A Simple Framework for Contrastive Learning of Visual Representations

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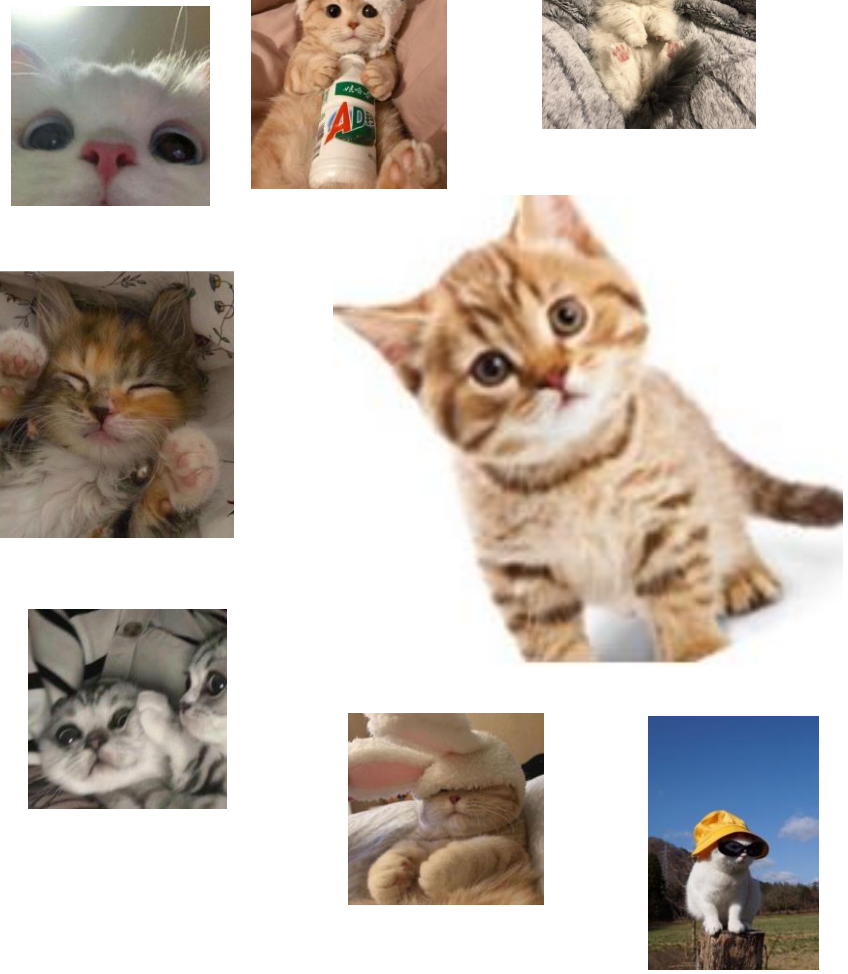
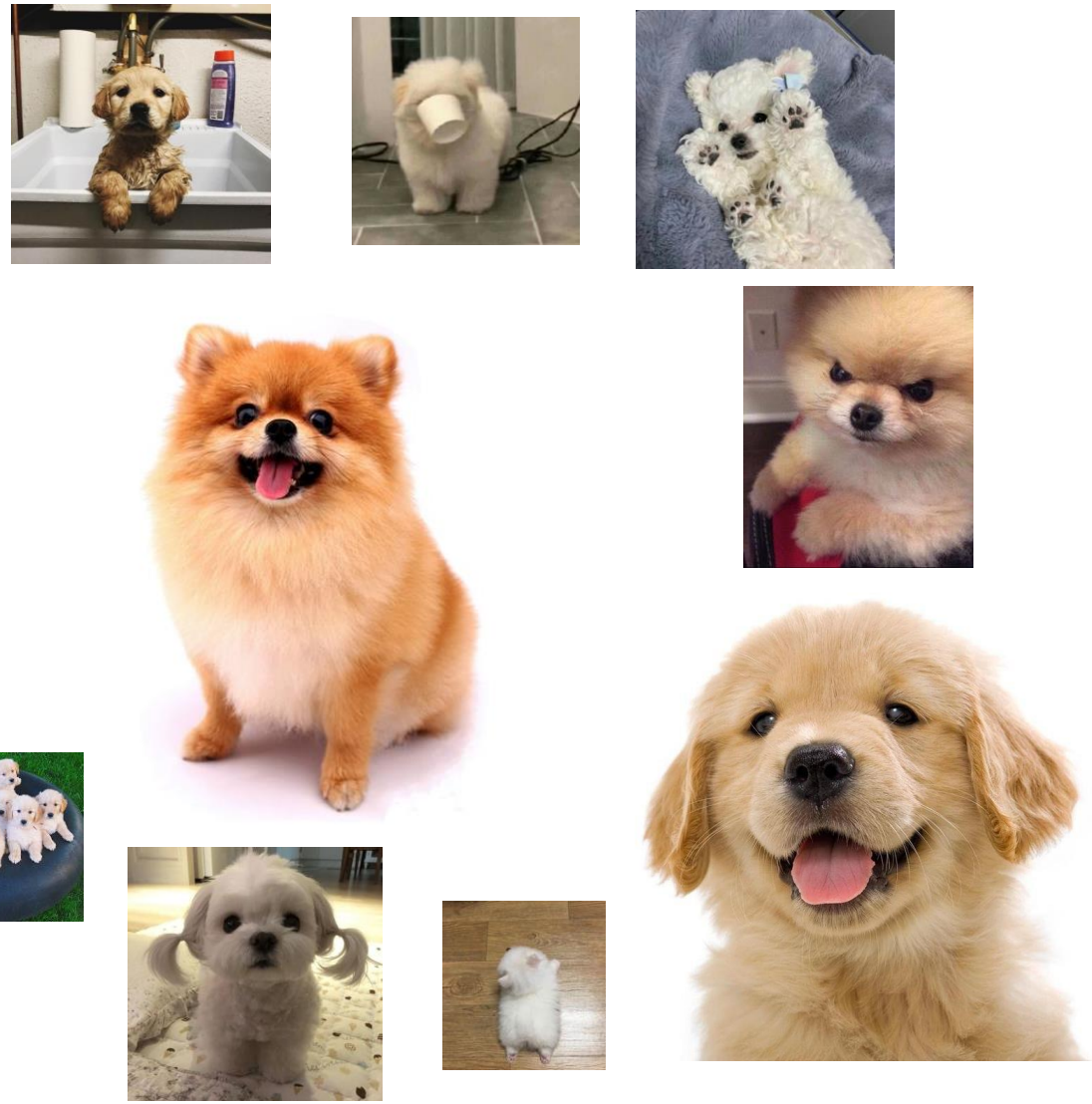
01. Introduction

01. Introduction : Representation Learning

How to Solve Cats VS Dogs problem?

01. Introduction : Representation Learning





01. Introduction : Representation Learning

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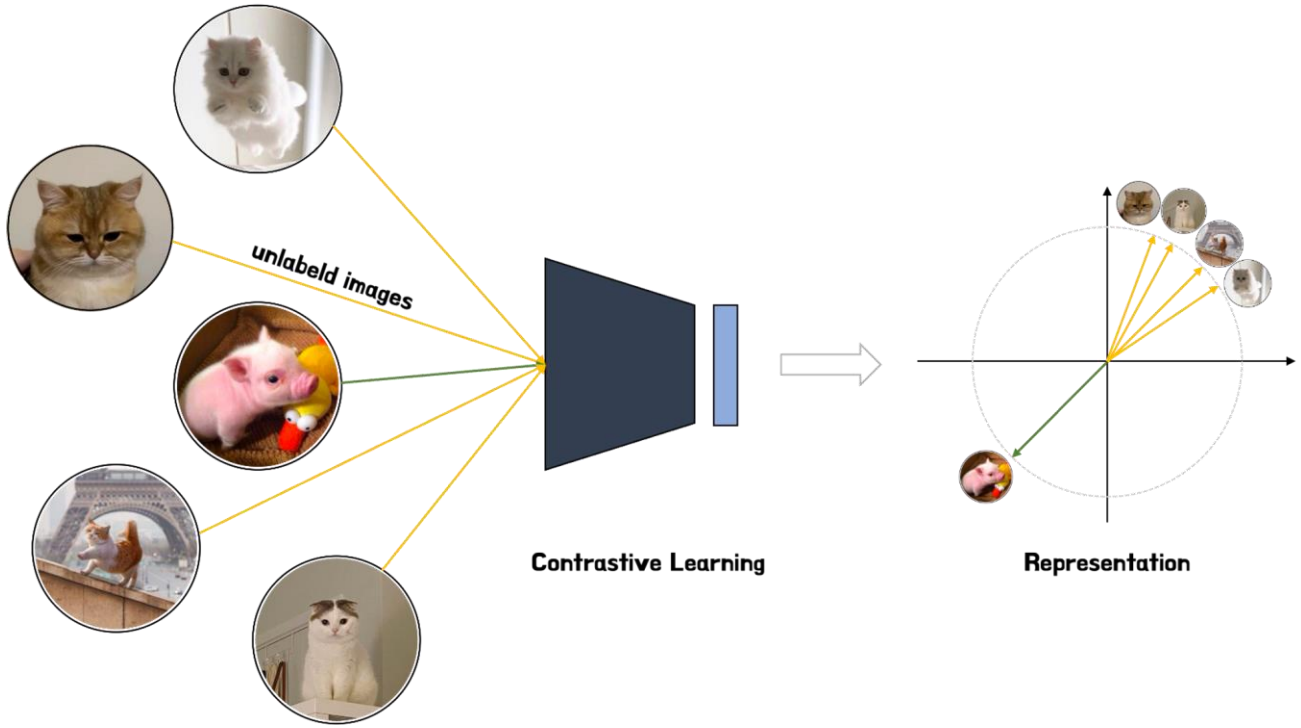
01. Introduction : Contrastive Learning

◇ Contrastive Learning

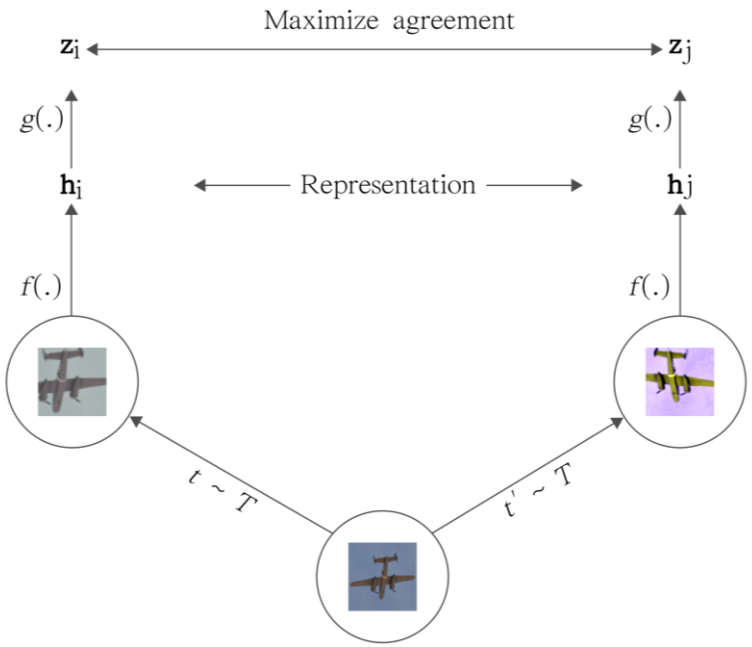
- 유사한 이미지가 저차원 공간에서 서로 가깝게, 다른 이미지는 서로 멀리 떨어져 있도록 저차원 공간에서 이미지를 인코딩하는 방법을 모델이 학습하는 것을 의미



01. Introduction : SimCLR

◇ A Simple Framework for Contrastive Learning of Visual Representations (SimCLR)
- 비슷한 이미지끼리는 이미지를 더 가까운 벡터로,
- 다른 이미지와는 더 먼 벡터로 만들어 주는 모델

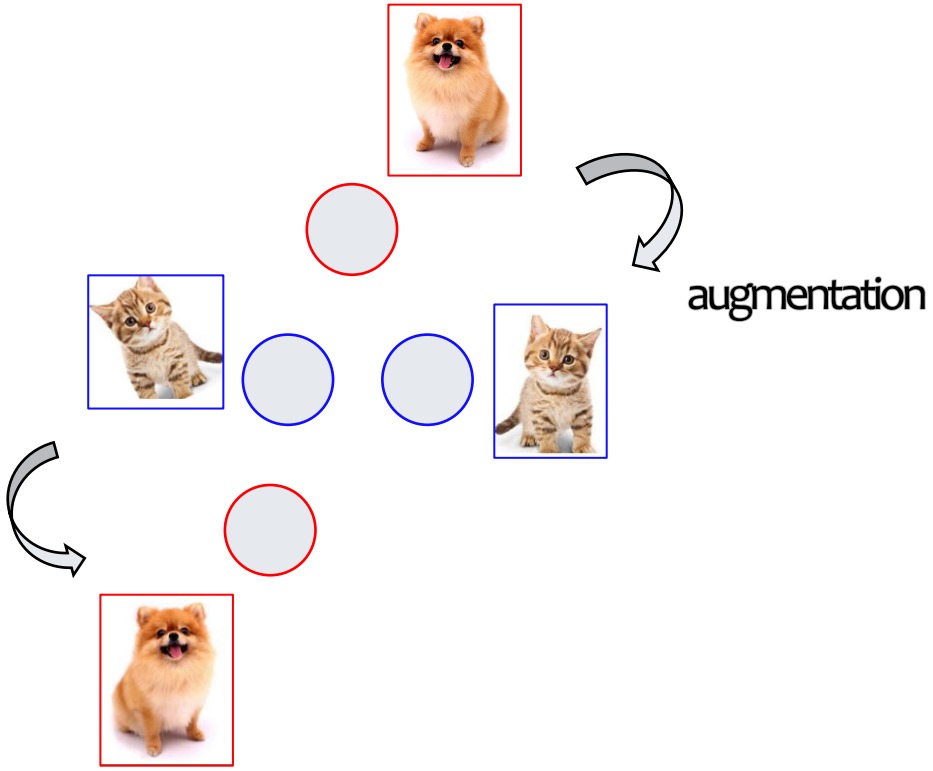
◇ 연구 내용
- Data augmentation을 활용한 representation learning
- Nonlinear transformation을 사용한 contrastive loss 설정
- Batch size와 contrastive learning의 관계



02. Design

02. Design: Overview

- Data augmentaion을 활용한 contrastive learning
  - Positive(cat) samples
  - Negative(dog) samples



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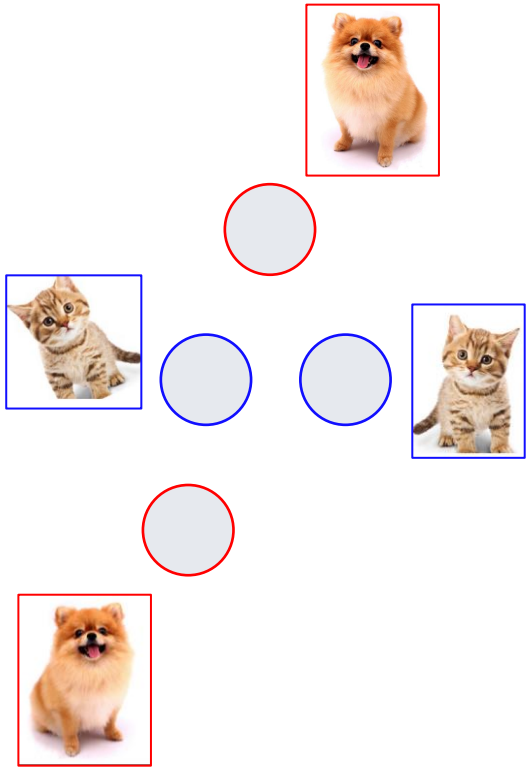
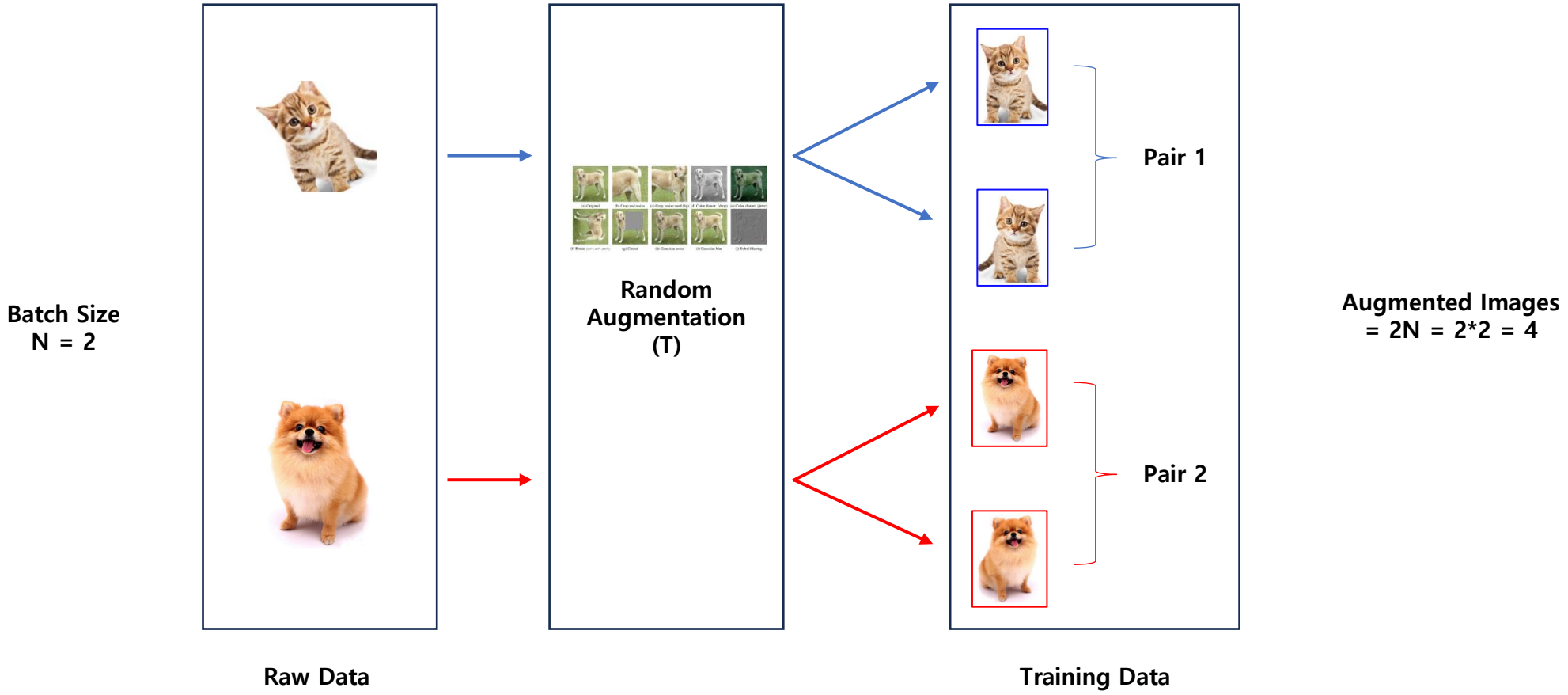
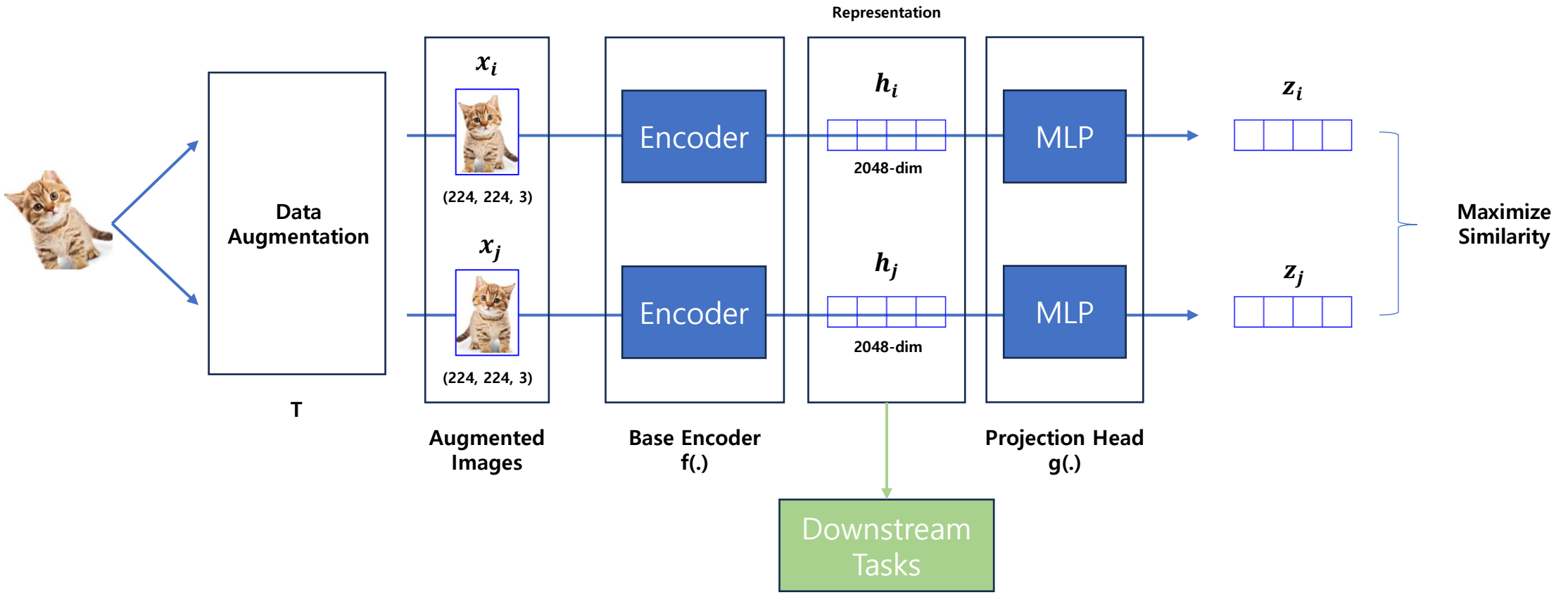


04. Design: Overview

02. Design: Data Augmentation



02. Design: Model Structure



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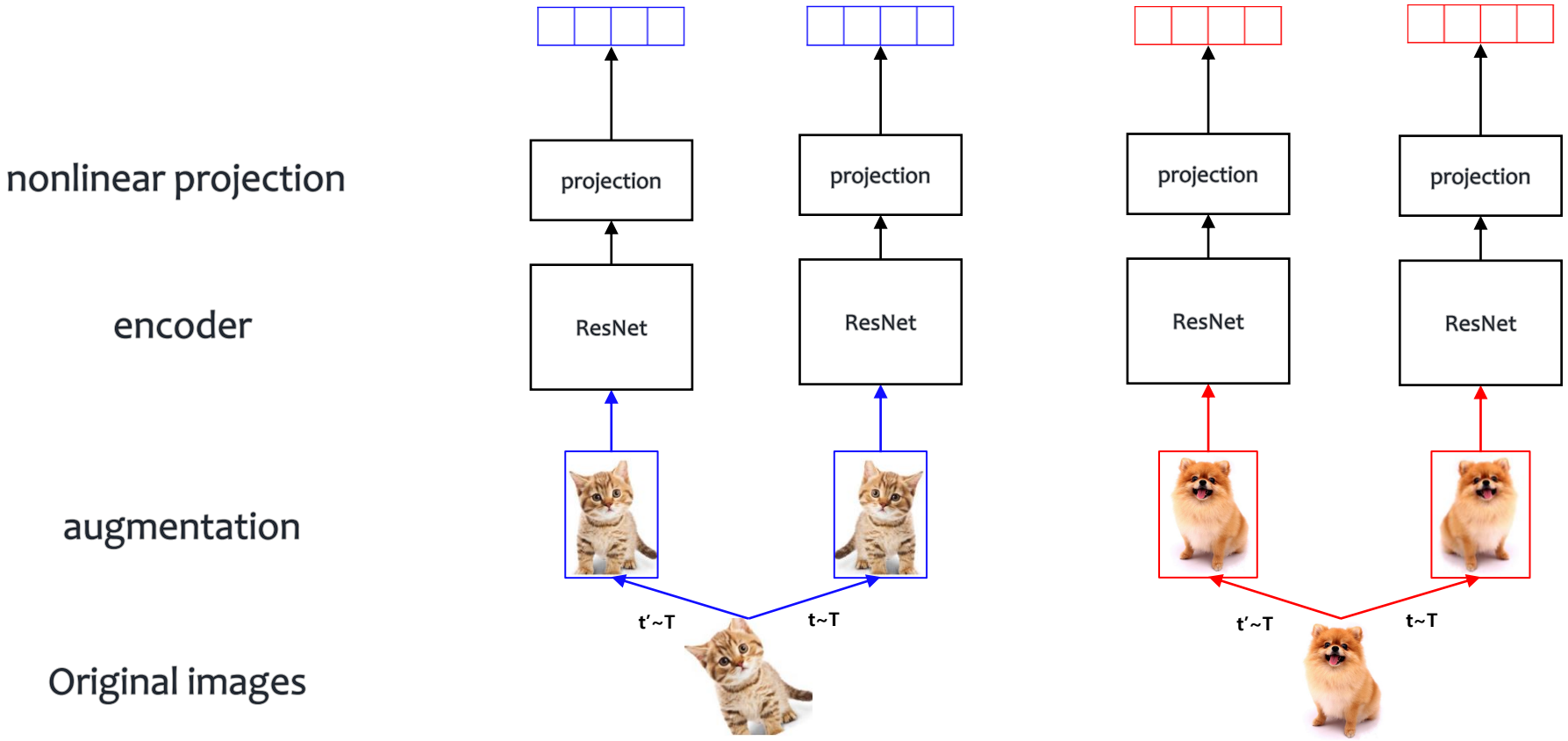

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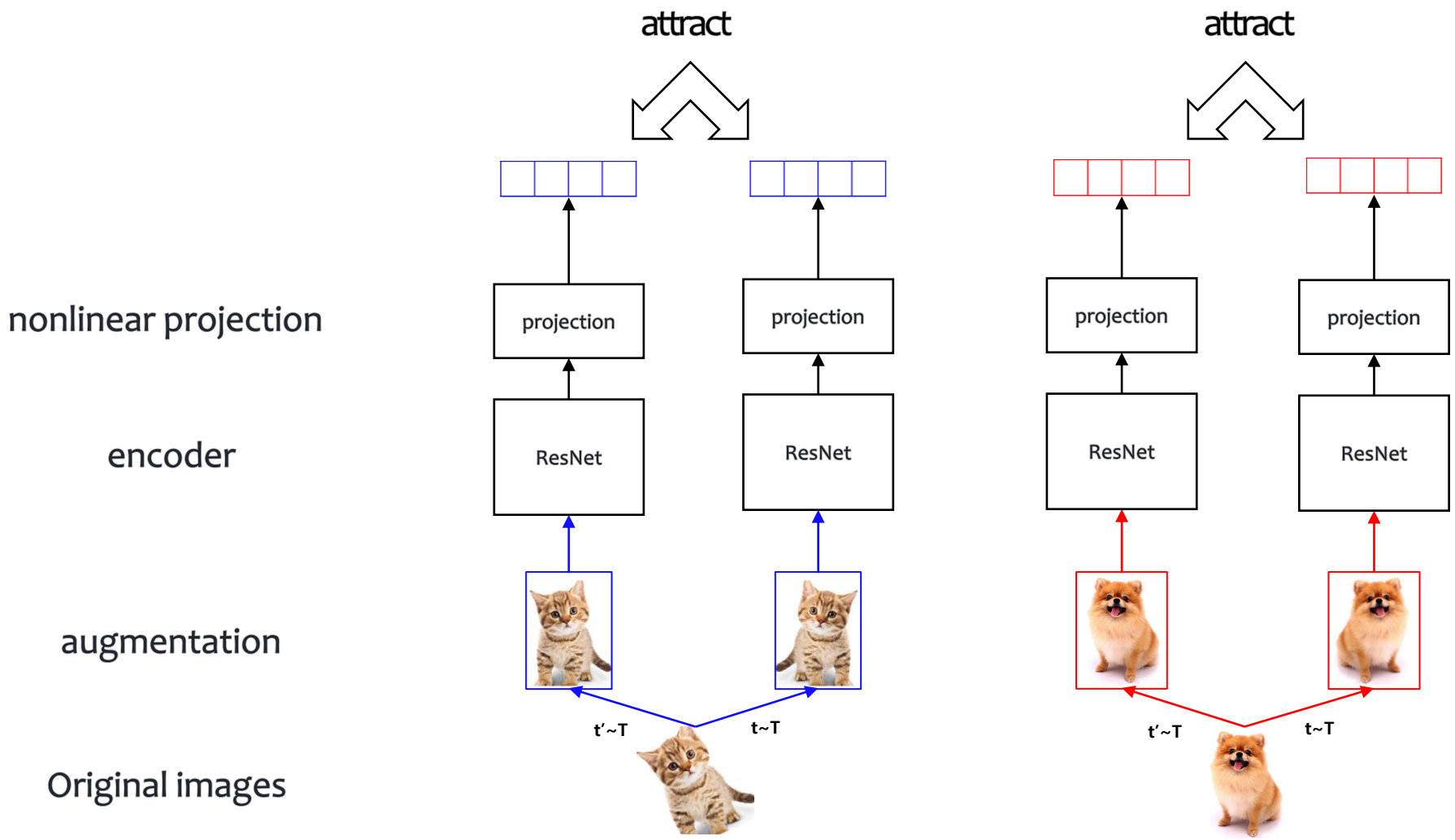

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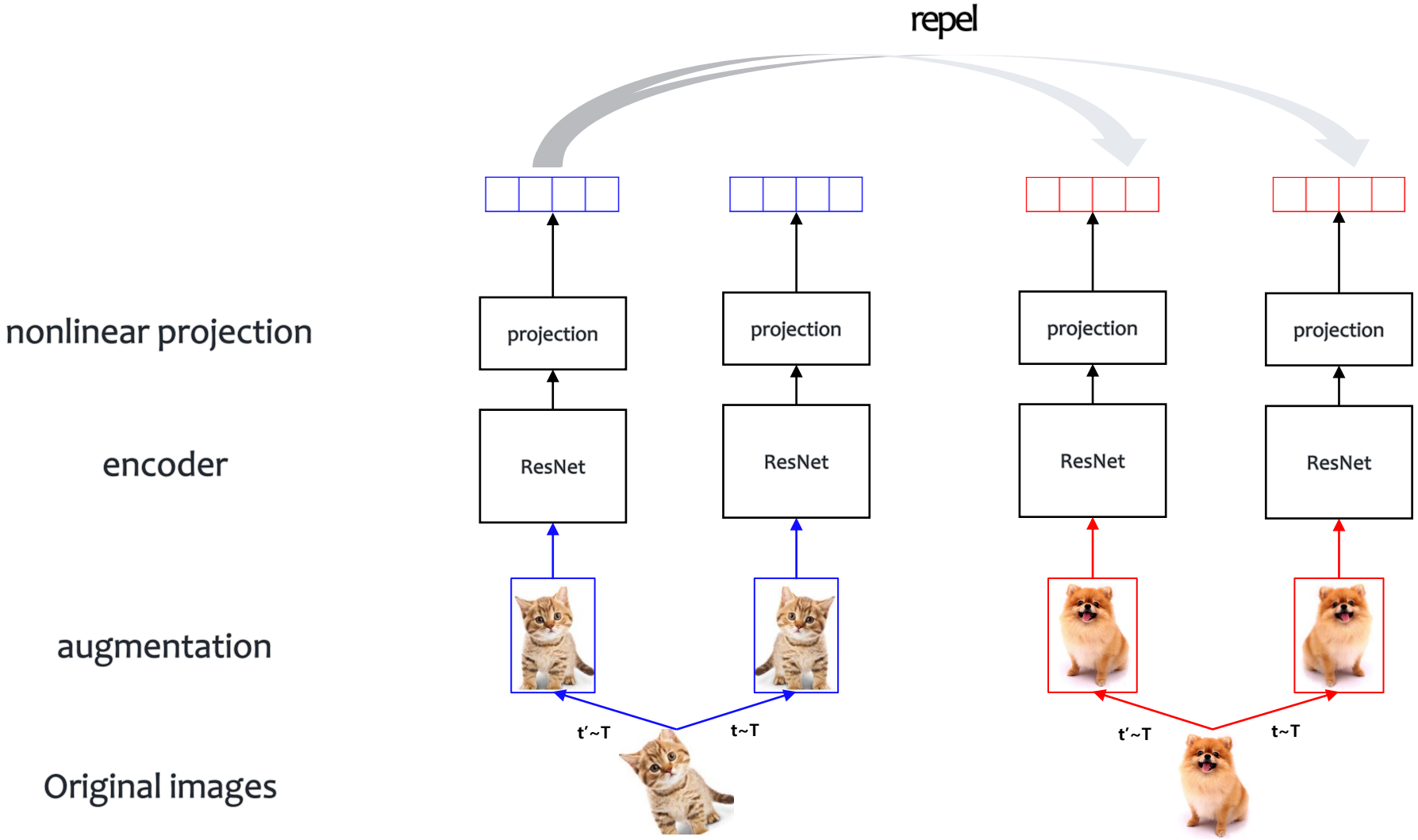

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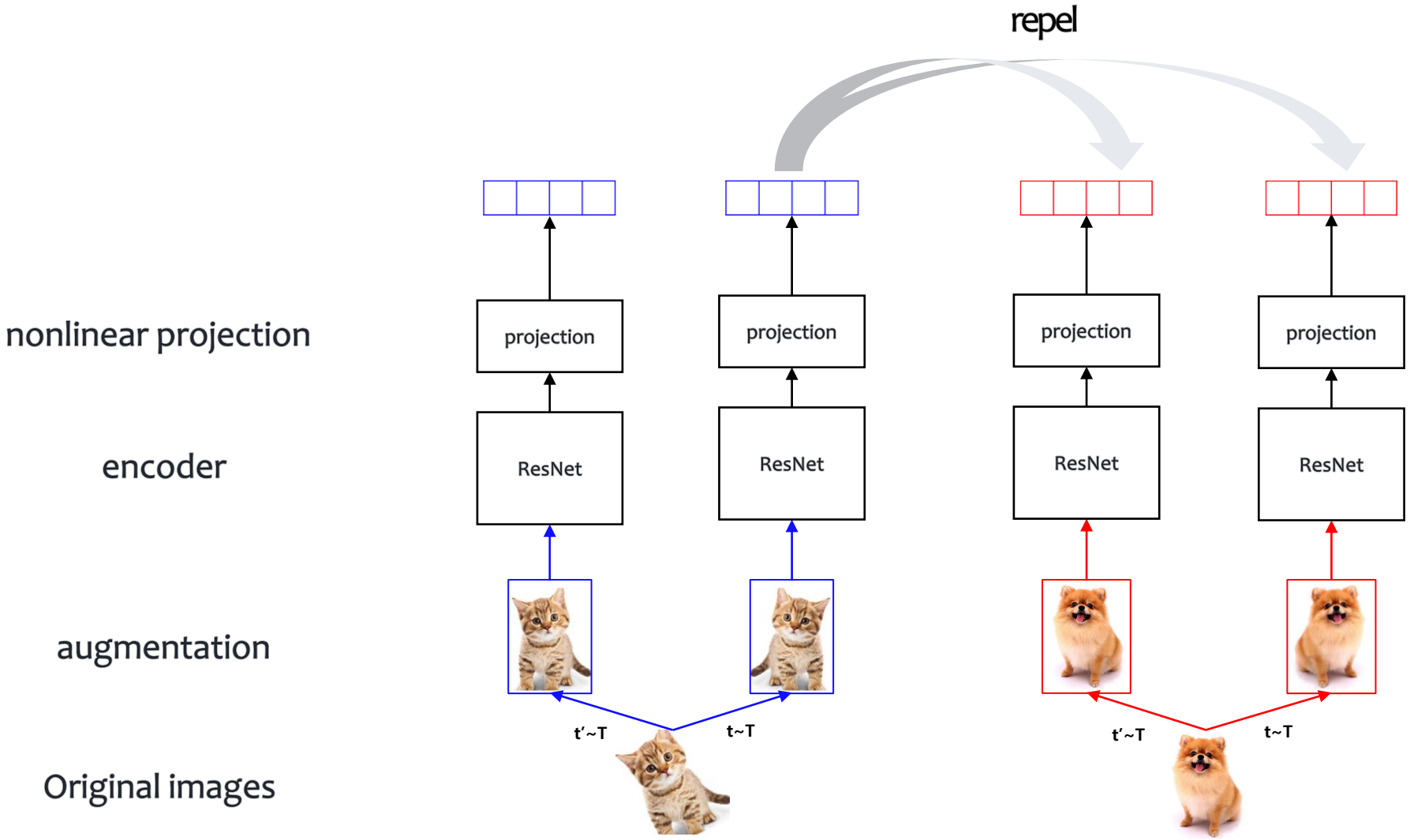
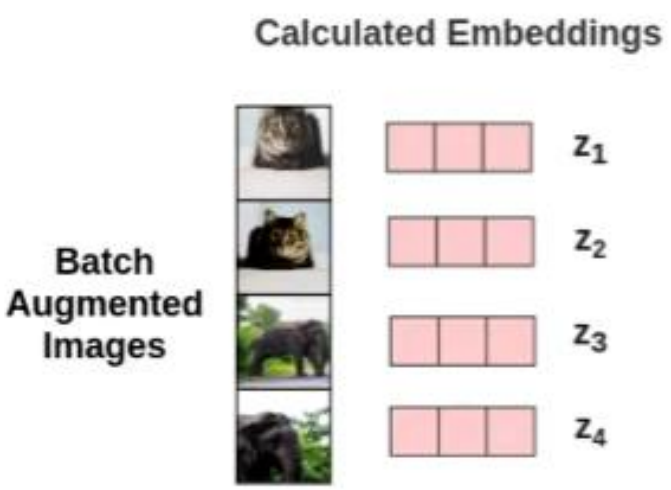
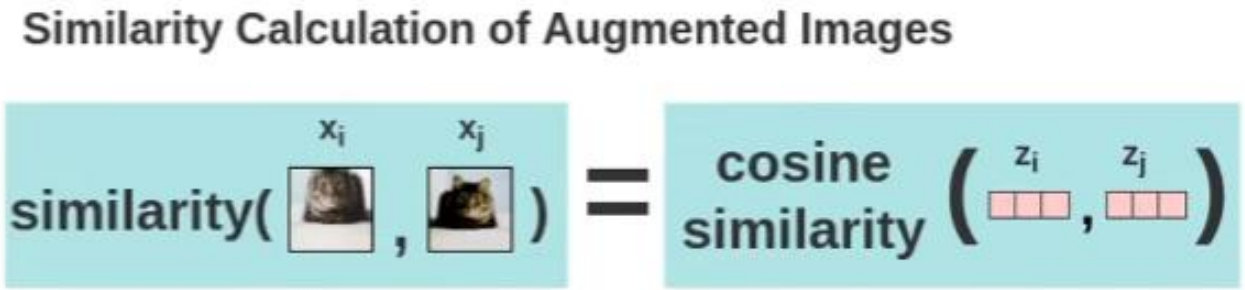


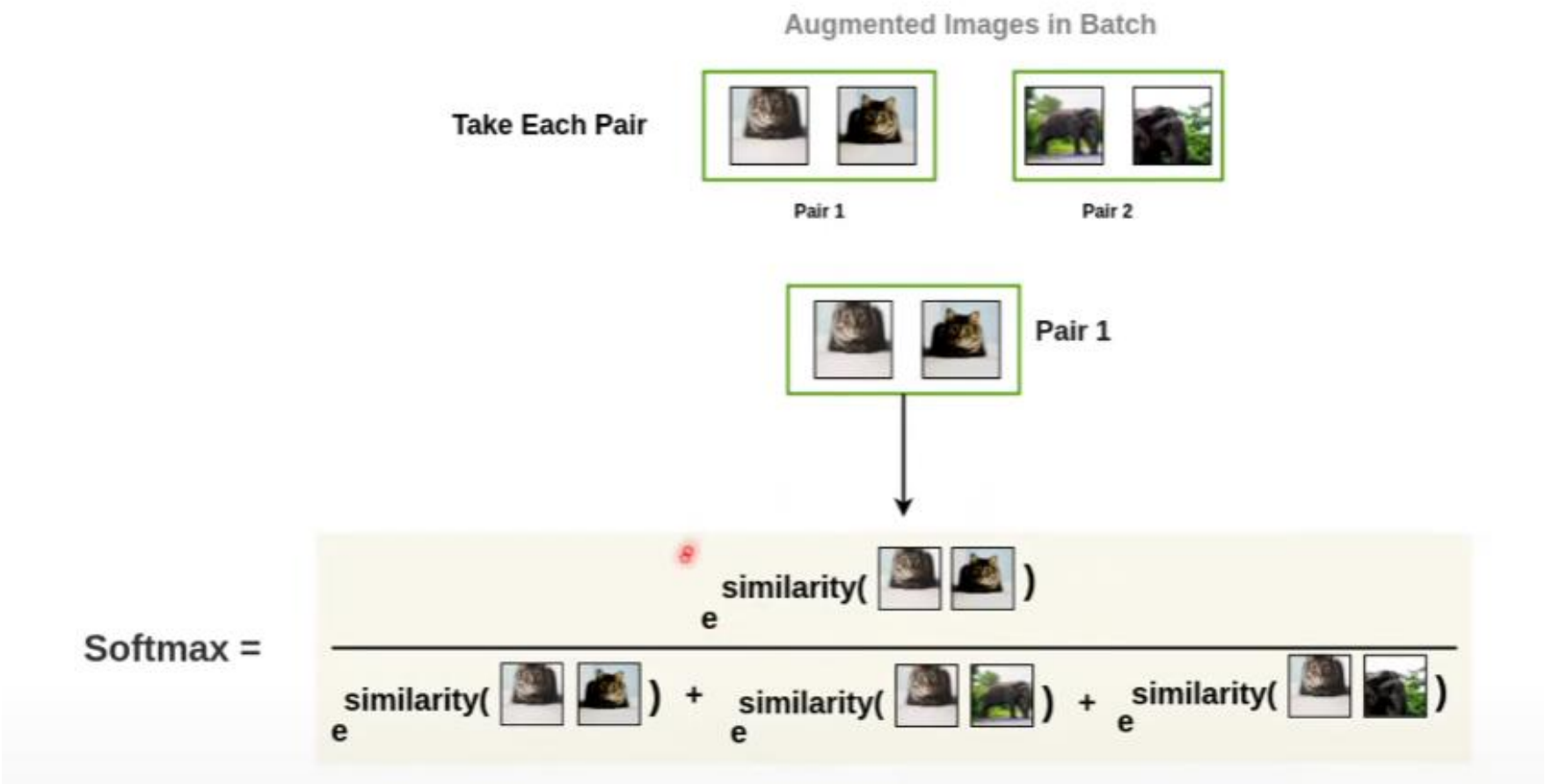
02. Design: Loss Function





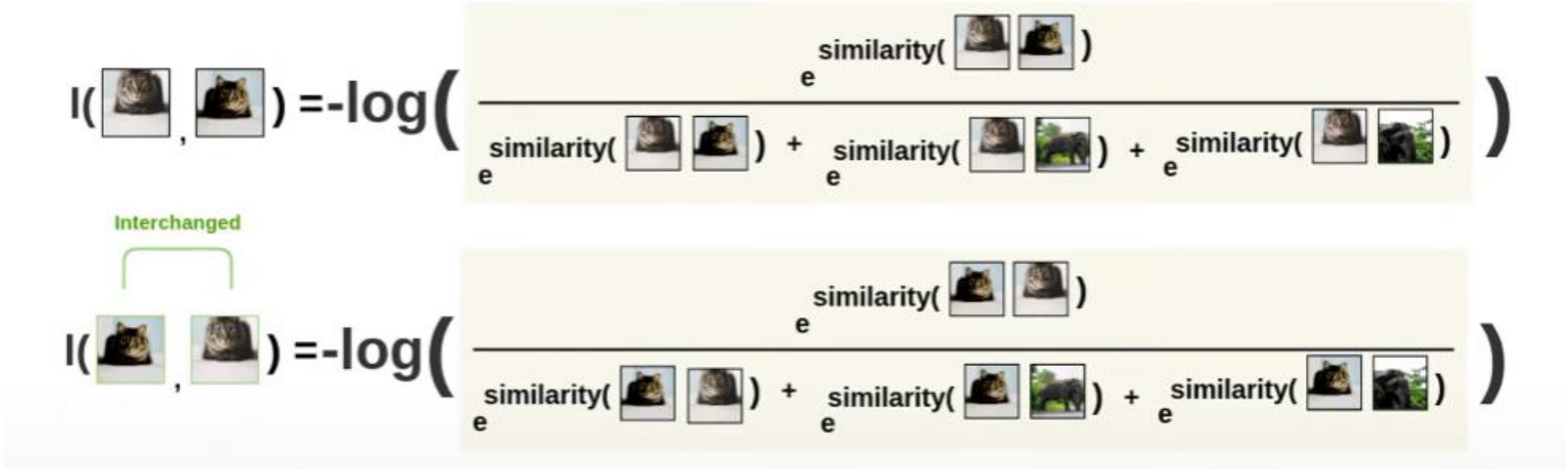
$$s_{i,j} = \frac{z_i^T z_j}{(\tau ||z_i|| ||z_j||)}$$

02. Design: Loss Function



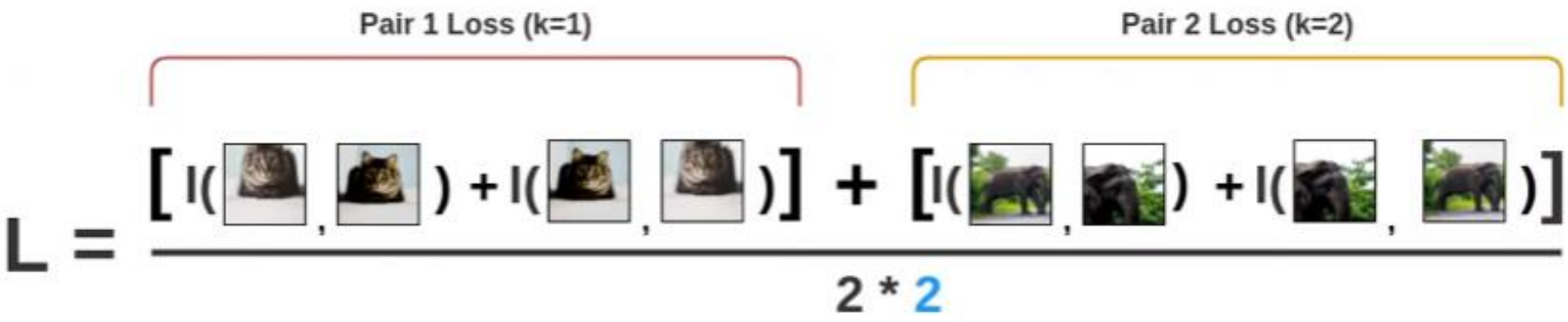
02. Design: Loss Function

$$l(i,j) = -log\frac{exp(s_{i,j})}{\sum_{k=1}^{2N} l_{[k!=i]}exp(s_{i,k})}$$



02. Design: Loss Function

$$L = \frac{1}{2N} \sum_{k=1}^{N} [l(2k-1, 2k) + l(2k, 2k-1)]$$



03. Evaluation

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Parameter and Dataset

- Training :
  - Batch size : 256 ~ 8192 (Default 값 : 4096)
  - Large Dataset에 적합한 LARS optimizer를 사용함
- Dataset
  - ImageNet 2012

03. Evaluation

- Data Augmentation

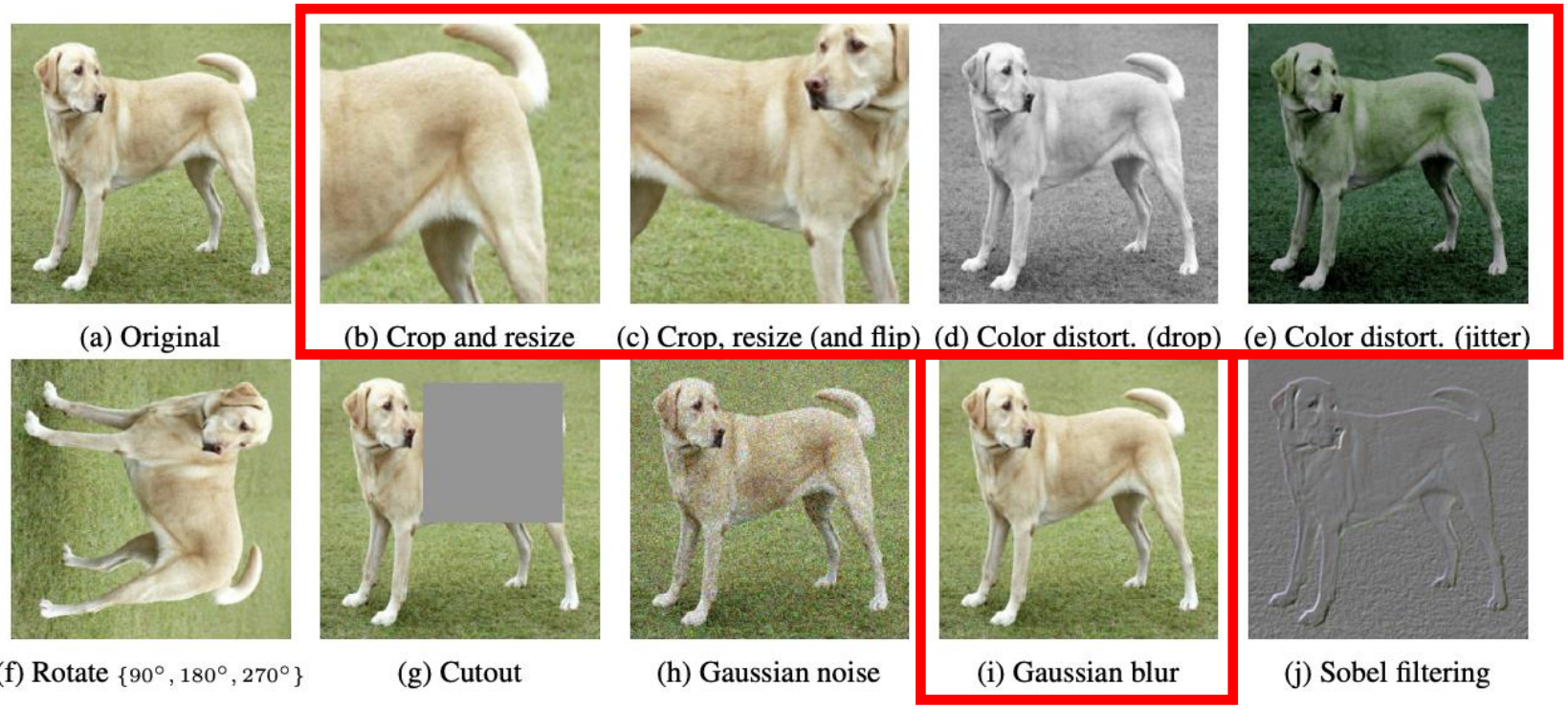
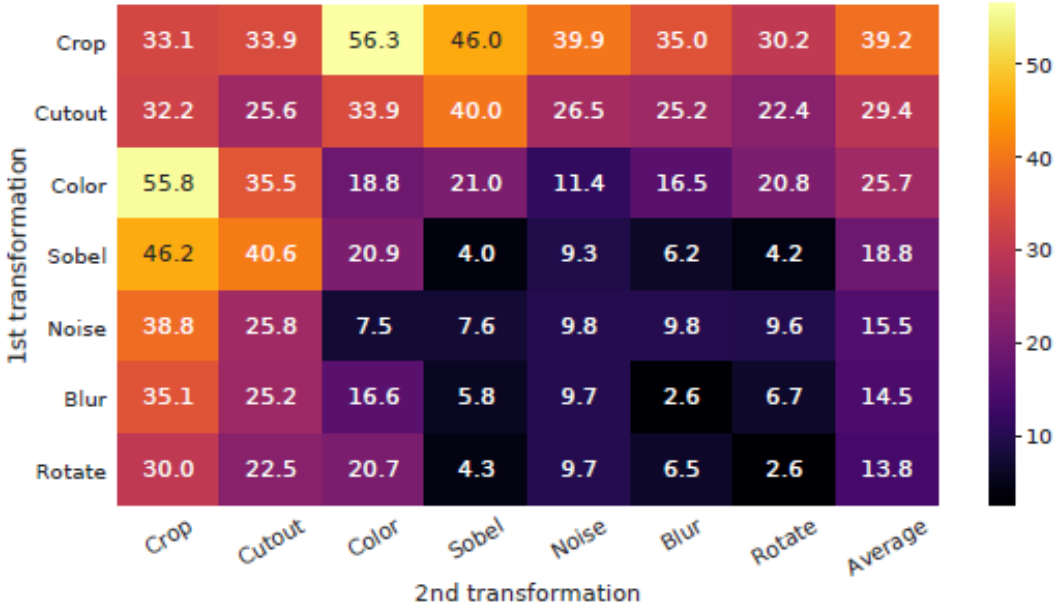


Figure 4. Illustrations of the studied data augmentation operators. Each augmentation can transform data stochastically with some internal parameters (e.g. rotation degree, noise level). Note that we *only* test these operators in ablation, the *augmentation policy used to train our models* only includes *random crop (with flip and resize)*, *color distortion*, and *Gaussian blur*. (Original image cc-by: Von.grzanka)

03. Evaluation

◇ Data Augmentation
- Augmentation 1개일 때 Cropping
- Augmentation 2개일 때 Cropping + coloring이 가장 좋은 결과를 내는 기법임을 알 수 있음



03. Evaluation

◇ Data Augmentation : Color Distortion

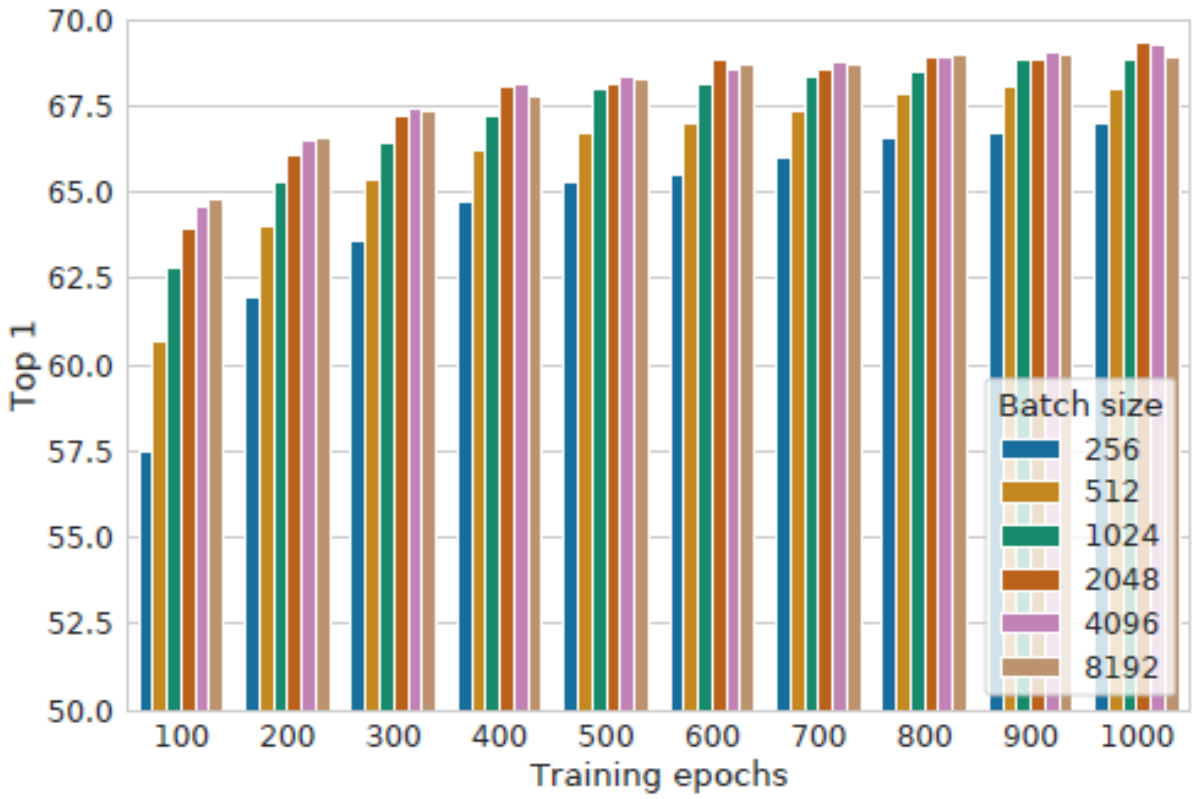
- Supervised learning에서 Color augmentation을 강하게 주면 성능이 떨어지는 경향이 있음
- SimCLR의 경우 Color augmentaion을 강하게 줄수록 점진적인 성능향상을 보임
- 데이터가 많아지면 더 성능이 비례적으로 좋아질 것임

Methods	Color distortion strength					AutoAug
	1/8	1/4	1/2	1	1 (+Blur)	
SimCLR	59.6	61.0	62.6	63.2	64.5	61.1
Supervised	77.0	76.7	76.5	75.7	75.4	77.1

03. Evaluation

◇ Batch Size

- Batch Size가 클수록, 학습 기간이 길수록 더 좋은 성능을 냄



03. Evaluation

- Comparison with supervised learning
  - SimCLR은 supervised learning에 못지 않게 좋은 성능을 낼 수 있음

	Food	CIFAR10	CIFAR100	Birdsnap	SUN397	Cars	Aircraft	VOC2007	DTD	Pets	Caltech-101	Flowers
Linear evaluation:												
SimCLR (ours)	**76.9**	**95.3**	80.2	48.4	**65.9**	60.0	61.2	**84.2**	**78.9**	89.2	**93.9**	**95.0**
Supervised	75.2	**95.7**	**81.2**	**56.4**	64.9	**68.8**	**63.8**	83.8	**78.7**	**92.3**	**94.1**	94.2
Fine-tuned:												
SimCLR (ours)	**89.4**	**98.6**	**89.0**	**78.2**	**68.1**	**92.1**	**87.0**	**86.6**	**77.8**	92.1	**94.1**	97.6
Supervised	88.7	98.3	**88.7**	**77.8**	67.0	91.4	**88.0**	86.5	**78.8**	**93.2**	**94.2**	**98.0**
Random init	88.3	96.0	81.9	**77.0**	53.7	91.3	84.8	69.4	64.1	82.7	72.5	92.5

04. Conclusion

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- ◇ Contrastive Learning을 통해 Visual Representation Embedding Vector에 대한 학습이 가능하게 하였음
- ◇ 이를 위한 간단한 Framework와 그 구현 방법을 제시하였음
- ◇ Framework Design 구성요소들을 활용하여 지도학습에 준하는 Downstream Task 성능을 얻음

Thank You
감사합니다