COMPARATIVE STUDY OF FEATURE SPACE PROJECTION METHODS FOR HYPERSPECTRAL IMAGE CLASSIFICATION

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OUTLINE

- Introduction
- Methodology
- Experiments and Analysis
- Conclusion

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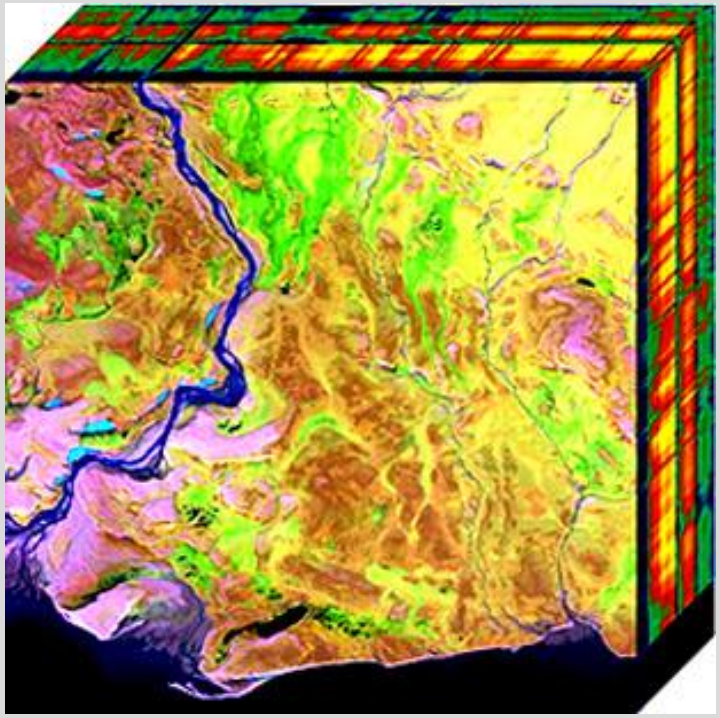
INTRODUCTION

- Hyperspectral Imagery



Dr. Nicholas M. Short, Sr. - NASA http://rst.gsfc.nasa.gov/

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METHODOLOGY

- Feature projection
  - » Supervised vs. unsupervised
  - » Linear vs. nonlinear
  - » Global vs. local
- Classifiers
  - » K-nearest neighbors
  - » Support vector machines
  - » Random forests

Supervised vs. unsupervised

- Supervised methods
  - » Use label information
  - » Related to supervised classification
- Unsupervised methods
  - » Use own characteristics of data
  - » Related to clustering

Linear vs. nonlinear

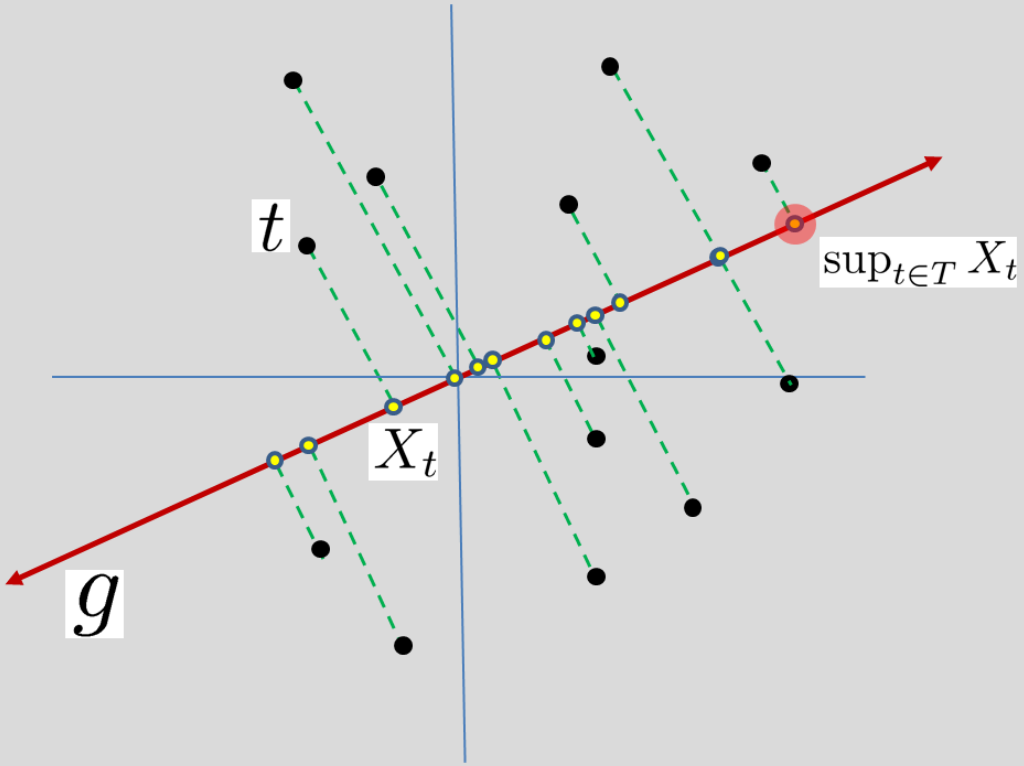
- Linear projection methods
  - » Rotation & scaling
- Nonlinear projection methods

GLOBAL VS. LOCAL

- Global methods: based on variance
- Local methods: based on local neighborhood

METHODS

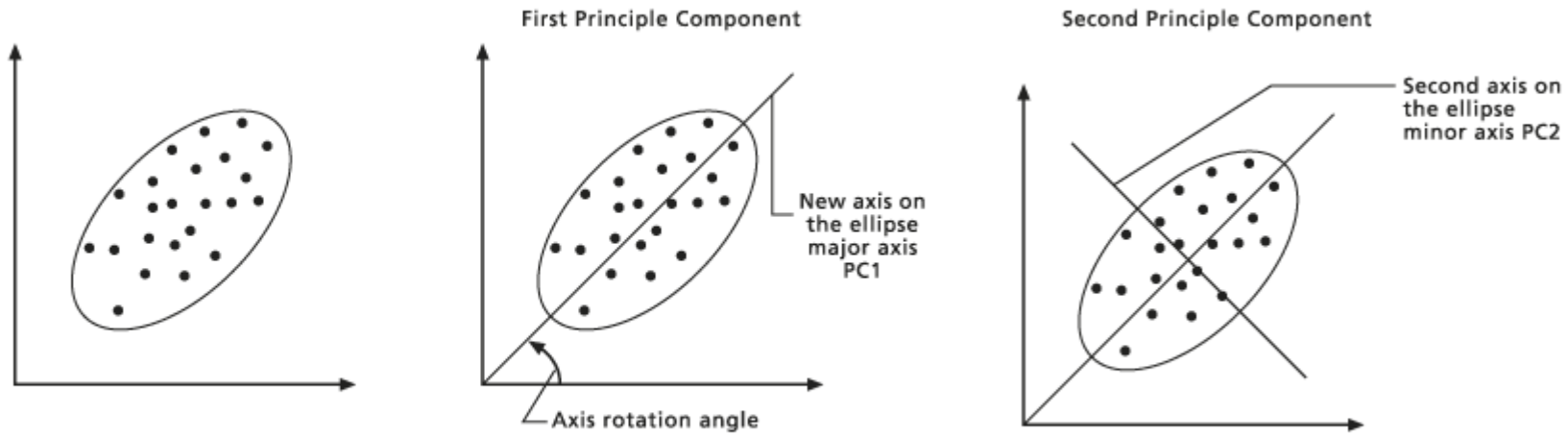
- Random projection (RP)



Unsupervised

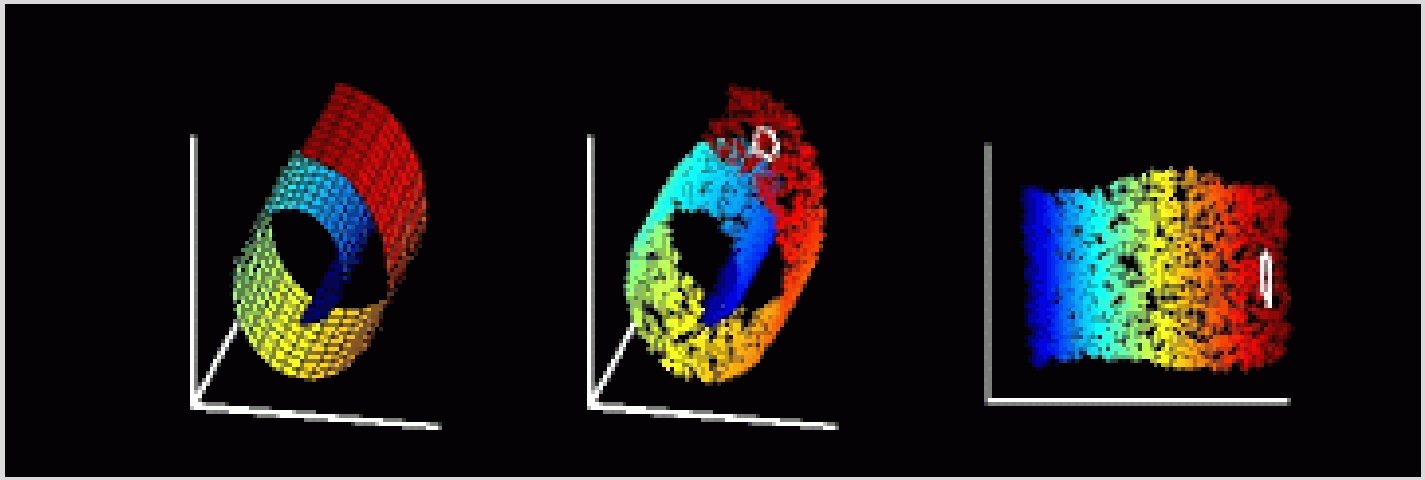
Linear

- Principal analysis component (PCA)



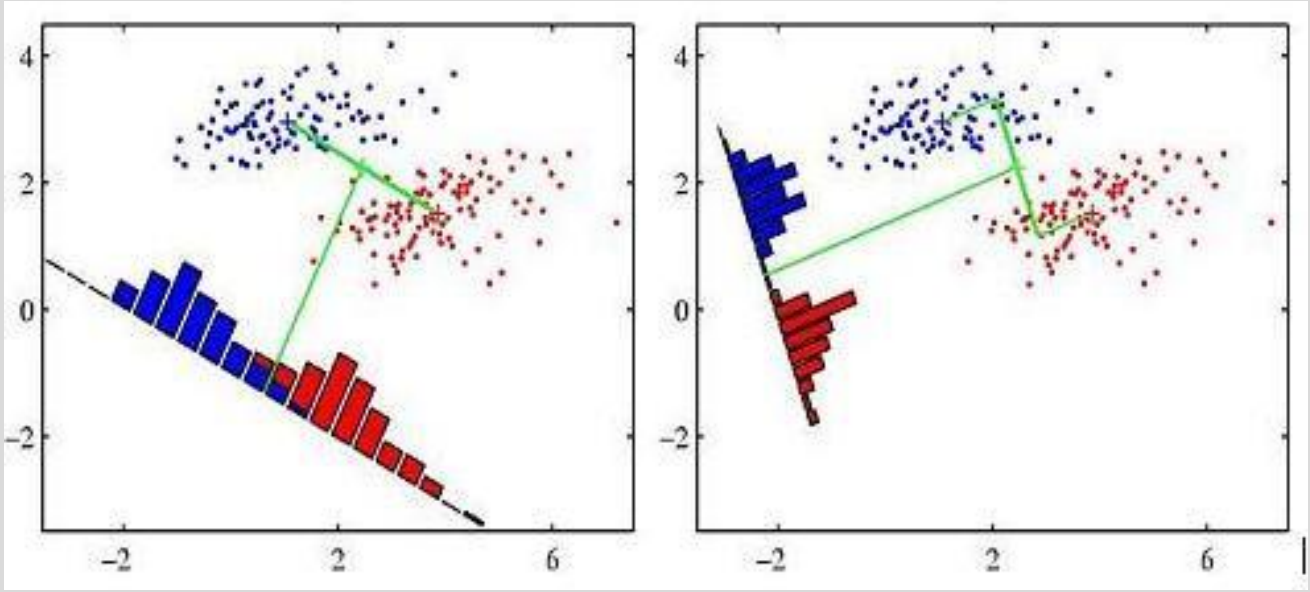
Unsupervised
Linear
Global

- Local linear embedding (LLE)



Unsupervised
Nonlinear
Local

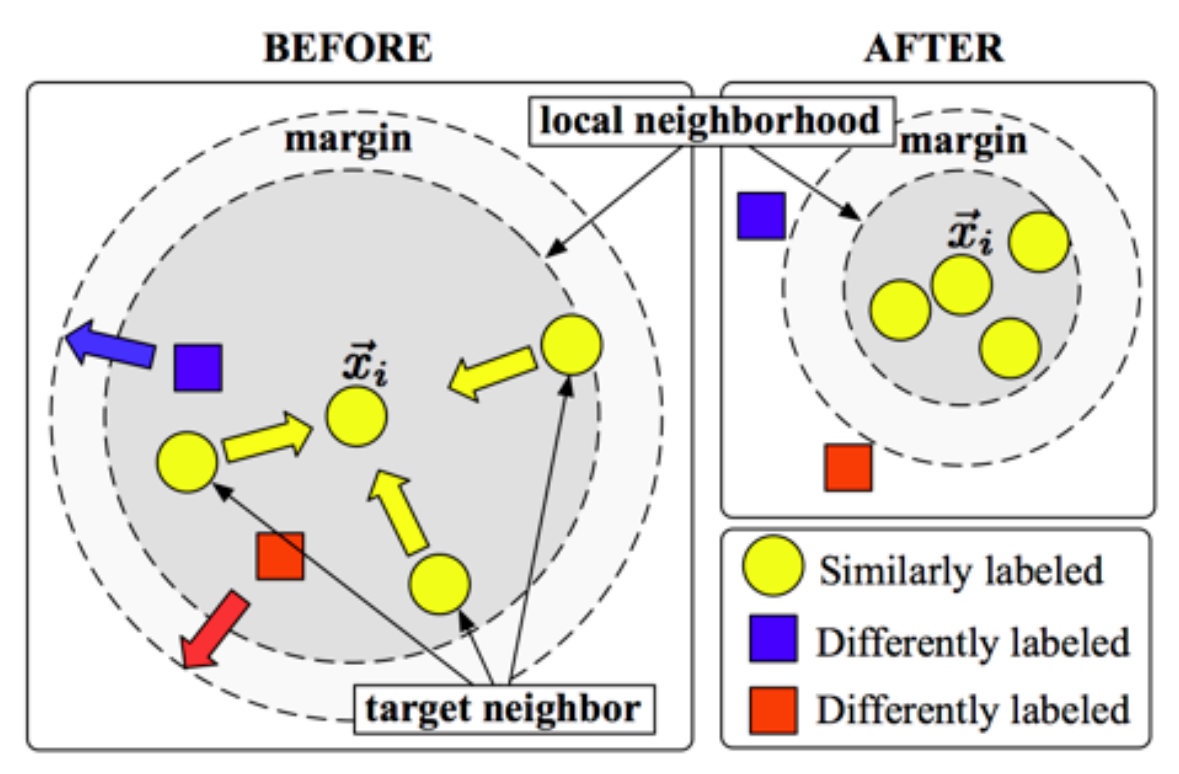
- Linear/Fisher discriminant Analysis (LDA/FDA)



Supervised; Linear; Global

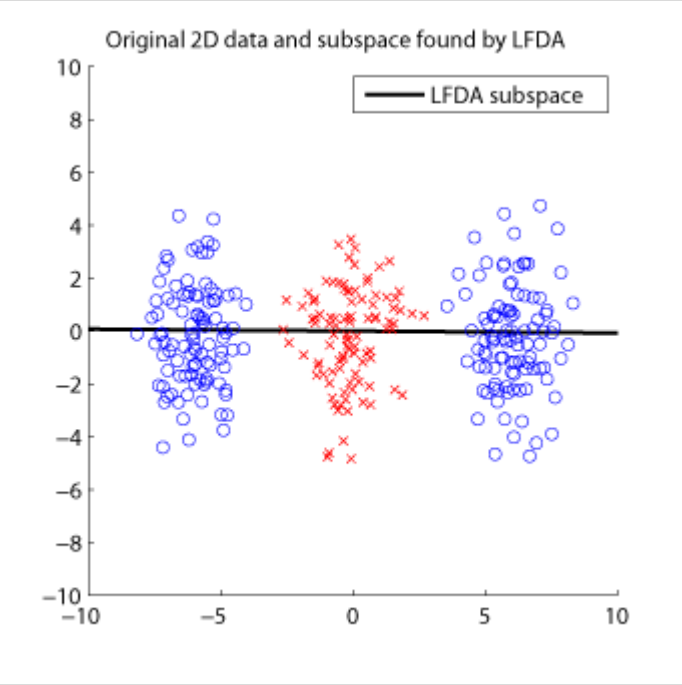
https://www.projectrhea.org/oldkiwi/index.php/Fisher's_Linear_Discriminant

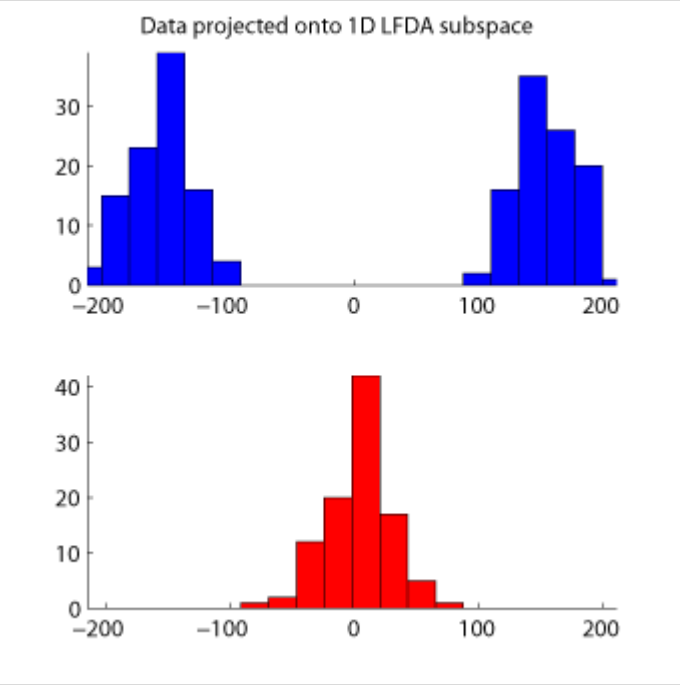
- Large Margin Nearest Neighbors (LMNN)



Supervised; linear; local

- Local Linear Fisher Discriminant (LFDA)





Linear; Supervised; Global + local

EXPERIMENTS

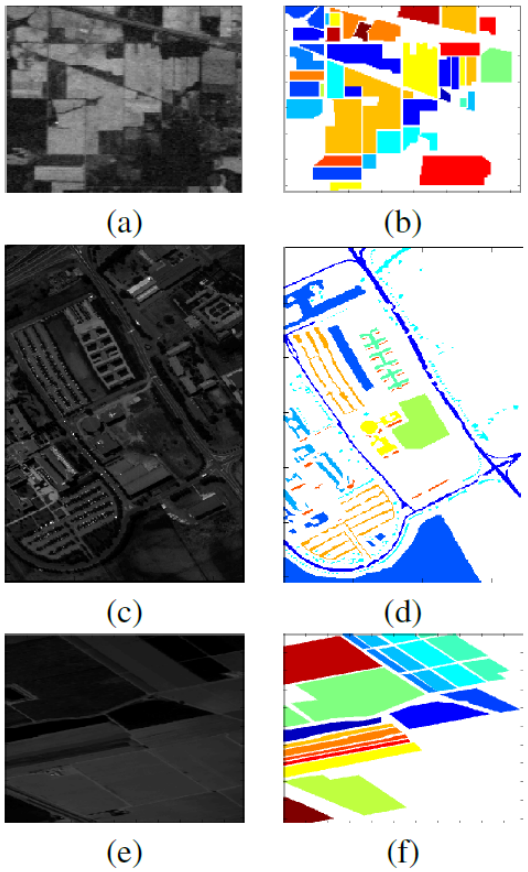


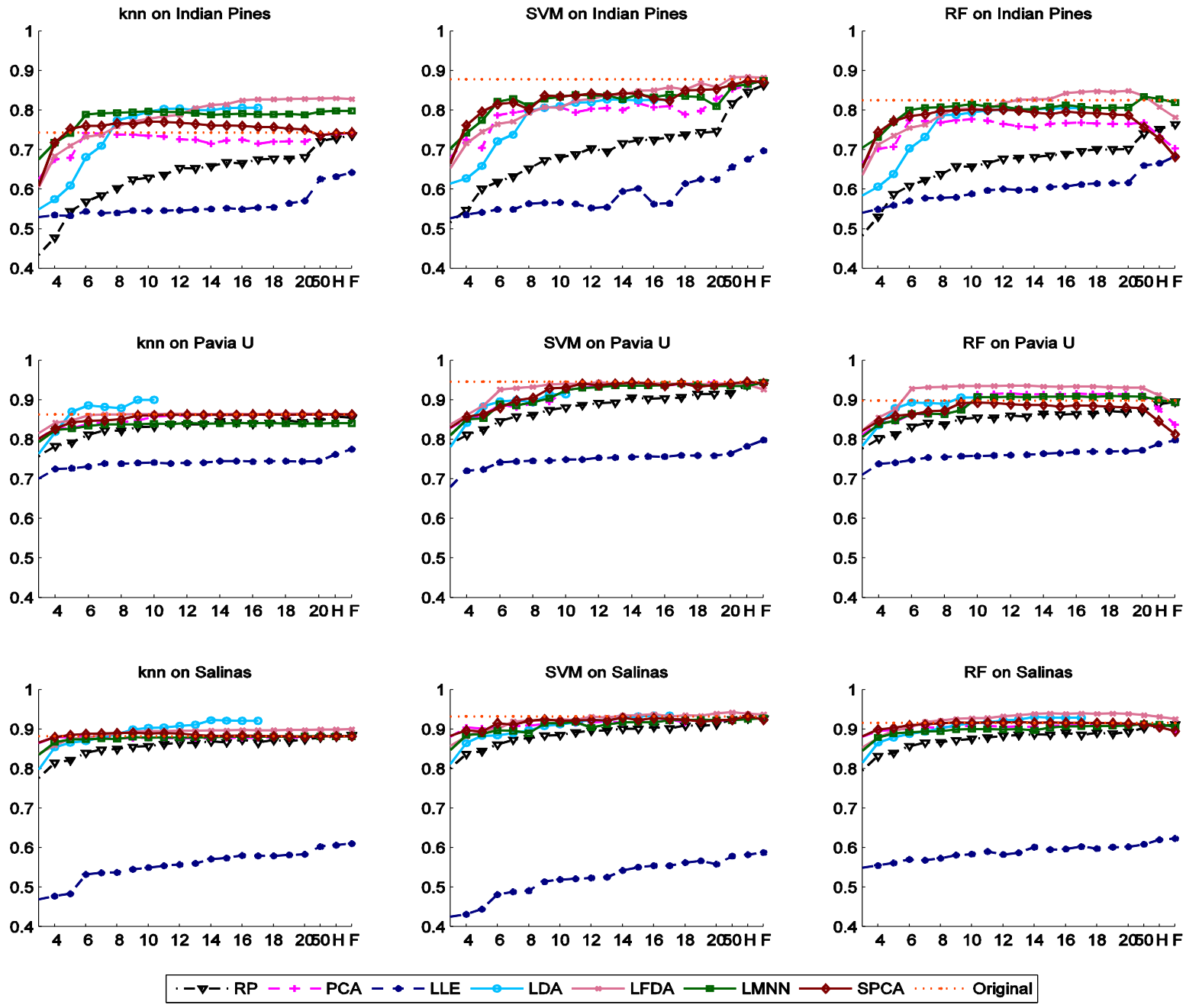
Fig. 1: Hyperspectral data sets (a) Indian pines (c) PaviaU (e) Salinas and their corresponding ground truth

-Indian Pine: 200 bands;

-University of Pavia: 103 bands;

-Salinas: 224 bands.

-10% training samples.


knn on Indian Pines
SVM on Indian Pines
RF on Indian Pines
knn on Pavia U
SVM on Pavia U
RF on Pavia U
knn on Salinas
SVM on Salinas
RF on Salinas
1
0.9
0.8
0.7
0.6
0.5
0.4
4 6 8 10 12 14 16 18 20 50 H F
RP
PCA
LLE
LDA
LFDA
LMNN
SPCA
Original

RESULTS

TABLE I: Best overall accuracy and corresponding projection method on reduced dimensions (2 to 20). Bold means highest accuracy among all classifiers.

Data	Indian Pines	PaviaU	Salinas
kNN	82.9%(LFDA)	90.0% (LDA)	92.1% (LDA)
SVM	**85.8%(LFDA)**	**94.4% (PCA)**	**93.9%(LFDA)**
RF	84.9%(LFDA)	93.1%(LFDA)	**93.9%(LFDA)**

TABLE II: Best accuracy and corresponding method on full-dimension feature space. Bold means accuracy is higher than that using reduced dimensions.

Data sets	Indian Pines	PaviaU	Salinas
kNN	82.8%(LFDA)	86.4%(LFDA)	90.0%(LFDA)
SVM	***88.3%(LFDA)***	***94.6% (original)***	***93.7%(LFDA)***
RF	82.5% (original)	89.8% (original)	92.6%(LFDA)

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CONCLUSION

- All of the projection methods except LLE can achieve better classification performance than random projection;
- The classification accuracy is close to or even better than using all the original features when dimension is significantly reduced;
- LFDA has the best overall performances when there are sufficient training samples.

Thank you!

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