# Face Recognition vi a Archetype Hull Ranking

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## Abstract

*In the recent years, the archetype hull model is playing an important role in large-scale data analytics and mining, but rarely applied to vision problems. In this paper, the authors migrated this geometric model together to solve face recognition and verification problems. By proposing a unified prototype hull ranking framework. Upon a scalable graph characterized by a compact set of archetype exemplars whose convex hull encompasses most of the training images, the proposed framework explicitly captures the relevance between any query and the stored archetypes, yielding a rank vector over the archetype hull.*


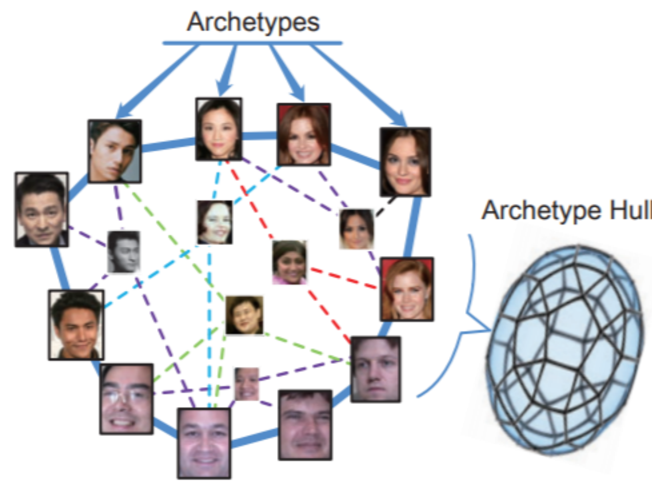


Figure 1. One visual example showcasing an archetype hull of face images. They view face images as points in the image space, where the polytope composed of a few archetype faces encloses almost all points. Any point can be represented by a convex combination of the archetypes, and these archetypes hence form a convex hull of the entire point set.

## 1. Introduction

The main purpose of facial analysis is to calculate robustness and effectiveness A measure of similarity between any input facial image pairs. Such a measure is expected to suppress intra-personal face variations due to varying expressions, poses, and illumination conditions. Today, fast-growing facial image resources from online photo albums and social networks offer new opportunities At the same time, it presents new challenges to existing facial treatment methods. How can they take advantage of the gigantic amount of face information on the Web? One feasible approach is to upgrade current face processing systems by augmenting web-crawled face images into their training datasets, which therefore requires the face systems to be easy for re-training and scalable to accommodate massive web data.

In pursuit of scalability, the authors used a small part archetype exemplars to represent a lot of facial training image. These archetypes form a convex shell Contains most faces in the training set. To the best of our knowledge, the archetype hull model has not been applied to the face area. The use of archetypes along with the produced archetype hull may open a new avenue to make traditional facial processing methods extendable to Large-scale face datasets. To illustrate, Fig. 1 showcases face archetypes and an archetype hull to model face images. In this paper, they seek such archetypes using an efficient simplex volume maximization algorithm. Subsequently, they build a scalable graph by virtue of the archetypes whose size is much smaller than the training data size.

## 2. Related Work

In the face recognition literature, a large number of subspace methods [2, 5, 6, 7, 3] working on holistic facial features have been proposed. Recently, local facial descriptors [1] achieved greater accuracy gains on many benchmark datasets. The local descriptors attempt to extract distinctive features of image textures like local micro-patterns of face shapes like LBP [1]. However, intra-personal variations caused by varying expressions, poses, and illumination conditions remain a potential obstacle to these appearance-based methods. As mentioned before, one of the major challenges of modern face recognition is the explosive growth of face data. Some efficient learning methods could provide promising solutions. For example, the LARK method [4] developed a special kind of features to obtain a training free classifier. Lately, a scalable neighborhood graph, Anchor Graph , was proposed to accommodate massive training samples, and has shown excellent performance in large-scale semi-supervised learning and image retrieval . In this paper, the authors employ the Anchor Graph model to deal with large quantities of face images since it scales linearly with the training set size in terms of both space and time complexities.

## References


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