

Python Machine Learning: The 5th Book Circle

Data Compression Algorithm: Principle Component Analysis and Linear Discriminant Analysis

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Disclaimer

All opinions and statements in this presentation are mine and do not in any way represent the company
Any comment or correction of error is welcome, please contact me
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Acknowledgement

Acknowledgement

Here I would like to thank for Binru Huang and Caj Zell in my group. The discussion between us made me understanding of PCA/LDA deeper

The Fifth Book Circle of Python Machine Learning

In this presentation belongs to **algorithm** part of the book

- If you have time, please read the book first. This slide could be used as complementary resource for the book
- We will try to go through every algorithm in chapter 5 of book Python Machine Learning, also show the mathematics behind each algorithm. But we only use the mathematics conclusion to explain algorithm rather than showing mathematical derivation
- All of us need to debug the python code, in order to get practice of implementing machine learning algorithm

Overview

1 Principle Component Analysis

- PCA, Modeled as Minimize SSE(Least Square Error) Problem
- PCA, From a LS Problem to Maximize Variance Problem
- Eigen Decomposition to Solve Maximize Variance Problem
- PCA, Another Explanation by Singular Value Decomposition
- Relationship with MIMO
- Relationship with OFDM

2 Linear Discriminant Analysis

3 Kernel for Principle Component Analysis

4 Conclusion

Algorithms in Chapter 5

From this slide we go through the data compression/dimension reduction algorithms PCA(unsupervised) and LDA(supervised) in chapter 5

Data set (\mathbf{y}, \mathbf{X})

Suppose we have L samples, each sample has D features/dimensions(So the input \mathbf{X} is L by D matrix, label \mathbf{y} is L by 1 vector). If we only consider the l^{th} data sample pair, \mathbf{x}_l is 1 by D vector which represents D features/dimension for l^{th} training data sample, \mathbf{w} is D by 1 vector which represents weight and y_l represents the label of l^{th} data sample

Outline for Section 1

1 Principle Component Analysis

- PCA, Modeled as Minimize SSE(Least Square Error) Problem
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The Main Idea Behind PCA

Model The Idea as a Least Square Error Problem

Maximize Variance Problem to Replace of LS Problem

Eigen Decomposition: Solution to Maximize Variance Problem

SVD

SVD: The Other View of PCA

MIMO

OFDM

Outline for Section 2

1 Principle Component Analysis

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2 Linear Discriminant Analysis

3 Kernel for Principle Component Analysis

4 Conclusion

LDA

Outline for Section 3

1 Principle Component Analysis

- PCA, Modeled as Minimize SSE(Least Square Error) Problem
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2 Linear Discriminant Analysis

3 Kernel for Principle Component Analysis

4 Conclusion

Kernel PCA for Nonlinear Mapping

Outline for Section 4

1 Principle Component Analysis

- PCA, Modeled as Minimize SSE(Least Square Error) Problem
- PCA, From a LS Problem to Maximize Variance Problem
- Eigen Decomposition to Solve Maximize Variance Problem
- PCA, Another Explanation by Singular Value Decomposition
- Relationship with MIMO
- Relationship with OFDM

2 Linear Discriminant Analysis

3 Kernel for Principle Component Analysis

4 Conclusion

Conclusion

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Conclusion



References



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Question?