LPP – Locality Preserving Projections

Agenda

Ground Work

1) Face recognition : Previous works of great gaints demonstrate that face recogniton can be significantly improved in low-dimensional **linear**-subspace.

2) Firstly to say, face is high-dimensional data, in terms of Computer Vision,so we have to reduce the dimensions.

Ground Work :

How do we reduce the dimensions ??

Ground Work

So we tie-up with mathematics, specifically **“Statistics”**

Ground Work

Since our great “Gaints” has said that face resides on **“Linear Sub-space”**

Researchers Concentrated on reducing techniques which are linear-subspace manifold.

Ground Work

Such as :

PCA (Principal Component Analysis)
And
LDA(Linear Discriminant Analysis)

And many improvements and variants of those.

Ground Work

But !!!!!

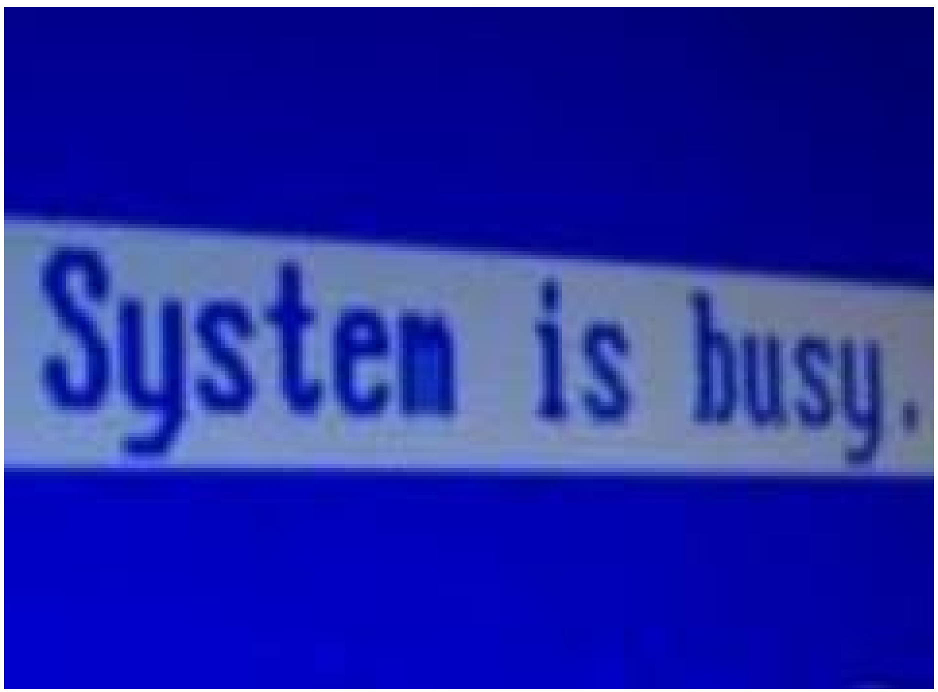
Recent researches has shown that, face images resides on “**non-linear”** manifold.

Ground Work

So, if face image lie in non-linear manifold, then our PCA and LDA methods does'nt give us the under lying structure.

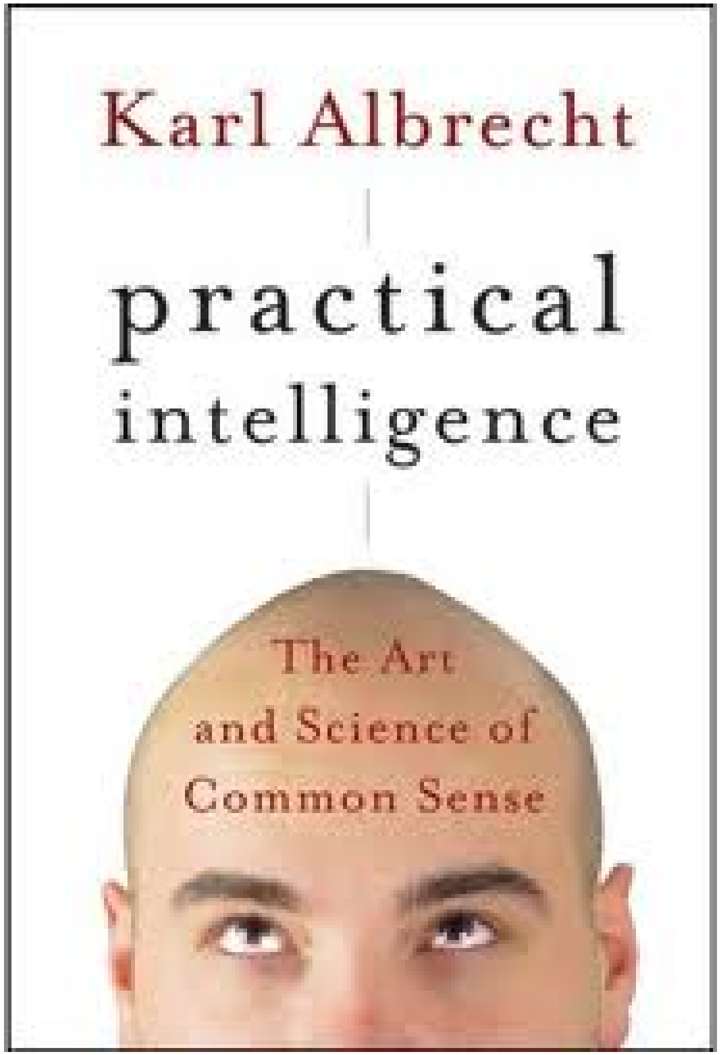
So we have to concentrate on non-linear methods.

Ground Work



- But Problem is Non-Linear methods are computationally expensive.
- To evaluate-map test data remains unclear

Ground work



So, What we need is common sense, means , with the complexity of linear computation we need the efficiency (working) of non-linear manifold

Ground work

So here's a method

LPP- Locality Preserving Projections

Locality Preseving Projections

Objective Function :

LPP is obtained by finding the optimal linear approximations to the eigen-functions of the Laplace Beltrami operator

$$\min_{\mathbf{y}} \sum_{ij} (y_i - y_j)^2 S_{ij}$$

Objective Function Simplification

$$
\begin{aligned}
&\frac{1}{2}\sum_{ij}(y_i - y_j)^2 S_{ij} \\
&= \sum_{ij}(\mathbf{w}^T\mathbf{x}_i - \mathbf{w}^T\mathbf{x}_j)^2 S_{ij} \\
&= \sum_i \mathbf{w}^T\mathbf{x}_i D_{ii}\mathbf{w}^T\mathbf{x}_i - \sum_{ij}\mathbf{w}^T\mathbf{x}_i S_{ij}\mathbf{w}^T\mathbf{x}_j \\
&= \mathbf{w}^T X(D-S)X^T\mathbf{w} \\
&= \mathbf{w}^T XLX^T\mathbf{w}
\end{aligned}
$$

We Impose Constraint

$$\mathbf{y}^T D\mathbf{y} = 1$$

$$\Rightarrow \ \mathbf{w}^T XDX^T\mathbf{w} = 1$$

Minimises

The transformation function that minimises the objective function is given by the minimum eigen value solution to generalise the eigen value problem

$$XLX^T\mathbf{w} = \lambda XDX^T\mathbf{w}$$

Advantages

1) LPP is linear but has similar properties as LLE (non-linear)

2) LPP is defined everywhere, where as non-linear methods are defined only on the test data.

3) Overcomes all the disadvantages of linear methods such as PCA and LDA.

Did we answer ??

Why LPP ?
What LPP is?
How it is applicable to our domain Face Recognition?


OPEN
QUESTIONS

Commitments

Detailed Explaination of Formaulas
Algorithm
Example Problem
Results