DOCTORAL THESIS

Studies on probabilistic tensor subspace learning

Zhou, Yang

Date of Award:
2019

Abstract

Most real-world data such as images and videos are naturally organized as tensors, and often have high dimensionality. Tensor subspace learning is a fundamental problem that aims at finding low-dimensional representations from tensors while preserving their intrinsic characteristics. By dealing with tensors in the learned subspace, subsequent tasks such as clustering, classification, visualization, and interpretation can be greatly facilitated. This thesis studies the tensor subspace learning problem from a generative perspective, and proposes four probabilistic methods that generalize the ideas of classical subspace learning techniques for tensor analysis.

Probabilistic Rank-One Tensor Analysis (PROTA) generalizes probabilistic principle component analysis. It is flexible in capturing data characteristics, and avoids rotational ambiguity. For robustness against overfitting, concurrent regularizations are further proposed to concurrently and coherently penalize the whole subspace, so that unnecessary scale restrictions can be relaxed in regularizing PROTA.

Probabilistic Rank-One Discriminant Analysis (PRODA) is a bilinear generalization of probabilistic linear discriminant analysis. It learns a discriminative subspace by representing each observation as a linear combination of collective and individual rank-one matrices. This provides PRODA with both the expressiveness of capturing discriminative features and non-discriminative noise, and the capability of exploiting the (2D) tensor structures.

Bilinear Probabilistic Canonical Correlation Analysis (BPCCA) generalizes probabilistic canonical correlation analysis for learning correlations between two sets of matrices. It is built on a hybrid Tucker model in which the two-view matrices are combined in two stages via matrix-based and vector-based concatenations, respectively. This enables BPCCA to capture two-view correlations without breaking the matrix structures.

Bayesian Low-Tubal-Rank Tensor Factorization (BTRTF) is a fully Bayesian treatment of robust principle component analysis for recovering tensors corrupted with gross outliers. It is based on the recently proposed tensor-SVD model, and has more expressive modeling power in characterizing tensors with certain orientation such as images and videos. A novel sparsity-inducing prior is also proposed to provide BTRTF with automatic determination of the tensor rank (subspace dimensionality).

Comprehensive validations and evaluations are carried out on both synthetic and real-world datasets. Empirical studies on parameter sensitivities and convergence properties are also provided. Experimental results show that the proposed methods achieve the best overall performance in various applications such as face recognition, photograph-sketch match, and background modeling.

Keywords: Tensor subspace learning, probabilistic models, Bayesian inference, tensor decomposition.

Table of Contents