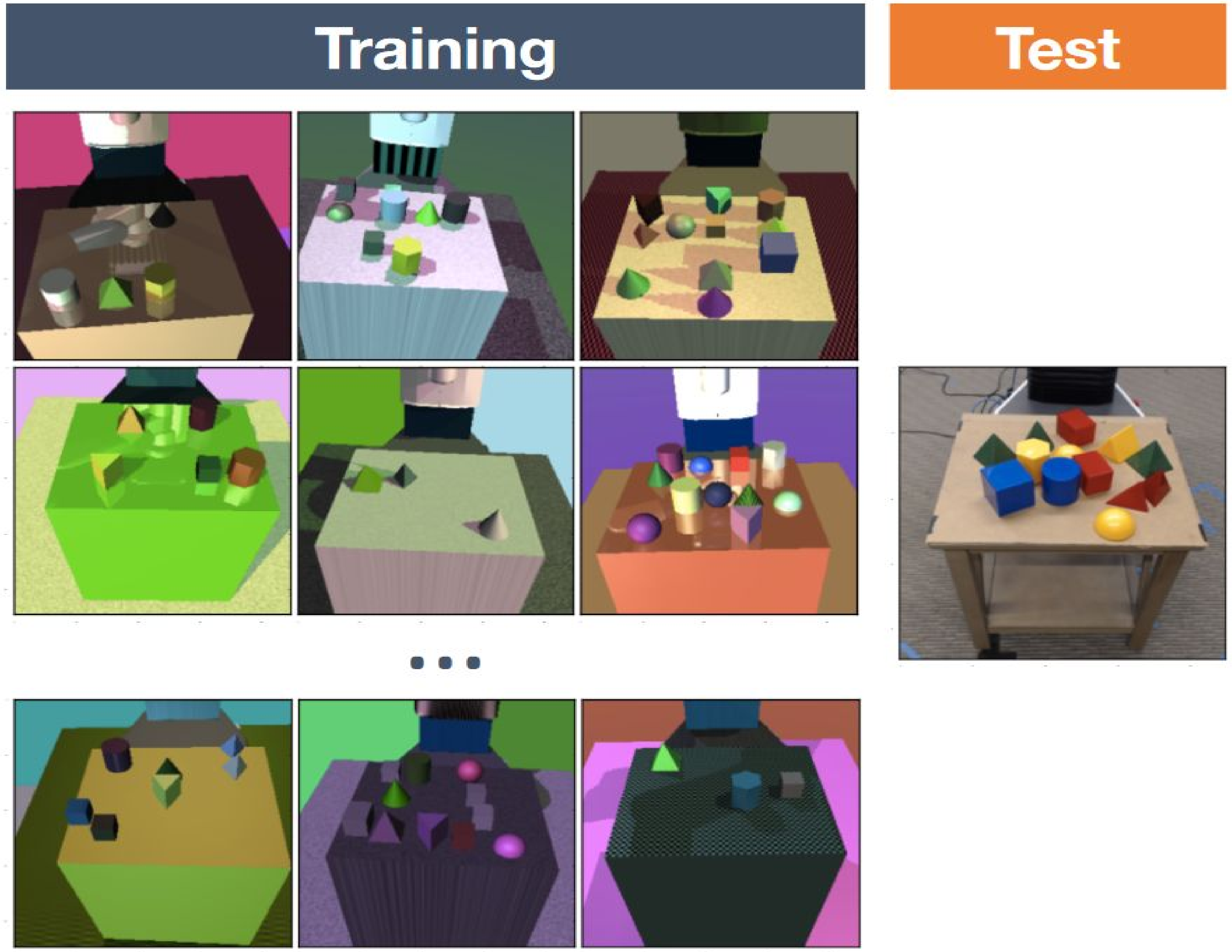
# Domain randomization

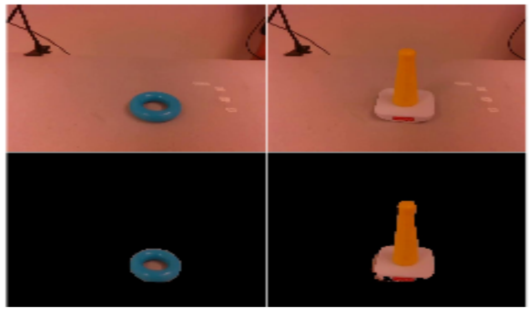



We create (automatically) tons of simulation environments  by randomizing textures and camera viewpoints. We use the simulation data to train object detectors

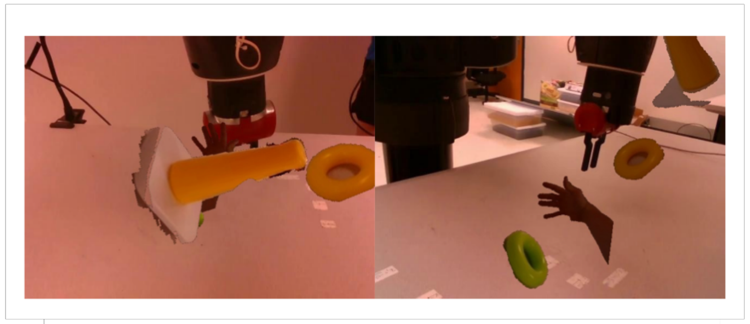
Domain Randomization for Transferring Deep Neural Networks from Simulation to the Real World, Tobin et al.

# Data dreaming

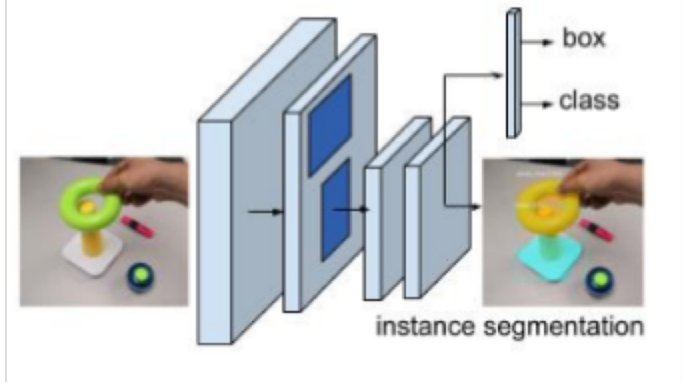
1. **Obtaining object masks**
   - background subtraction gives ground truth object masks



2. **Creating synthetic labelled data**
   - Massive augmentation of ground truth masks by random transformations/occlusions and random backgrounds



3. **Training object detectors**
   - Mask R-CNN

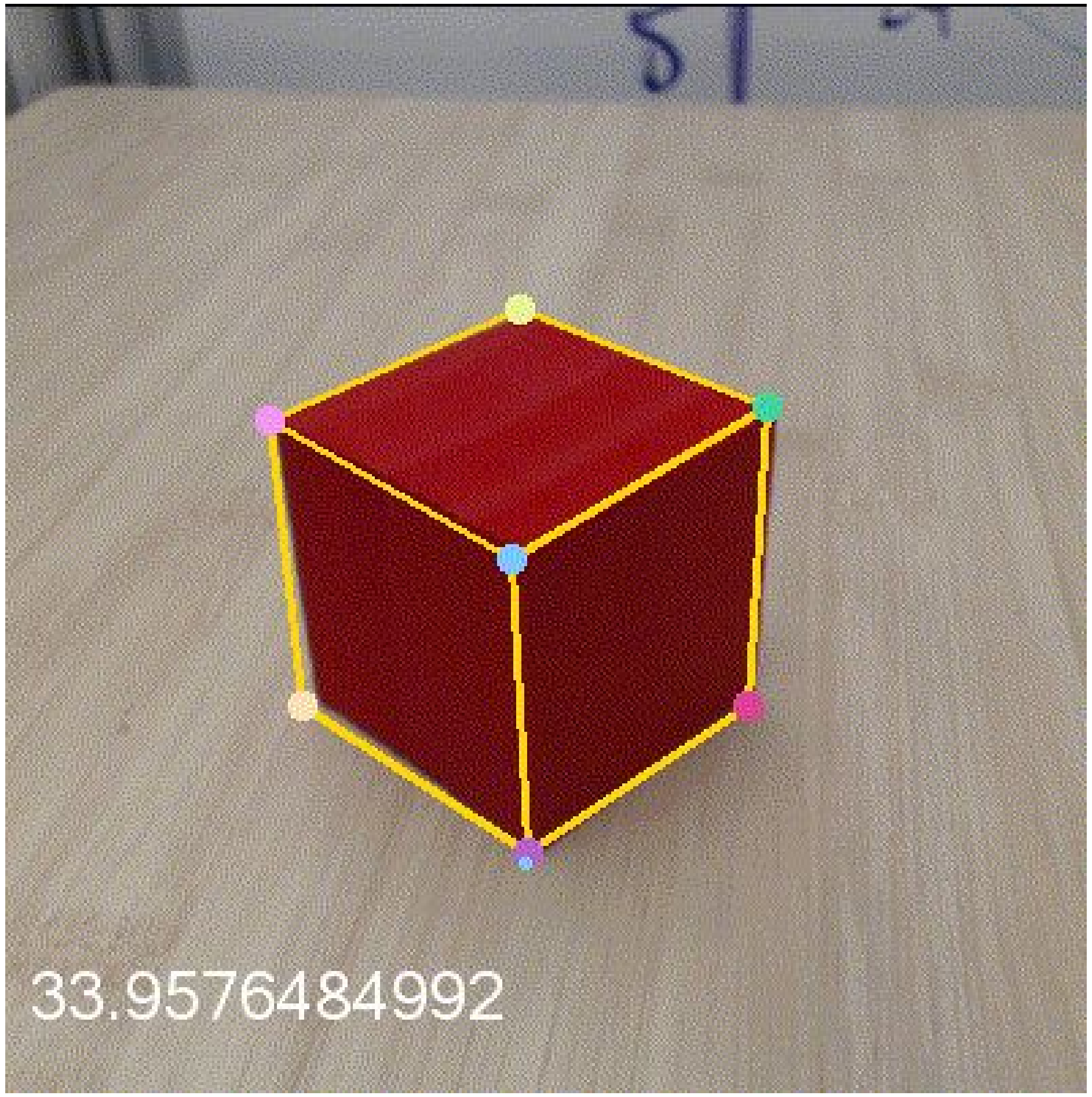



Similar randomization can be used for training object detectors on-the-fly **in the real world** directly

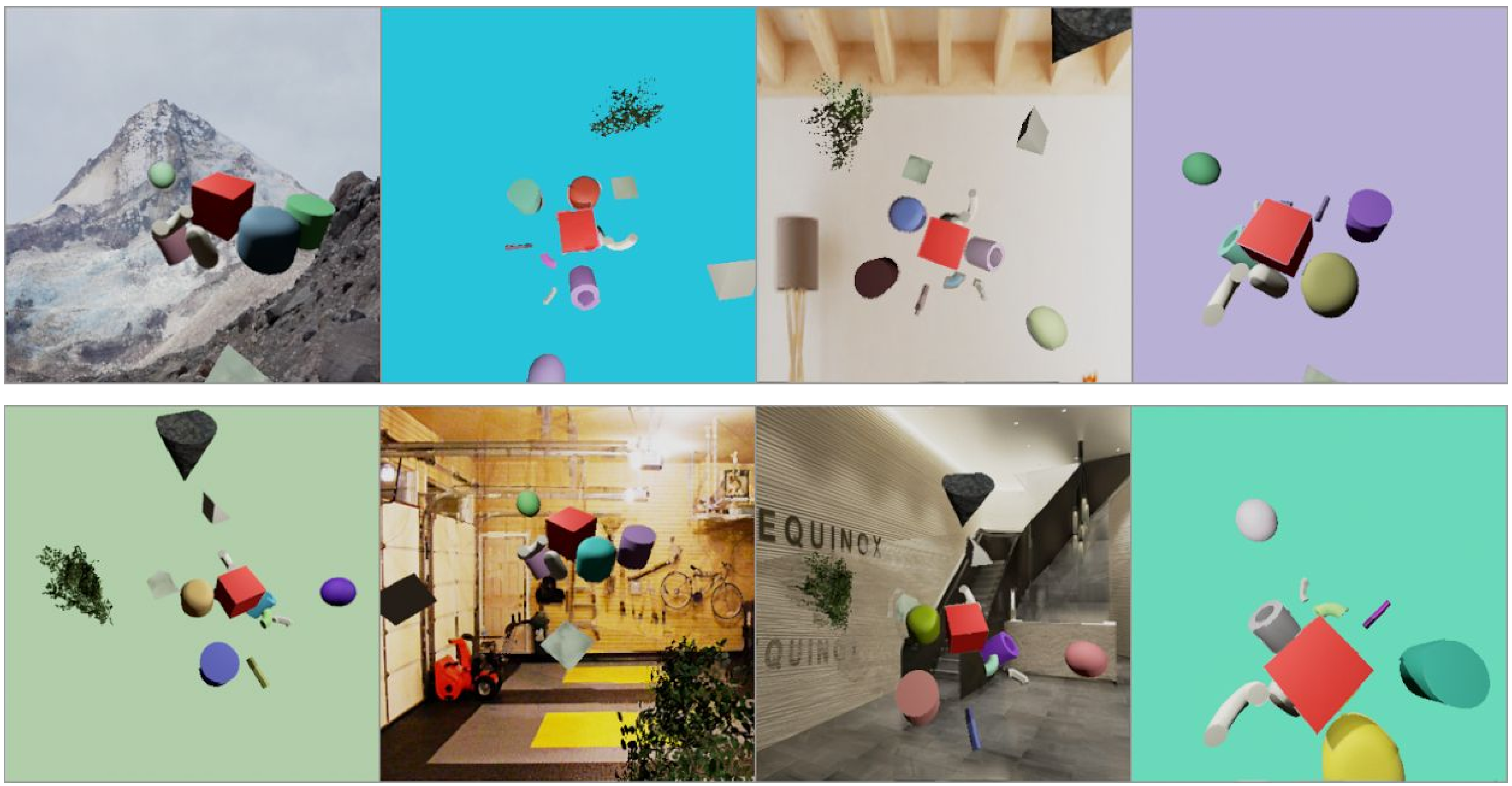
Data Dreaming for Object Detection: Learning Object-Centric State Representations for Visual Imitation, Sieb et al.

# Let's try a more fine grained task

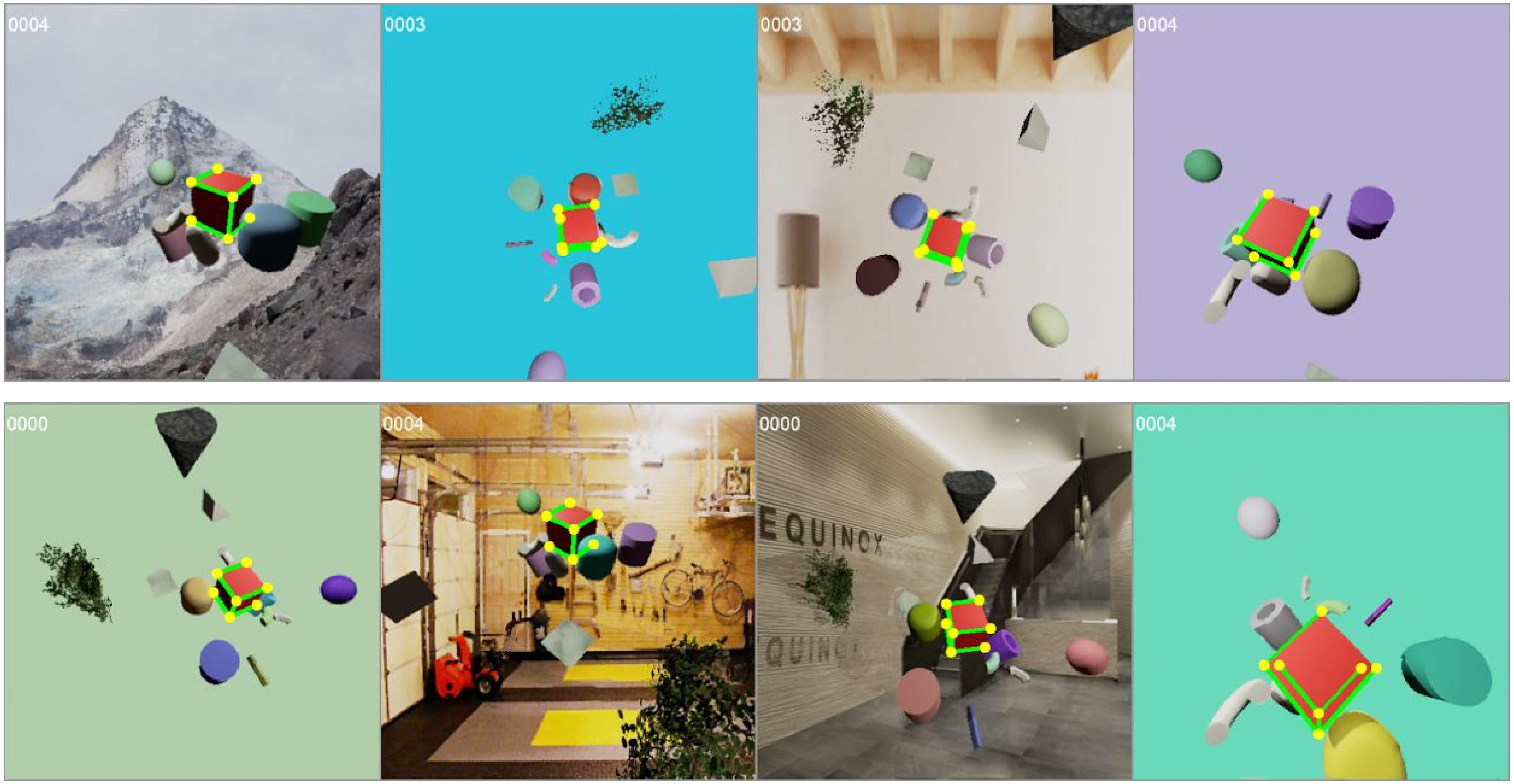
Cuboid Pose Estimation



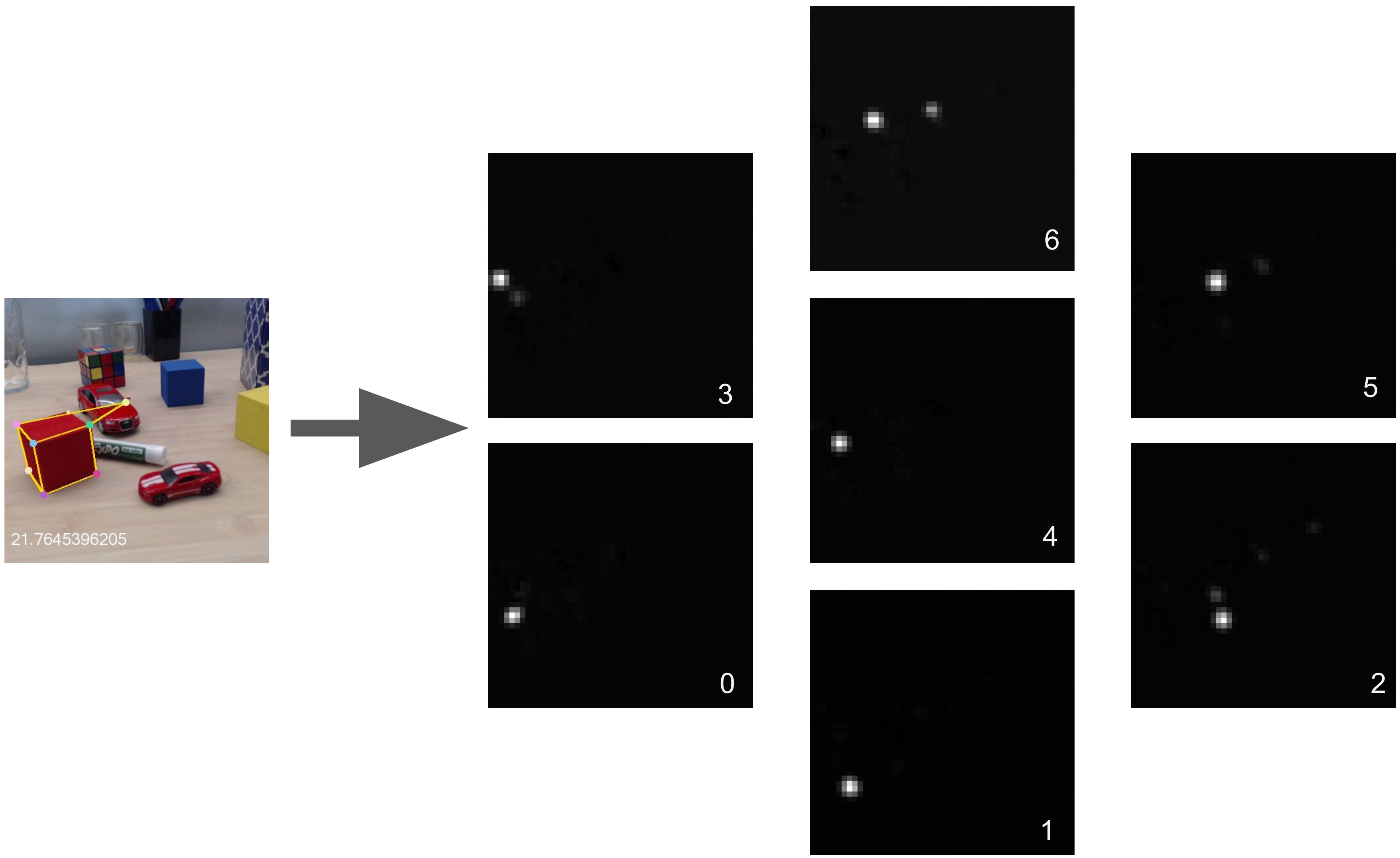
# Synthetic data generation



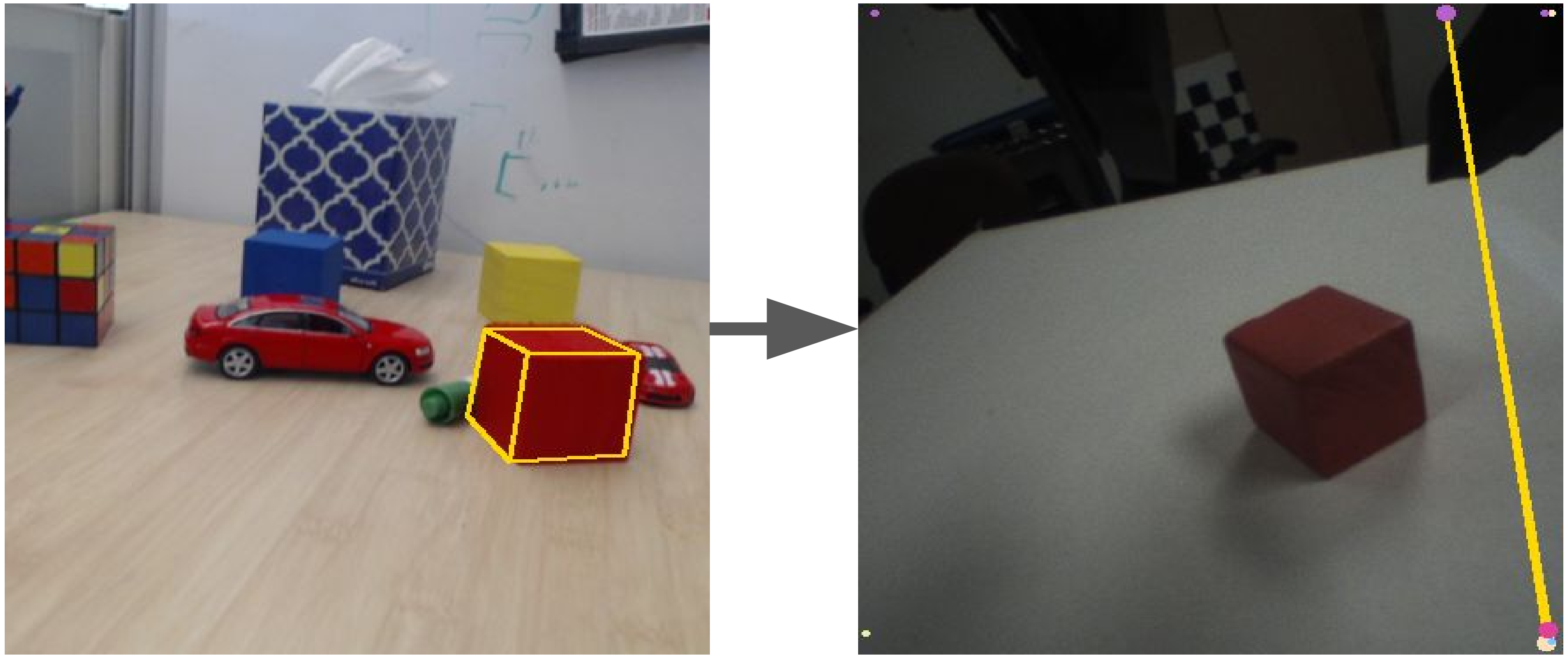
# Synthetic data generation



# Regressing to vertices



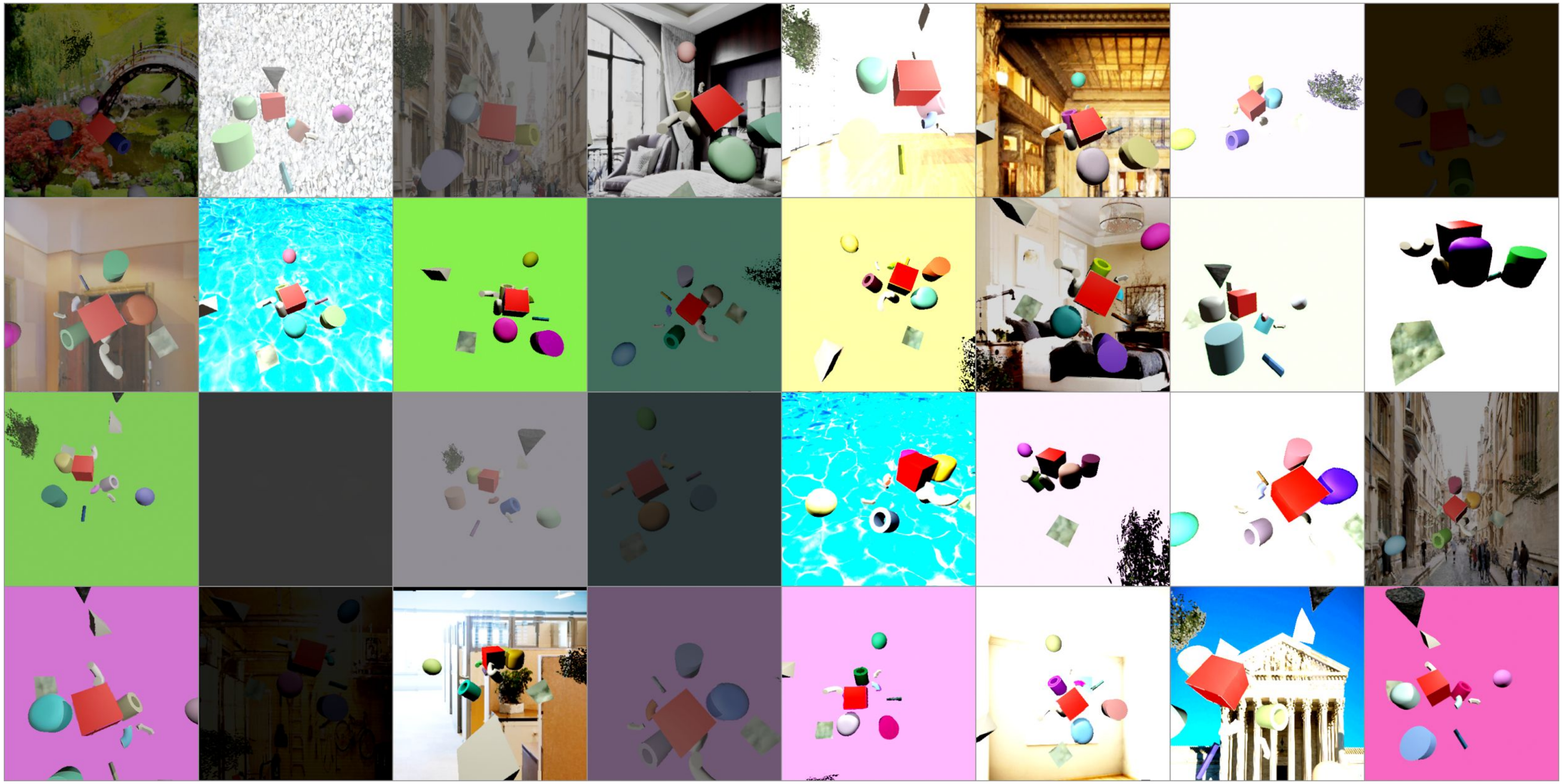
# SIM2REAL



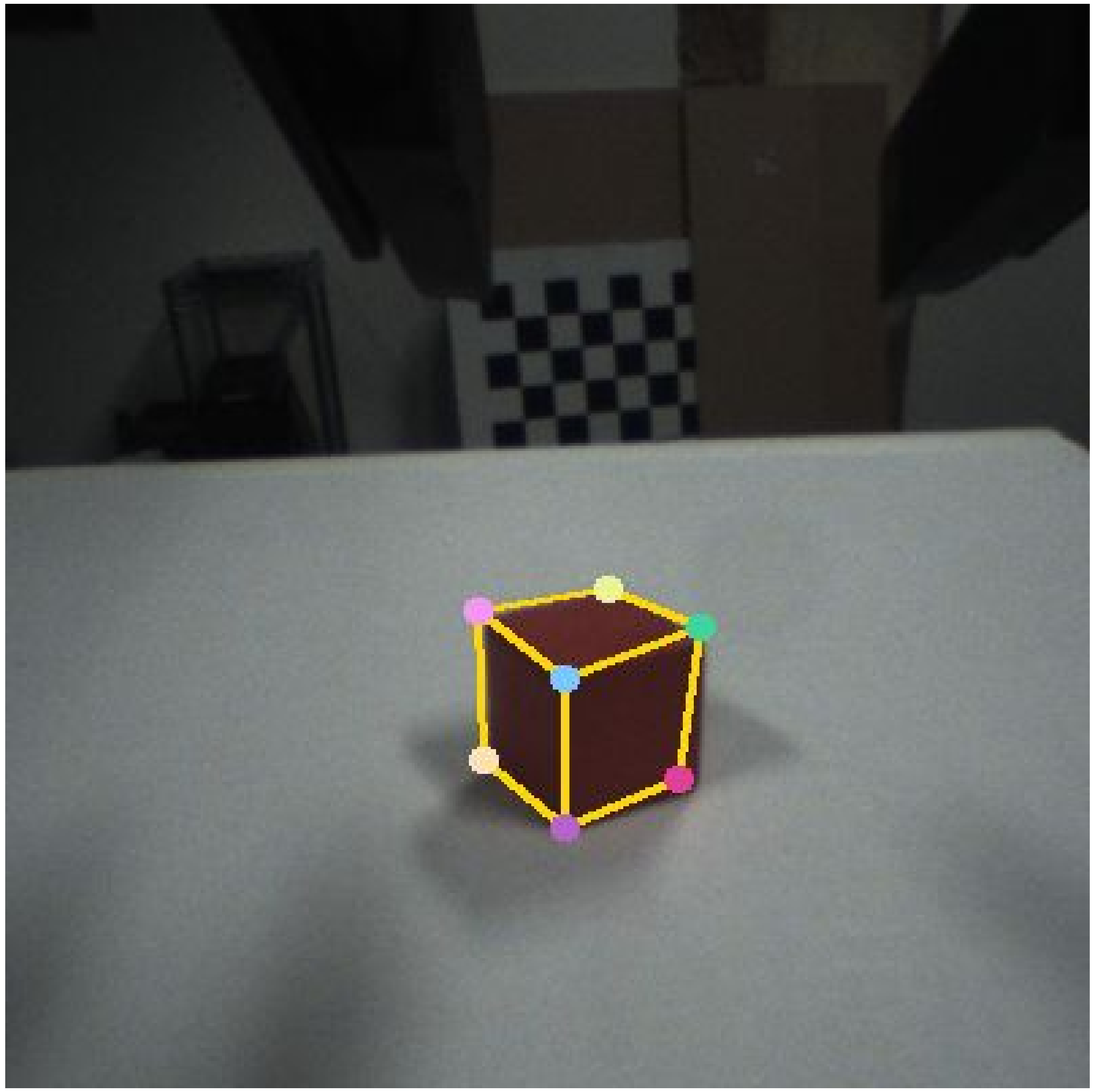
- Pose detector fails when the brightness of the image changes. What will we do?
- Randomize also the brightness

# Synthetic data generation

## Data - Contrast and Brightness



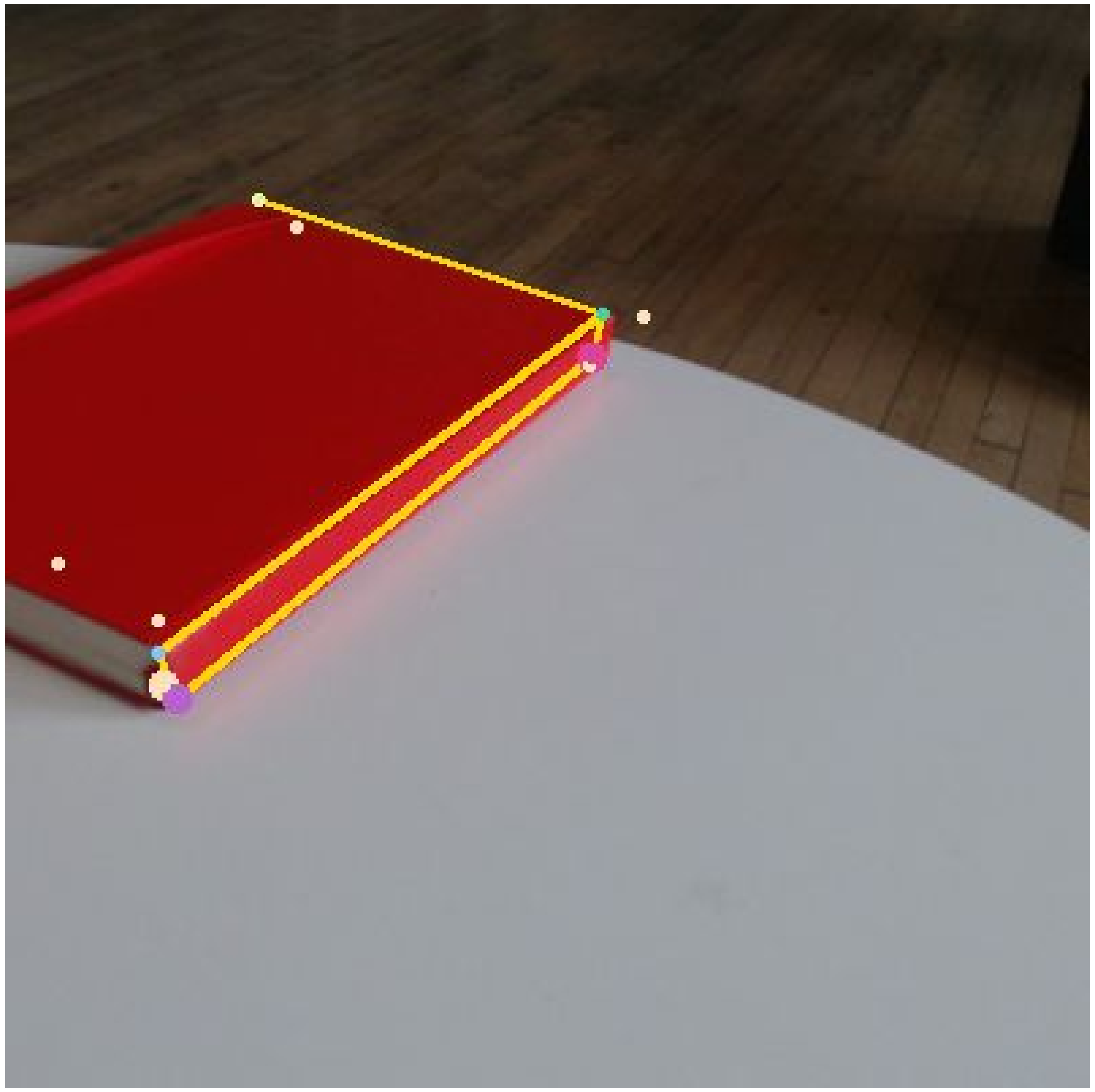
# SIM2REAL



- Now it works..

# SIM2REAL

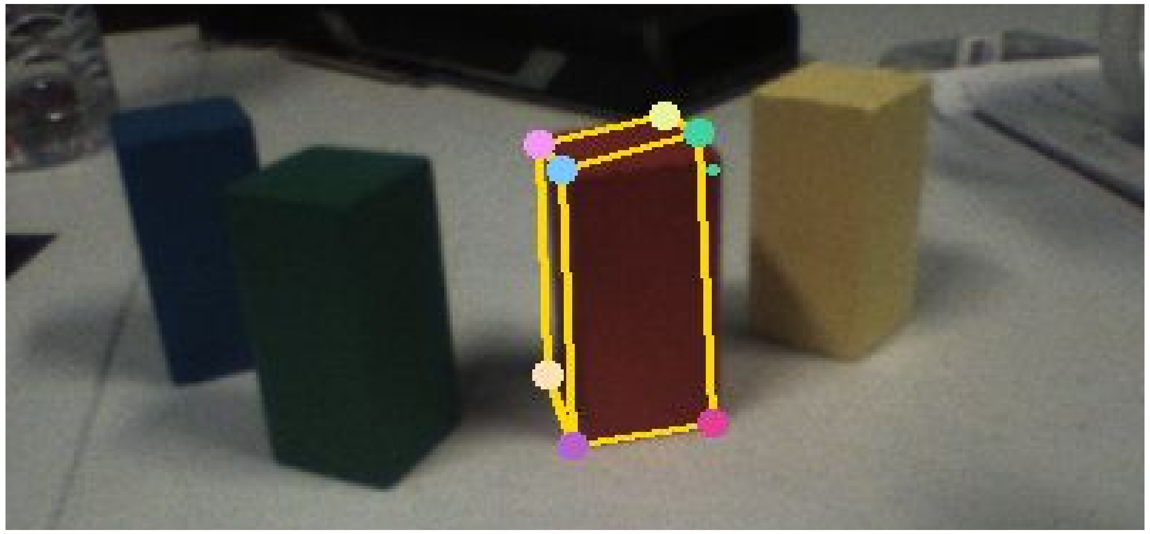
## Surprising Result

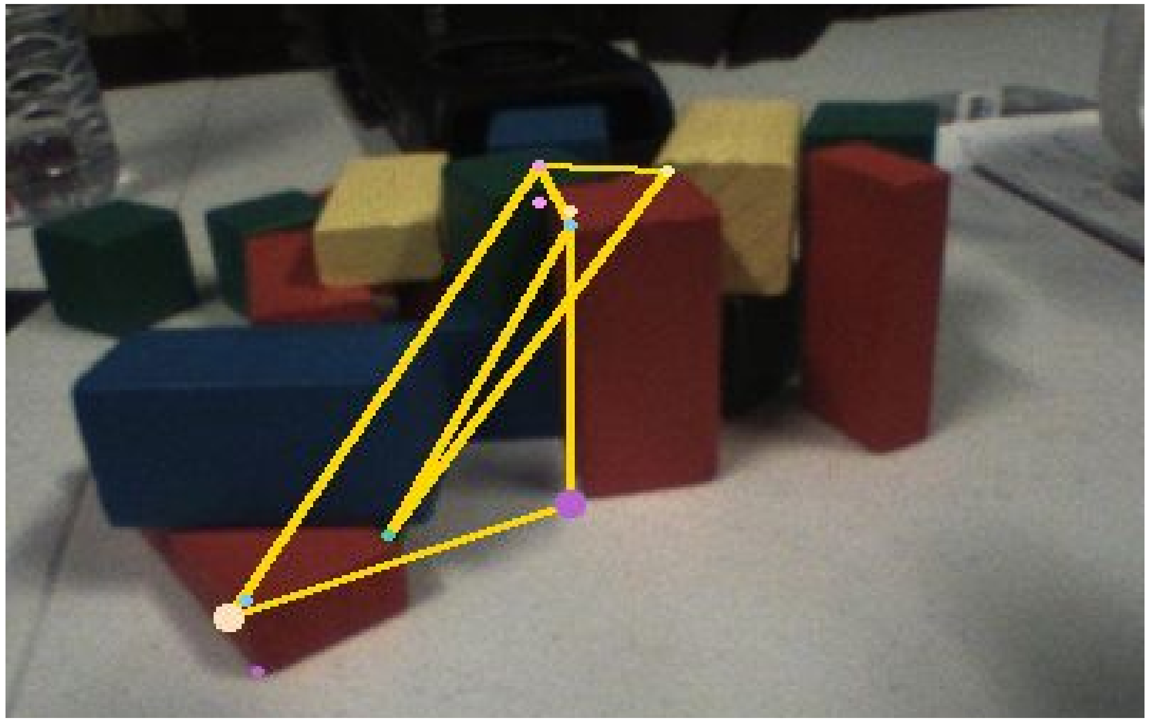


- Even for non cube objects sometimes

# SIM2REAL

## Baxter’s camera





- It can fail under heavy clutter.
- Solution: use an architecture from  computer vision research: combine object detection with pose regression, do not regress directly to vertices with the whole image as input

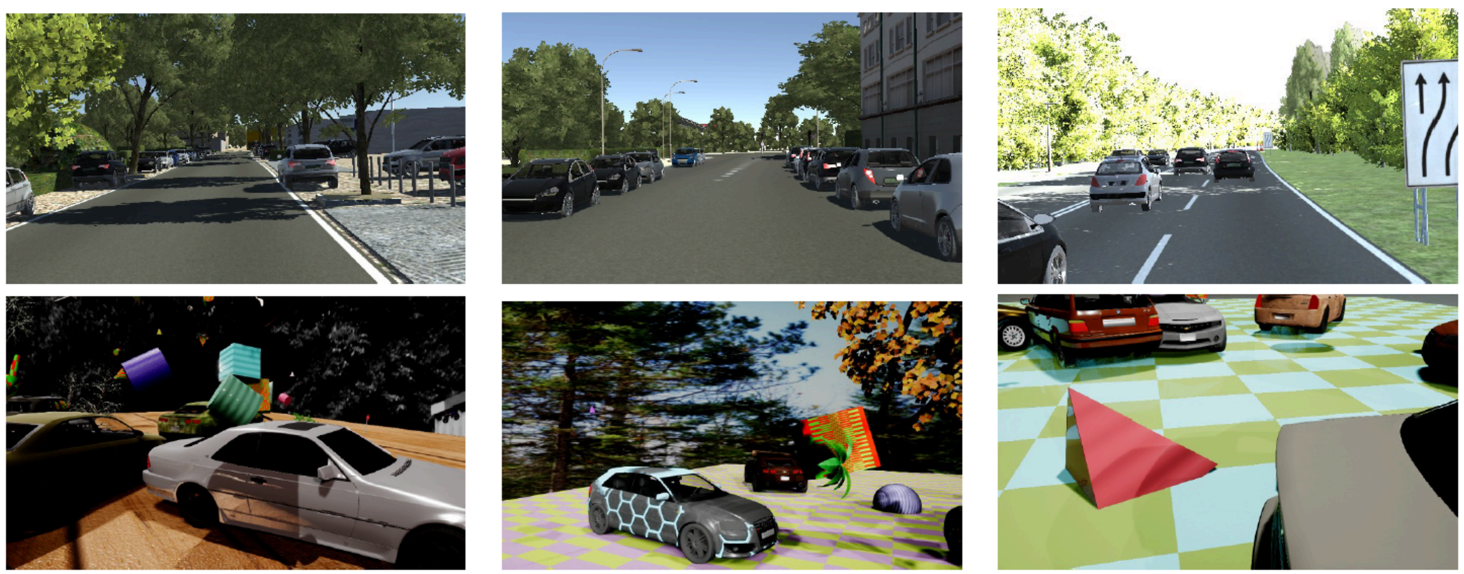
# Car detection

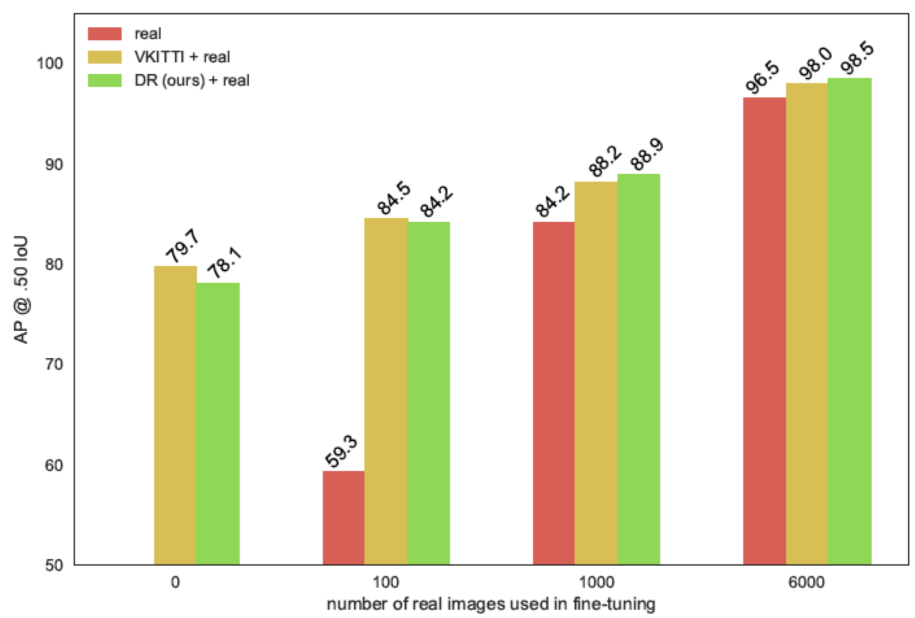
VKITTI: a carefully designed simulation dataset to mimic real driving conditions, large engineering effort

DR: an automatically created simulation dataset with non-realistic visuals and content, small engineering effort

VKITTI

DR






The fewer the real labelled data, the larger the gain from synthetic data

Training Deep Networks with Synthetic Data: Bridging the Reality Gap by Domain Randomization, NVIDIA

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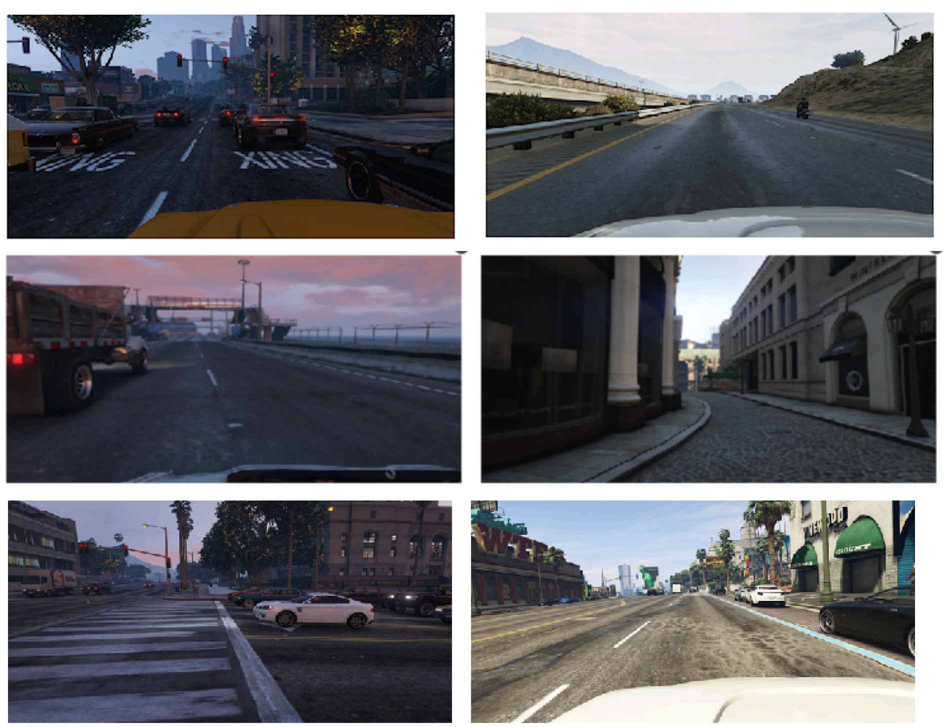
# Domain adaptation for visual observations

**GTA:** synthetic data of urban scenes from a camera mounted on a car

**Cityscapes:** real data of urban scenes from a camera mounted on a car



19 object classes to be detected: people, cars, stop signs, poles, etc.

**source** **target**

Our goal: Train detectors and pixel labelers on GTA that generalize to Cityscapes

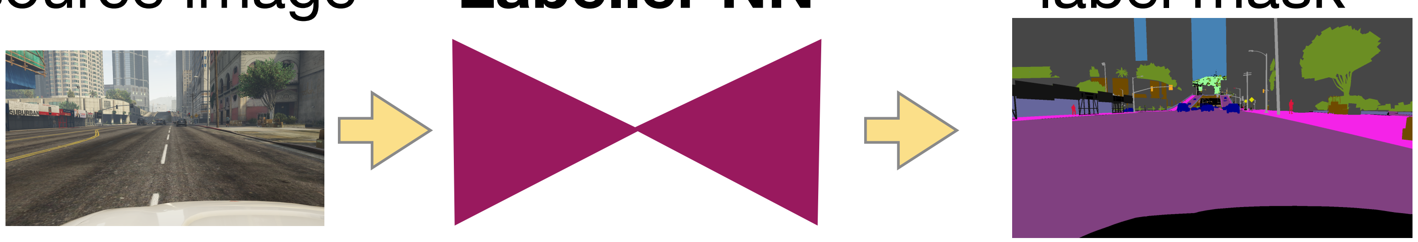
# Baseline

**Train a classifier on source and test it on the target, and hope it generalizes**

1. Pick a network architecture, e.g. ResNet101 or VGG
2. Download a pertained neural network, e.g., trained for image classification on Imagenet, or trained for pixel labelling in PASCAL
3. Finetune it on the source domain (GTA)
4. Apply on the target domain (Cityscapes)

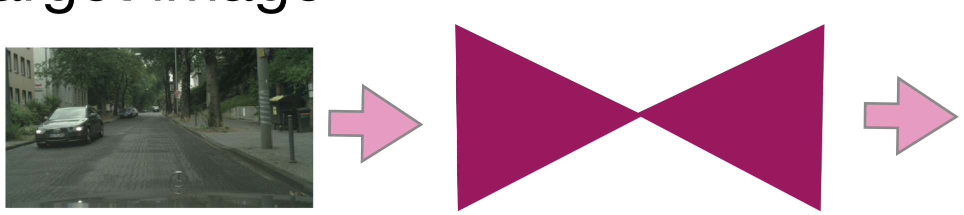
**Training**

source image **Labeller NN** label mask



**Testing**

target image **Labeller NN**



**?**

Image classification in Imagenet

pixel labelling in PASCAL

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Pretrain on Imagenet -> finetune in GTA->test in GTA: 53% meanIoU
Pretrain on Imagenet -> finetune in GTA->test in Cityscapes: 28% meanIoU

Pretrain on PASCAL -> finetune in GTA->test in GTA: 58.84% meanIoU
Pretrain on PASCAL -> finetune in GTA->test in Cityscapes: 32% meanIoU

Pretrain on PASCAL -> cotrain in GTA/PASCAL->test in Cityscapes: 39% meanIoU

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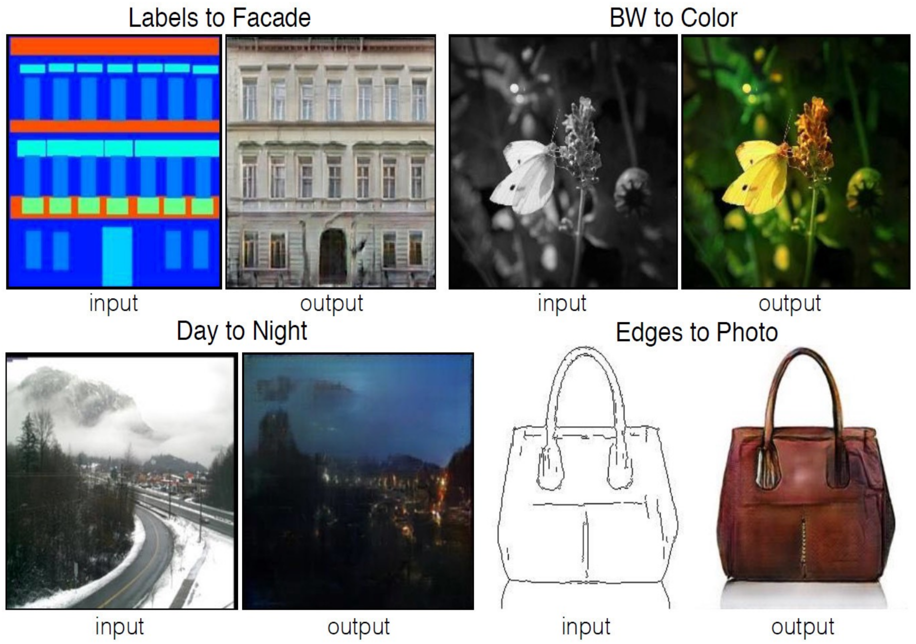
Catastrophic forgetting:

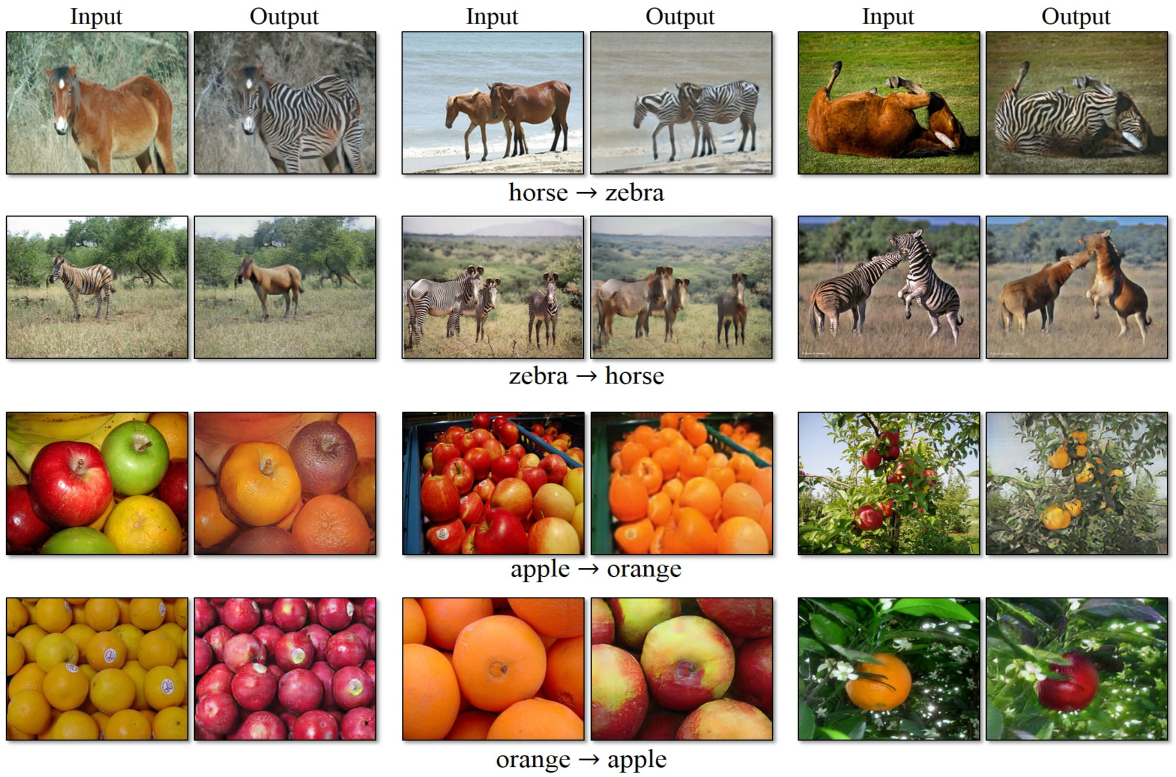
- During fine-tuning, the network forgets the general and nicely transferable PASCAL features!
- Finetuning a neural net on a very limited domain is a bad idea for transfer

# Learning to translate images

- Paired

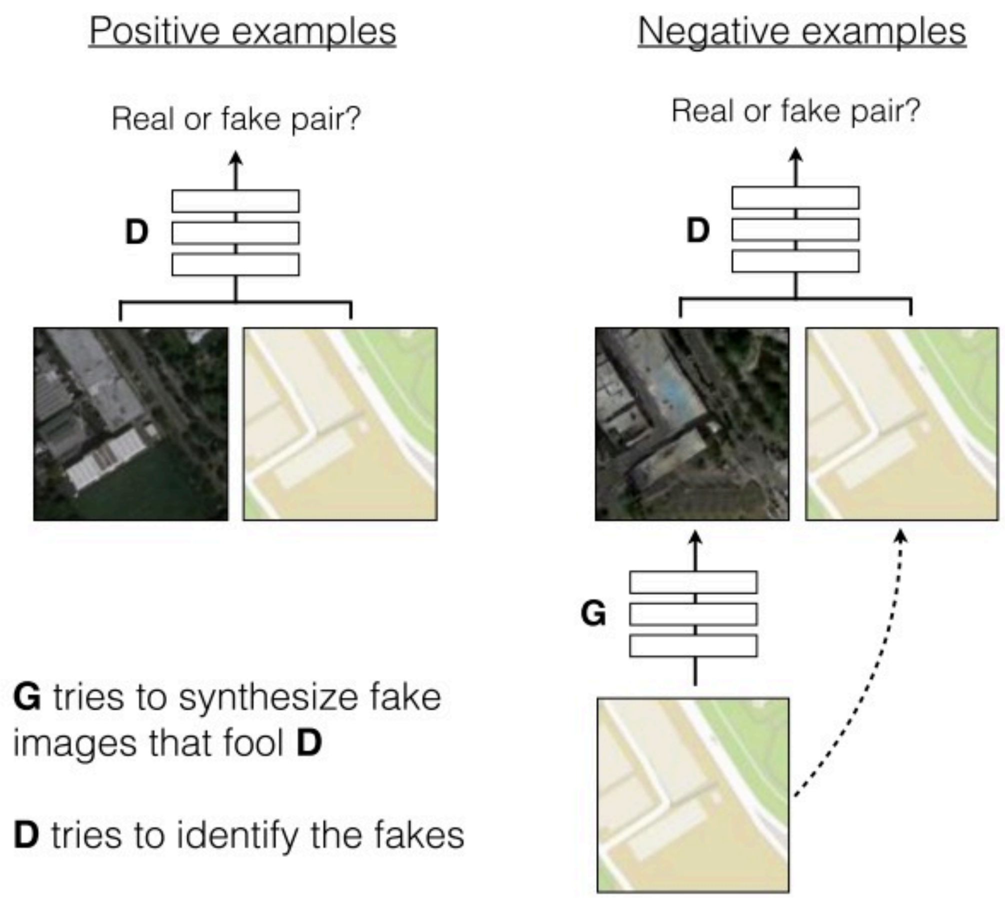



- Unpaired (this is our case)

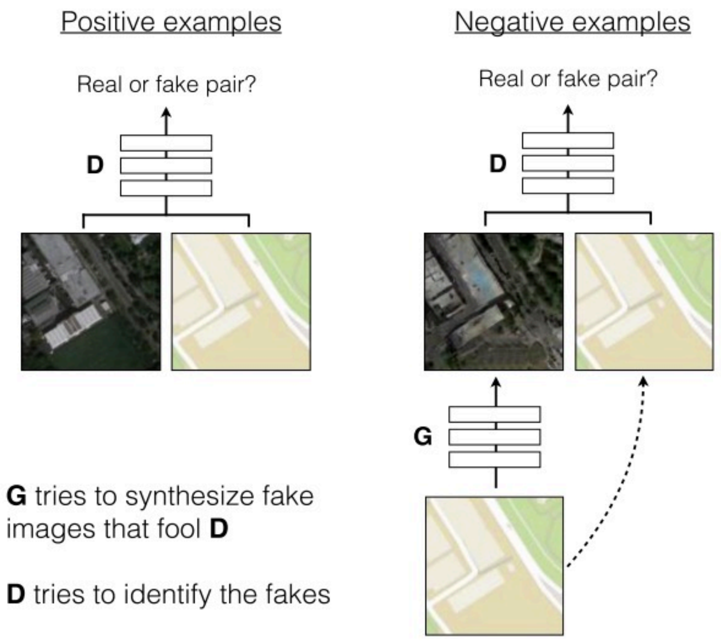


# Paired case

- The generator takes the (source) image as input and tries to output the corresponding target image
- Pairs of source-target images as input to discriminator



# Paired case

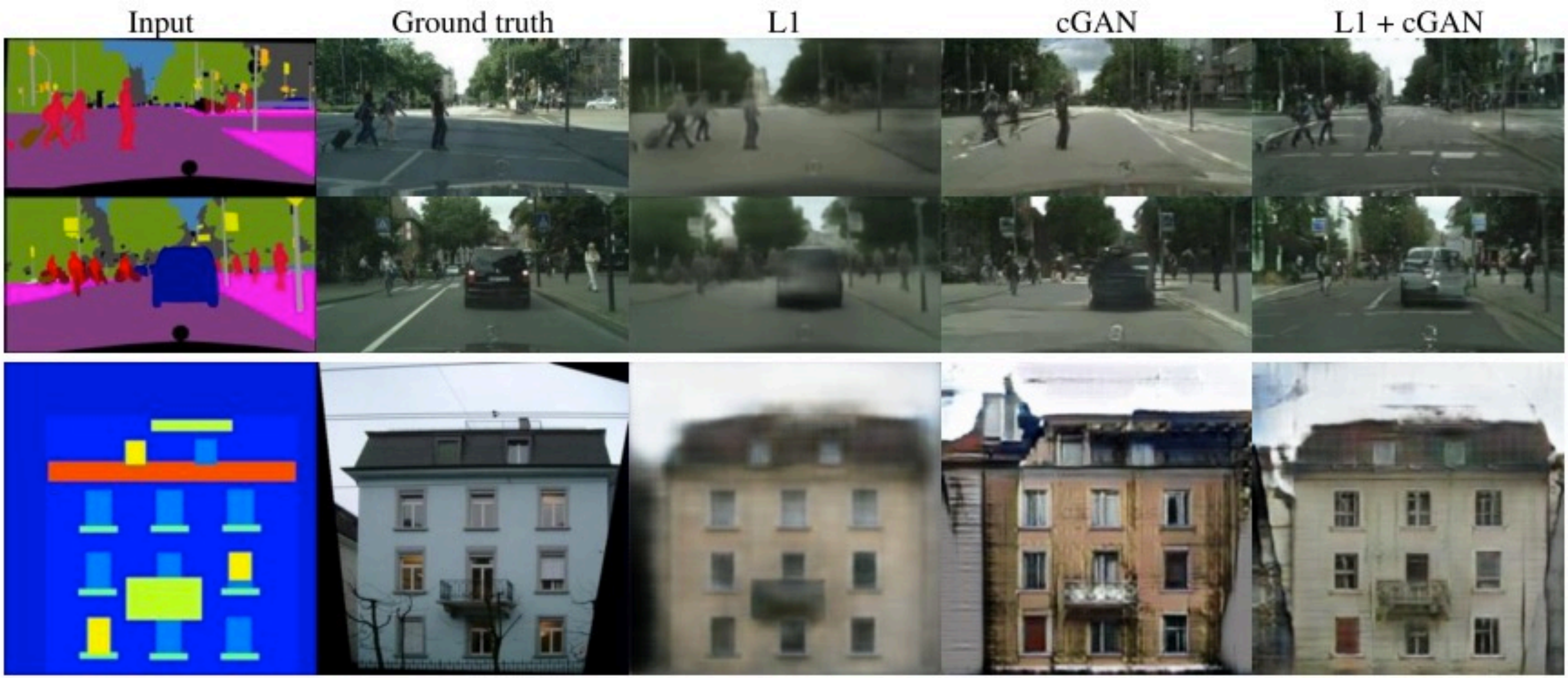



$x$: source image, $y$: target image, $z$: noise

$$\mathcal{L}_{cGAN}(G, D) = \mathbb{E}_{x,y \sim p_{data}(x,y)}[\log D(x, y)] + \mathbb{E}_{x \sim p_{data}(x), z \sim p_z(z)}[\log(1 - D(x, G(x, z)))]$$

$$\mathcal{L}_{L1}(G) = \mathbb{E}_{x,y \sim p_{data}(x,y), z \sim p_z(z)}[||y - G(x, z)||_1]$$

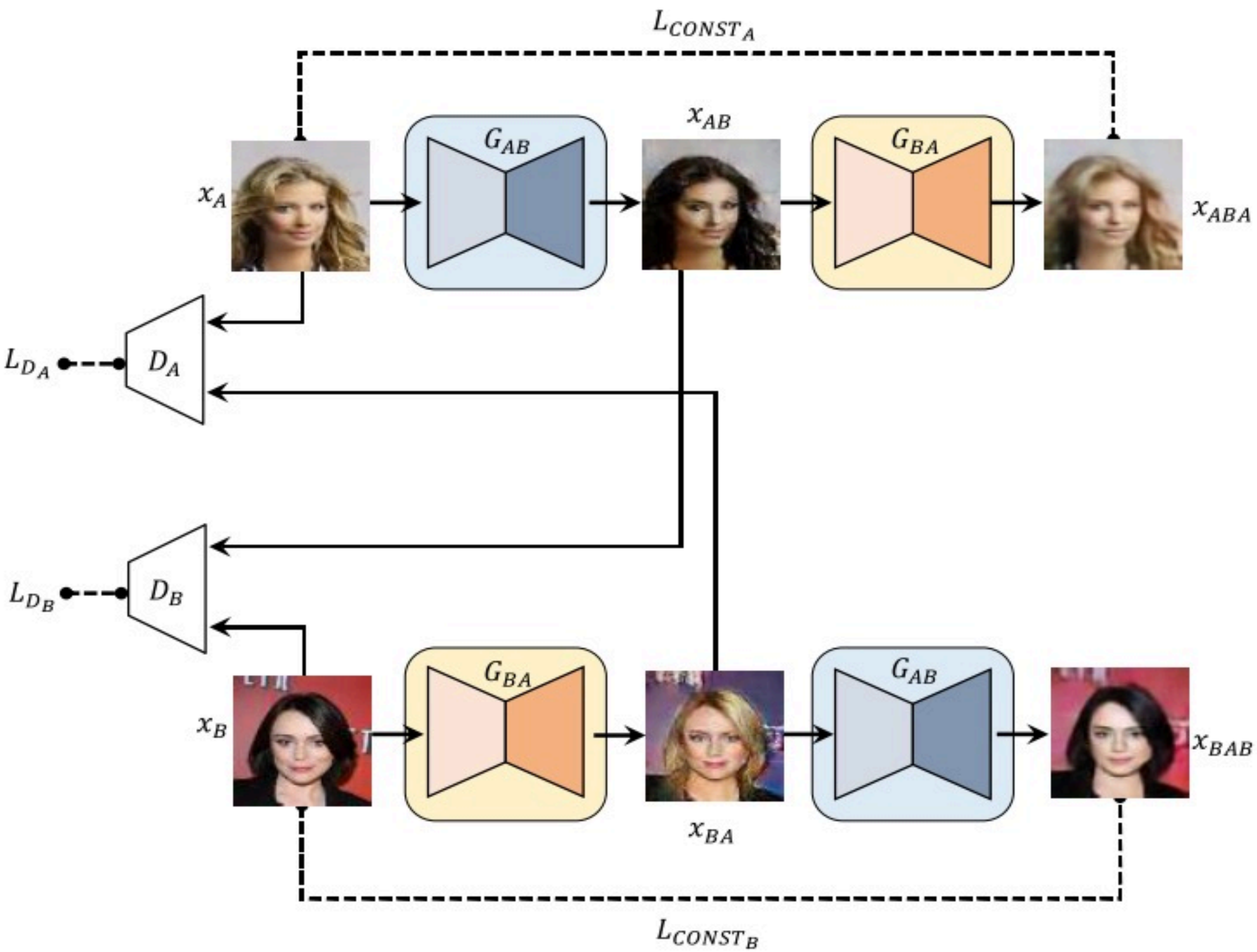
# Paired case



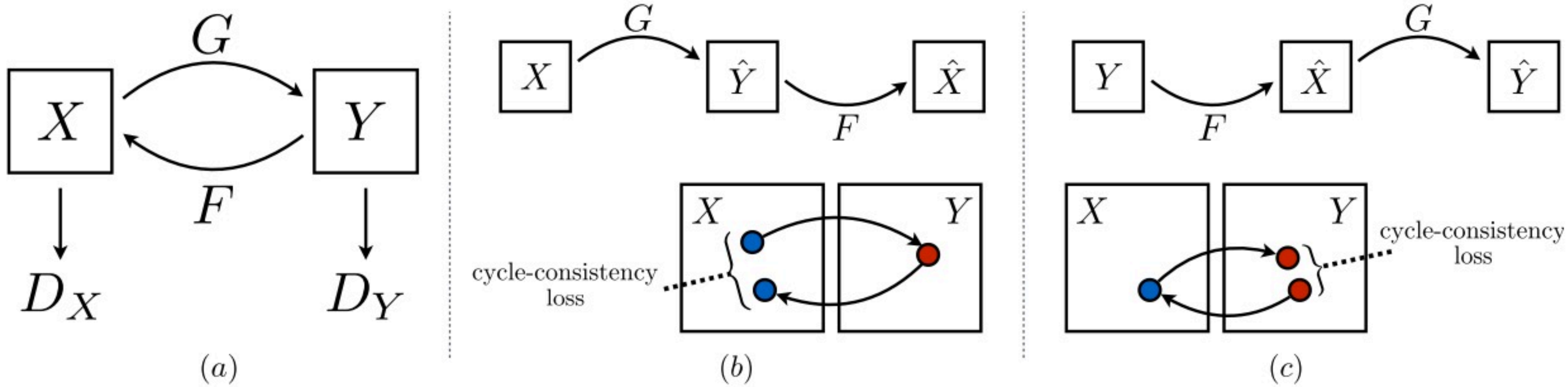
# Paired case

# Paired case

# Unpaired case



# Cycle GAN / DISCO GAN



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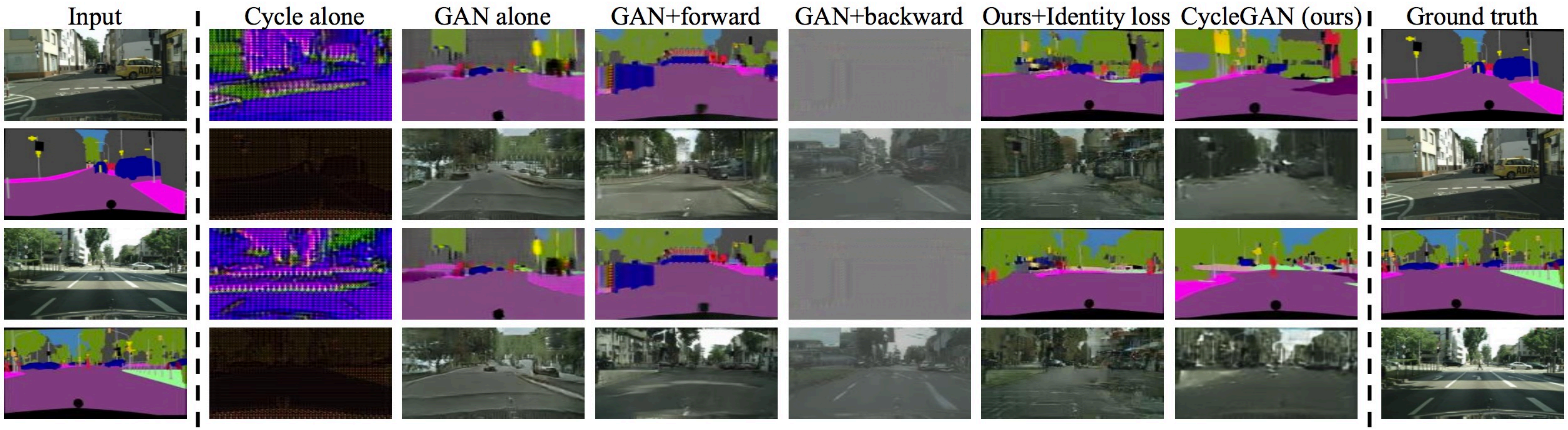
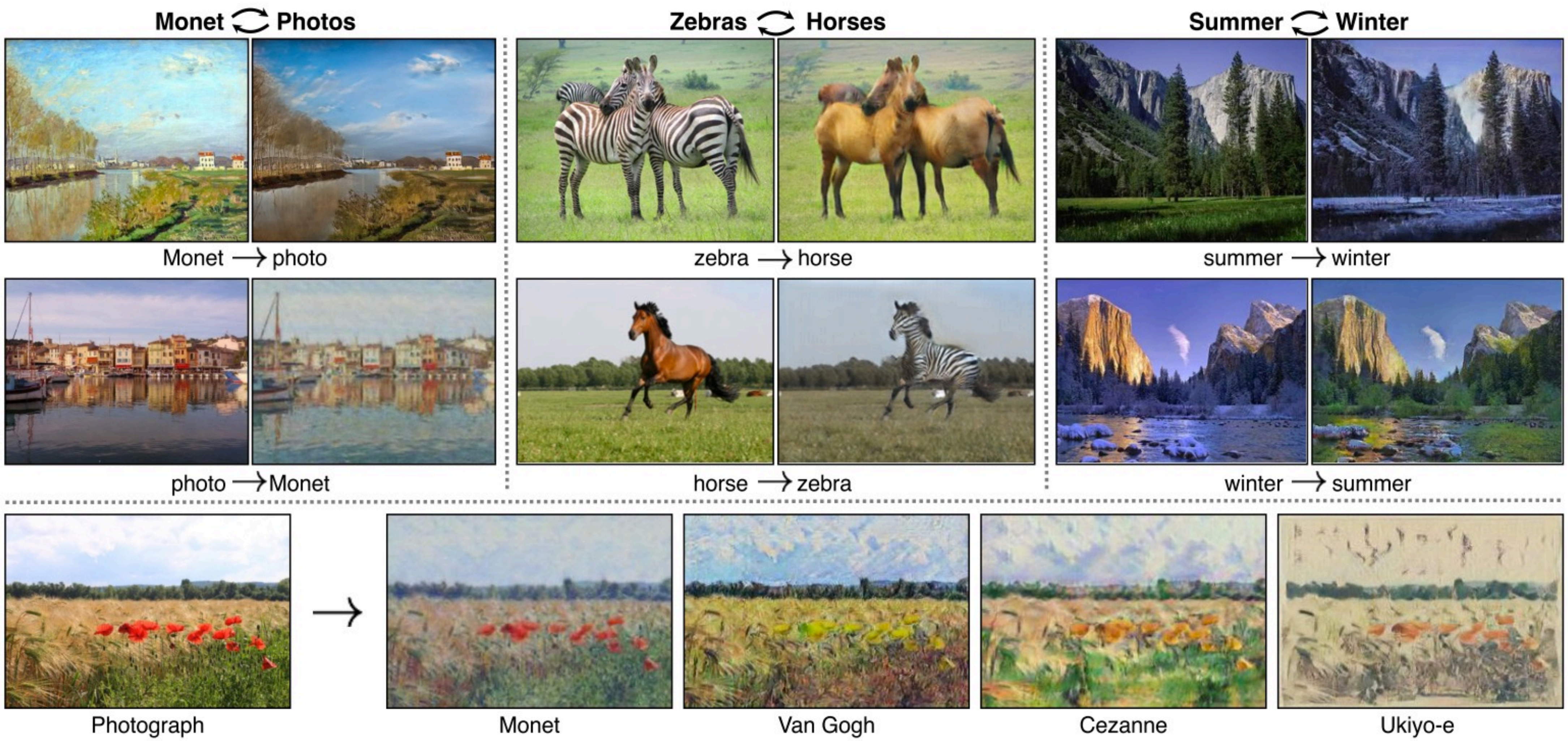
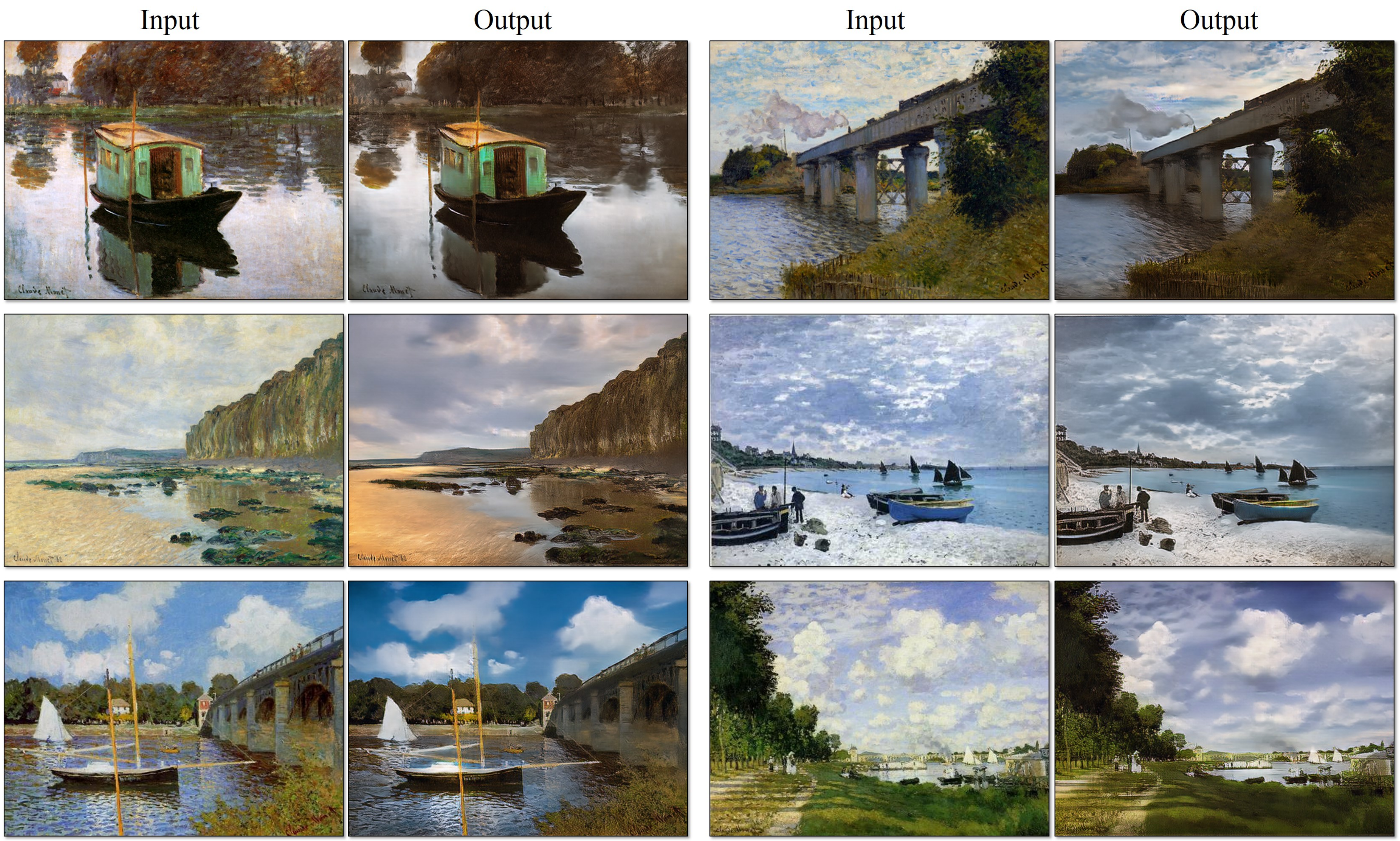



Figure 7: Different variants of our method for mapping labels↔photos trained on cityscapes. From left to right: input, cycle-consistency loss alone, adversarial loss alone, GAN + forward cycle-consistency loss ($F(G(x)) \approx x$), GAN + backward cycle-consistency loss ($G(F(y)) \approx y$), CycleGAN (our full method), and ground truth. Both *Cycle alone* and *GAN + backward* fail to produce images similar to the target domain. *GAN alone* and *GAN + forward* suffer from mode collapse, producing identical label maps regardless of the input photo.

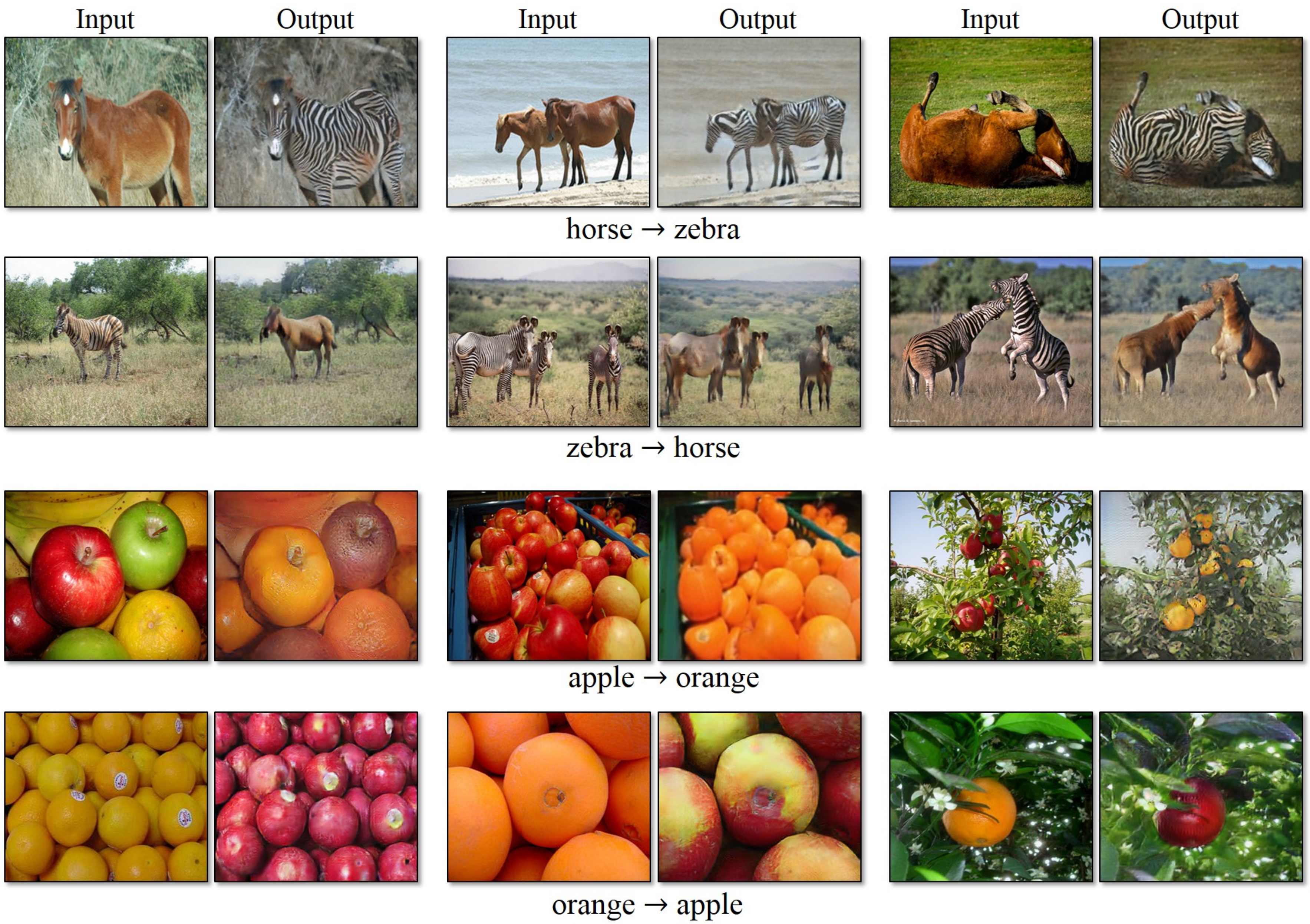
# Unpaired case



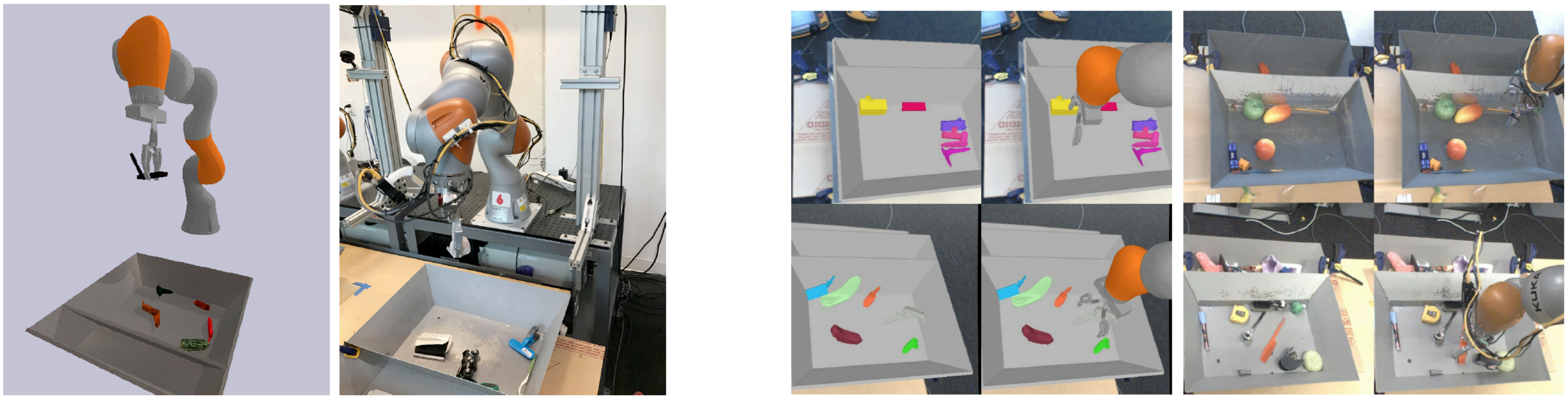
# Unpaired case



# Unpaired case



# SIM2real for learning to grasp

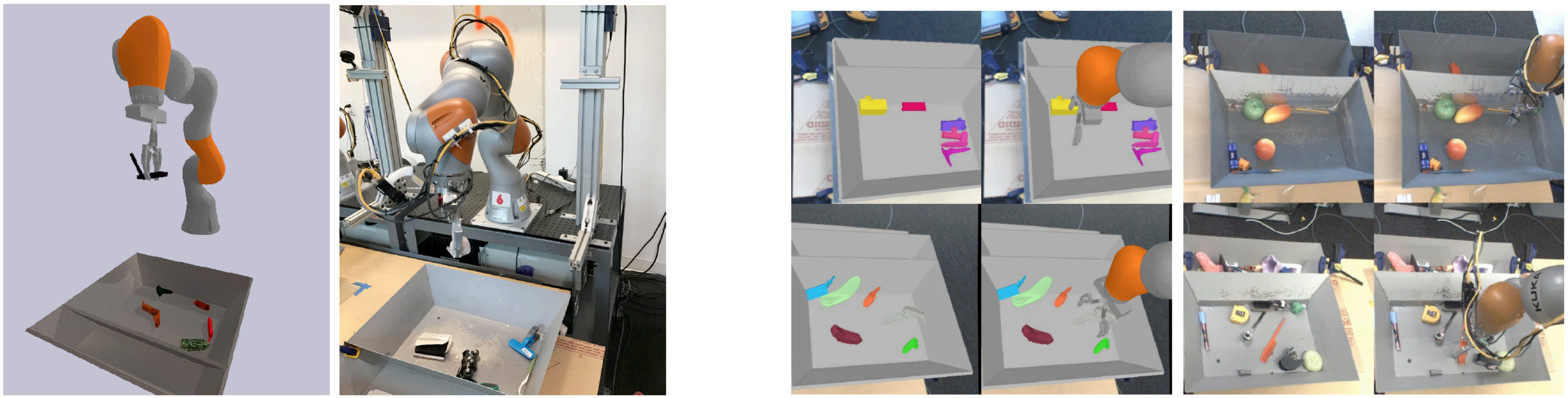


(a) Simulated World (b) Real World (c) Simulated Samples (d) Real Samples

- $\text{Grasp}(I, v, \theta)$: given image I and end-effector motion v, will I eventually successfully grasp?
- $\text{Grasp}(I, v, \theta)$ can be trained with supervised learning. I want to use a simulated environment to quickly collect lots of samples. What I train I want it to generalize to the real world
- Two approaches: a feature level sim2real adaptation and a pixel level sim2real adaptation

Using Simulation and Domain Adaptation to Improve Efficiency of Deep Robotic Grasping, Google, CVPR 2017

# SIM2real for learning to grasp



(a) Simulated World (b) Real World (c) Simulated Samples (d) Real Samples

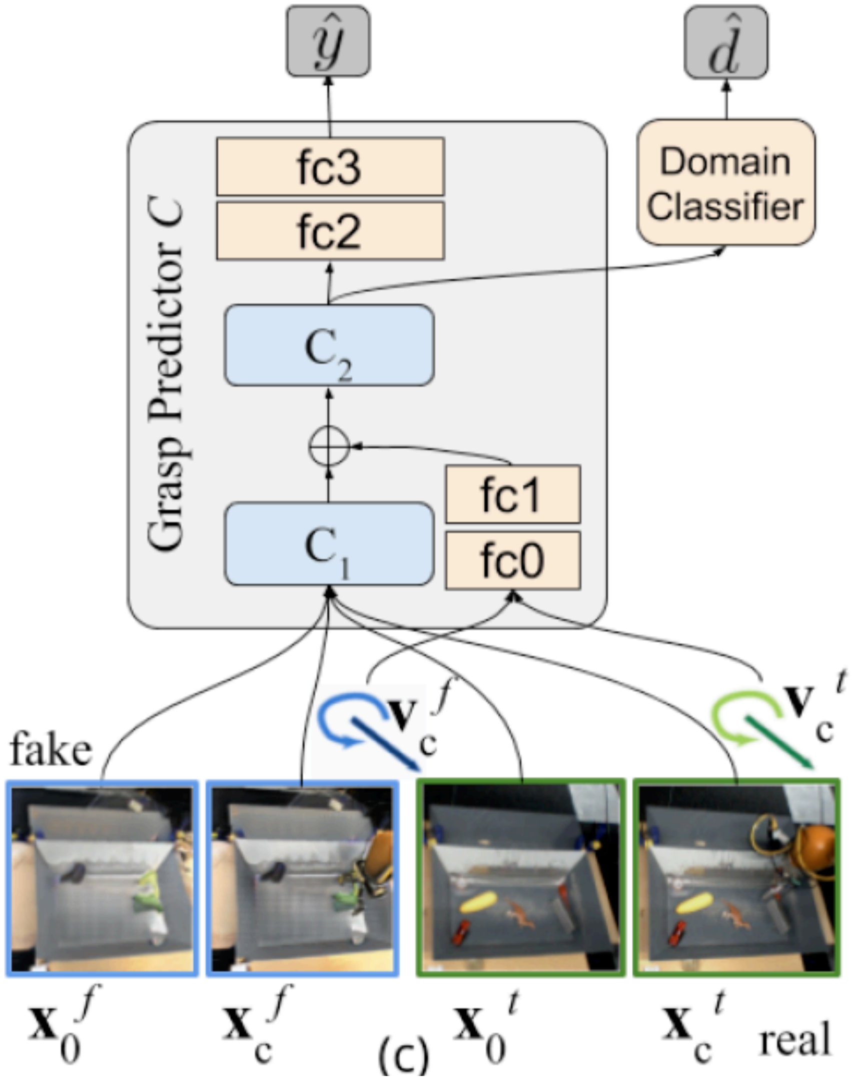
- Use Bullet simulator to emulate the Kuka hardware setup. Camera is mounted over the Kuka shoulder
- 51300 ShapeNet 3d models
- Use progressively better grasping models to collect data
- Randomization: both visuals and dynamics were randomized in simulation: the background image, object masses, textures, coefficients of friction.

Using Simulation and Domain Adaptation to Improve Efficiency of Deep Robotic Grasping, Google, CVPR 2017

# Feature adaptation

Two losses: domain confusion loss and grasping prediction loss

Grasping prediction (task loss)




We add a domain classifier, that attempts to classify the domain the features come from

$$\mathcal{L}_{\mathrm{DANN}} = \sum_{i=0}^{N_s+N_t} \{d_i \log \hat{d}_i + (1-d_i)\log(1-\hat{d}_i)\}$$

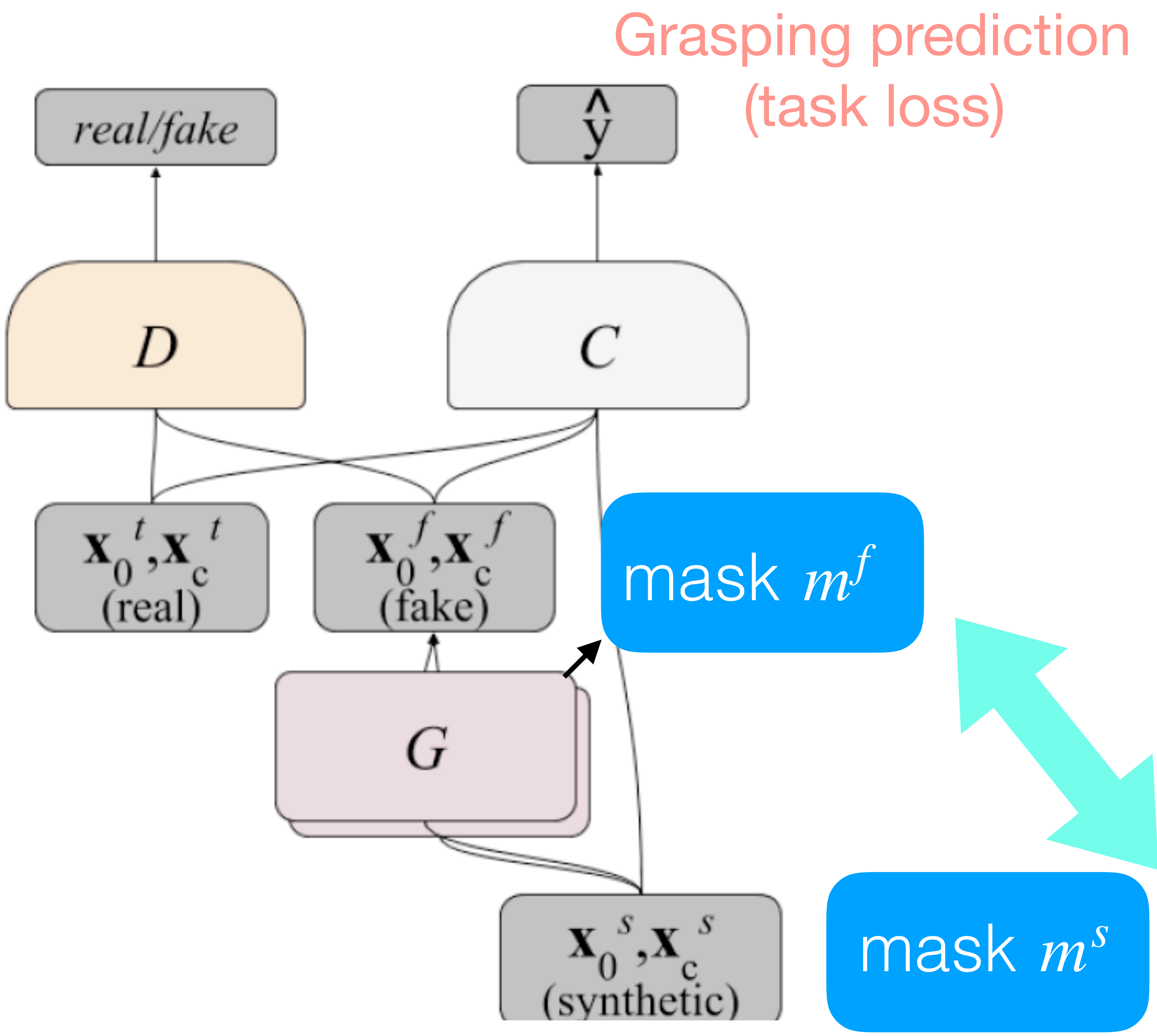
The shared features C1, C2 attempt to confuse the domain classifier (maximize its loss), while the domain classifier features attempts to min. its loss.

Using Simulation and Domain Adaptation to Improve Efficiency of Deep Robotic Grasping, Google, CVPR 2017

# Pixel Adaptation

Goal: we want our generator to refine simulated images so that:

1. they do well in the task loss (grasping),
2. look real
3. retain the same semantics as their simulated counterparts

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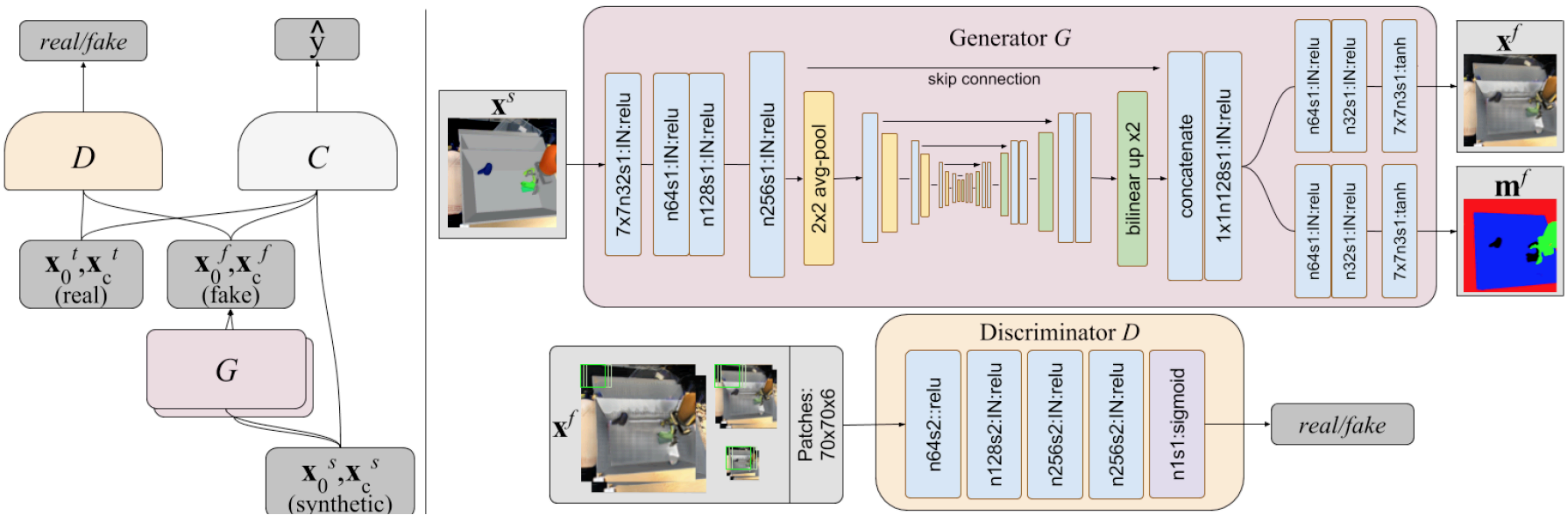
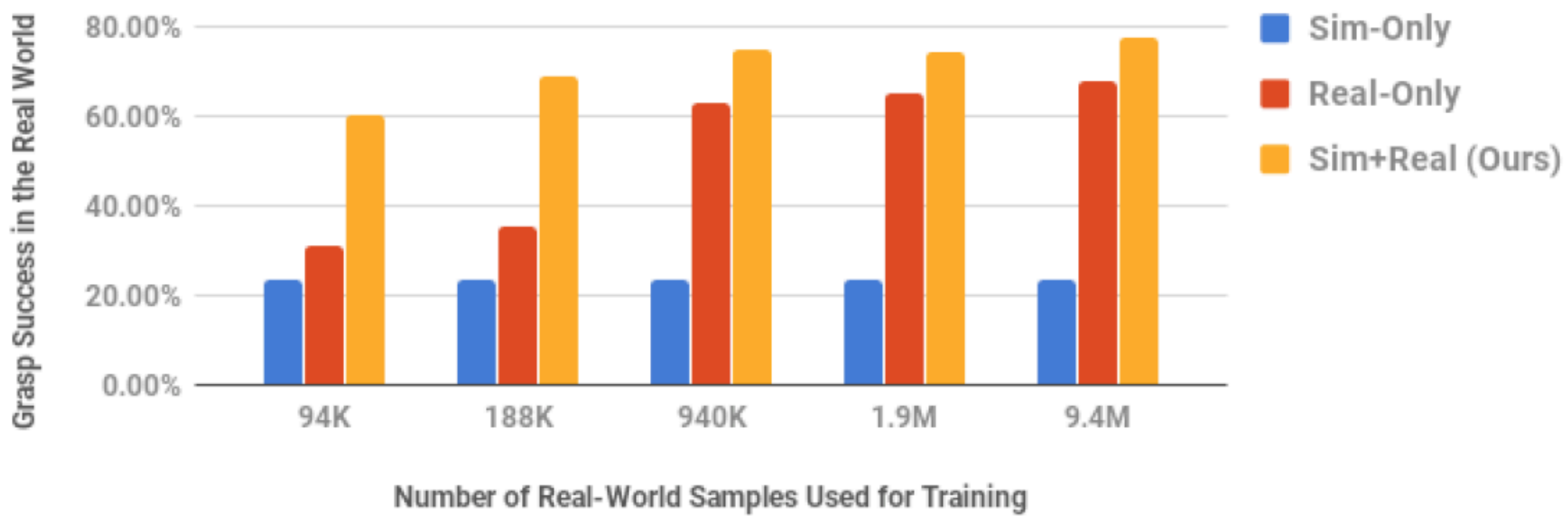



Using Simulation and Domain Adaptation to Improve Efficiency of Deep Robotic Grasping, Google, CVPR 2017

# Results




(a) Procedural (b) ShapeNet [31] (c) Real

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# EPOPT: LEARNING ROBUST NEURAL NETWORK POLICIES USING MODEL ENSEMBLES

**Aravind Rajeswaran**[1], **Sarvjeet Ghotra**[2], **Balaraman Ravindran**[3], **Sergey Levine**[4]
aravraj@cs.washington.edu, sarvjeet.13it236@nitk.edu.in,
ravi@cse.iitm.ac.in, svlevine@eecs.berkeley.edu
[1] University of Washington Seattle
[2] NITK Surathkal
[3] Indian Institute of Technology Madras
[4] University of California Berkeley

Ideas:

- Consider a distribution over simulation models instead of a single one for learning policies robust to modeling errors that work well under many ``worlds”. Hard model mining.
- Progressively bring the simulation model distribution closer to the real world.

# Policy Search under model distribution

Learn a policy that performs best in expectation over MDPs in the source domain distribution:

$$\boxed{\mathbb{E}_{p\sim\mathcal{P}}}\left[\mathbb{E}_{\hat{\tau}}\left[\sum_{t=0}^{T-1}\gamma^t r_t(s_t,a_t)\,\middle|\,p\right]\right]$$

p: simulator parameters

I consider a distribution over simulation parameters, as opposed to a single set

# Policy Search under model distribution

Learn a policy that performs best in expectation over MDPs in the source domain distribution:

$$\mathbb{E}_{p\sim\mathcal{P}}\left[\mathbb{E}_{\hat{\tau}}\left[\sum_{t=0}^{T-1}\gamma^t r_t(s_t,a_t)\,\middle|\,p\right]\right]$$

p: simulator parameters

**Hard world model mining**

Learn a policy that performs best in expectation over the worst \epsilon-percentile of MDPs in the source domain distribution

$$\max_{\theta,y}\int_{\mathcal{F}(\theta)}\eta_{\mathcal{M}}(\theta,p)\mathcal{P}(p)dp \qquad s.t.\quad \mathbb{P}\left(\eta_{\mathcal{M}}(\theta,P)\le y\right)=\epsilon$$

# Hard model mining

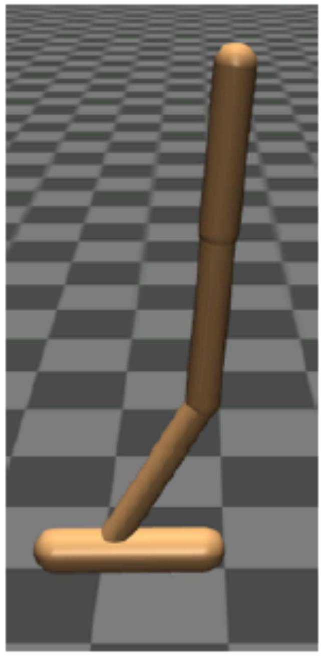
**Algorithm 1:** EPOpt–$\epsilon$ for Robust Policy Search

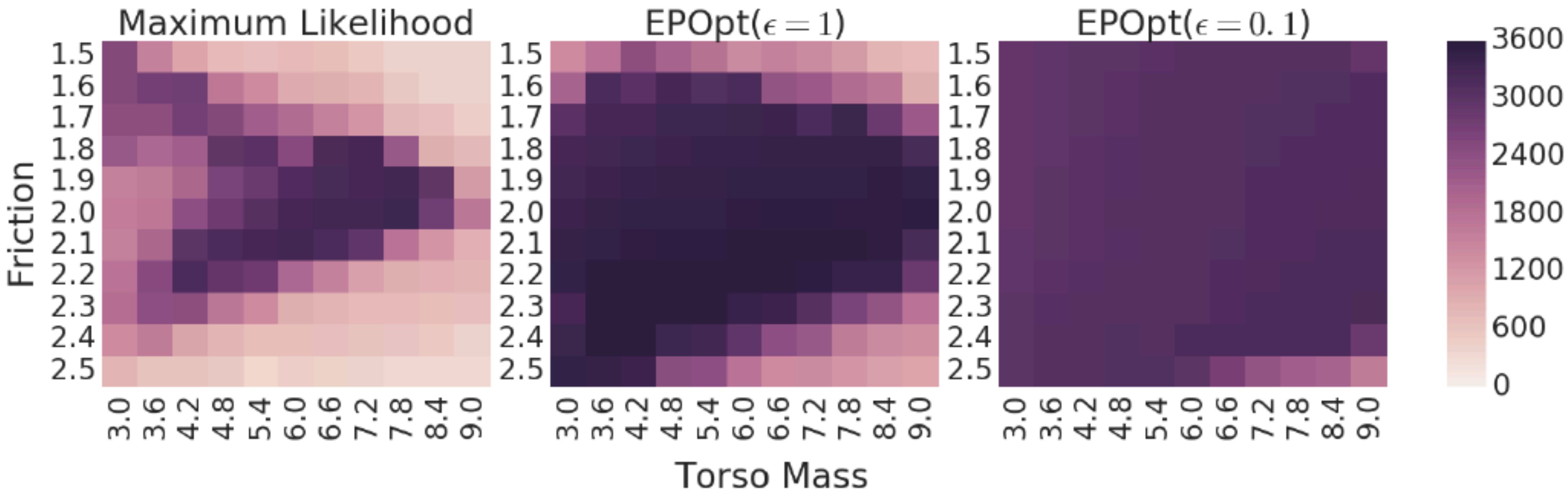
```
Input: ψ, θ_0, niter, N, ε
for iteration i = 0, 1, 2, ... niter do
    for k = 1, 2, ... N do
        sample model parameters p_k ~ P_ψ
        sample a trajectory τ_k = {s_t, a_t, r_t, s_{t+1}}_{t=0}^{T-1} from M(p_k) using policy π(θ_i)
    end
    compute Q_ε = ε percentile of {R(τ_k)}_{k=1}^N
    select sub-set T = {τ_k : R(τ_k) ≤ Q_ε}
    Update policy: θ_{i+1} = BatchPolOpt(θ_i, T)
end
```

Select the simulation parameters where the current policy fails

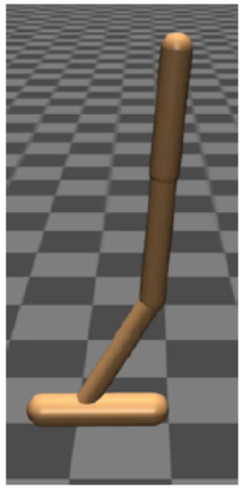
# Hard model mining results

Hard world mining results in policies with high reward over wider range of parameters



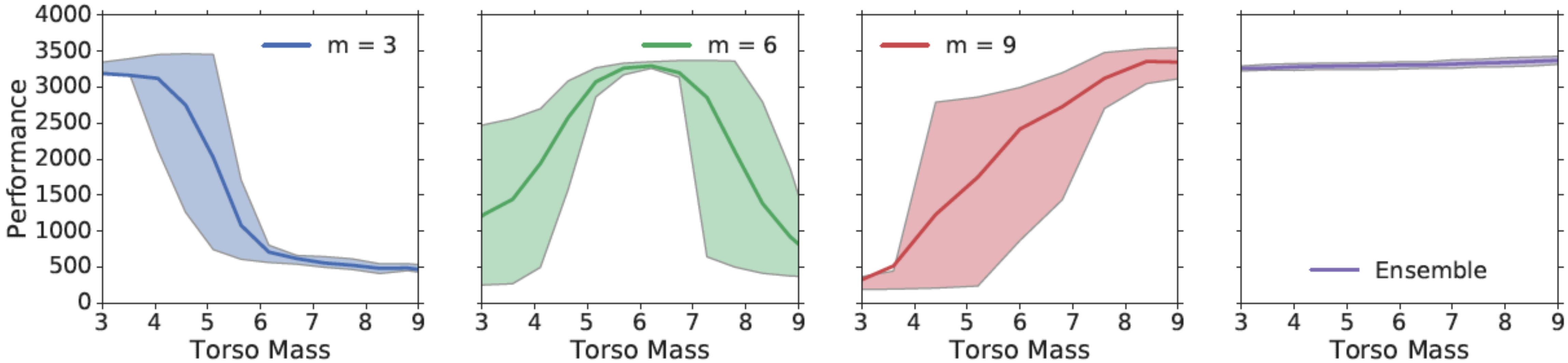


# Performance on hopper policies



trained on single source domains

trained on Gaussian distribution of mean mass 6 and standard deviation 1.5



# What can go wrong with dynamics randomization?

- Overly conservative policies
- Same instances of the problem may not have solution and hinder policy search
- Instead: try to bring the simulation dynamics closeto the real world dynamics

# What has shown to work

- Domain randomization (dynamics, visuals)
- Learning to adapt the textures of the simulator to match the real domain
- Learning to adapt the dynamics of the dymulator to match the real domain
- Learning not from pixels but rather from label maps-> semantic maps between simulation and real world are closer than textures
- Learning higher level policies, not low-level controllers, as the low level dynamics are very different between Sim and REAL

# Adapting the source domain distribution

Sample  sets of simulation parameters    from a sampling distribution S.

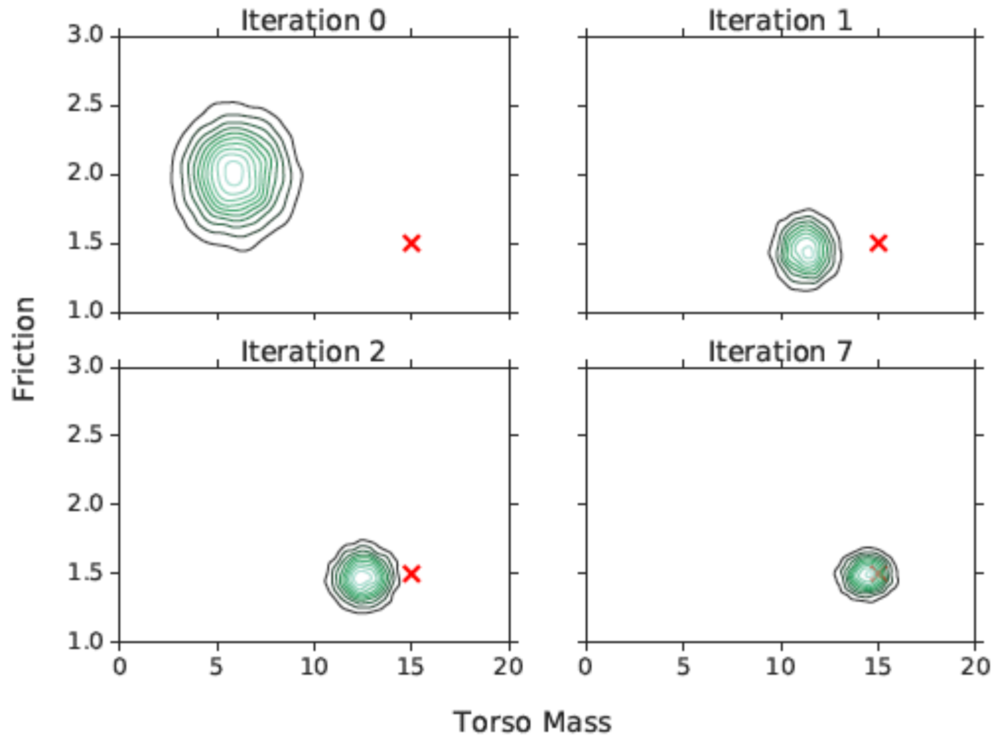
Posterior of parameters p_i:

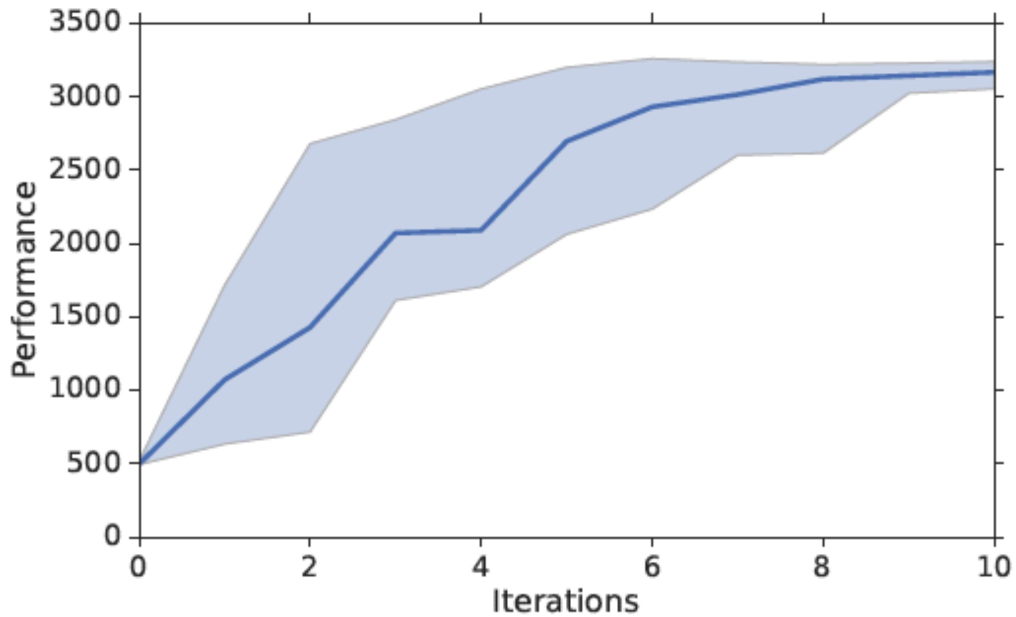
$$\mathbb{P}(p_i|\tau_k) \propto \prod_t \boxed{\mathbb{P}(S_{t+1} = s_{t+1}^{(k)}|s_t^{(k)}, a_t^{(k)}, p_i)} \times \frac{\mathbb{P}_P(p_i)}{\mathbb{P}_S(p_i)}$$

Fit a Gaussian model over simulator parameters based on posterior weights of the samples

The more probable is an observed target state-action trajectory, the more probable the simulation model

# Source Distribution Adaptation



# Closing the Sim-to-Real Loop: Adapting Simulation Randomization with Real World Experience

Yevgen Chebotar[1,2] Ankur Handa[1] Viktor Makoviychuk[1]
Miles Macklin[1,3] Jan Issac[1] Nathan Ratliff[1] Dieter Fox[1,4]

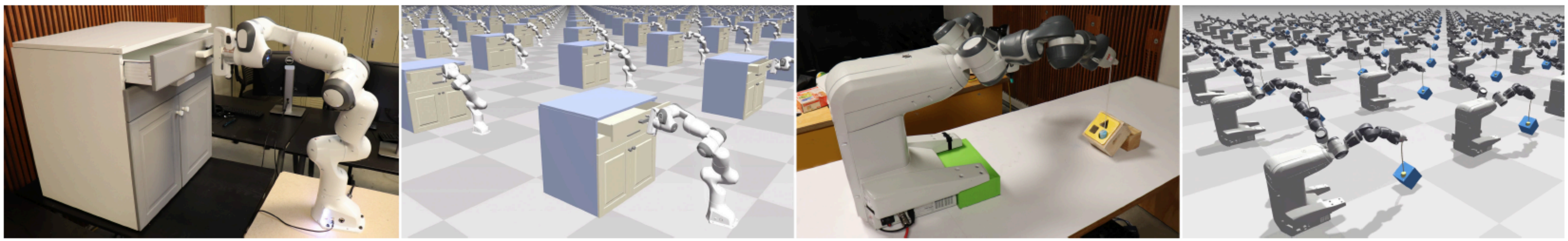
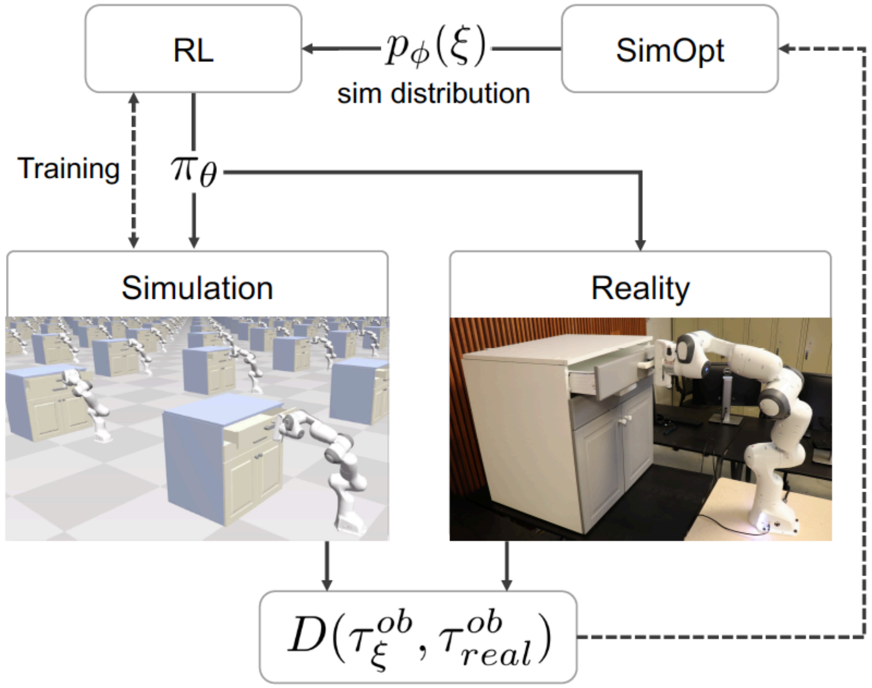


Fig. 1. Policies for opening a cabinet drawer and swing-peg-in-hole tasks trained by alternatively performing reinforcement learning with multiple agents in simulation and updating simulation parameter distribution using a few real world policy executions.

# Adapting simulation to the real world

**Algorithm 1** SimOpt framework

1: $p_{\phi_0} \leftarrow$ Initial simulation parameter distribution
2: $\epsilon \leftarrow$ KL-divergence step for updating $p_\phi$
3: **for** iteration $i \in \{0, \ldots, N\}$ **do**
4: env $\leftarrow$ Simulation$(p_{\phi_i})$
5: $\pi_{\theta, p_{\phi_i}} \leftarrow$ RL(env)
6: $\tau^{ob}_{real} \sim$ RealRollout$(\pi_{\theta, p_{\phi_i}})$
7: $\xi \sim$ Sample$(p_{\phi_i})$
8: $\tau^{ob}_{\xi} \sim$ SimRollout$(\pi_{\theta, p_{\phi_i}}, \xi)$
9: $c(\xi) \leftarrow D(\tau^{ob}_{\xi}, \tau^{ob}_{real})$
10: $p_{\phi_{i+1}} \leftarrow$ UpdateDistribution$(p_{\phi_i}, \xi, c(\xi), \epsilon)$




$$\min_{\phi_{i+1}} \mathbb{E}_{P_{\xi_{i+1} \sim p_{\phi_{i+1}}}} \left[ \mathbb{E}_{\pi_{\theta, p_{\phi_i}}} \left[ D(\tau^{ob}_{\xi_{i+1}}, \tau^{ob}_{real}) \right] \right]$$
$$\text{s.t.} \quad D_{KL}\left(p_{\phi_{i+1}} \| p_{\phi_i}\right) \le \epsilon,$$

https://sites.google.com/view/simopt

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# Driving Policy Transfer via Modularity and Abstraction

**Matthias Müller**
Visual Computing Center
KAUST, Saudi Arabia

**Alexey Dosovitskiy**
Intelligent Systems Lab
Intel Labs, Germany

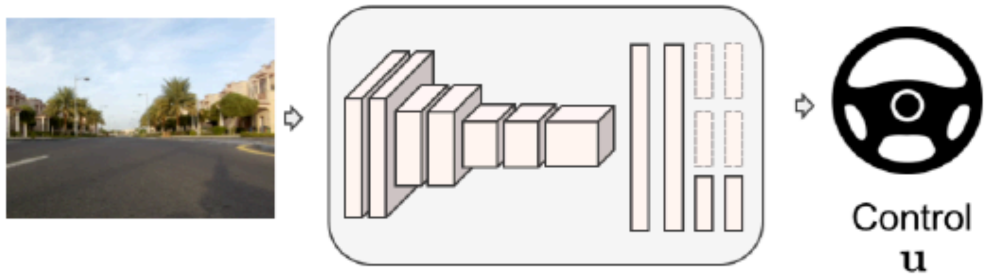
**Bernard Ghanem**
Visual Computing Center
KAUST, Saudi Arabia

**Vladlen Koltun**
Intelligent Systems Lab
Intel Labs, USA

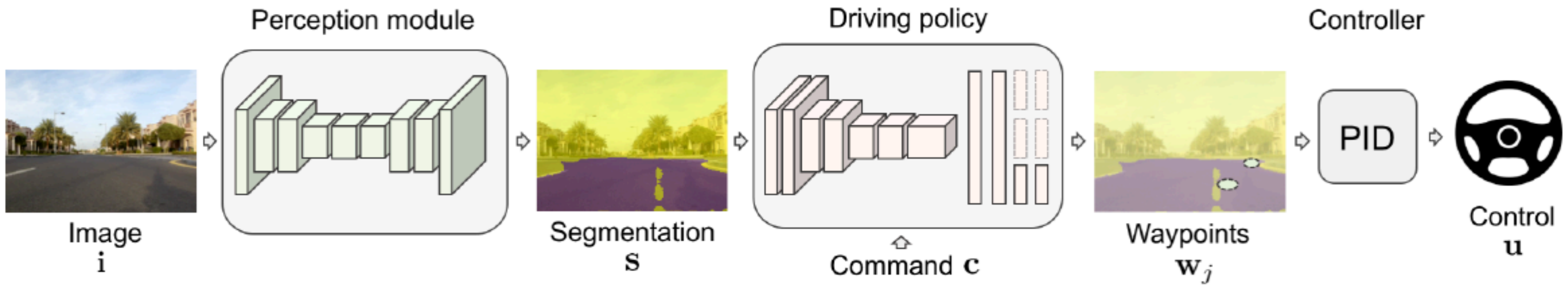
Idea: the driving policy is not directly exposed to raw perceptual input or low-level vehicle dynamics.

# Main idea

Pixels to steering wheel mapping is not SIM2REAL transferable: image textures and car dynamics mismatch

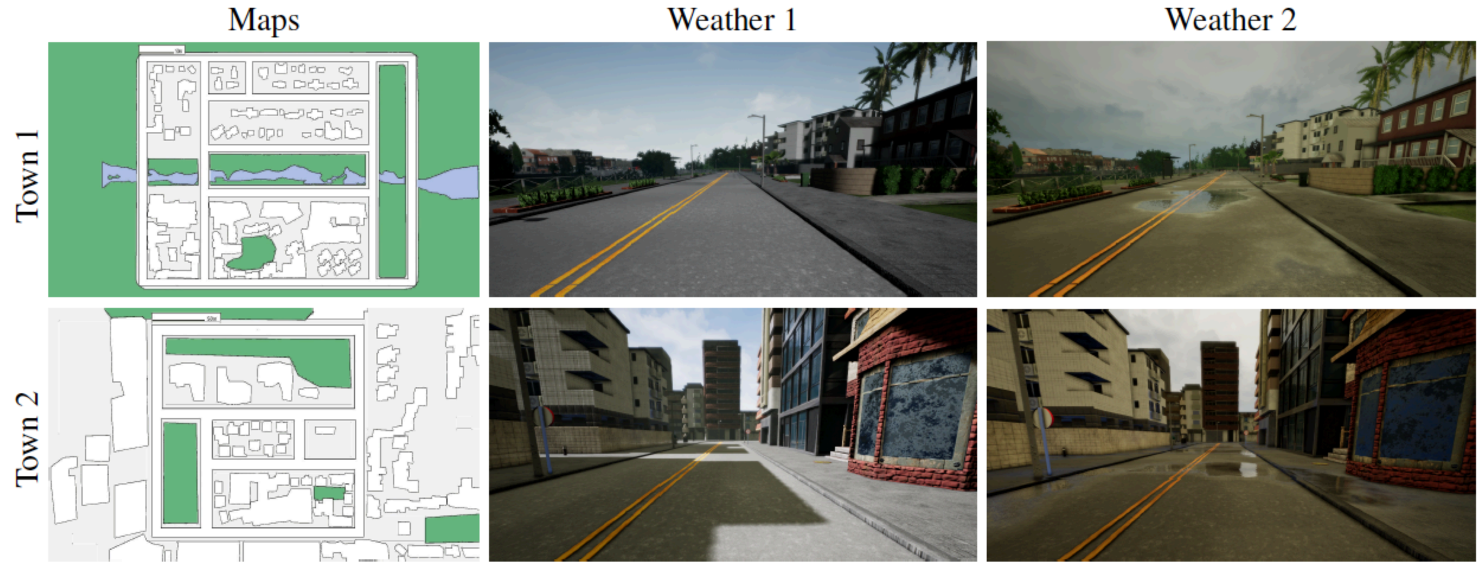



Instead: label maps to waypoint mapping is better SIM2REAL transferable: label maps and waypoints are similar across SIM and REAL. A low-level controller will take the car from waypoint to waypoint in the real world



# Train/Test


We train policies via behaviour cloning (standard regression loss) in Town1/ Weather1 dataset, and evaluate them on all four.



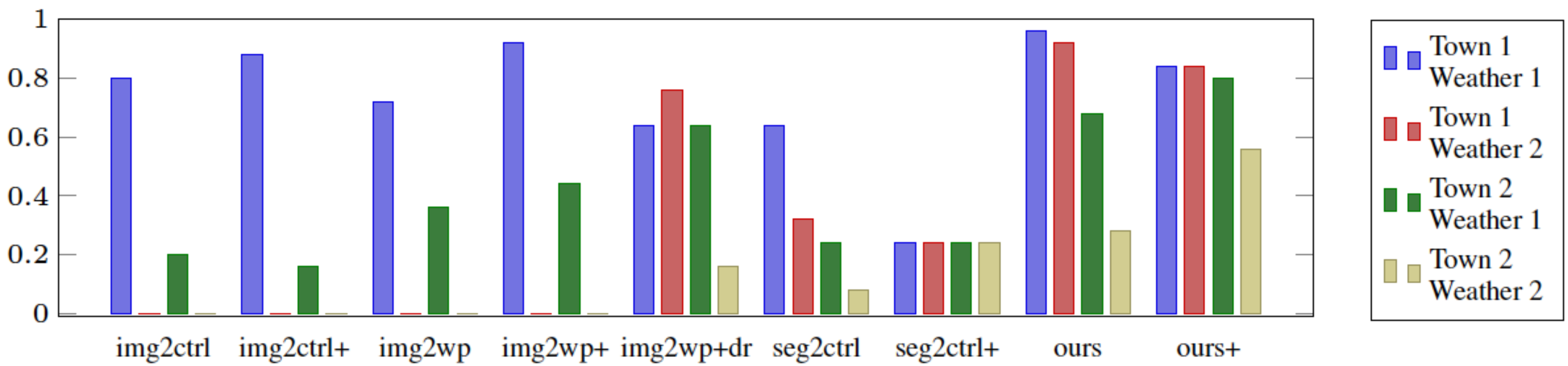




Figure 4: Quantitative evaluation of goal-directed navigation in simulation. We report the success rate over 25 navigation trials in four town-weather combinations. The models have been trained in Town 1 and Weather 1. The evaluated models are: *img2ctrl* – predicting low-level control from color images; *img2wp* – predicting waypoints from color images; *seg2ctrl* – predicting low-level control from the segmentation produced by the perception module; *ours* – predicting waypoints from the segmentation produced by the perception module. Suffix '+' denotes models trained with data augmentation, and '+dr' denotes the model trained with domain ramdomization.