

Big Data Research Project

USING VAE AND AE ENCODER AS FEATURE EXTRACTOR FOR FACE VERIFICATION

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CONTENT

Introduction to Variational Autoencoders (VAE) and their underlying mechanism

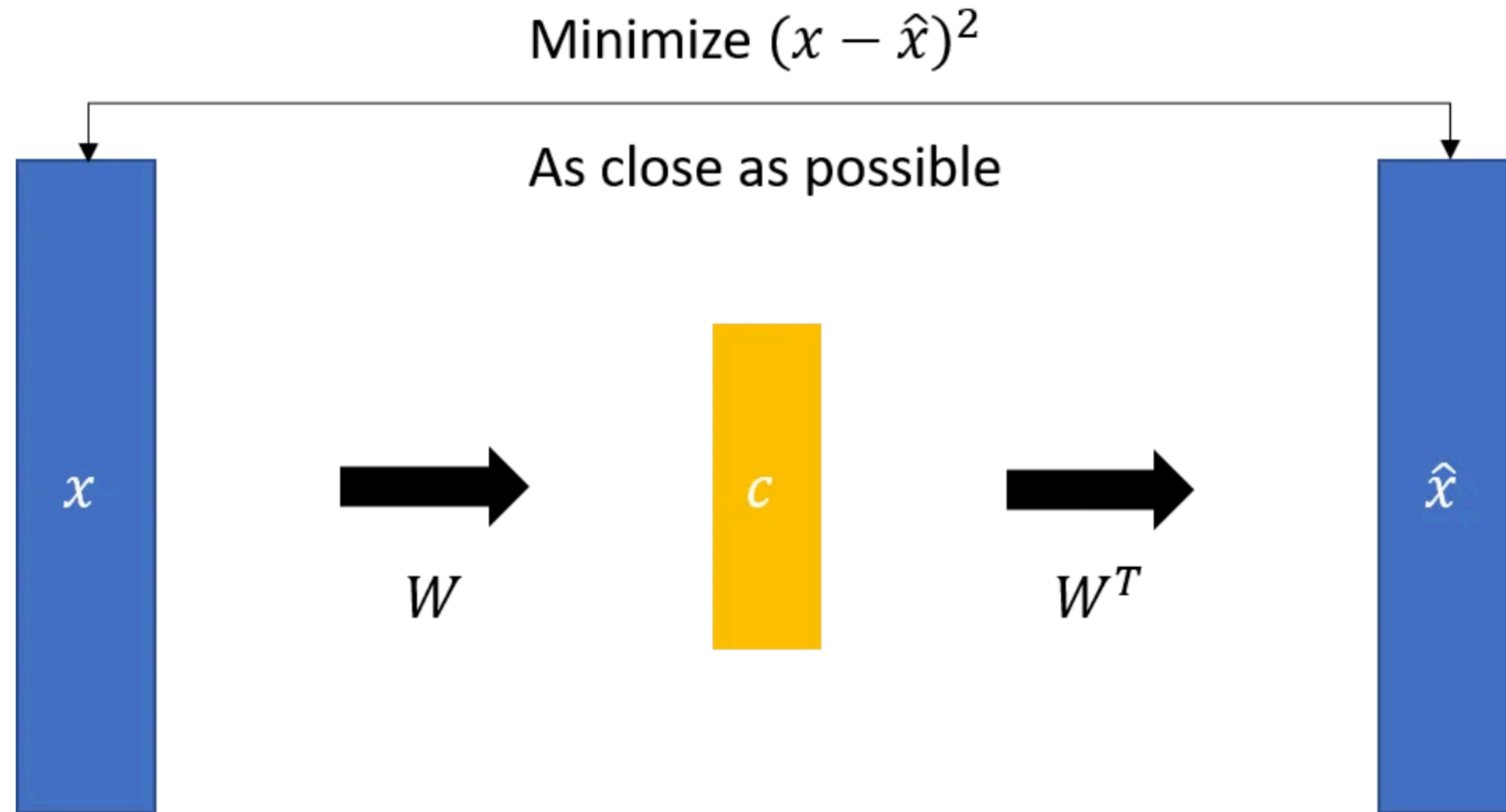
Literature Review -Techniques of FR & FV

Project Announcement

Project Pipeline

Completed Steps -accomplished in the project

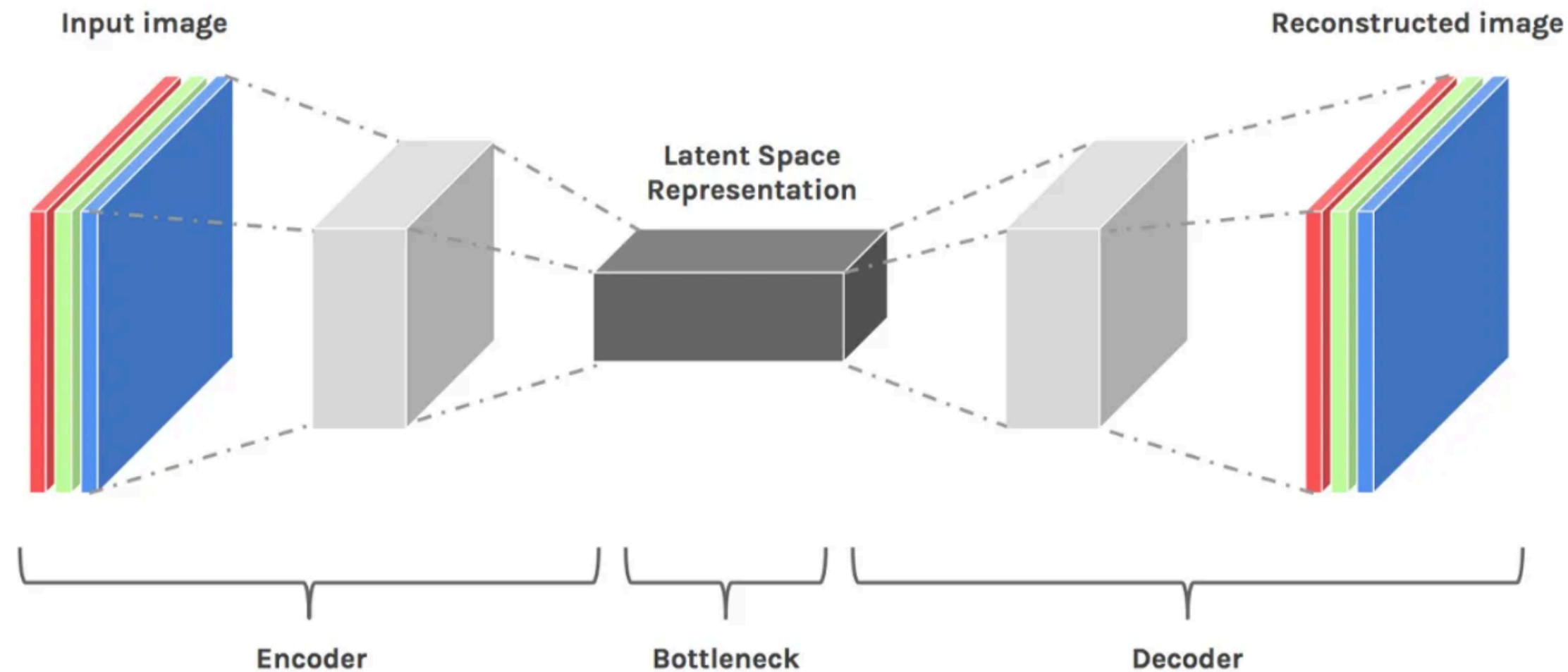
DIMENSIONALITY REDUCTION, PCA AND AE



PCA is to find a W through SVD (singular value decomposition) so that the matrices x and \hat{x} be as consistent as possible.

**HOWEVER, THE DIFFERENCE BETWEEN AE AND PCA IS
THAT AE USES NEURAL NETWORKS INSTEAD OF SVD.**

INTRODUCTION TO VAE

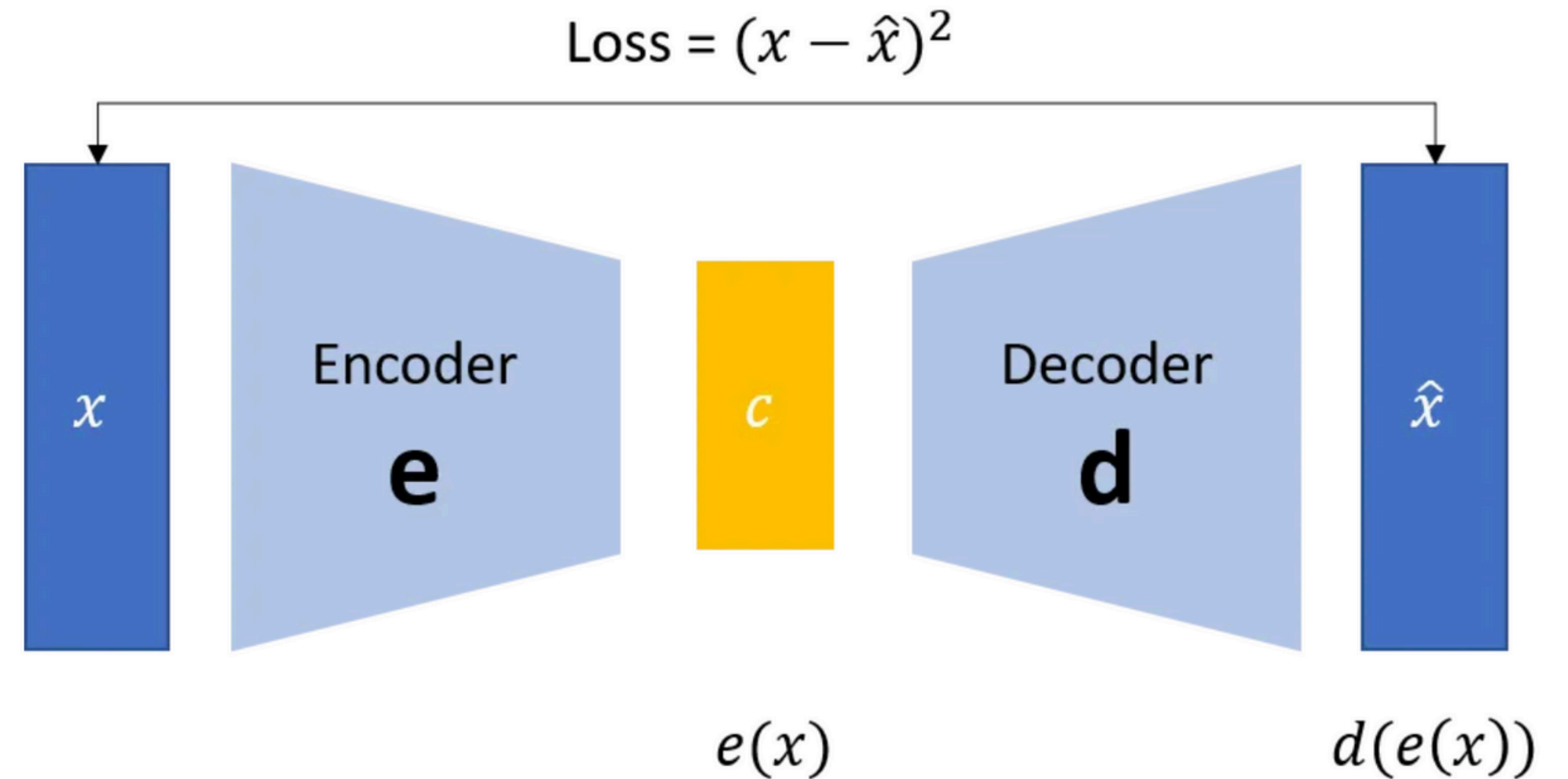


The basic scheme of a variational autoencoder

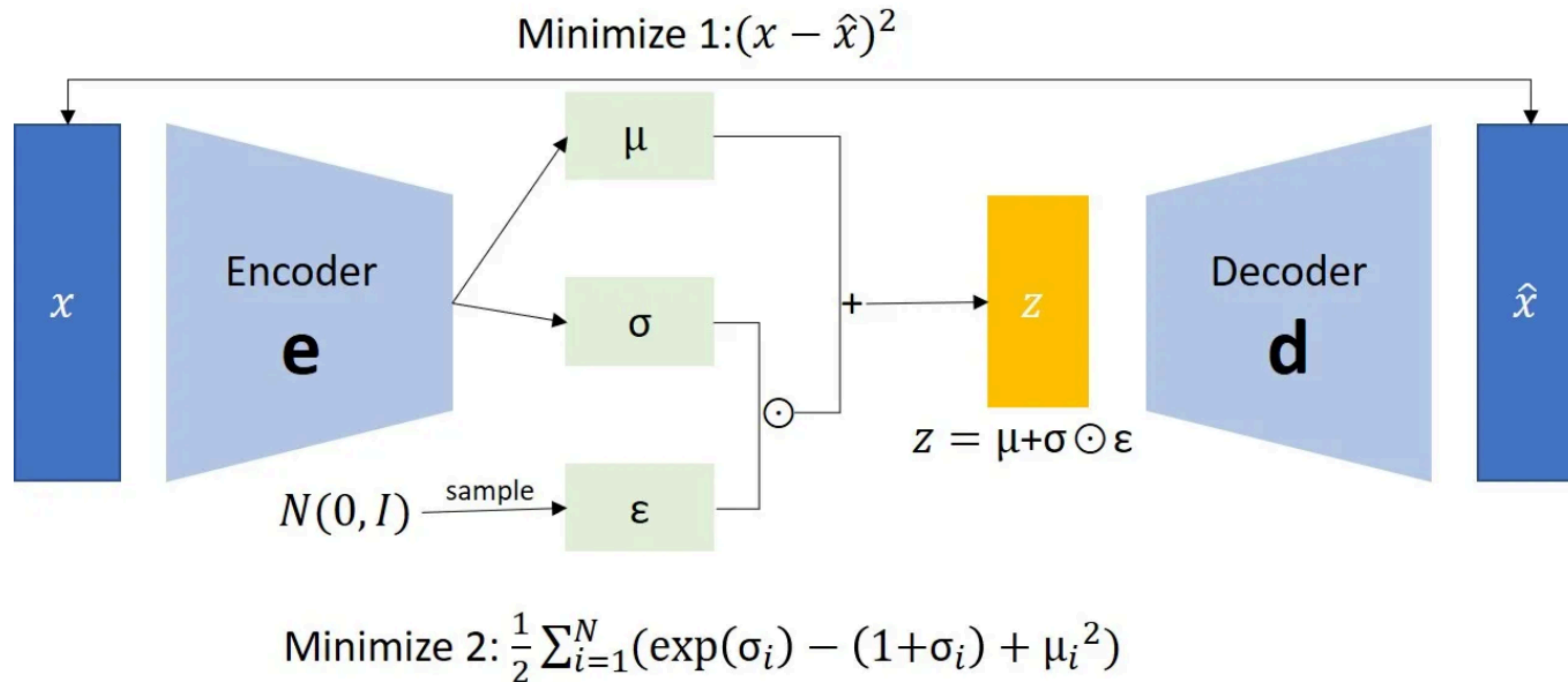
- 1) The model receives x as **input**
- 2) The encoder compresses it into the latent space
- 3) The decoder receives as input the information sampled from the latent space and produces x' as similar as possible to x

WHAT IS AUTOENCODER?

1. Compress **(encode)** input data to its essential features.
2. Reconstruct **(decode)** the original input from this compressed representation.



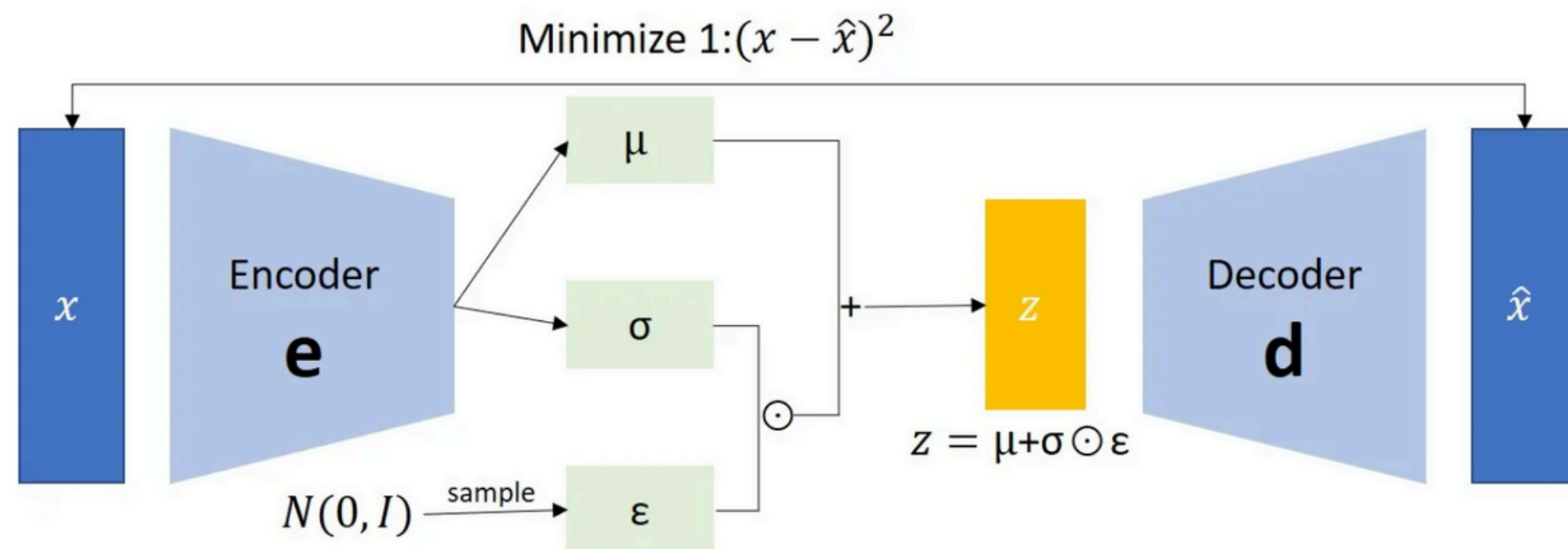
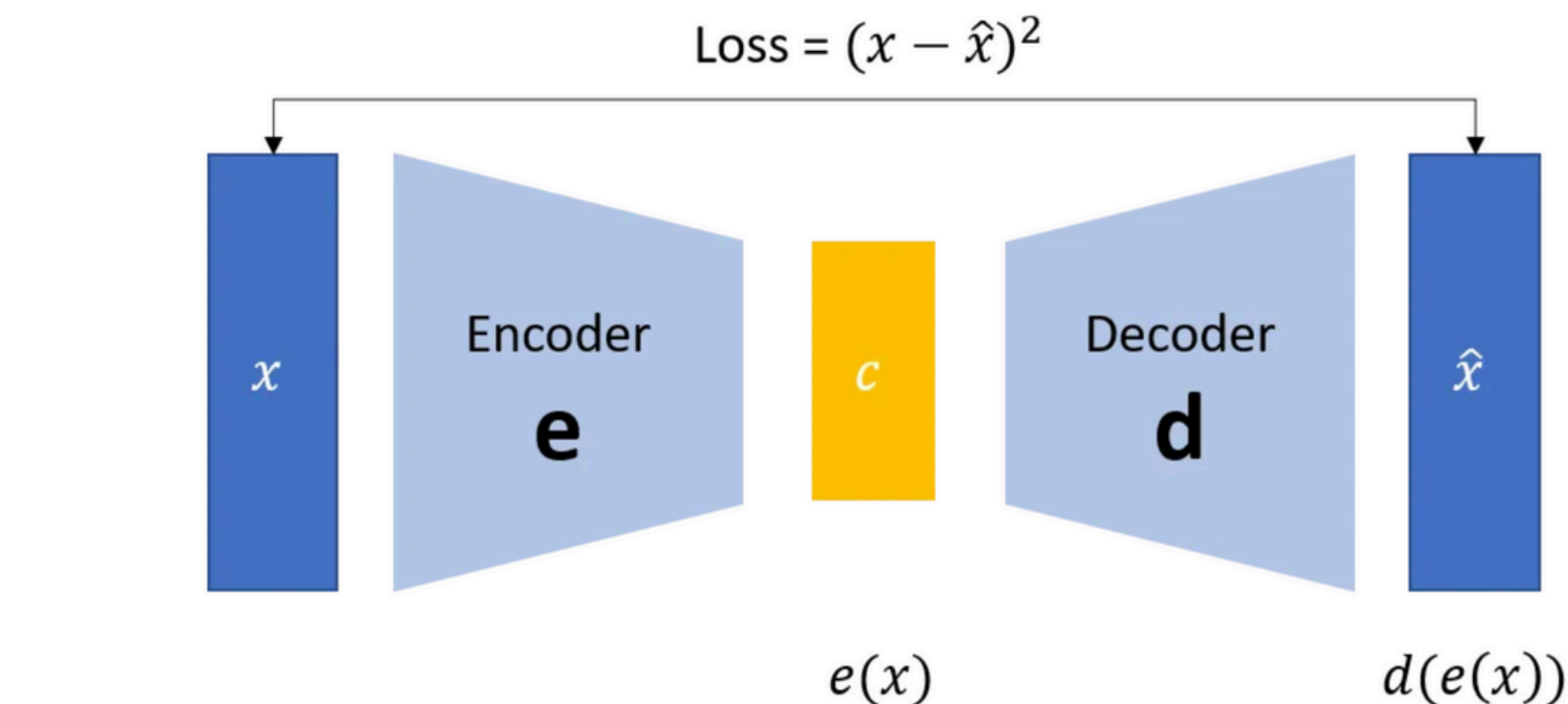
WHAT IS THE VARIATIONAL AUTOENCODER?



WHAT IS THE DIFFERENCE?

1. Most autoencoders learn discrete latent space models, VAEs learn continuous latent variable models.

2. VAEs model two different vectors: a vector of means, “ μ ,” and a vector of standard deviations, “ σ .”



$$\text{Minimize 2: } \frac{1}{2} \sum_{i=1}^N (\exp(\sigma_i) - (1 + \sigma_i) + \mu_i^2)$$

LITERATURE REVIEW – TECHNIQUES FOR FR & FV

1. Holistic methods :

Eigenfaces (PCA)

- Reduce face image data to eigenfaces
- Focus on variations in facial structure

Fisherfaces (LDA)

- Focus on features that maximize class separability
- More robust to lighting variations

LITERATURE REVIEW – TECHNIQUES FOR FR & FV

2. Feature-based methods :

Hidden Markov Model

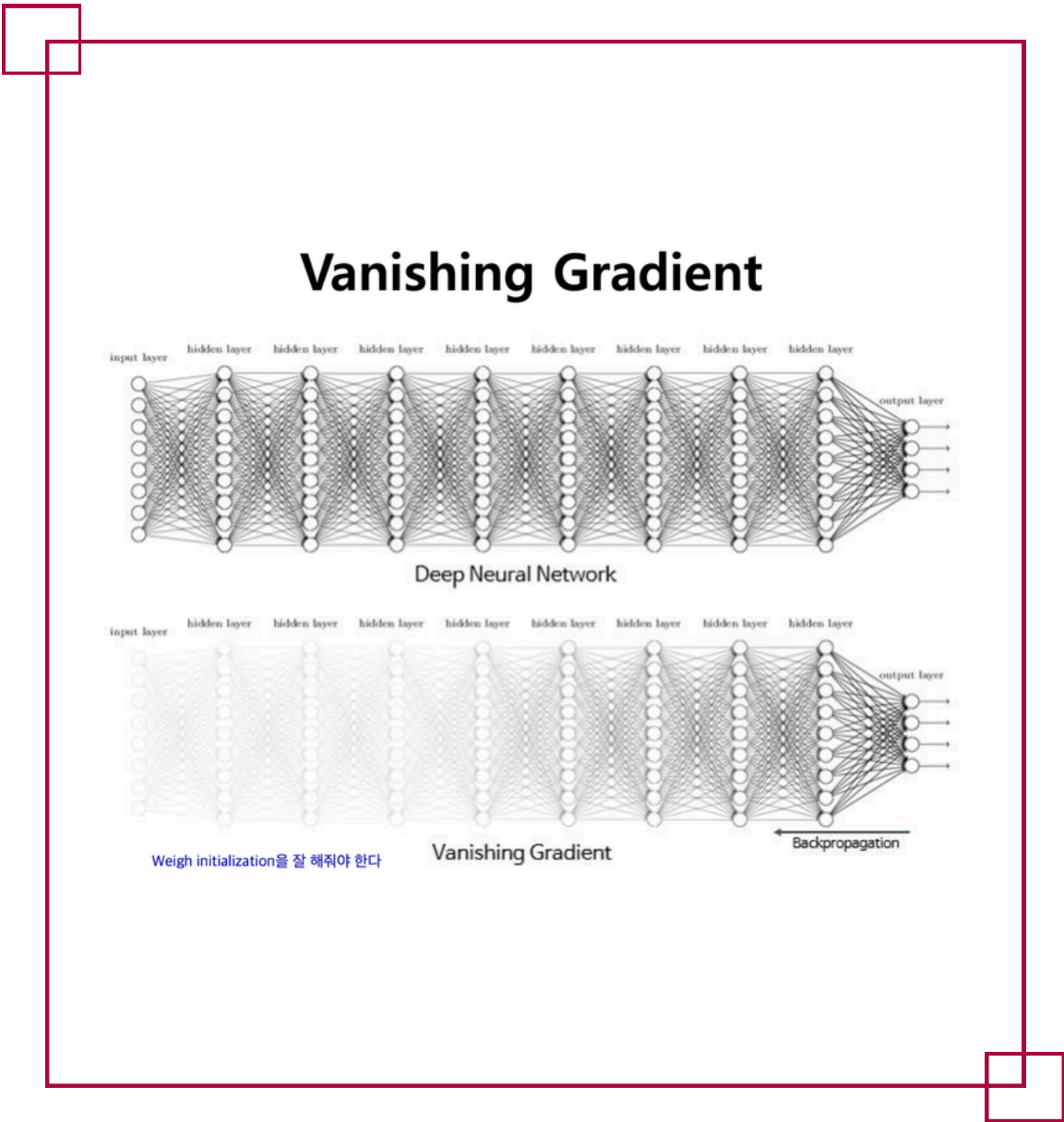
- Dividing the face into several regions
- Treating regions as a sequence of observations

CNN

- Deep learning models that learn hierarchical features from images
- Each layer detects increasingly complex patterns

RESNETS

Problem with CNNs



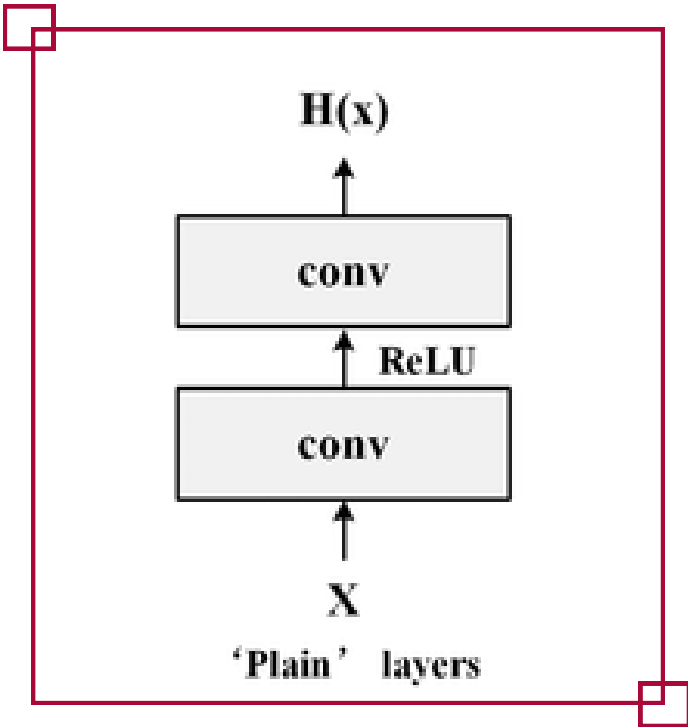
Resnets

Results

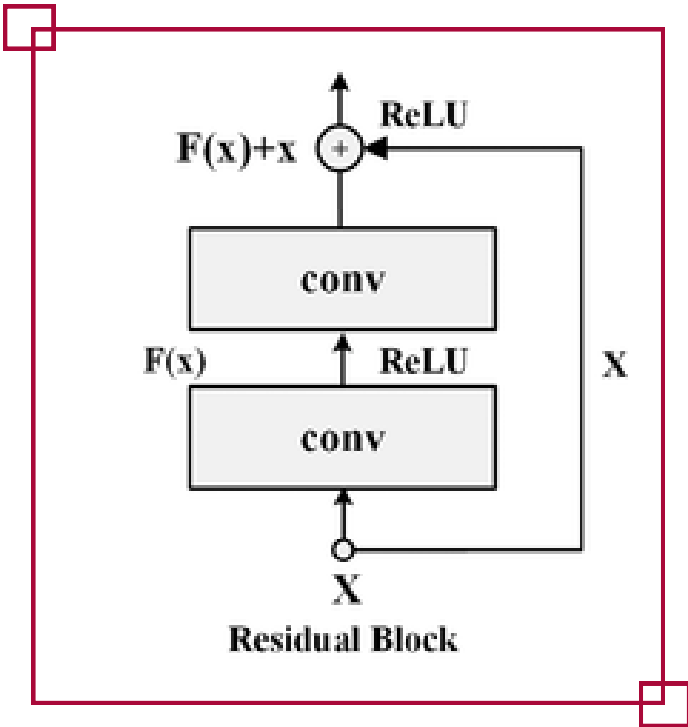
- The 152-layer ResNet achieved a top-5 error rate of 3.57% on the ImageNet Dataset.
- Contributed to multiple 1st-place wins in the COCO 2015 competition in tasks like object detection, segmentation.
- On the CIFAR-10 dataset, ResNets showed their ability to train networks with over 1,000 layers effectively.

RESNETS : OVERVIEW

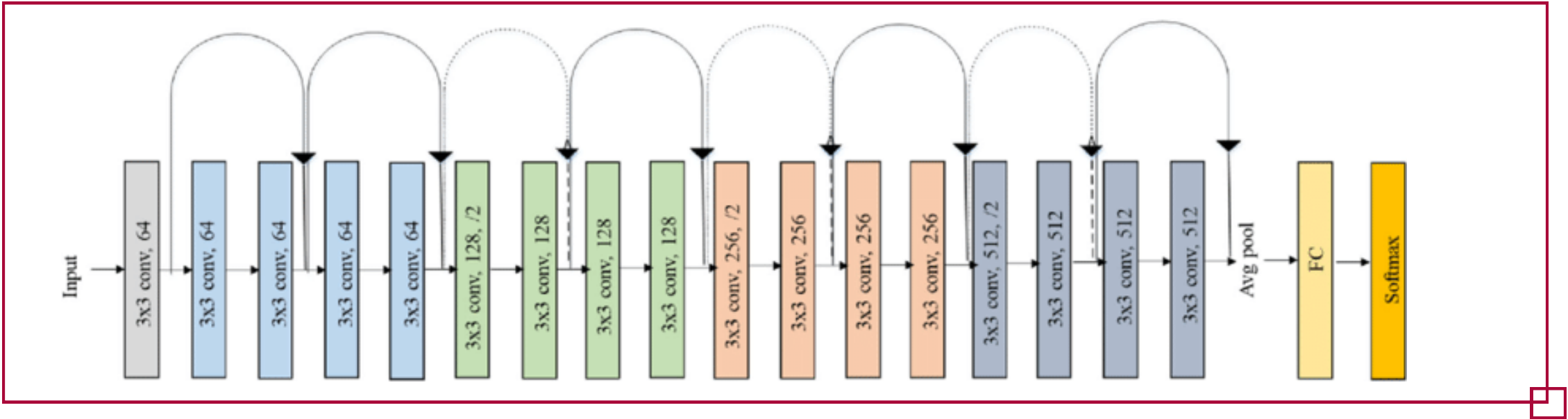
Plain Layer



Resnet block

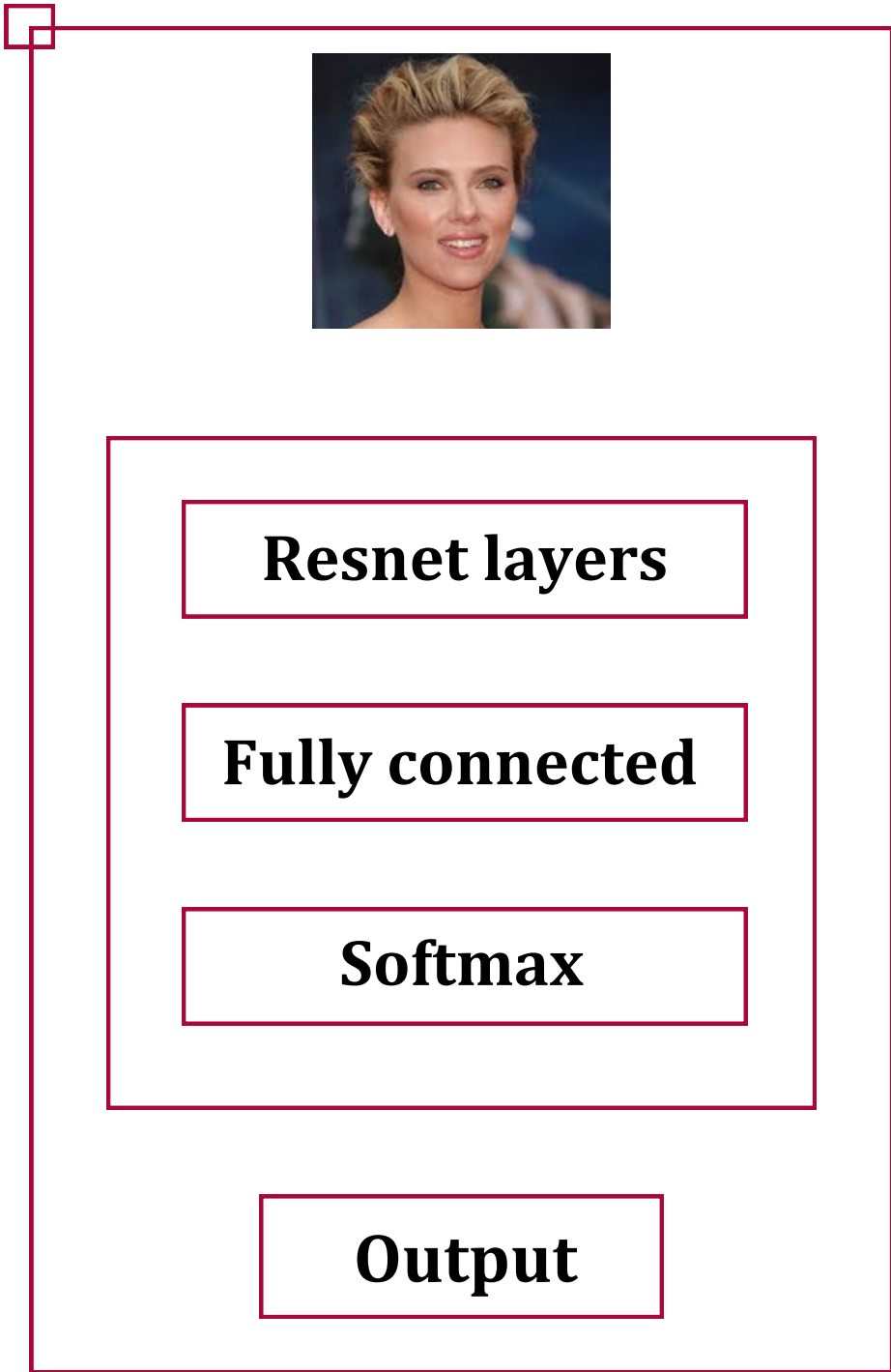


Exemple of Resnet18



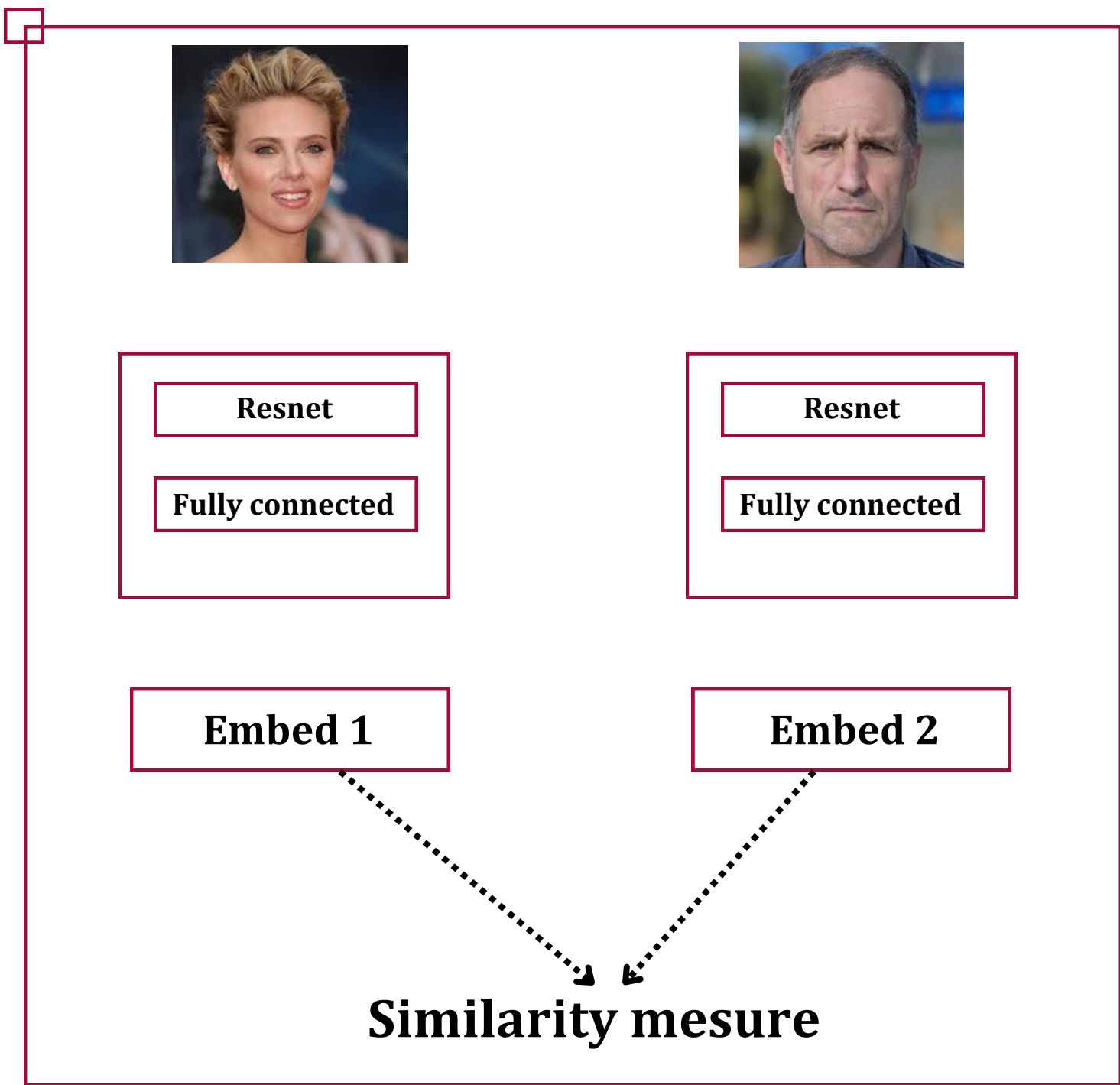
RESNETS : FACE VERIFICATION TASK

Training phase



Weights

Test Phase



PROJECT ANNOUNCEMENT

Objectives

Perform Face verification task using Variational Auto-encoders and compare the results with the baseline

Dataset

Casia Dataset : Introduced by Yi et al. in Learning Face Representation from Scratch. it contains 494,414 face images of 10,575 real identities collected from the web.

Loss

Arcface Loss

LOSS FUNCTION

ArcFace loss:

❏ Introduces an angular margin to the softmax loss

❏ Improves separability between classes

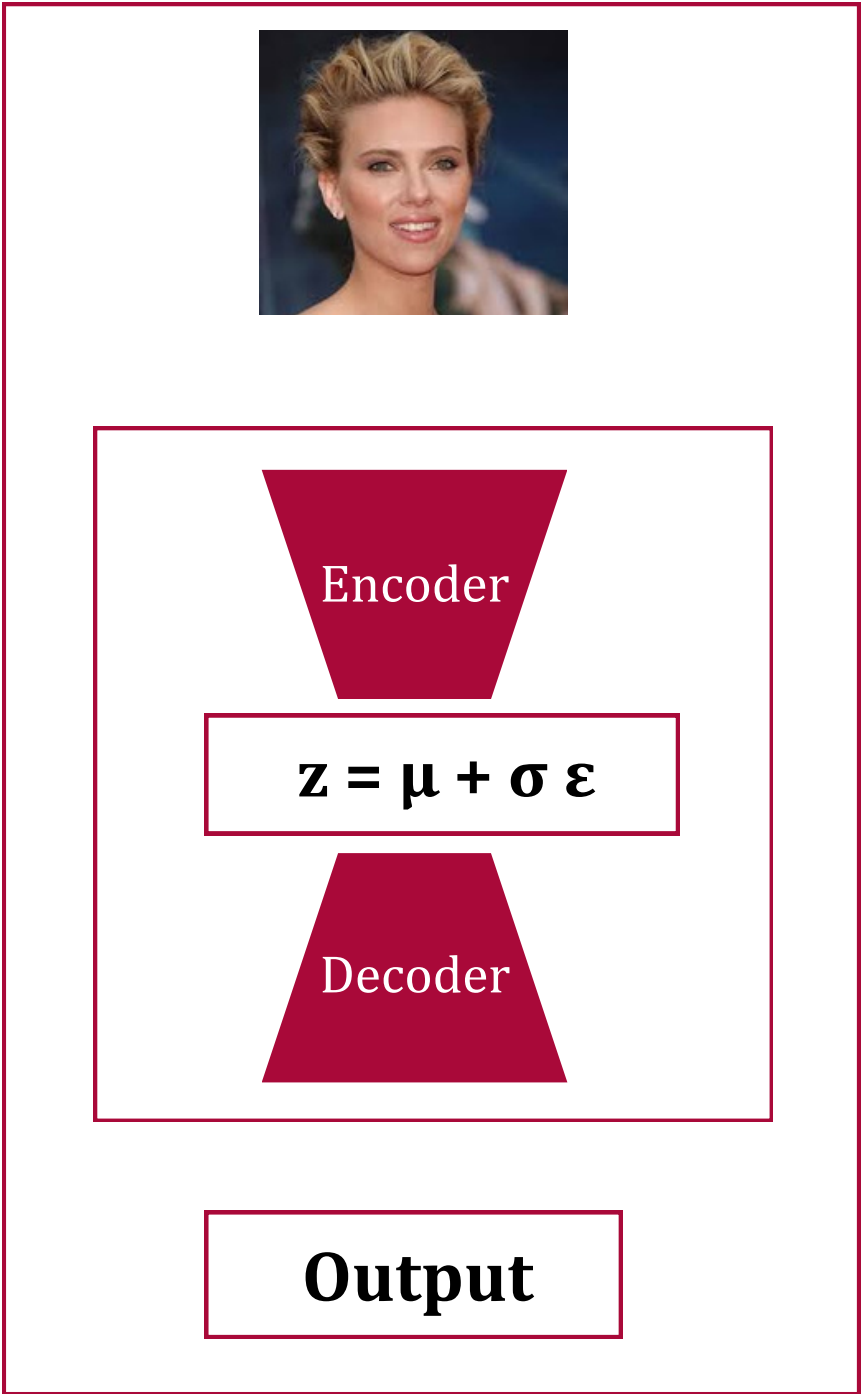
$$L = -\frac{1}{N} \sum_{i=1}^N \log \frac{e^{s(\cos(\theta_{y_i} + m))}}{e^{s(\cos(\theta_{y_i} + m))} + \sum_{j=1, j \neq y_i}^C e^{s \cos \theta_j}}$$

❏ Replace the euclidean distance with an angular distance between classes

❏ Used to increase the interclass margin of embeddings

PROJECT ANNOUNCEMENT

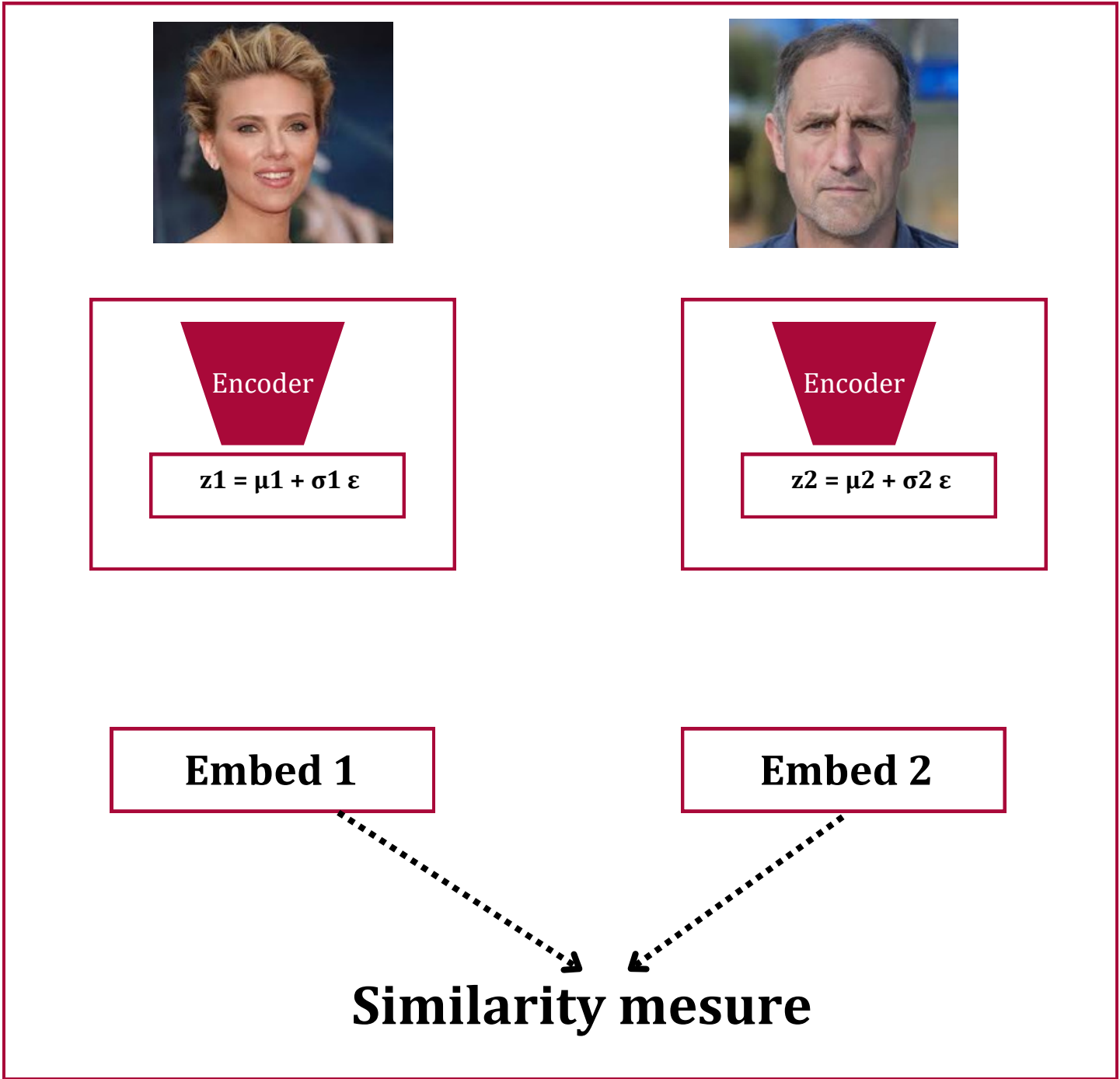
Training phase



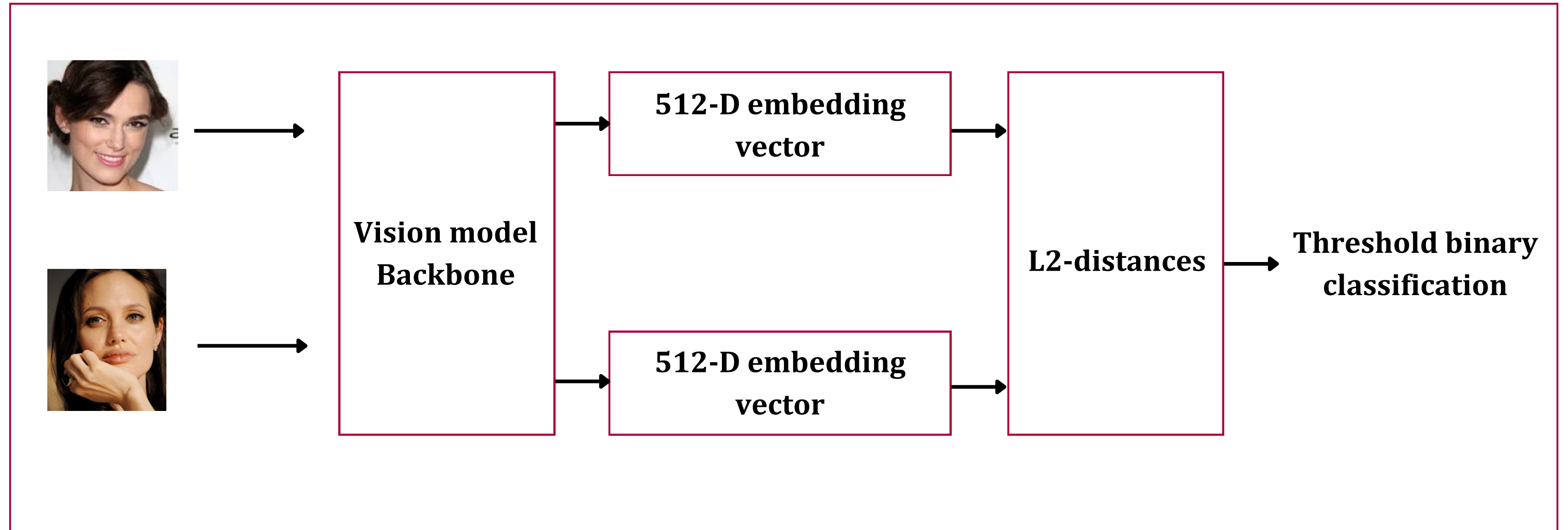
Weights



Test Phase

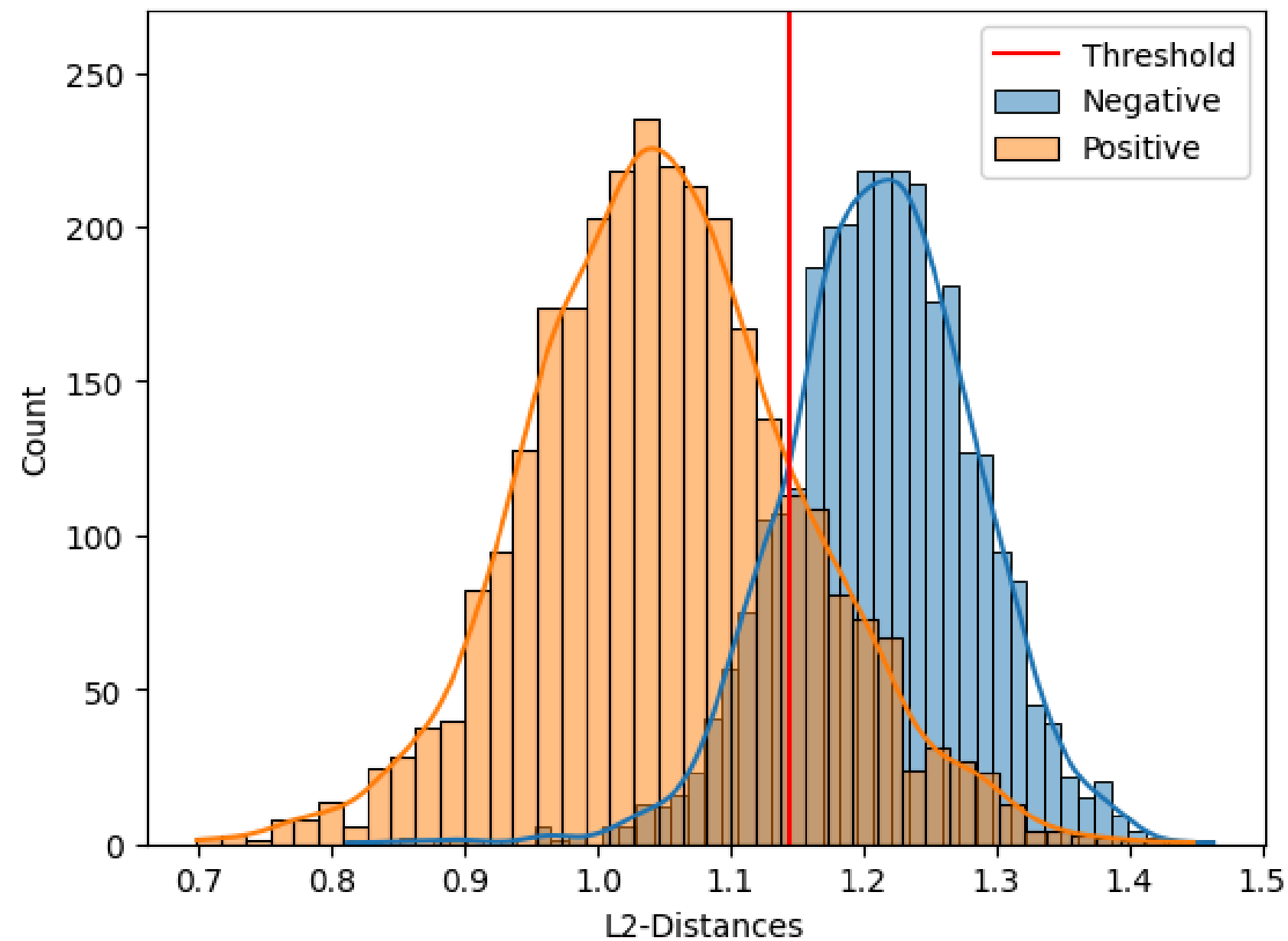


EVALUATION PIPELINE



EVALUATION PIPELINE

Using LFW-c dataset:



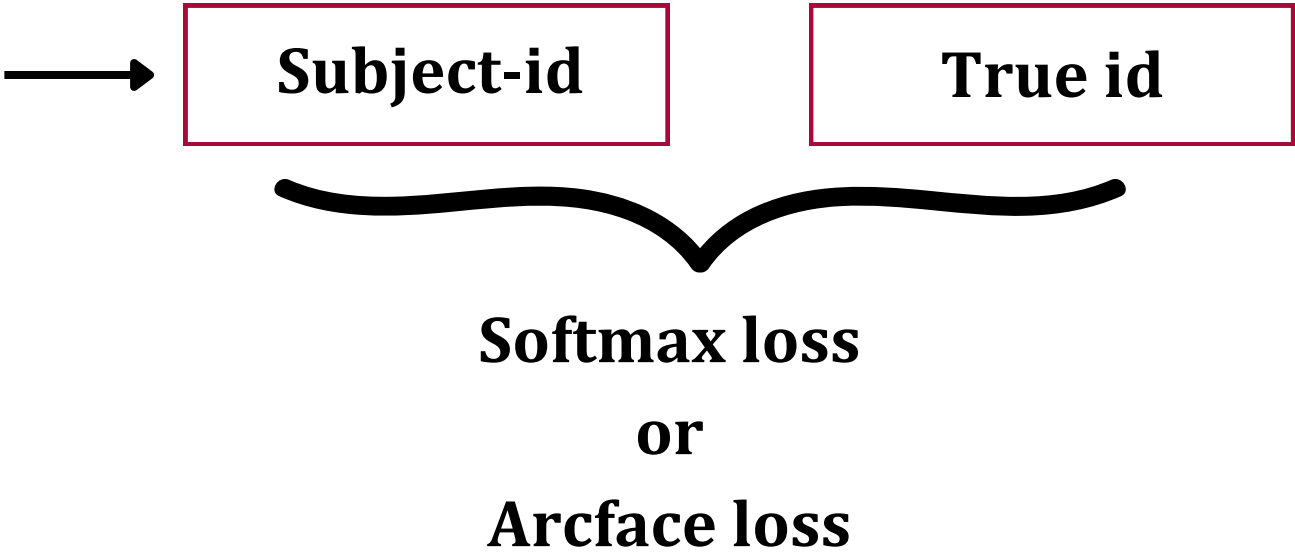
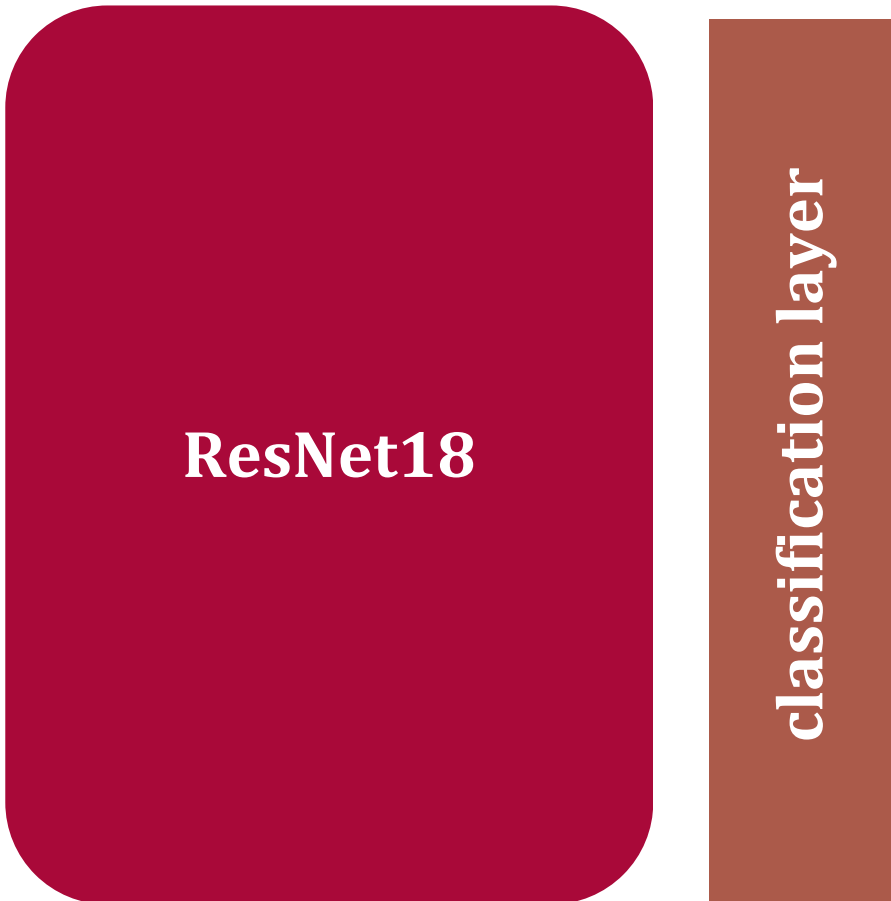
- 10 fold cross validation
- mean threshold : 1.145
- mean accuracy : 0.85

BASELINE METHODS

ResNet18 training (Arcface vs. Softmax loss):

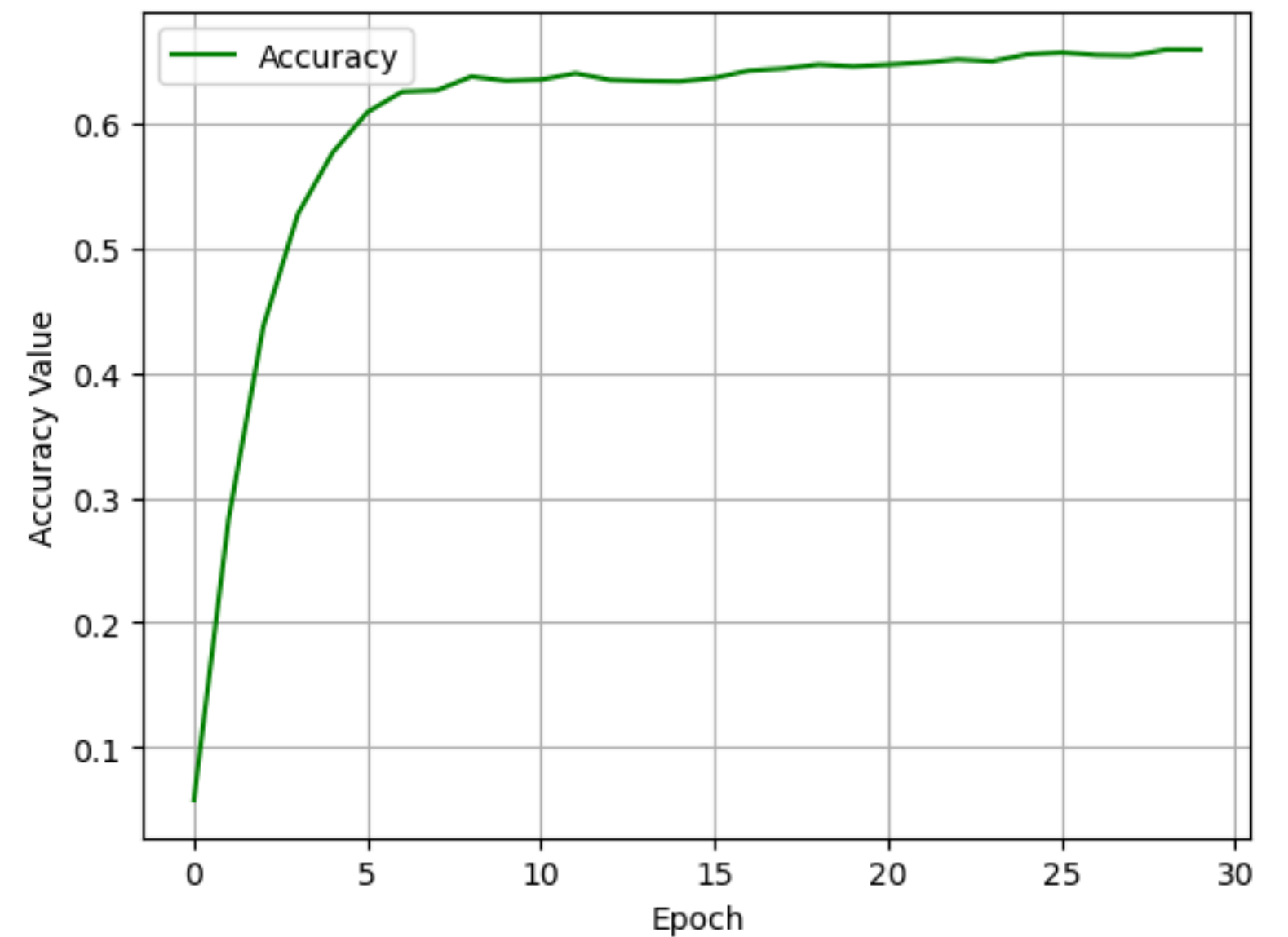
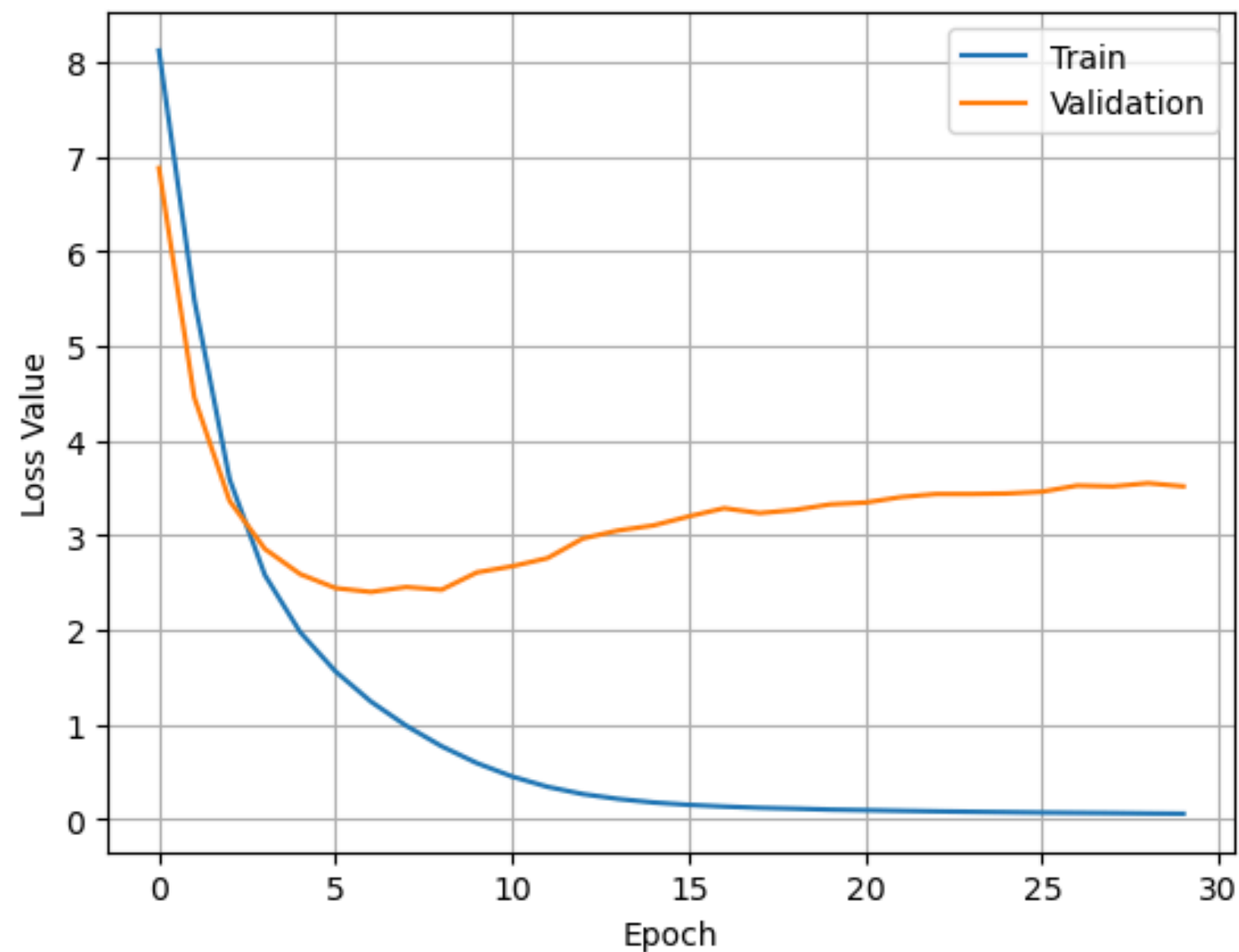


Casia Face Dataset



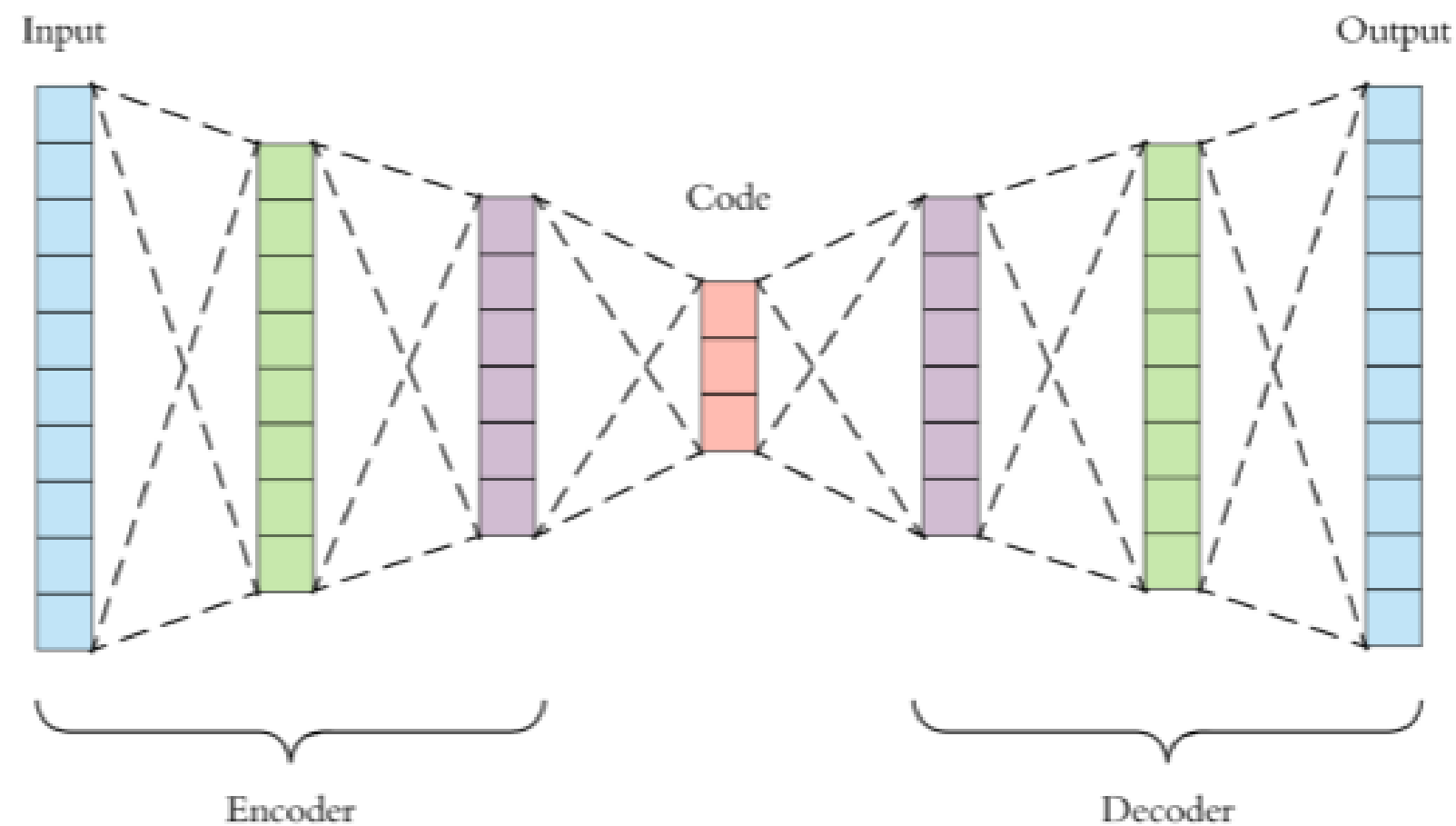
BASELINE METHODS

Training results with softmax loss



- Batch size : 64
- Optimizer : Adam
- Learning rate: $1e-4$
- Final accuracy : 0.65

BUILDING VAE FROM SCRATCH

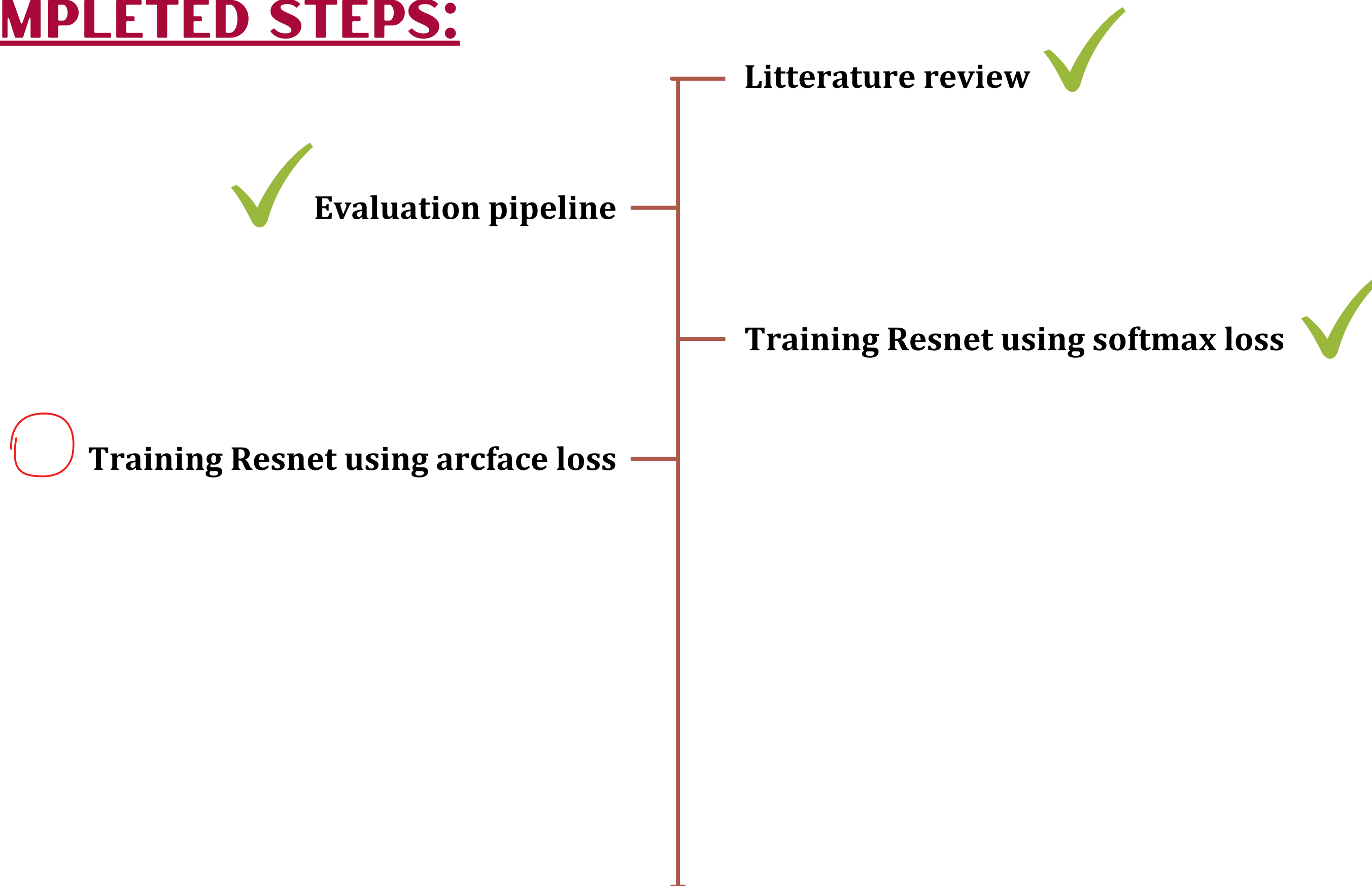


- Fully convolutional architecture
- Minimize reconstruction loss
- Encoder: feature extractor
- Goal: learning compact representations of faces

Suggestion:

The decoder could be used for data augmentation during training.

COMPLETED STEPS:



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