PAPER ANALYSIS

Presented by Yannis He

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Paper: **Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks**

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https://arxiv.org/pdf/1703.10593.pdf

OVERVIEW

Abstract:

- Contribution:
  - Approach for learning to translate an image from a source domain to a target domain in the absence of paired examples.
    - Learn mapping, G: X → Y, such that distribution of image from G(X) is indistinguishable from distribution Y using an adversarial loss.
  - Found that this *highly under-constrained* mapping can be inverse:
    - There exists F: Y→ X, such that F(G(X)) ≈ X

Intro:

- The translation can be made in the absence of any paired training examples
  - Assume there are underlying relationship between domains
  - Lack of supervision in forms of pairs
    - But can exploit supervision at level of sets
- Motivation:
  - Only a couple of datasets exist for semantic segmentation task
    - And those dataset are small
  - Obtaining input-output pairs are expensive
    - Some output are even not well-defined
      - E.g. zebra <-> horse

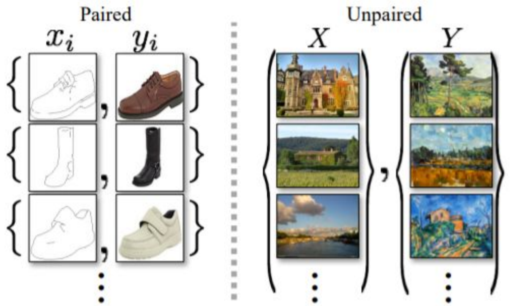


Figure 2: *Paired* training data (left) consists of training examples $\{x_i, y_i\}_{i=1}^N$, where the correspondence between x_i and y_i exists [22]. We instead consider *unpaired* training data (right), consisting of a source set $\{x_i\}_{i=1}^N$ ($x_i \in X$) and a target set $\{y_j\}_{j=1}^M$ ($y_j \in Y$), with no information provided as to which x_i matches which y_j.

OVERVIEW (CONT')

- Ideas:
  - First attempts
    - Using adversary train, to train a mapping G: X→Y, where $\tilde{\mathbf{y}}$ = G(x) & x∈X, such that $\tilde{\mathbf{y}}$ is indistinguishable from y∈Y
      - Ideally, we just obtained an $\tilde{\mathbf{Y}}$ that distributes identically to Y
      - However, such translation does not guarantee a meaningful pair-up
        - It is difficult to optimize adversarial objective in isolation
          - Often lead to "mode collapse"
  - Second attempts (our proposal)
    - Using two inverted translator: G: X→Y & F: Y→X, which should lead the mapping to be bijection
      - Train both mapping simultaneously
      - with a cycle consistency loss along with a adversarial loss on domains X and Y

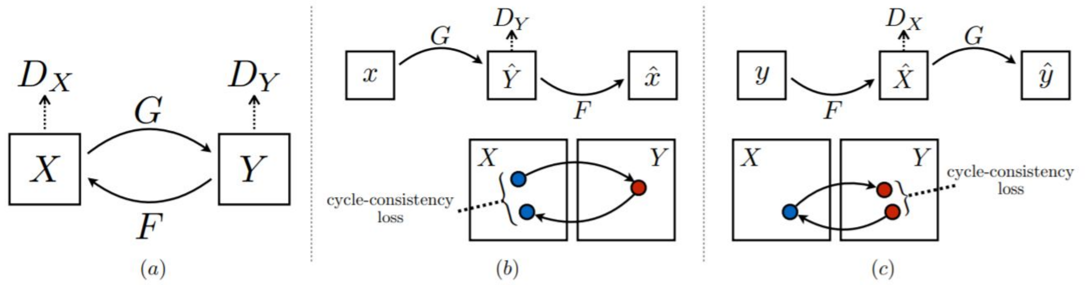


Figure 3: (a) Our model contains two mapping functions $G : X \to Y$ and $F : Y \to X$, and associated adversarial discriminators D_Y and D_X. D_Y encourages G to translate X into outputs indistinguishable from domain Y, and vice versa for D_X and F. To further regularize the mappings, we introduce two *cycle consistency losses* that capture the intuition that if we translate from one domain to the other and back again we should arrive at where we started: (b) forward cycle-consistency loss: $x \to G(x) \to F(G(x)) \approx x$, and (c) backward cycle-consistency loss: $y \to F(y) \to G(F(y)) \approx y$

RELATED WORK

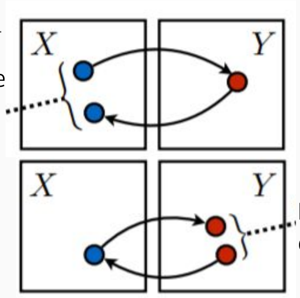
- Generative Adversarial Networks (GANs)
- Image-to-Image Translation
- Unpaired Image-to-Image Translation (some other approaches)
    - Bayesian framework including a prior based on a patch-based Markov random field
    - Weight-sharing strategy to learn common representation across domains
        - CoGAN
        - Cross-modal scene networks
    - Variational Autoencoders (VAEs) + GANs
    - * different from above approach, the proposed method does not rely on any task-specific, predefined similarity function, nor we assumed both domain lie in the same low-dimensional embedding space.
        - I.e. the proposed approach is **general-purpose solution**
- Cycle Consistency
    - Using transitivity as a way to regularize structured data
    - Back translation and reconciliation
        - Used in language translation by human and machines
    - High-order cycle consistency
        - Used from motion, 3D shape matching, co-segmentation, dense semantic alignment, etc.
    - Cycle consistency loss: a way of using transitivity to supervise CNN training (most similar to proposed method)
- Neural Style Transfer
    - Learning mapping between two collections rather than two specific images

FORMULATION

- Setup:
    - Two inverted mappings: G: X→Y & F: Y→X
    - Two adversarial discriminators: D_x and D_y
        - D_x aims to distinguish between images {x} and translated images {F(y)}
        - D_y aims to distinguish between images {y} and translated images {G(x)}
    - Objectives:
        - Adversarial losses: matching the distribution of generated images to the data distribution in target domains

$$\begin{aligned}\mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) &= \mathbb{E}_{y \sim p_{\text{data}}(y)}[\log D_Y(y)] \\ &+ \mathbb{E}_{x \sim p_{\text{data}}(x)}[\log(1 - D_Y(G(x))], \end{aligned} \tag{1}$$

        - Cycle consistency losses: prevent the learned mapping from contradicting each
            - Requires the functions to be cycle-consistent



$$\begin{aligned}\mathcal{L}_{\text{cyc}}(G, F) &= \mathbb{E}_{x \sim p_{\text{data}}(x)}[\|F(G(x)) - x\|_1] \\ &+ \mathbb{E}_{y \sim p_{\text{data}}(y)}[\|G(F(y)) - y\|_1]. \end{aligned} \tag{2}$$

- Overall objectives:

$$\begin{aligned}\mathcal{L}(G, F, D_X, D_Y) =& \mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) \\ &+ \mathcal{L}_{\text{GAN}}(F, D_X, Y, X) \\ &+ \lambda \mathcal{L}_{\text{cyc}}(G, F), \end{aligned} \tag{3}$$

$$G^*, F^* = \arg \min_{G,F} \max_{D_x, D_Y} \mathcal{L}(G, F, D_X, D_Y). \tag{4}$$

IMPLEMENTATION

- Network Architecture:
    - 3 Convolutions, several residual blocks
    - 2 fractionally-strided convolution with ½ stride
    - 1 convolution that maps features to RGB
- Implementation:
    - Use 6 blocks for 128 x 128 images and 9 blocks for 256 x 256 and higher-resolution training images
    - Use instance normalization
    - Use 70 x 70 PatchGANs for discriminator networks
        - To classify whether 70 x 70 overlapping image patches are real or fake
- Training
    - Two training techniques to stabilize our model training procedure
        - Fro L_{GAN} (eqn 1), we use least-square instead of negative log likelihood since the former is more stable in this case
        - To reduce model oscillation, we update discriminator using a history of generated images rather than the one produced by the latest generators. (the authors keep an image buffer that stores 50 previously created images)
    - λ = 10 is used in eqn 3
    - Adam solver
    - batch_size = 1
    - lr = 0.0002 (for first 100 epochs) and linearly decay to 0 over the next 100 epoches

RESULTS

- Evaluation:
  - Metrics: pix2pix, FCN Score, Semantic segmentation metrics
  - Baseline: CoGAN, SimGAN, Feature loss + GAN, BiGAN/ALI, pix2pix
- Analysis:
  - Both GAN loss and cycle-consistency loss are important
  - Bidirectional are important. Single directional leads to mode collapse
  - Image resolutions would not drop during the transformation
- Applications:
  - Collection style transfer
  - Object transfiguration
  - Season transfer
  - Photo generation from paintings
  - Photo enhancement
- Limitations and Discussion:
  - Results are far from uniformly positive
    - Good at: tasks involving color and texture changes
    - Not good at: tasks involving geometric changes
  - Some failure caused by distribution characteristics of the training datasets
  - Lingering gap between paired training data vs unpaired method
    - Potential solution: integrating weak or semi-supervised data