Soft Label and Discriminant Embedding Estimation for Semi-Supervised Classification

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- 1. Introduction
- 2. Proposed method
- 3. Experiments & Comparisons
- 4. Conclusion







- What are some best practices for machine learning?
- > How can data labeling be done efficiently?
- > What is Semi-supervised learning?
- What is the benefits of dimensionality reduction or manifold learning methods.

Introduction

Dimensionality Reduction

machine learning models

High dimensional data

The processing is a challenging task

Need for a low dimensional representation of high dimensional data that preserves the intrinsic information of data. This is what we call dimensionality reduction or manifold learning methods.









Introduction





Semi-Supervised Learning





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Introduction

Related work

- An iterative paradigm of joint feature extraction and labeling for semisupervised discriminant analysis (ISDA) [Ren 2018]
- Semi-supervised linear discriminant analysis(SLDA) [Wang 2016]
- Semi-supervised Discriminant Analysis (SDA) [Cai 2007]
- Semi-supervised Discriminant Embedding (SDE) [Huang 2012]
- Flexible Manifold Embedding (FME) [Nie 2010]

Proposed method

Criterion



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Proposed method







(1) S_b is between-class graph, E is a matrix of ones.







Databases

Dataset Name	Number of samples	Number of classes	~Samples/class	Dimension of a sample	Dataset type
ORL	400	40	10	32×32	Face Images
UMIST	575	20	29	28×23	Face Images
Extended Yale	1774	28	63	32 × 32	Face Images
USPS	1100	10	110	16×16	Handwritten digits
COIL-20	360	20	18	51 × 51	Object Images

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Results

EXT - Yale	1 Sample		2 Samples		3 Samples	
Method	Т	U	Т	U	Т	U
FME	36.8%	40.7%	51.2%	54.7%	56.2%	59.9%
KFME	27.5%	29.3%	45.3%	46.5%	52.2%	56.3%
SDA	32.8%	35.0%	48.5%	50.7%	54.6%	58.2%
SDE	43.8%	46.0%	61.4%	60.5%	65.4%	67.1%
TR-FSDA	41.8%	45.2%	59.4%	58.6%	63.4%	64.0%
GLPP	25.5%	28.1%	41.0%	42.6%	49.7%	54.4%
SLDA	47.9 %	51.1%	63.4%	64.3%	67.1%	69.7%
ISDA	47.9 %	51.1%	63.3%	63.9%	67.2%	69.4%
JSLDE	46.4%	49.4%	65.4%	67.0%	68.8%	71.9%

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Results

UMIST	1 Sample		2 Samples		3 Samples	
Method	Т	U	Т	U	Т	U
FME	37.8%	60.2%	45.2%	72.7%	51.4%	87.5%
KFME	39.3%	58.8%	48.7%	72.5%	57.0%	87.1%
SDA	39.6%	60.1%	57.3%	79.1%	63.0%	84.4%
SDE	40.1%	65.0%	51.0%	78.9%	58.9%	82.4%
TR-FSDA	38.3%	57.5%	46.7%	68.1%	53.3%	77.3%
GLPP	40.3%	59.7%	57.1%	78.7%	65.0%	88.3%
SLDA	37.6%	57.8%	47.8%	74.9%	58.0%	79.8%
ISDA	38.1%	59.3%	47.5%	75.1%	57.6%	80.6%
JSLDE	44.2%	72.3%	53.3%	80.0%	63.0%	89.2 %







Figure: Recognition accuracy vs. feature dimension obtained with the EXT Yale and Coil-20 datasets (test evaluation).







Figure: t-SNE visualization of the ORL dataset. (a) Face images using their original features. (b) Face images using their projection obtained by JSLDE.





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- We introduced a framework that is able to jointly estimate the soft labels and linear embedding for a semi-supervised context.
- The iterative criterion enforces the smoothness of both the predicted labels and the linear projection of the data samples.





Thanks for your attention

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