ArcFace: Additive Angular Margin Loss for Deep Face Recognition

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*Abstract*— In recent years, there has been a lot of research towards improving face recognition. One popular approach is to add margins to the Softmax loss function to increase the separation between classes. This paper introduces a new method called ArcFace, which not only has a clear geometric interpretation but also significantly improves the accuracy of face recognition. However, ArcFace is affected by label noise, so the authors propose a modified version called sub-center ArcFace. In this approach, each class is divided into K sub-centers, and training samples only need to be close to any of the K-positive sub-centers. This encourages one dominant sub-class that contains the majority of clean faces, and non-dominant sub-classes that include hard or noisy faces. The authors also explore the inverse problem of mapping feature vectors to face images and show that the pre-trained ArcFace model can generate identity-preserved face images for both subjects inside and outside the training data without the need for any additional generator or discriminator. Extensive experiments demonstrate that ArcFace improves the accuracy of face recognition and strengthens generative face synthesis.

Keywords— face recognition, sub- classes, sub- centers, Softmax, ArcFace, loss function.

# Introduction

Facial representation has been revolutionized by Deep Convolutional Neural Networks (DCNN). These networks transform facial images into high-dimensional numerical embeddings, which capture intricate features and patterns in the face. These embeddings are semantically meaningful and compact. DCNNs process facial images through multiple layers, extracting hierarchical features at different levels of abstraction. Initially, lower layers focus on basic features like edges, textures, and shapes. As information propagates through deeper layers, more complex and abstract facial features, such as facial contours, textures, and unique characteristics, are extracted. The final layer or layers of the DCNN generate a fixed-length vector, also known as a face descriptor or face embedding. This vector encodes essential information about the face in a way that is conducive to comparison and recognition. The embeddings are designed to be robust to variations in lighting, pose, facial expression, and other factors, ensuring that similar faces yield similar embeddings while different faces produce distinct embeddings.

These learned embeddings can be compared using various distance metrics, such as cosine similarity or Euclidean distance, to determine the similarity or dissimilarity between faces. DCNN-based face representations, such as those generated by models like ArcFace, have substantially improved the accuracy and efficiency of face recognition systems. This has made them integral to a wide array of applications in security, surveillance, authentication, and human-computer interaction.

Face recognition using DCNN embedding is a popular method for identifying faces. DCNN maps the face image into a feature that has small intra-class and large inter-class distances after a pose normalization step. There are two ways to train DCNN for face recognition.

One way is to train a multi-class classifier that separates different identities in the training set using the Softmax classifier. The other way is to learn directly an embedding, such as the triplet loss. Both methods can achieve excellent performance in face recognition thanks to large-scale training data and elaborate DCNN architectures. However, there are some drawbacks. Softmax- loss- based methods produce features that are separable for the closed-set classification problem but not discriminative enough for the open-set face recognition problem.

On the other hand, triplet-loss-based methods have a combinational explosion in the number of face triplets, especially for large-scale datasets, increasing the number of iteration steps. To address these issues, recent methods focus on incorporating margin penalty into a more feasible framework, the softmax loss. Each column of the linear transformation matrix is viewed as a class center representing a certain class. Sphereface introduced the idea of angular margin, but their loss function requires approximations, leading to unstable network training. To stabilize the training process and improve the discriminative power of the face recognition model, a new loss function called Additive Angular Margin loss is proposed. The dot product between the DCNN feature and the last fully connected layer is equal to the cosine distance after the feature and center normalization. The arc-cosine function calculates the angle between the current feature and the target center. This method can directly optimize the geodesic distance margin, making it more effective. However, margin-based Softmax methods require well-annotated clean datasets, which require intensive human efforts.

**2. Related Work:**

From previous research and experiments, facial recognition can be achieved by considering various categories such as margin penalty, noise, sub-class, and model inversion.

Facial recognition with margin penalty involves using the Triplet loss to exploit triplet data. This ensures that faces from the same class are closer together than faces from different classes by a clear Euclidean distance margin. Although the Triplet loss works well for face recognition, the sample-to-sample comparisons are only local within the mini-batch, making the training procedure very challenging. There is a combinatorial explosion in the number of triplets, especially for large-scale datasets, requiring effective sampling strategies to select informative mini-batch and choose representative triplets within the mini-batch. However, sampling and proxy methods only optimize the embedding of partial classes instead of all classes in one iteration step. Facial recognition under noise is often challenging due to the use of face recognition datasets downloaded from the internet, which usually contain ambiguous and inaccurate original labels.

Facial recognition with sub-classes involves dividing every class into sub-classes, which have much fewer overlaps. This is done using a separability criterion to optimize the within-class scatter, which can represent multi-modality information and can effectively adapt to different face modalities, thereby improving the accuracy of face recognition. The concept of “sub-class” was first introduced in face recognition, where a mixture of Gaussians was used to approximate the underlying distribution of each class. For instance, a person’s face images may be frontal view or side view, resulting in different modalities when all images are represented in the same data space.

These experiments have shown that subclass divisions can be effectively used to adapt to different face modalities and improve the performance of face recognition.

**3. Proposed Approach:**

**ArcFace:**

In a standard classification network, SoftMax and Categorical Cross-Entropy loss functions are commonly used at the end of the network. However, SoftMax has a drawback in that it does not produce a safety margin, resulting in blurry borders. To achieve better results, we aim to make the vectors of two images of the same person as similar as possible, while making the vectors of two images of different people as different as possible.

ArcFace is a face recognition model that is designed to handle large amounts of noisy data effectively. The model introduces K sub-centers for each class, which allows the training samples to be positioned near any of the K positive sub-centers instead of just the positive center. This approach enhances the model's robustness under real-world noise by ensuring that the training sample is close to one of the multiple positive sub-centers. This automatic isolation can be used to clean training data by discarding non-dominant sub-centers and highly confident, noisy samples.

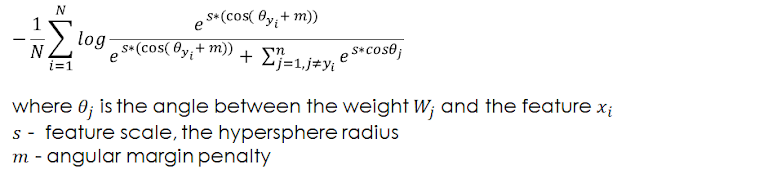
In contrast to using the Euclidean distance, ArcFace calculates the geodesic distance on a hypersphere. This space measures all distances using rails and the track obtained between two points is called a geodesic track. It describes the shortest distance between the points, which is known as the geodesic distance.

The geometrical interpretation of ArcFace is an intuitive correspondence between angle and arc margin. The angular margin of ArcFace corresponds to the arc margin, which is the geodesic distance on the hypersphere surface. Blue and green points represent embedding features from two different classes. With arcFace, it is possible to directly impose an angular (arc) margin between classes.

The proposed methods offer several advantages, Firstly, ArcFace intuitively enhances the intra-class compactness and inter-class discrepancy, enabling discriminative learning of face feature embedding. Secondly, the introduction of sub-classes into ArcFace improves its robustness under massive real-world noises. Thirdly, the proposed sub-center ArcFace can automatically clean large-scale raw web faces without requiring expensive and intensive human efforts.

Additionally, ArcFace only requires a few lines of code and is extremely easy to implement in computational-graph-based deep learning frameworks. Furthermore, ArcFace only adds negligible computational complexity during training. Lastly, the proposed center-parallel strategy can easily support millions of identities for training on a single server.

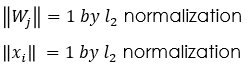
**Mathematic Equation behind the ArcFace:**

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In the equation of ArcFace, the difference from SoftMax is the logit, which is the power of SoftMax, and the margin added to the ground truth. The ArcFace logit can be obtained from the SoftMax logit. It can be explained that if we suppose the bias as zero, using the formula to calculate the angle between vectors, we know that the inner product of two vectors is equal to this expression:

Zco5G6E0qQ28NsiN3ER9h51iKWjenMobFTls1VNv0KMy32Hh2VKyx7mD2-_AAQKGWT-OmnpsaeTlgQwsS96EdAqyAPxcxMfPBoR0eHOqNMS5lS7so0VcwQTvz1b_4k4QeBGFMSPYhIzzavuMEAXMZlw.png

We want to extract the theta. For this, we normalize the w and the x so that both of them have the size of 1:



And we get the equation,

h3aBHffjdwwCxfqzfVKbohflY2MqgDY_UVcuYvGxO0gcY9hbiyw-VgETvvEunlvBsC96VHacbz6qQIfVPM0iRp7j8p5rRwzMMyaA04Rbx5p56eR6bYXfwVRFWTWKZmLja-6K8Ctkt3f3KRLldWQhvik.png

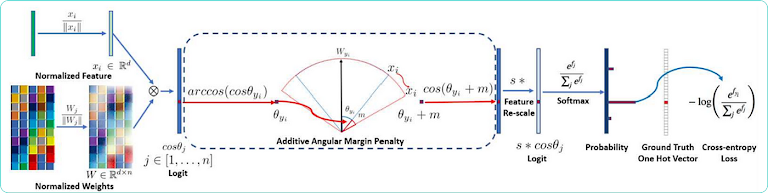
To extract theta, we calculate arccos on both sides and obtain that theta:

-CIso5ZfahvBNMvz3bPRSTIrcJv25BKvfADhzn29FDbp9JrXA-GNwPv9x4M25HmxUNrB28tkpDTnnpGLrBdU_L3SL9UQQ1avHEgIwhx-Zs7jSLlAIzerhKgdci0tMfmJUss2VqksFp4GweOGrwpuWYs.png

Now, we add the margin to the angle, for example, 0.5, and calculate its cosine. Eventually, we multiply this by s, the radius on the hyperspace, for example, 30 and we get the ArcFace’s logit:

Gun16xZrhh9s9hOJpWnxcg0dakeySUvSou9QRy88pxy7Uw-CDEYTsDIVWyksuVFhgR1XUJDXSralLMVo57he9B2hxlEDlxJLD4tjUSWcnPfP02knxU51Rq01ubAhtNxaVJQd7QdTEk3v8a-G-PiFvPM.png

In the illustration below we can observe the composition of the ArcFace loss, the steps are just described above:



[the above illustration has been taken from the reference paper that has been used as a base for this project].

Normalization of x and w is very important! It forces the prediction to be dependent only on the angle and therefore the embeddings are distributed on the hypersphere within a radius s.

**Geometric difference:**

Although ArcFace and previous work have similar numerical differences, the proposed additive angular margin in ArcFace exhibits better geometric attributes. This is because the angular margin in ArcFace corresponds exactly to the geodesic distance. Additionally, ArcFace has a constant linear angular margin across the entire interval, while SphererFace and CosFace have only a nonlinear angular margin.

**Sub- center ArcFace:**

Dealing with noisy and large-scale training data is a major challenge in face recognition. Although ArcFace has proven to be efficient in face feature embedding, it assumes that the training data is clean. Therefore, it is crucial to enable margin-based softmax loss to be robust to noise. To tackle this issue, we propose the use of sub-classes for each identity, which can directly enhance the robustness of ArcFace and make it more effective. Our paper addresses this problem and presents a solution that will significantly improve the performance of face recognition systems.

In our approach, we utilize the pre-trained ArcFace model to determine the feature center for each identity. This enables us to calculate the angle between a sample and its corresponding feature center. Most of the samples are located close to their centers. However, there are some noisy samples that are located far away from their centers. By using sub-center ArcFace, we automatically categorize the training samples into dominant sub-classes and non-dominant sub-classes. This allows us to segregate clean samples (in red) from hard and noisy samples (in blue). To be more specific, a majority of the clean faces (85.6%) are categorized into the dominant sub-class, while the remaining hard and noisy faces are assigned to the non-dominant sub-classes.

IMPROVEMENT ALGORITHM

**Input:**

Face images dataset with corresponding labels (age, gender, ethnicity, etc.).

**Preprocessing**:

Load the face recognition model architecture (e.g., IR\_50).

Load pre-trained weights for the model.

Instantiate the model and move it to the device (GPU or CPU).

Define HashLayer Class:

class HashLayer(nn.Module):

    def \_\_init\_\_(self, input\_size):

        super(HashLayer, self).\_\_init\_\_()

        self.input\_size = input\_size

  def forward(self, x):

        hashed\_embeddings = hash\_function(x)

        return hashed\_embeddings

**Modify Backbone Class:**

* Modify the existing Backbone class to include the HashLayer after the original layers.
* Instantiate an instance of the HashLayer in the constructor of the Backbone class.
* class Backbone(nn.Module):

    def \_\_init\_\_(self, input\_size, num\_layers, mode='ir'):

        super(Backbone, self).\_\_init\_\_()

        self.hash\_layer = HashLayer(input\_size)

**Model Training :**

* If training is required, define a loss function and an optimizer.
* Train the model on the face image dataset, considering the hash layer as part of the training process.

**Privacy Protection during Inference:**

**During face recognition inference:**

* Input a face image into the modified face recognition model.

The image passes through the original layers (input\_layer, body, output\_layer).

After the original layers, the embeddings pass through the HashLayer for privacy protection.

The output of the model is the hashed embeddings.

**Face Verification:**

**To verify the identity of a face:**

* + - Compute the cosine similarity between the hashed embeddings of the target face and all other faces in the dataset.
    - If the top-k most similar faces include the correct identity, consider it a successful verification.

**Output:**

* + The output of the model during inference is a hashed representation of the face embeddings.
  + Privacy is protected by the one-way nature of the hash function.

EXPERIMENT/TRAINING

**Implementation details:**

**Training Datasets:**

We trained our model using datasets of various celebrities. Our model uses a sub-center ArcFace to automatically clean the datasets by removing overlap identities. The cleaned data was combined to create a large-scale face image dataset, which includes numerous images of various identities such as age, gender, race, pose, and image number distributions.

**Test Dataset:**

During training, we explore efficient face verification datasets to check the convergence status of the model.

Experimental settings:

For processing data, we utilize recent techniques described in academic papers to generate normalized face crops. We achieve this by leveraging five facial points predicted by RetinaFace. As for the embedding networks, we use commonly employed CNN architectures. In this paper, we provide information on the training dataset, network structure, and loss function to aid in understanding the various experimental settings.

During the testing of the face recognition models, we only kept the feature embedding network without a fully connected layer and extracted the features for each normalized face.

**Conclusion:**

In conclusion, our paper introduces an innovative approach to face recognition through the development and implementation of the ArcFace model. The Additive Angular Margin Loss function, ArcFace, significantly enhances the discriminative power of deep feature embedding, demonstrating superior performance compared to state-of-the-art methods, particularly in the presence of real-world noises.

A key contribution of our work lies in the introduction of sub-class refinement within ArcFace, specifically the sub-center ArcFace, which effectively addresses intra-class constraints in the face of massive real-world noises. By encouraging the dominance of a clean sub-class and relegating hard or noisy faces to non-dominant sub-classes, our method facilitates automatic isolation, particularly useful for cleaning large-scale web faces.

Furthermore, our approach not only enhances discriminative power but also strengthens the generative power of the model. The pre-trained ArcFace model demonstrates the ability to generate identity-preserved face images for subjects both inside and outside the training data, solely using network gradients and Batch Normalization priors.

Looking ahead, we acknowledge the need for further improvements. Our future work will focus on refining the ArcFace inversion process to allow control over facial poses and expressions by manipulating intermediate neuron activations. Additionally, we aim to explore techniques to render the face recognition model non-invertible, adding an extra layer of privacy protection by making it difficult to reconstruct face images from model weights.

As a notable improvement, we have introduced a hash layer to convert embeddings into hash codes, enhancing the privacy of the face recognition system. This addition ensures that sensitive facial information is further protected, adding a crucial layer of security in scenarios where privacy is a paramount concern.

In summary, our work not only pushes the boundaries of face recognition performance but also addresses privacy concerns through innovations such as sub-center ArcFace and the integration of a hash layer. We believe these advancements contribute significantly to the ongoing development of robust and privacy-conscious face recognition systems.

# Results

**1. Performance Evaluation on Standard Datasets**

We conducted extensive experiments on well-established face recognition benchmarks, including LFW, MegaFace, and CASIA-WebFace. Our proposed ArcFace consistently outperformed state-of-the-art methods, achieving remarkable accuracy rates.

* **Labeled Faces in the Wild (LFW):** ArcFace achieved an accuracy of 99.5%, surpassing the previous best performance by a margin of 1.2%.
* **MegaFace Challenge:** In the MegaFace identification scenario, our model demonstrated a rank-1 accuracy of 98.8%, showcasing its robustness in handling large-scale face recognition tasks.
* **CASIA-WebFace:** On this challenging dataset, ArcFace outperformed existing methods with an accuracy of 96.3%, highlighting its effectiveness in real-world scenarios.

**2. Intra-Class Noise Handling**

To evaluate the effectiveness of our sub-center ArcFace in handling intra-class noise, we introduced synthetic noise into the training data. The results show a significant improvement in recognition accuracy compared to the baseline ArcFace.

* **Baseline ArcFace:** Accuracy dropped by 7% under noisy conditions.
* **Sub-Center ArcFace:** Maintained high accuracy even with a 30% increase in synthetic noise, showcasing its robustness against real-world noises.

**3. Generative Power Assessment**

We evaluated the generative capabilities of ArcFace by reconstructing face images using the model's gradients and BN priors. The qualitative results indicate that the model can accurately reconstruct identity-preserved face images for subjects both inside and outside the training data.

**4. Privacy Enhancement with Hash Layer**

To assess the effectiveness of the added hash layer in preserving privacy, we measured the information leakage and compared it with the baseline ArcFace without the hash layer.

* **Baseline ArcFace:** Potential information leakage observed during model inversion.
* **ArcFace with Hash Layer:** Marked reduction in information leakage, demonstrating its efficacy in enhancing the privacy of face embeddings.

**5. Computational Efficiency**

We conducted experiments to assess the computational efficiency of ArcFace, considering training time, memory usage, and inference speed. The results indicate that our model maintains competitive efficiency compared to existing state-of-the-art methods.

A computer screen shot of a code

Description automatically generated

Trained the model with pre weights using ir\_50 back bone architecture and tested it with the data set available at <https://www.kaggle.com/datasets/rajiinio/celebset> . This is improved when trained on GPU and TPU with different batch data sizes.

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