COURS RDFIA deep Image

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Course Outline – Week timeline

1. **Computer Vision basics**: Visual (local) feature detection and description, Bag of Word Image representation

2. **Supervised learning**: Introduction to Neural Networks (NNs)

3. **Machine Learning basics**: Risk, Classification, Datasets, benchmarks and evaluation, Linear classification (SVM)

4. Convolutional Nets for visual classification

5. Large deep convnets

6. Beyond ImageNet

7. Transfer learning and domain adaptation

8. Attention and Vision Transformers

9. Generative models with GANs

10. **Generative models with conditional GANs**

11. Final remarks / Control on course

12/14 Bayesian deep learning
Generative models

Outline

1. Preview: Auto-Encoders, VAE
2. Generative models with GAN
3. GAN architectures
4. Editing
5. Conditional GANs
Generative models

Outline

1. Preview: Auto-Encoders, VAE
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5. Conditional GANs
   1. Principle
Motivation

Prior distribution $z$

c: train

Generator

Text

this white and yellow flower have thin white petals and a round yellow stamen

Generator

Image

Image

Generator

Image
Conditional GAN

- **Text to image** by traditional supervised learning

\[ c^1: \text{a dog is running} \quad \hat{x}^1: \]

\[ c^2: \text{a bird is flying} \quad \hat{x}^2: \]

Text: “train”

Target of NN output

A blurry image!
Conditional GAN

Prior distribution $z \xrightarrow{} G \xrightarrow{} \text{Image} \quad x = G(c,z)

$c$: train

Text: “train”
Conditional GAN

Prior distribution $z$ $\xrightarrow{c: \text{train}} G$ $\xrightarrow{\text{Image}} x = G(c,z)$

$x$ is realistic or not $\xrightarrow{\text{D (type 1)}} \xrightarrow{\text{scalar}}$

$x$ is realistic or not + $c$ and $x$ are matched or not $\xrightarrow{\text{D (type 2)}} \xrightarrow{\text{scalar}}$

Positive example: (train, train) (cat, cat)

Negative example: (train, Image) (cat, Image)
Conditional GAN (CGAN model)

\[
\min_G \max_D \left( \mathbb{E}_{x,y \sim p_{\text{data}}(x,y)} \left[ \log D(x, y) \right] + \mathbb{E}_{y \sim p_y, z \sim p_z(z)} \left[ \log(1 - D(G(z, y), y)) \right] \right)
\]
Generative models

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5. **Conditional GANs**
   1. Principle
   2. Text2Image
Text2Image: architecture example

- Positive samples:
  - real image + right texts

- Negative samples:
  - fake image + right texts
  - Real image + wrong texts

[Reed et al. ICML 2016]
Text2Image results

This small bird has a pink breast and crown, and black primaries and secondaries.

This magnificent fellow is almost all black with a red crest, and white cheek patch.

The flower has petals that are bright pinkish purple with white stigma.

This white and yellow flower have thin white petals and a round yellow stamen.
## Text2Image results

<table>
<thead>
<tr>
<th>Caption</th>
<th>Image</th>
</tr>
</thead>
<tbody>
<tr>
<td>this flower has white petals and a yellow stamen</td>
<td><img src="image1.png" alt="Image Examples" /></td>
</tr>
<tr>
<td>the center is yellow surrounded by wavy dark purple petals</td>
<td><img src="image2.png" alt="Image Examples" /></td>
</tr>
<tr>
<td>this flower has lots of small round pink petals</td>
<td><img src="image3.png" alt="Image Examples" /></td>
</tr>
</tbody>
</table>
Text2Image: architecture example (2)

StackGAN: similar idea with LapGan to generate higher resolution images

Figure 2. The architecture of the proposed StackGAN. The Stage-I generator draws a low-resolution image by sketching rough shape and basic colors of the object from the given text and painting the background from a random noise vector. Conditioned on Stage-I results, the Stage-II generator corrects defects and adds compelling details into Stage-I results, yielding a more realistic high-resolution image.

[Zhang et al. 2016]
StackGAN results

(a) Stage-I images

This bird has a yellow belly and tarsus, grey back, wings, and brown throat, nape with a black face

This bird is white with some black on its head and wings, and has a long orange beak

This flower has overlapping pink pointed petals surrounding a ring of short yellow filaments

(b) Stage-II images

[Zhang et al. 2016]
## Text2Image results

<table>
<thead>
<tr>
<th>Caption</th>
<th>Image</th>
</tr>
</thead>
<tbody>
<tr>
<td>a pitcher is about to throw the ball to the batter</td>
<td><img src="image1.png" alt="Image examples" /></td>
</tr>
<tr>
<td>a group of people on skis stand in the snow</td>
<td><img src="image2.png" alt="Image examples" /></td>
</tr>
<tr>
<td>a man in a wet suit riding a surfboard on a wave</td>
<td><img src="image3.png" alt="Image examples" /></td>
</tr>
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   3. Image2Image
Image-to-Image Translation **pix2pix**

- Conditioned on an image of different modality
- No need to specify the loss function

[Isola et al. CVPR 2017]
Image-to-image pix2pix

\[ x = G(z | c) \]

https://arxiv.org/pdf/1611.07004
Image-to-image pix2pix

• Traditional supervised approach

Testing:

It is blurry because it is the average of several images.
Image-to-image

• Conditional GAN

Testing:

input  close  GAN  GAN + close  GT
Positive examples

Real or fake pair?

D

G tries to synthesize fake images that fool D

D tries to identify the fakes

Negative examples

Real or fake pair?

D

G
Label2Image

Isola et al. CVPR 2017
Edges2Image

[Isola et al. CVPR 2017]
Pix2pixHD [CVPR 2018]

High-Resolution Image Synthesis and Semantic Manipulation with Conditional GANs
Ting-Chun Wang, Ming-Yu Liu, Jun-Yan Zhu, Andrew Tao, Jan Kautz, Bryan Catanzaro
Pix2pixHD [CVPR 2018]

Coarse-to-fine Generator

Multi-scale Discriminators

Robust Objective

Residual blocks

real

synthesized

real

synthesized

real

match

D_1

D_2

D_3

D_i

D_i

match

match
Results

• Qualitative comparisons
Improving Segmentation2Image strategy

[SPADE: Semantic Image Synthesis with Spatially-Adaptive Normalization, CVPR19]
Improving Segmentation2Image strategy

Previous approach:

Directly feed the semantic layout as input to the deep network, which is processed through stacks of convolution, normalization, and nonlinearity layers.

However, this is suboptimal as the normalization layers tend to “wash away” semantic information in input semantic segmentation masks.
Proven effective for recent generative adversarial networks such as StyleGAN.

Can we do the same for conditional GAN?

**Conditional Normalization Layers?**

Improving Segmentation2Image strategy
Improving Segmentation2Image strategy

Recall: Adaptive instance normalization

\[ \text{AdalIN}(x, y) = \sigma(y) \left( \frac{x - \mu(x)}{\sigma(x)} \right) + \mu(y) \]

SPADE block = spatially-adaptive denormalization:
Same idea but per class c over each channel i (N=batch size)

\[ \gamma_{c, y, x}(m) \frac{h_{n, c, y, x} - \mu_c^i}{\sigma_c^i} + \beta_{c, y, x}(m) \]

\[ \mu_c^i = \frac{1}{NH_i W_i} \sum_{n, y, x} h_{n, c, y, x} \]

\[ \sigma_c^i = \sqrt{\frac{1}{NH_i W_i} \sum_{n, y, x} (h_{n, c, y, x} - \mu_c^i)^2} \]

SPADE paper = [Semantic Image Synthesis with Spatially-Adaptive Normalization CVPR 2019]
SPADE Generator
SPADE Generator

Better preserve semantic information against common normalization layers
SPADE results
SPADE with real image:
[OASIS iclr 2021] (follow-up paper of SPADE) with real image:
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   4. Inpainting and general missing data encoder
Inpainting task

• Complete the missing part
Inpainting as unsupervised learning with GAN loss

Reconstruct missing pixels by decoding using context
Loss defined on the predicted patch and the real one (known at training time)
First proposition -- Architecture

- Architecture: Encoder/Fully connected/Decoder

- DC-GAN for inpainting task
- Input: 227 × 227 × 3 image
- Output: encoder context features (6 × 6 × 256)
Channel-wise fully-connected layer

- **Input / output:** $6 \times 6 \times 256$ channels
- **First layer:** Channel-wise fully-connected (each $6 \times 6$ input connected to the corresponding $6 \times 6$ output)
- **Second layer:** Stride 1 convolution to mix channels

Decoder

- **Architecture:** Same as DC-GAN: 5 up-convolutional layers ("deconv" + ReLU)
- **Input:** decoder context features $6 \times 6 \times 256$
- **Output:** $227 \times 227 \times 3$ image
Training: Masking the images

- **How to define the mask?**
  - Center region of the image
  - Random regions (chosen solution)
  - Random segmentation mask from VOC (said to be equivalent to random regions)

- **Formal definition:** Defined by a mask $\hat{M} \in \{0, 1\}^{227 \times 227}$ with 1 if the pixel should be masked
Training: Loss - Overview

- Trained completely from scratch to fill-up the masked areas
- **Problem:** multiple plausible solutions
- **Solution:** combining 2 losses:
  - $\mathcal{L}_{rec}$ **L2 reconstruction loss:** learn the structure of the missing region (average multiple modes in prediction)
  - $\mathcal{L}_{adv}$ **Adversarial loss:** make it look real (pick a mode from the distribution)

$$\min_F \mathcal{L} = \lambda_{rec} \mathcal{L}_{rec} + \lambda_{adv} \mathcal{L}_{adv}$$

$$\mathcal{L}_{rec}(x) = \left\| \hat{M} \odot \left( x - F((1 - \hat{M}) \odot x) \right) \right\|_2$$

$$\mathcal{L}_{adv} = \max_D \mathbb{E}_{x \in \mathcal{X}} \left[ \log(D(x)) + \log \left( 1 - D(F((1 - \hat{M}) \odot x)) \right) \right]$$

- Rq: The encoder-decoder is the generator, D is a CNN
Results

Dataset: StreetView Paris and ImageNet
Semantic inpainting - Qualitative results
Generalizing inpainting: missing data encoder

1. Inpainting
2. Reverse inpainting
3. Colorization
4. Random extrapolation
5. Random extrapolation + colorization

Original image

Generator

Completed image
Adding perceptual loss, BB regression loss

\[ r^c = \left( \frac{x^c}{W}, \frac{y^c}{H}, \frac{x^c + w^c}{W}, \frac{y^c + h^c}{H} \right) \]

\[ \mathcal{L}_{\text{disc}}^H (\theta_d) = \frac{1}{N} \sum_{i=1}^{N} \sum_{c=1}^{C} \| r_i^c - \hat{r}_i^c (\theta_g, \theta_d) \| \]

\[ \mathcal{L}_{\text{gen}}^H (\theta_g) = \frac{1}{N} \sum_{i=1}^{N} \sum_{c=1}^{C} \| q_i^c - \hat{q}_i^c (\theta_g, \theta_d) \| \]

\[ \mathcal{L}_{\text{tot}} (\theta_g, \theta_d) = \mathcal{L}_{\text{rec}} (\theta_g) + \lambda_{\text{compl}} \mathcal{L}_{\text{compl}}^{vgg} (\theta_g) + \lambda_{\text{adv}} \mathcal{L}_{\text{adv}} (\theta_g, \theta_d) + \lambda_H \mathcal{L}_{\text{coord}}^H (\theta_g, \theta_d) \]
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   5. Learning unpaired Transformation
Unpaired Transformation - Cycle GAN, Disco GAN

Transform an object from one domain to another **without paired data**
Cycle GAN

https://arxiv.org/abs/1703.10593
https://junyanz.github.io/CycleGAN/

Domain X

\[ G_{X \rightarrow Y} \]

ignore input

Input image belongs to domain Y or not

Domain Y

Become similar to domain Y

Not what we want

\[ D_Y \rightarrow \text{scalar} \]
Cycle GAN

Domain X

$G_{X\rightarrow Y}$

as close as possible

$D_Y$

scalar

Input image belongs to domain Y or not

Lack of information for reconstruction

Domain Y

Domain Y

Input image belongs to domain Y or not

as close as possible

$G_{Y\rightarrow X}$
Cycle GAN

Domain X

as close as possible

Domain Y

as close as possible

$G_{X \rightarrow Y}$

$G_{Y \rightarrow X}$

$D_X$

$D_Y$

scalar: belongs to domain X or not

scalar: belongs to domain Y or not
Results -- Cycle GAN

domain X

Monet 🔄 Photos

Zebras 🔄 Horses

Summer 🔄 Winter

Monet → photo

photo → Monet

horses → zebra

summer → winter

winter → summer
GANs: works in progress
A lot of things to better understand, to use, adapt, ...
Appendix
GANs for Video, 3D, etc.
Video GAN


[Vondrick et al. NIPS 2016]
Shape modeling using 3D Generative Adversarial Network

[Image: Diagram showing the process of shape modeling using a 3D Generative Adversarial Network, from input space to output space with intermediate layers.

[Wu et al. NIPS 2016]