컴퓨터 공학 특강

FaceNet

A Unified Embedding for Face Recognition and Clustering

한양대학교 HANYANG UNIVERSITY

인공지능 연구실
김지성, 조건희

Introduction

FaceNet

Identification

FaceNet

array([-0.07440512, 0.13833548, 0.01550988, -0.04143589, -0.11708137,
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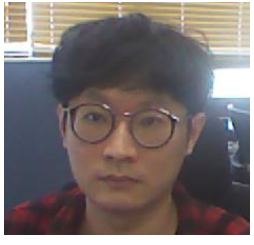
128d 벡터

Introduction

목표

A인물의 사진1



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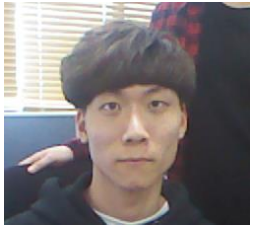

B인물의 사진1

FaceNet

FaceNet

FaceNet

128d 벡터

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Euclidean distance

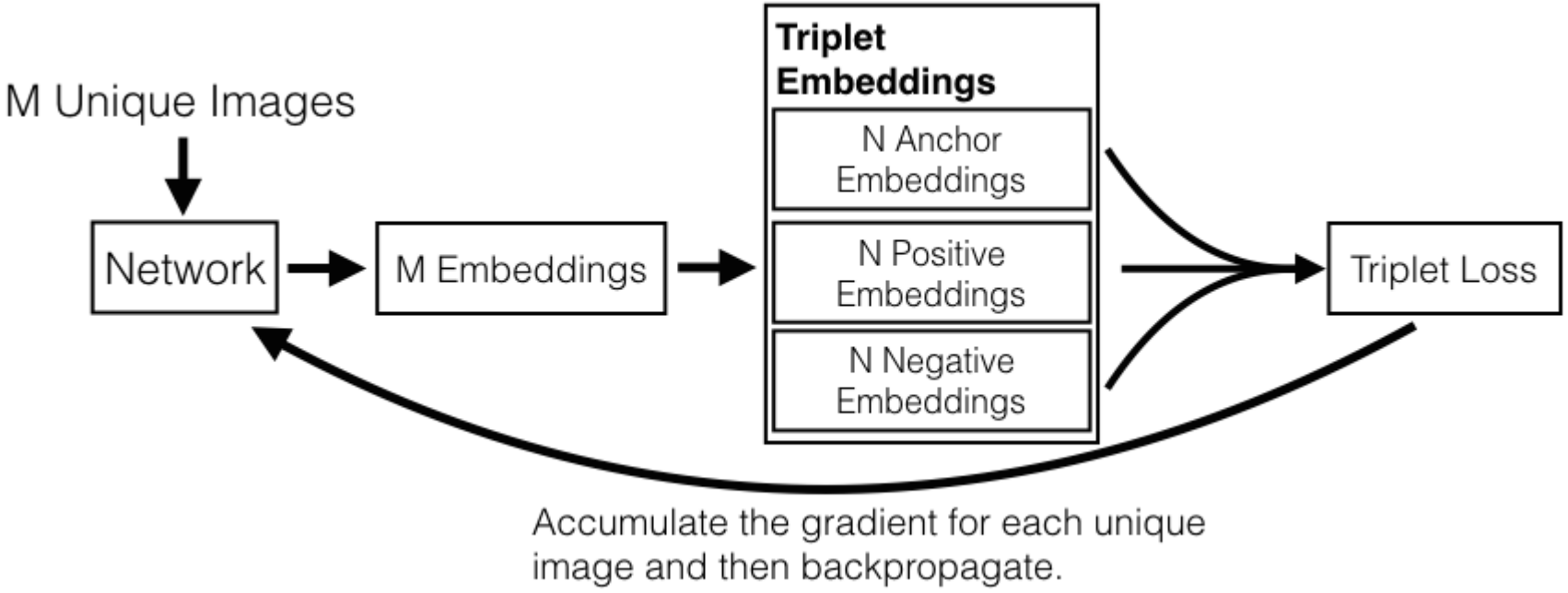
0.78

1.27

1.33

Introduction

구조



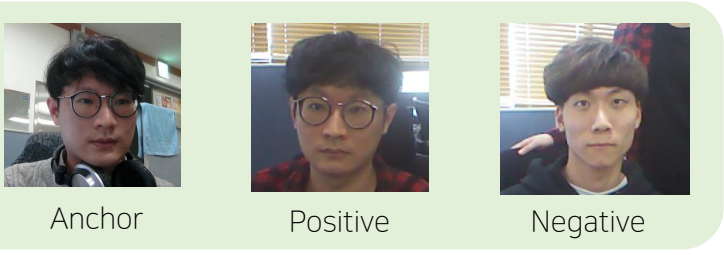
FaceNet Architecture

Method

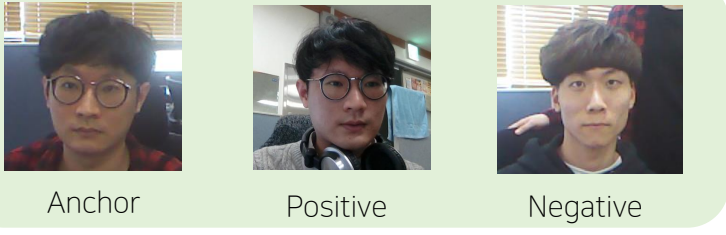
FaceNet - Triplet

Triplet : 세 개의 데이터

- Anchor(x_i^a) : 기준 얼굴의 벡터
- Positive(x_i^p) : 기준과 같은 인물의 얼굴의 벡터
- Negative(x_i^n) : 기준과 다른 인물의 얼굴의 벡터

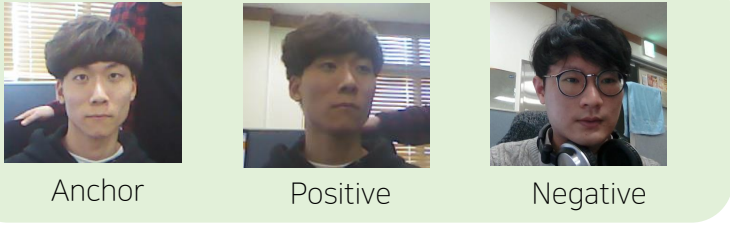


Triplet 1



Triplet 2

...



Triplet N

Method

FaceNet - Triplet

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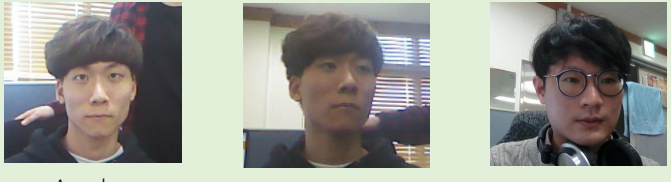
Triplet 1

Triplet 2

...



Triplet N

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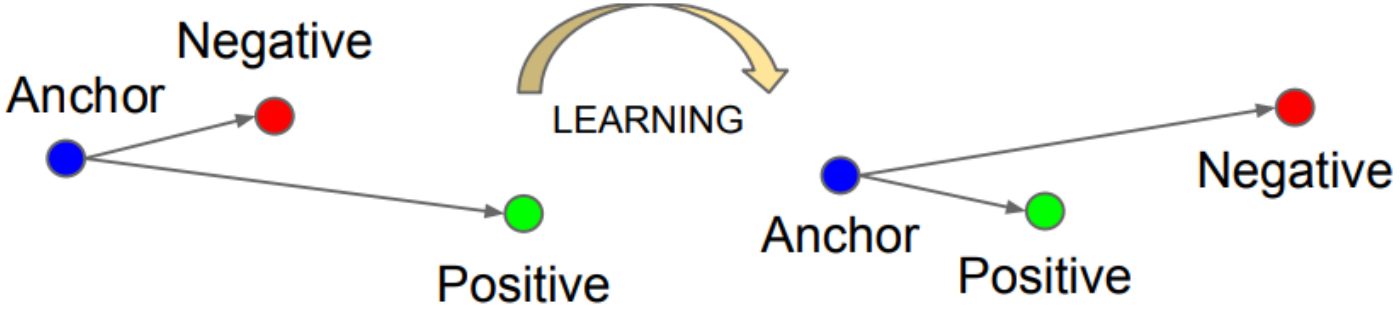

기준 얼굴과 같은 얼굴은 가깝도록, 기준 얼굴과 다른 얼굴은 멀도록

Method

FaceNet - Triplet

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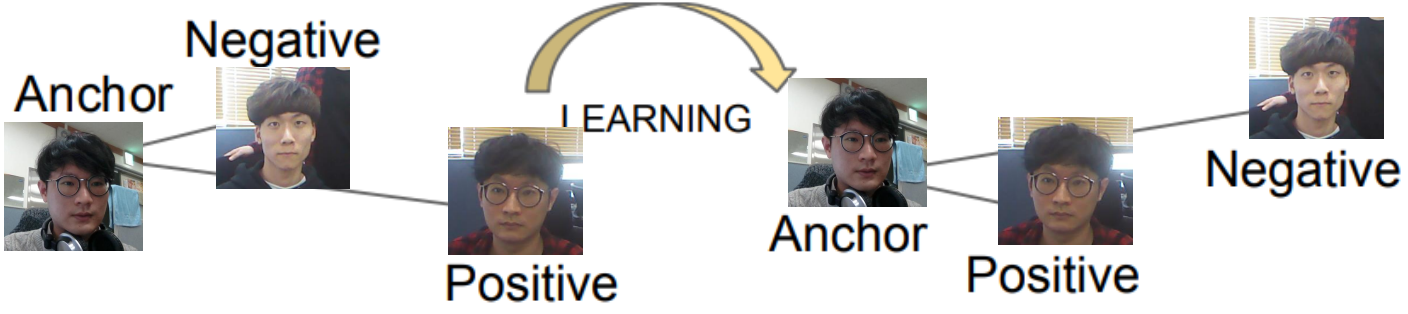


기준 얼굴과 같은 얼굴은 가깝도록, 기준 얼굴과 다른 얼굴은 멀도록

Method

Triplet - Loss

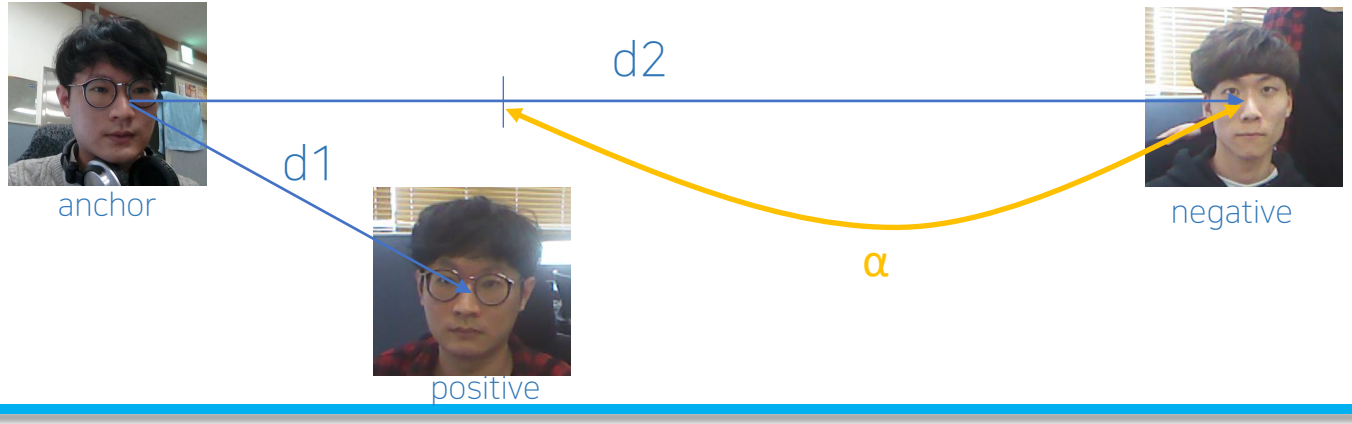
d1 d2

$$\|f(x_i^a) - f(x_i^p)\|_2^2 + \alpha < \|f(x_i^a) - f(x_i^n)\|_2^2 \,, \tag{1}$$

- x : 이미지
- $f(x)$: 임베딩 함수
- α : 마진

- x_i^a : 기준 얼굴(anchor) 이미지
- x_i^p : 기준과 같은 인물(positive)의 얼굴 이미지
- x_i^n : 기준과 다른 인물(negative)의 얼굴 이미지

Anchor와 Negative의 제곱거리가 Anchor와 Positive의 제곱거리보다 α 만큼 떨어져 있고 싶다!



Method

Triplet - Loss

$$\|f(x_i^a) - f(x_i^p)\|_2^2 + \alpha < \|f(x_i^a) - f(x_i^n)\|_2^2 \,, \tag{1}$$

- x : 이미지
- $f(x)$: 임베딩 함수
- α : 마진

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- x_i^n : 기준과 다른 인물(negative)의 얼굴 이미지

Anchor와 Negative의 제곱거리가 Anchor와 Positive의 제곱거리보다 α 만큼 떨어져 있고 싶다!

$$\text{LOSS} = \sum_i^N \left[\|f(x_i^a) - f(x_i^p)\|_2^2 - \|f(x_i^a) - f(x_i^n)\|_2^2 + \alpha\right]_+ . \tag{2}$$

$$= \sum_i^N \text{Max}(\|f(x_i^a) - f(x_i^p)\|_2^2 - \|f(x_i^a) - f(x_i^n)\|_2^2 + \alpha, 0)$$

Method

Triplet – Triplet Selection

각 Triplet이 학습하는데 미치는 영향은 전부 다르다.
학습에 미치는 영향이 큰 Triplet들을 학습하는 것이 수렴속도를 높인다.
따라서 어려운 문제를 골라서 해결하기 위해 Hard Negative, Hard Positive가 있는 Triplet 선택해야 한다.

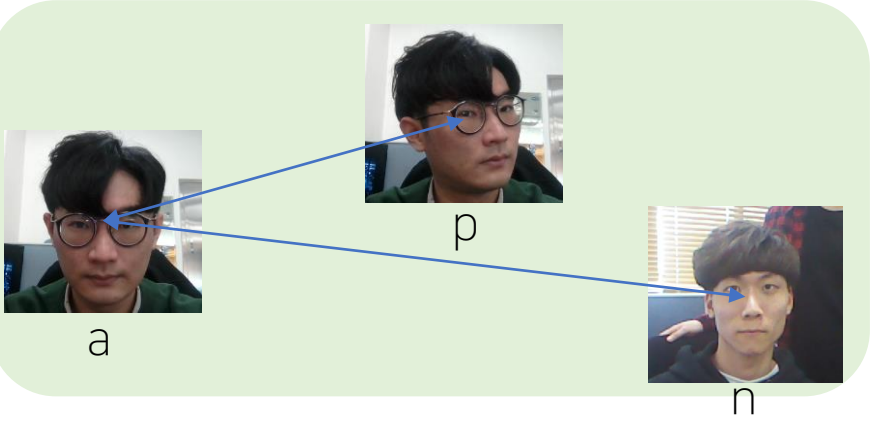
x_i^a Anchor가 주어졌을 때

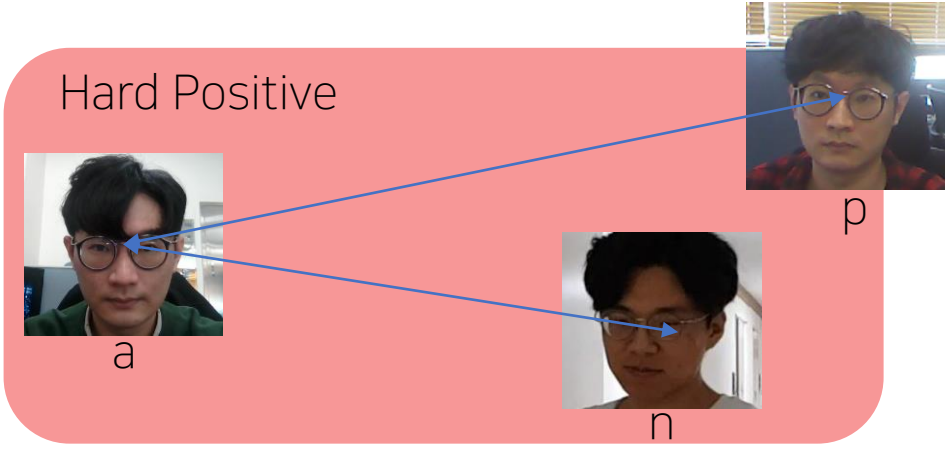
$\text{argmin}_{x_i^n} \|f(x_i^a) - f(x_i^n)\|_2^2$ Hard Negative : 가장 가까이 있는 Negative

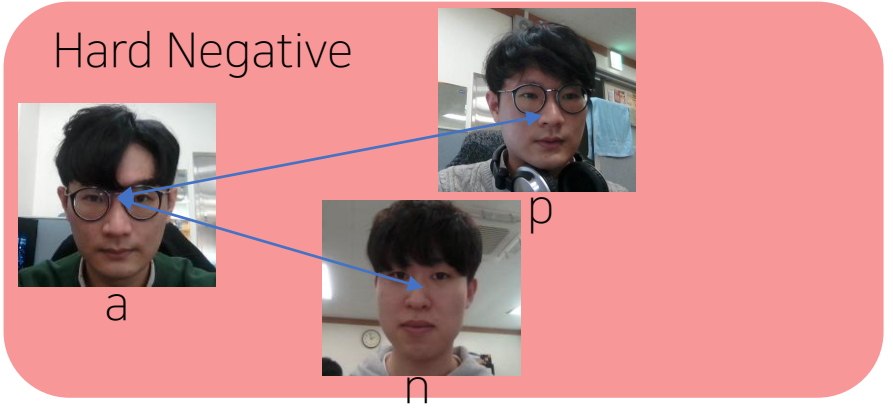
$\text{argmax}_{x_i^p} \|f(x_i^a) - f(x_i^p)\|_2^2$ Hard Positive : 가장 멀리 있는 Positive

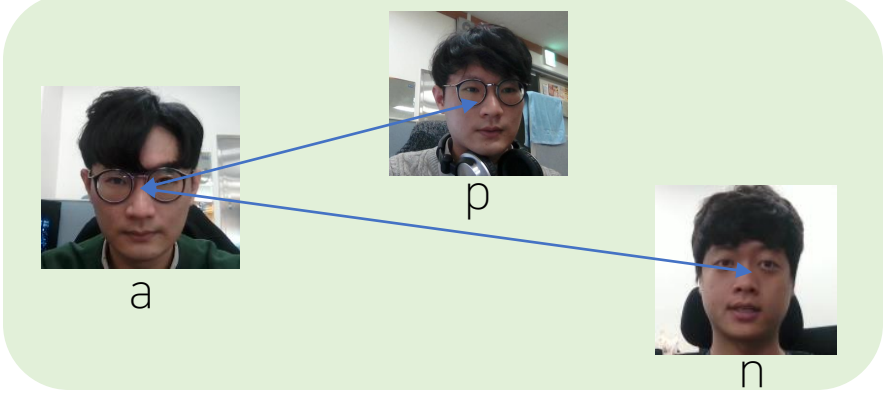
Method

Triplet – Triplet Selection







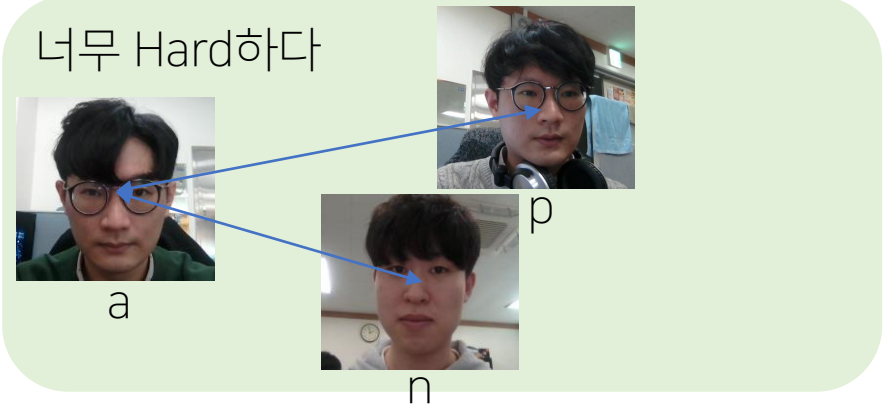


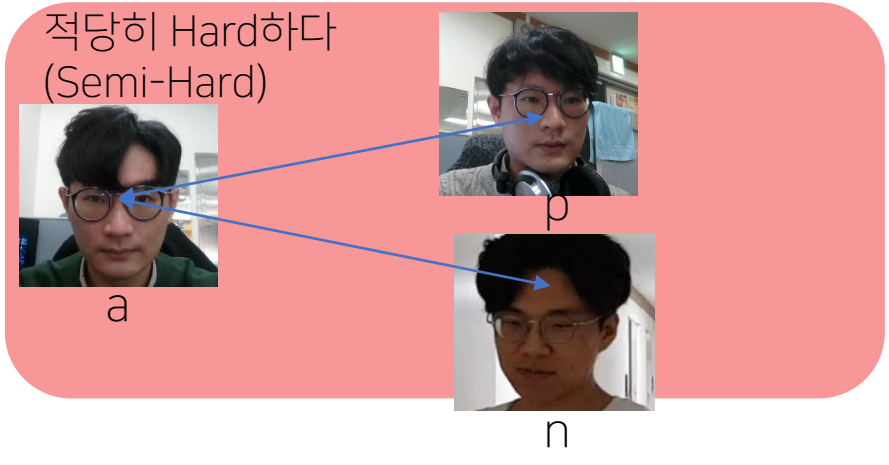
Method

Triplet – Triplet Selection(Detail)

- 가장 Hard한 negative를 선택하면 local-minima에 빠지기 쉽다
  - 학습 초반에 너무 어려운 문제를 해결하기 힘들다
  - Semi-hard negative를 선택해야함
    - Positive보다는 먼 negative 가 있는 Triplet을 선택
    - Positive와 거리가 비슷해서 Hard라고 말할 수 있다

$$\|f(x_i^a) - f(x_i^p)\|_2^2 < \|f(x_i^a) - f(x_i^n)\|_2^2 \ . \qquad (3)$$





Method

Triplet – Triplet Selection

두 명의 사람이 각 10장의 사진을 가질 때 가능한 Triplet의 수 :
Class x Anchor x Positive x Negative = 2 x 10 x 9 x 10 = 1800

매번 모든 triplet을 계산해서 Semi-Hard 한 문제를 찾는 것은 너무 비 효율적이다.

Mini Batch가 필요하다!

Method

Triplet – mini batch

이미지셋

랜덤으로 한 ID에서 40개

40개

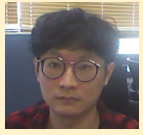
Negative faces 중 랜덤으로 1960개

1960개

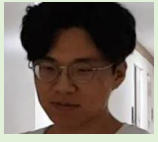
크기 2000의 미니배치

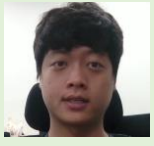
Method

Triplet – mini batch


40개

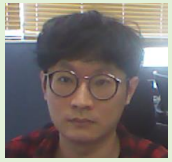





1960개

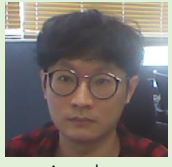
크기 2000의 미니배치

FaceNet


Anchor Positive Negative

Triplet 1

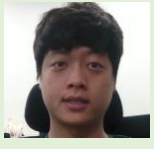


Anchor Positive Negative

Triplet 2

...



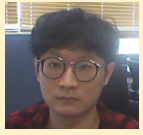


Anchor Positive Negative

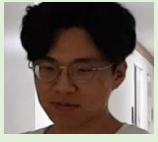
Triplet N

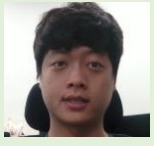
Method

Triplet – mini batch


40개

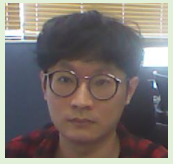





1960개

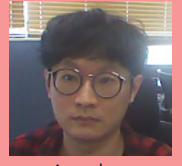
크기 2000의 미니배치

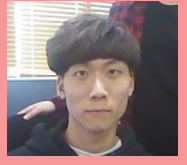
FaceNet


Anchor Positive Negative

Triplet 1



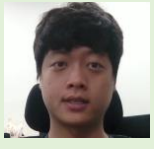


Anchor Positive Negative

Triplet 2

...



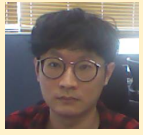


Anchor Positive Negative

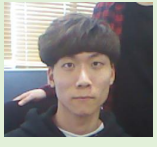
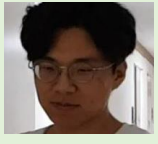
Triplet N

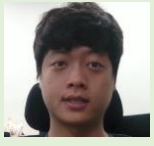
Method

Triplet – mini batch


40개

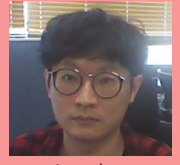



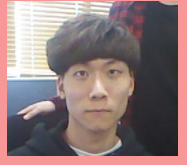


1960개

크기 2000의 미니배치

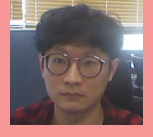
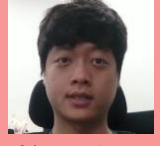
FaceNet





Anchor Positive Negative

Triplet 2

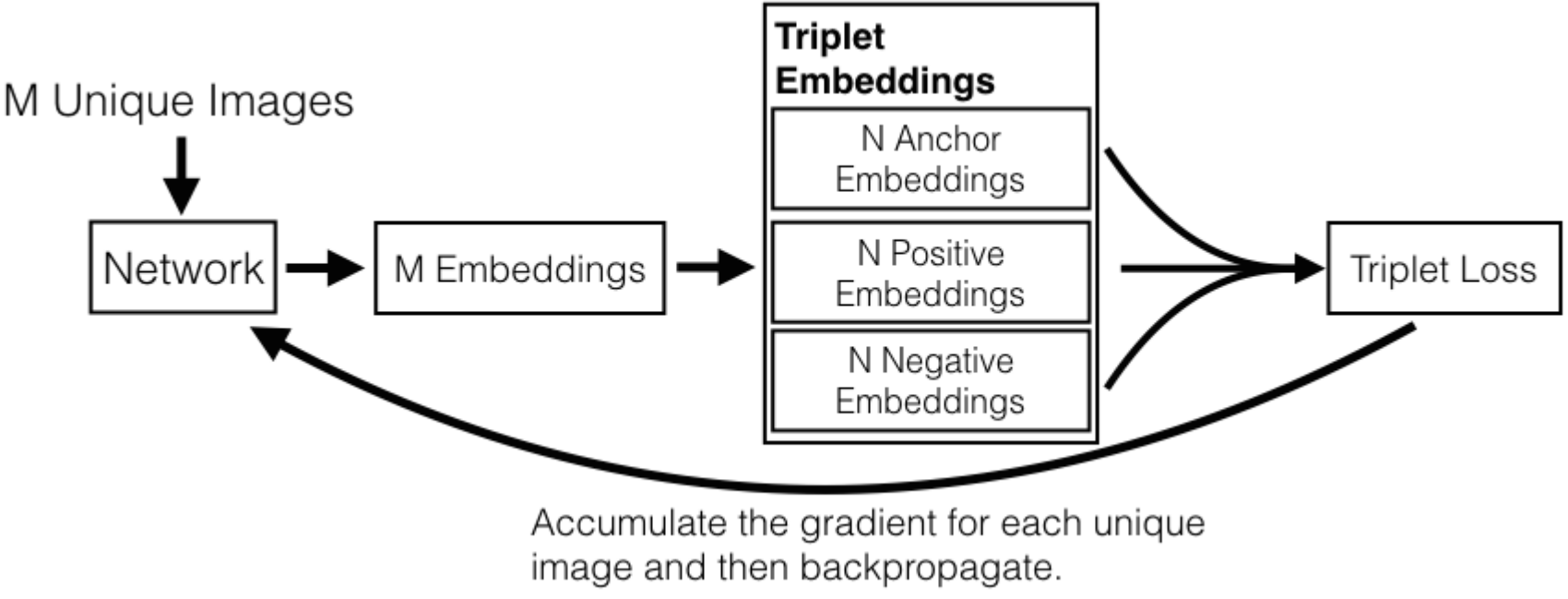




Anchor Positive Negative

Triplet N

Method

Triplet – Triplet Selection(Detail)



FaceNet Architecture

Experiments

실험에 사용된 CNN 모델

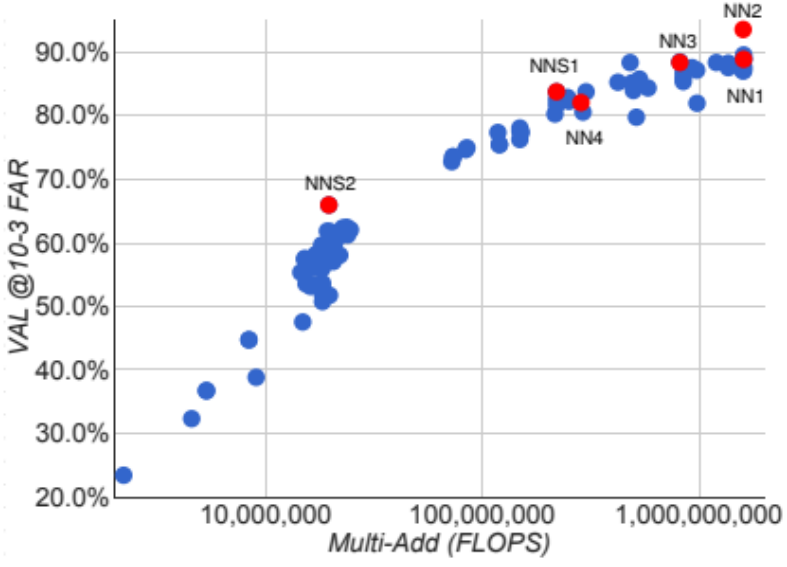
Comparison with the State of the Art (LFW Unrestricted Protocol)

No.	Method	# Training Images	# Networks	Accuracy
1	Fisher Vector Faces	-	-	93.10
2	DeepFace	4 M	3	97.35
3	DeepFace Fusion	500 M	5	98.37
4	DeepID-2,3	Full	200	99.47
5	FaceNet	200 M	1	98.87
6	FaceNet+ Alignment	200 M	1	99.63
7	VGG Face	2.6 M	1	98.95

Experiments

실험에 사용된 CNN 모델

architecture	VAL
NN1 (Zeiler&Fergus 220×220)	87.9% ± 1.9
NN2 (Inception 224×224)	89.4% ± 1.6
NN3 (Inception 160×160)	88.3% ± 1.7
NN4 (Inception 96×96)	82.0% ± 2.3
NNS1 (mini Inception 165×165)	82.4% ± 2.4
NNS2 (tiny Inception 140×116)	51.9% ± 2.9



FLOPS vs. Accuracy

Testset : Personal Photos

Evaluation

- VAL(d) : Validation Rate
  같은 사람을 같다고 예측한 비율
- FAR(d) : False Accept Rate
  다른 사람을 같다고 예측한 비율

Category1 : Zeiler & Fergus : ZF Net 기반 모델

- NN1
  - 1x1 convolution

Category 2 : GoogLeNet 기반 모델(Inception v1)

- NN2
  - NN1과 비교
  - 약 20배 적은 파라미터
  - 최대 5배 까지 적은 FLOPS
- NN2~4
  - 입력 크기 220x220, 160x160, 96x96
- NNS1~4
  - 모바일을 위한 경량 모델

Experiments

FLOPS vs. Accuracy

#pixels	val-rate
1,600	37.8%
6,400	79.5%
14,400	84.5%
25,600	85.7%
65,536	86.4%

이미지 크기에 따른 정확도

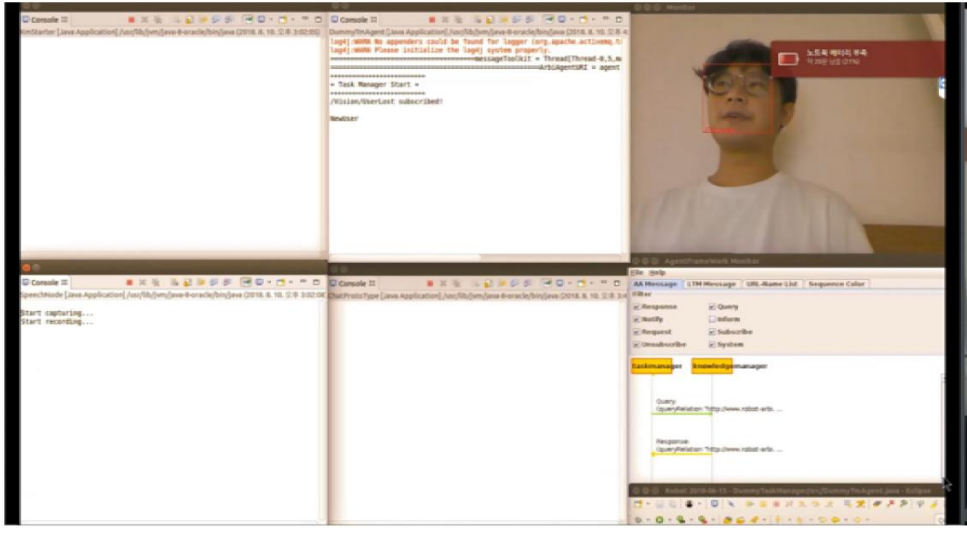
#dims	VAL
64	86.8% ± 1.7
128	87.9% ± 1.9
256	87.7% ± 1.9
512	85.6% ± 2.0

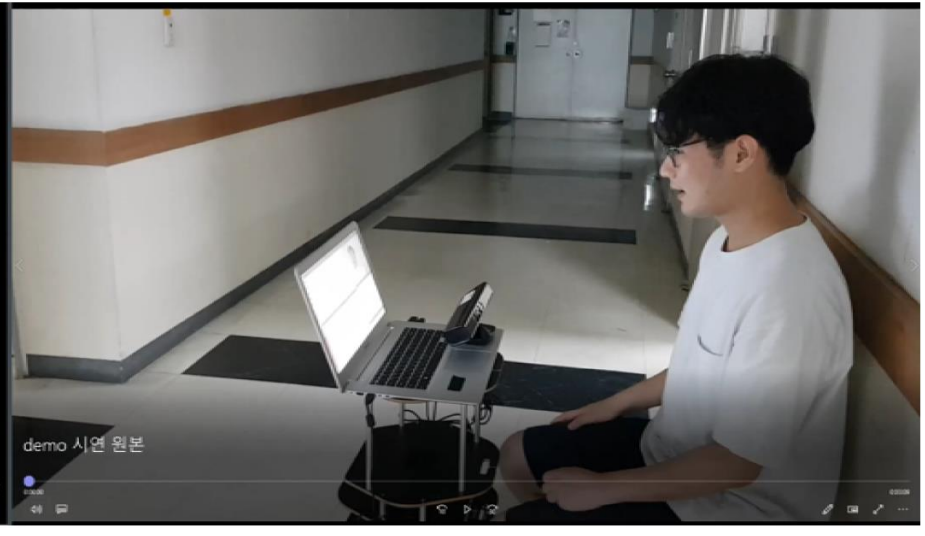
임베딩 벡터 차원에 따른 정확도

#training images	VAL
2,600,000	76.3%
26,000,000	85.1%
52,000,000	85.1%
260,000,000	86.2%

데이터셋 양에 따른 정확도

Experiments






감사합니다.