

# Domain adaptation

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Минск, 2018

# Domain adaptation

- Small [un]labeled dataset from target domain.
- Huge labeled dataset in a relevant domain.

# Domain adaptation





(a) GTA



(b) Cityscapes

# Domain adaptation

Model	Loss	Accuracy
GTA 64x64	0.5892	0.7049
GTA 128x128	1.1422	0.6808
GTA 256x256	1.0450	0.6714
GTA 512x512	1.4202	0.6742
Cityscapes 64x64	0.3859	0.8473
Cityscapes 128x128	0.4728	0.7930
Cityscapes 256x256	0.3717	0.8325
Cityscapes 512x512	0.4498	0.8011

- Feature space  $X$ .
- Probability distribution  $P(X)$ .
- Domain  $D = \{X, P(X)\}$ .
- Objective prediction function  $f(x) = P(Y|X)$ .

- $D^s = \{X, P_s(X)\}.$
- $D^t = \{X, P_t(X)\}.$
- $P_s(X) \rightarrow P_t(X).$

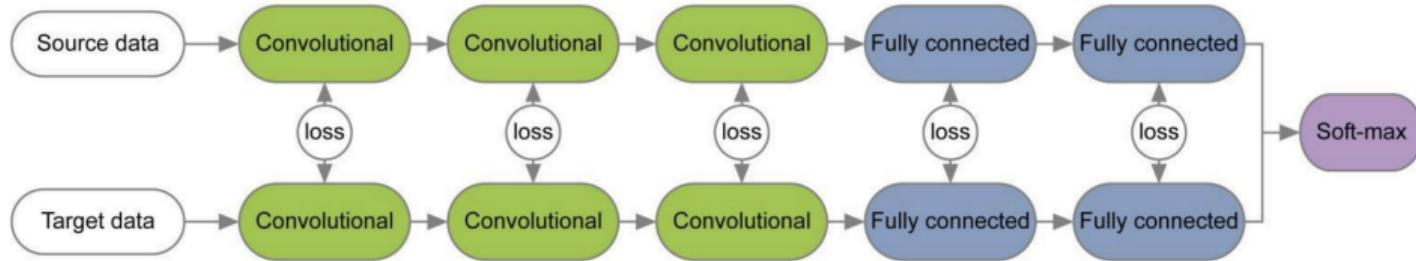
- Shallow
  - Fine-tuning
- Deep
  - SimGAN
  - CyCADA
  - GeoConGAN

# Fine-tuning methods

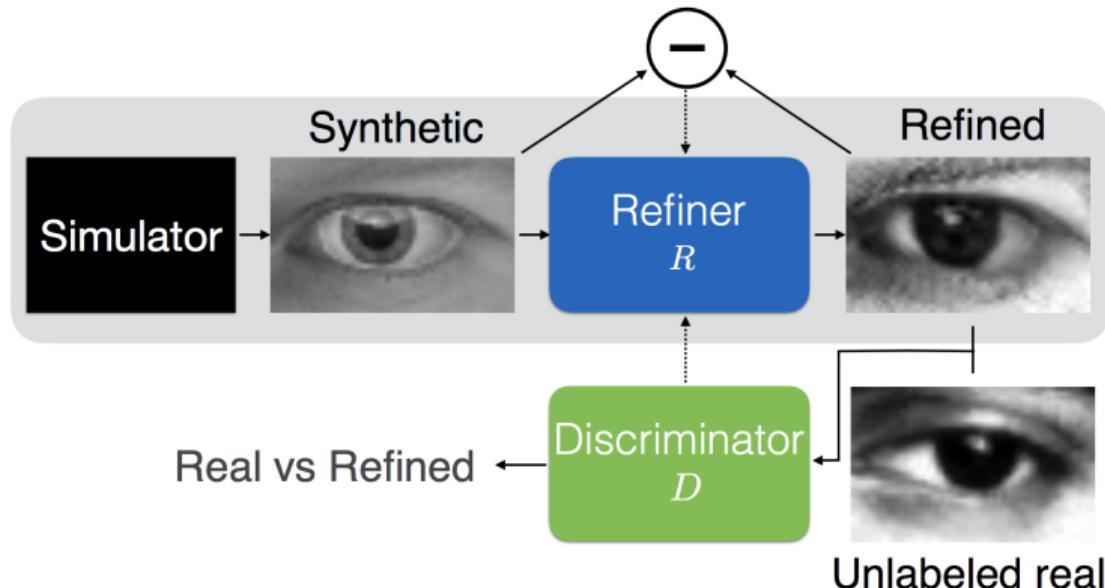
- Class criterion.
- Architecture criterion.

- Use pre-trained on ImageNet model as a universal feature extractor. and train a linear classifier (SVM) on extracted features.
- Fine-tune pre-trained model.

# Architecture criterion

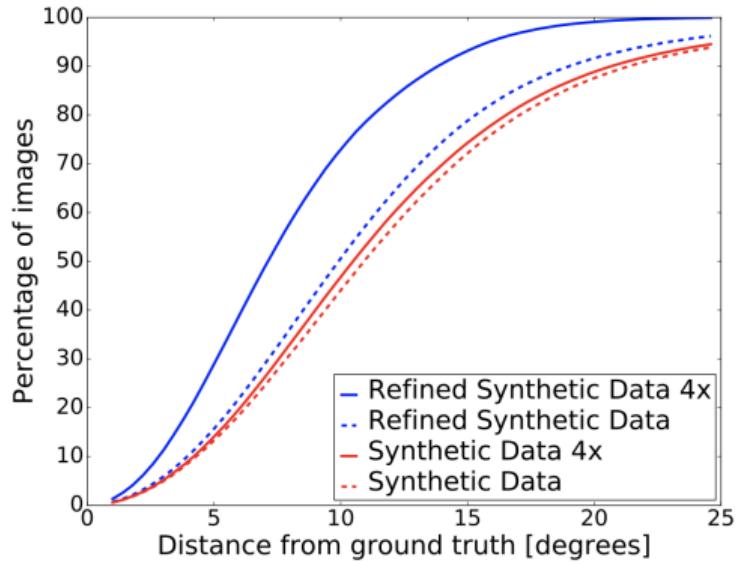


$$r_w(\theta_j^s; \theta_j^t) = \exp \left( \|\theta_j^s - \theta_j^t\|^2 \right) - 1$$



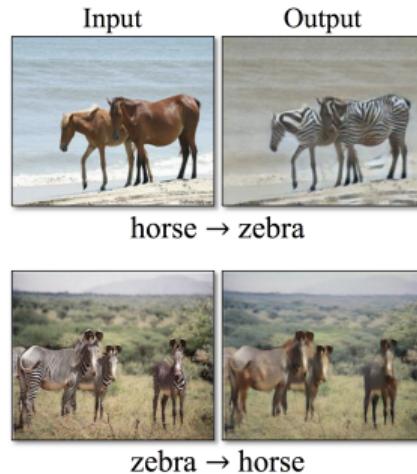
$$\begin{aligned} L_R(\theta) &= \sum_i \ell_{real}(\theta; x_i, Y) + \lambda \ell_{reg}(\theta; x_i) = \\ &= - \sum_i \log(1 - D_\phi(R_\theta(x_i))) + \\ &\quad + \lambda \|\psi(R_\theta(x_i)) - \psi(x_i)\| \end{aligned}$$

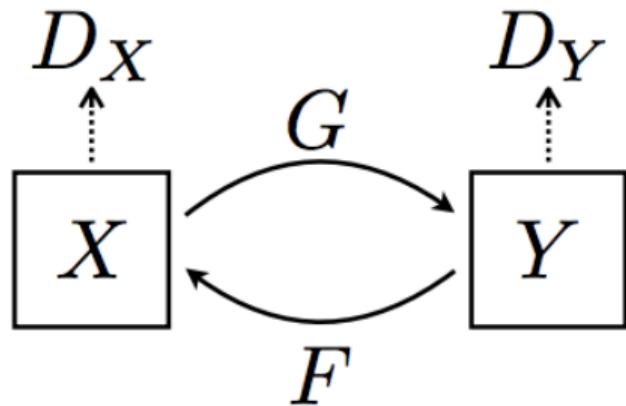
$\psi$  - identity or any other transformation.



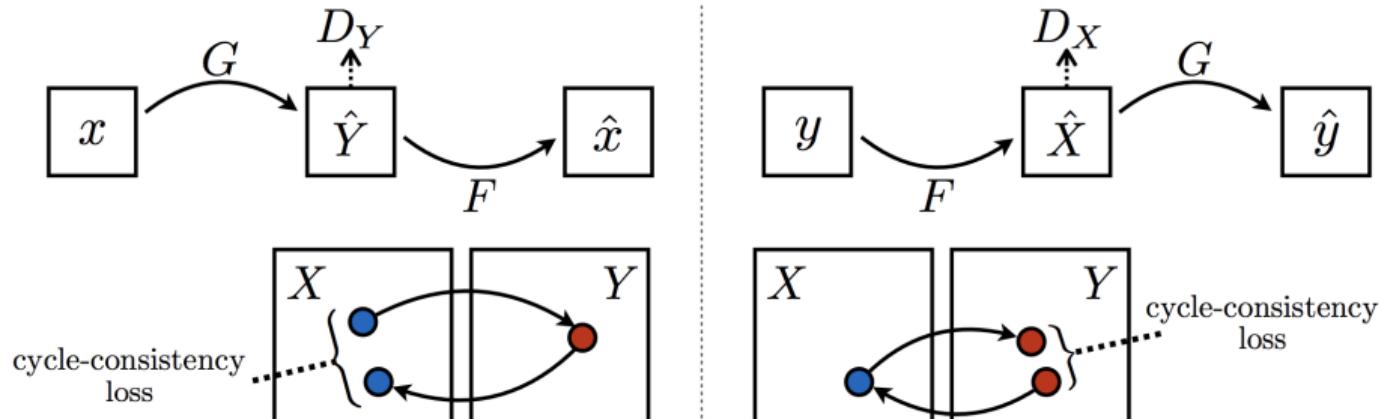
Method	R/S	Error
Support Vector Regression (SVR) [33]	R	16.5
Adaptive Linear Regression ALR) [23]	R	16.4
Random Forest (RF) [36]	R	15.4
kNN with UT Multiview [47]	R	16.2
CNN with UT Multiview [47]	R	13.9
k-NN with UnityEyes [43]	S	9.9
CNN with UnityEyes Synthetic Images	S	11.2
CNN with UnityEyes Refined Images	S	<b>7.8</b>

# CycleGAN





# CycleGAN



$$\begin{aligned} L(G, F, D_X, D_Y) = & L_{GAN}(G, D_Y, X, Y) + \\ & + L_{GAN}(F, D_X, Y, X) + \\ & + \lambda L_{cyc}(G, F) \end{aligned}$$

$$\begin{aligned} L_{GAN}(G, D_Y, X, Y) = & E_{y \sim p_{data}(Y)}[\log D_Y(y)] + \\ & + E_{x \sim p_{data}(X)}[\log(1 - D_Y(G(x)))] \end{aligned}$$

$$\begin{aligned} L_{cyc}(G, F) = & E_{x \sim p_{data}(X)}[||F(G(x)) - x||_1] + \\ & + E_{y \sim p_{data}(Y)}[||G(F(y)) - y||_1] \end{aligned}$$

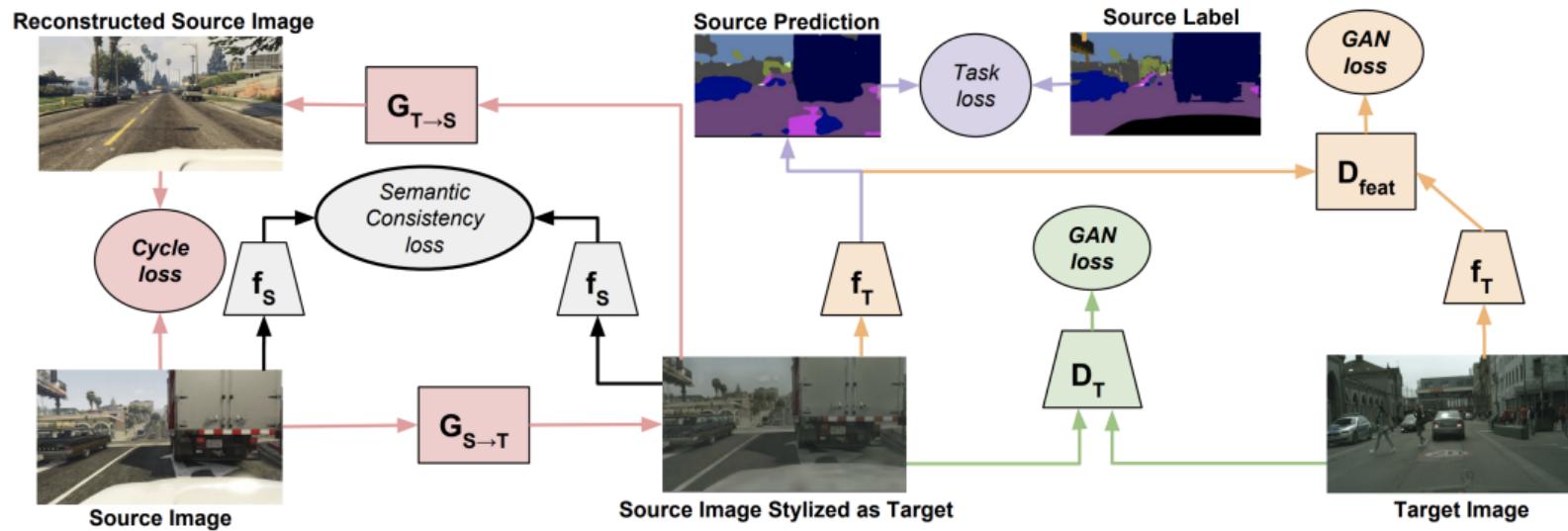
# CycleGAN

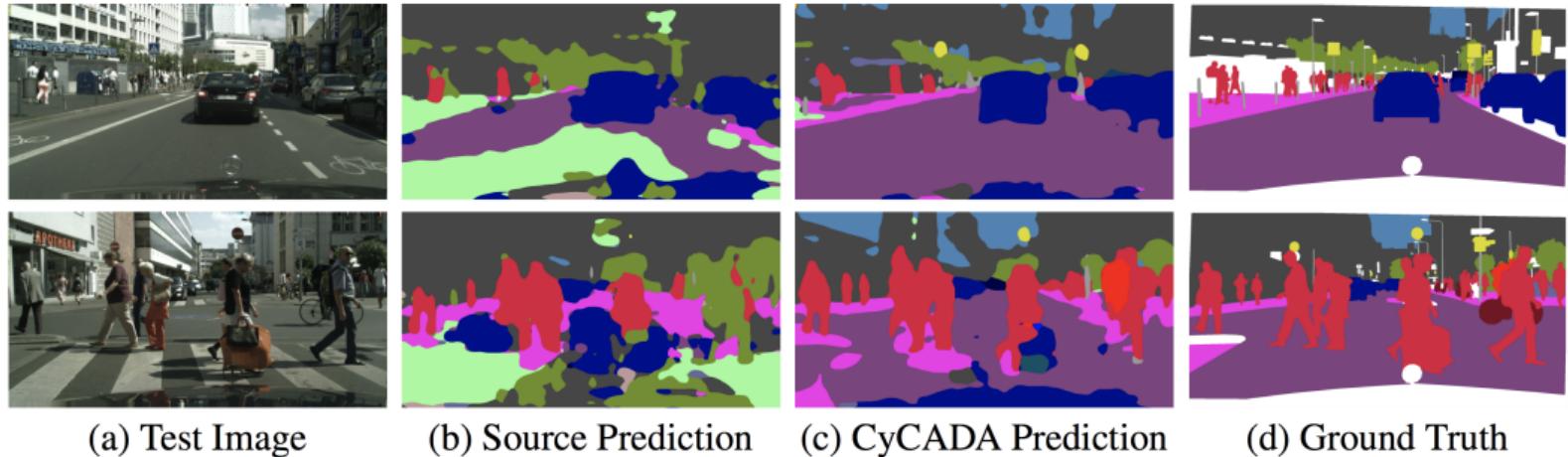


(c) Source



(d) Generated





$$L_{task}(f_S, X_S, Y_S) = -E_{(x_s, y_s) \sim (X_S, Y_S)} \sum_{k=1}^K \log(\sigma(f_S^{(k)}(x_s)))$$

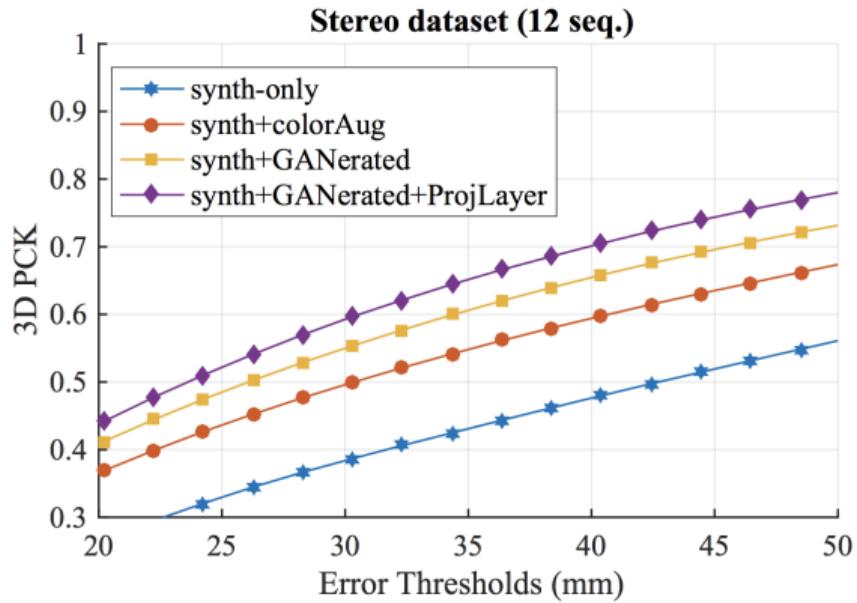
$$\begin{aligned} L_{sem}(G_{S \rightarrow T}, G_{T \rightarrow S}, X_S, X_T, f_S) = & L_{task}(f_S, G_{T \rightarrow S}(X_T), p(f_S, X_T)) + \\ & + L_{task}(f_S, G_{S \rightarrow T}(X_S), p(f_S, X_S)) \end{aligned}$$

Method	mIOU
Source only	21.7
CyCADA feat-only	31.7
CyCADA pixel-only	37
CyCADA pixel+feat	39.5

Synthetic CycleGAN GANerated Synthetic CycleGAN GANerated



- Based on CycleGAN.
- Extra cross-entropy loss for segmented images to preserve annotations.



# Domain adaptation

Thank You!