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Locality Condensation: A New Dimensionality Reduction Method for Image Retrieval

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ABSTRACT

Content-based image similarity search plays a key role in multimedia retrieval. Each image is usually represented as a point in a high-dimensional feature space. The key challenge of searching similar images from a large database is the high computational overhead due to the “curse of dimensionality”. Reducing the dimensionality is an important means to tackle the problem. In this paper, we study dimensionality reduction for top- k image retrieval. Intuitively, an effective dimensionality reduction method should not only preserve the close locations of similar images (or points), but also separate those dissimilar ones far apart in the reduced subspace. Existing dimensionality reduction methods mainly focused on the former. We propose a novel idea called Locality Condensation (LC) to not only preserve localities determined by neighborhood information and their global similarity relationship, but also ensure that different localities will not invade each other in the low-dimensional subspace. To generate non-overlapping localities in the subspace, LC first performs an *elliptical condensation*, which condenses each locality with an elliptical shape into a more compact hypersphere to enlarge the margins among different localities and estimate the projection in the subspace for overlap analysis. Through a convex optimization, LC further performs a *scaling condensation* on the obtained hyperspheres based on their projections in the subspace with minimal condensation degrees. By condensing the localities effectively, the potential overlaps among different localities in the low-dimensional subspace are prevented. Consequently, for similarity search in the subspace, the number of false hits (i.e., distant points that are falsely retrieved) will be reduced. Extensive experimental comparisons with existing methods demonstrate the superiority of our proposal.

Categories and Subject Descriptors

H.3.3 [Information Storage and Retrieval]: Information Search and Retrieval

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General Terms

Algorithms, Measurement, Experimentation

Keywords

Dimensionality Reduction, Top- k Image Retrieval, Locality Condensation

1. INTRODUCTION

Multimedia similarity search aims at automatically retrieving multimedia objects similar to query objects from large databases based on their visual content, usually represented by some high-dimensional low-level features, such as color, texture and shape [21, 3]. In particular, top- k retrieval (or k -nearest neighbor search) finds the k most similar objects with respect to a query [24, 15, 6, 21, 3]. Since the dimensionality of a feature space is usually very high (up to hundreds of dimensions), directly indexing the original high-dimensional feature space usually fails for effective search due to the known phenomenon of the “curse of dimensionality” [27]. Dimensionality reduction that maps the original data onto a low-dimensional subspace becomes a promising way to alleviate this problem. Generally, dimensionality reduction can be used for the following purposes:

Simplifying complex data: For many applications, particularly in database and information retrieval, a high dimensionality of the feature space leads to high complexity of the data representation. The dimensionality has to be reduced to achieve a fast query response for an indexing structure or retrieval method. Typical methods include Discrete Fourier transform (DFT) and Discrete Wavelet Transform (DWT) [28], Adaptive Piecewise Constant Approximation (APCA) [7], Principal Component Analysis (PCA) [20] and its various improvements [26, 8, 24], Latent Semantic Indexing (LSI) [10] and its variants [17], Locality Preserving Projection (LPP) [16, 32, 14, 5], etc. For these types of applications, the process of dimensionality reduction must have an explicit mapping function to map the query points onto the low-dimensional subspace for similarity search.

Modelling and analyzing data: For many applications, particularly in machine learning and pattern recognition, the underlying data structure is often embedded in a much lower-dimensional subspace. The task of recovering meaningful low-dimensional structures hidden in high-dimensional observation data is also known as “manifold learning”. Typical methods include Independent Component Analysis (ICA) [18], Multidimensional Scaling (MDS) [30], Isometric feature mapping (Isomap) [25] and its im-