[Deep Learning Seminar]
Season 2 : Deep Learning Paper Review

# Learning to Discover Cross-Domain Relations with Generative Adversarial Networks

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Introduction	Model			Experiment		
	Baseline Models	:	DiscoGAN	Toy Experiment	Real Domain Experime	nt

#### Introduction

- "비슷한 스타일(Similar style)"을 이해하는 것은 사람에게는 아주 쉬운 일.
- 즉, 서로 다른 도메인의 데이터에서 관련성
   (Cross-domain relation)을 찾아내는 것을 사람은 쉽게 할 수 있음.

Baseline Models

■ 오른쪽 예시

• 공통점 : 비슷한 스타일/질감

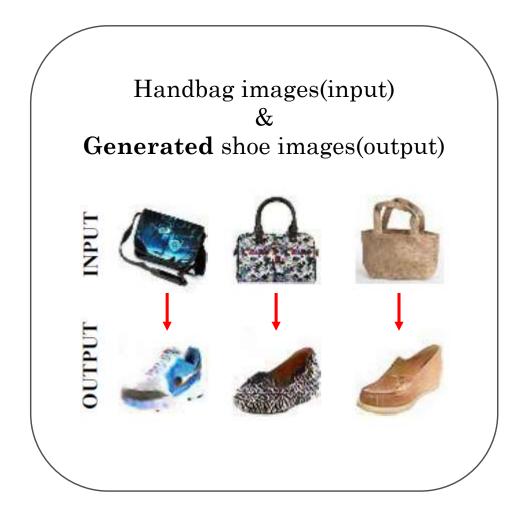
• 차이점 : 도메인(가방/신발)



DiscoGAN

#### Introduction

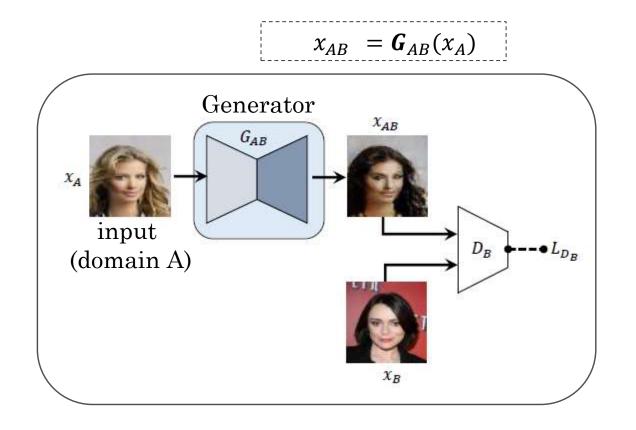
- 서로 다른 도메인의 두 이미지의 연관성을 찾 는 것을 학습시키려면 어떻게 해야 할까?
- →이 논문에서는 "Cross domain relation discovery" 문제를 해결하는 것이 조건부 이미지 생성 문제(conditional image generation)를 해결하는 것과 같다고 생각함.



#### Model - Baseline models

#### Standard GAN

- Relation Discovery Task 를 위해 가장 먼저 시도한 모델.
- 기존 GAN 은 이미지를 생성해주는 Generator 의 input으로 Gaussian noise를 사용하지만, 이 논문에서는 GAN의 input으로 이미지 자체를 사용.
- 이러한 모델을 이용하면 오직 한쪽 방향
   (domain A → domain B)으로만 학습이 가능함.



#### Model - Baseline models

- GAN with reconstruction loss
  - Standard GAN 모델에 Reconstruction 단계  $(G_{RA})$ 를 추가해준 모델.
    - $\checkmark L_{GAN_{B}}$ : Standard GAN□| generator Loss
    - $\checkmark L_{CONST_A}$ : Reconstruction Loss

realistic?

■ Standard GAN Loss와 Reconstruction Loss를 동시에 최적화해주는 식으로 학습 진행.

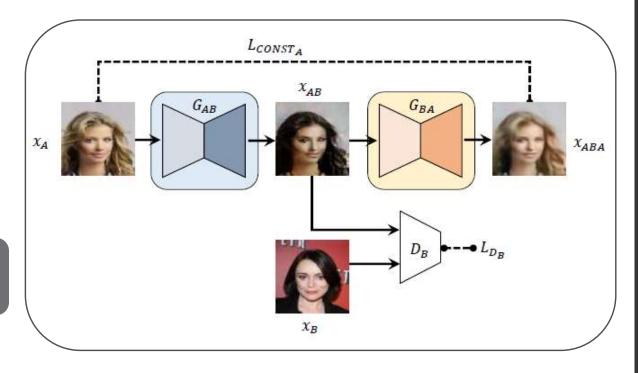
$$\checkmark L_{G_{AB}} = L_{GAN_B} + L_{CONST_A}$$
 How much similar?

$$x_{AB} = \mathbf{G}_{AB}(x_A)$$

$$x_{ABA} = \mathbf{G}_{BA}(x_{AB}) = \mathbf{G}_{BA} \circ \mathbf{G}_{AB}(x_A)$$

$$L_{CONST_A} = d(\mathbf{G}_{BA} \circ \mathbf{G}_{AB}(x_A), x_A)$$

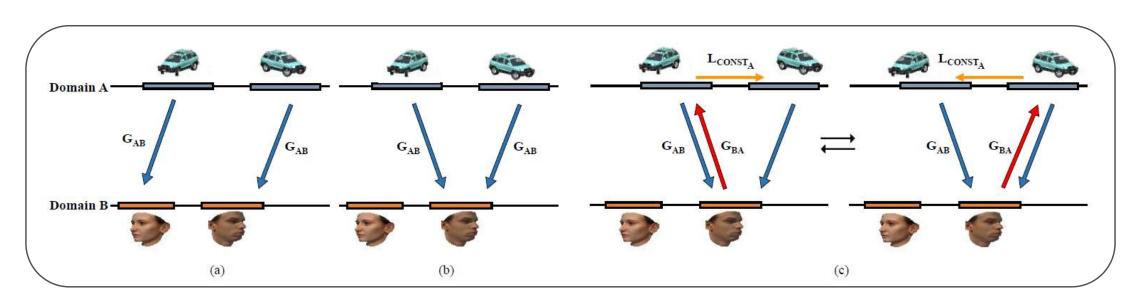
$$L_{GAN_B} = -\mathbb{E}_{x_A \sim P_A}[\log \mathbf{D}_B(\mathbf{G}_{AB}(x_A))]$$



#### Model - Baseline models

- 한계점 : 한 방향(injection, not bijection)으로만 학습하기 때문에 Cross-Domain relation이 보장되지 않음.
  - → Mode collapse 현상

- (a) ideal mapping
- (b) GAN model failure
- (c) GAN with reconstruction model failure



#### Model - DiscoGAN

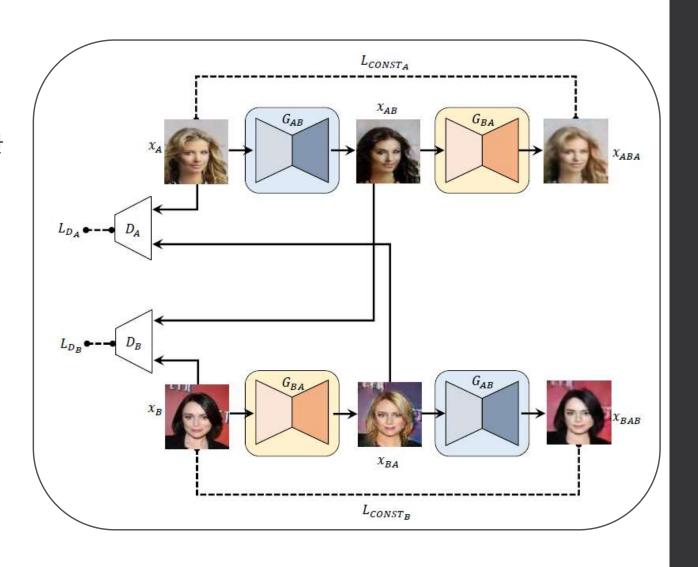
#### Discovery GAN

- GAN with reconstruction 모델 2개를 결합한 형태의 모델.
- 2개의 신경망이 동시에 학습되며 파라미터를 공유하기 때문에 bijective mapping 가능.
- 즉, Cross-domain relation discover.

$$L_G = L_{GAB} + L_{GBA}$$

$$= L_{GAN_B} + L_{CONST_A} + L_{GAN_A} + L_{CONST_B}$$

$$\bullet L_D = L_{D_A} + L_{D_B}$$

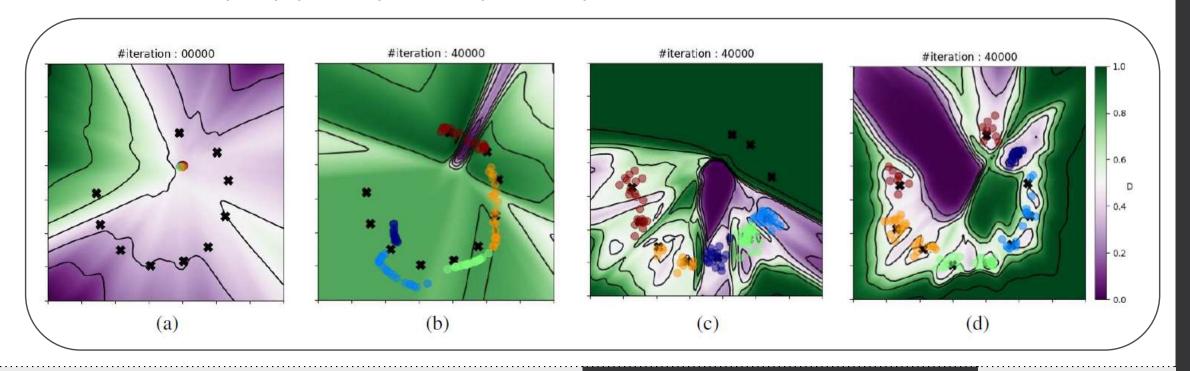


Real Domain Experiment

## Experiment – Toy experiment

- Background color : discriminator □ output
- 'x' 마크 : B 도메인의 특정 모드(mode)
- color 점 : A 도메인에서 B 도메인으로 매핑한 결과

- (a) initial state
- (b) standard GAN
- (c) GAN with reconstruction
- (d) DiscoGAN

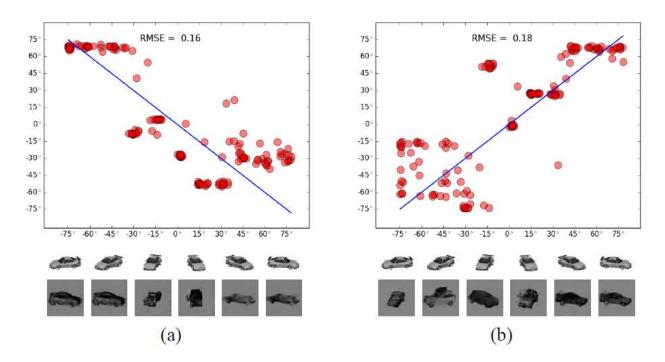


Conclusion

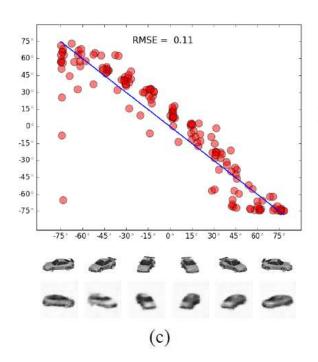
DiscoGAN

Baseline Models

- Mode collapse 현상 해결
  - Car to Car translation experiment

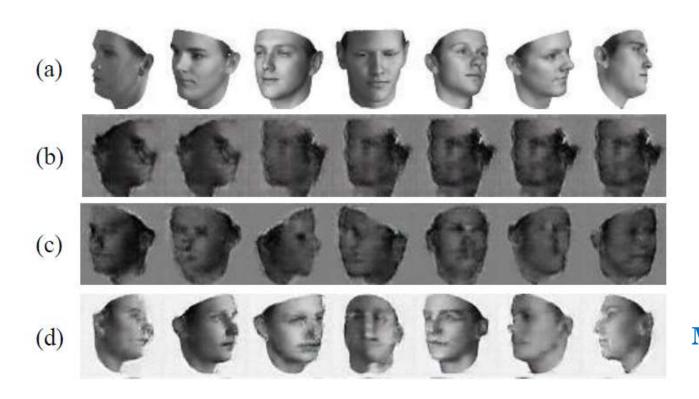


- (a) standard GAN
- (b) GAN with reconstruction
- (c) DiscoGAN



Correlation 가장 높음 = Mode collapse 현상 해결

- Mode collapse 현상 해결
  - Face to Face translation experiment



- (a) input face image
- (b) standard GAN
- (c) GAN with reconstruction
- (d) DiscoGAN

Mode collapse 현상 해결

DiscoGAN

- 도메인 간 거의 모든 feature 공유
  - Face conversion

- (a) gender translation
- (b) gender translation with background



## $Experiment-{\tt Real\ domain\ experiment}$

- 도메인 간 거의 모든 feature 공유
  - Face conversion

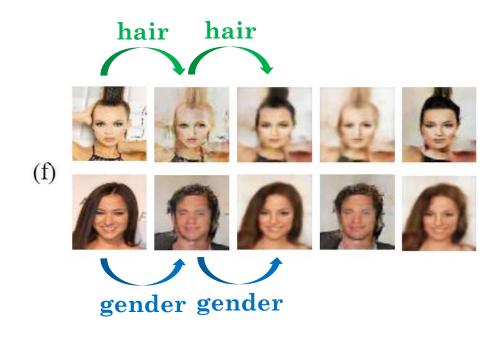
- (c) hair color translation
- (d) eyeglasses translation



- 도메인 간 거의 모든 feature 공유
  - Face conversion



- (e) sequence of conversion of gender and hair
- (f) repeatedly applying same conversions

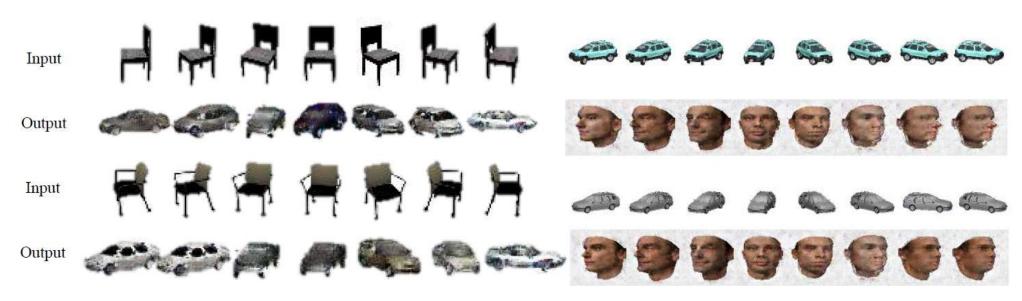


Baseline Models

**Experiment** 

- 도메인 간 feature 1개만 공유
  - Chair to Car
     Car to Face

    "바라보는 방향" 이라는 feature 하나만 같다.



(a) Chair to Car

(b) Car to Face

**Experiment** 

	Conclusion
+	

Baseline Models

- 1-to-N problem
  - Edge-to-Photos



- (a) sketches of bags to colored image
- (b) sketches of shoes to colored image

Conclusion

(c) colored image to sketches

- 도메인 간 공유된 explicit feature 없음(visually very different)
  - Handbag to Shoes
  - Shoes to Handbag



(b) Handbag images (input) & Generated shoe images (output)



(c) Shoe images (input) & Generated handbag images (output)

- 논문이 소개한 것
  - A learning method to discover cross-domain relations with a generative adversarial network called DiscoGAN.
  - Without any explicit pair labels
  - Learn to relate datasets from very different domains
- 결론
  - DiscoGAN은 스타일 변화된 high-quality 이미지를 생성해낼 수 있다.
- 코드 예시
  - SK T-Brain official : <a href="https://github.com/SKTBrain/DiscoGAN">https://github.com/SKTBrain/DiscoGAN</a>
  - carpedm20(김태훈): <a href="https://github.com/carpedm20/DiscoGAN-pytorch">https://github.com/carpedm20/DiscoGAN-pytorch</a>

Introduction	Model	Experiment	
	: Baseline Models : DiscoGAN	Tov Experiment Real Domain Experiment	Conclusion

# Thank you