

# Advanced Machine Learning

(COMP 5328)

Week 6 Tutorial:

Dictionary Learning and Non-negative Matrix Factorisation

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#### **Tutorial Contents**



- Review (20min):
  - Lecture 4: Dictionary Learning and Non-negative Matrix
     Factorisation
- Tutorial exercise & QA (40min):

## Key points



- Dictionary Learning
- Non-negative Matrix Factorisation

### Announcements



- Assignment I is online now
  - Assignment I due on 9/10/2025, I I:59pm
  - Group-based (3-4 students per group). Find you teammates by yourselves.
  - Put your team member names in the report

What is a dictionary in machine learning?

A dictionary is a collection of words in one specific languages.

Can we find some common "words" (elements) to express data?





#### **Step 1. Data with Labels**

#### **Training Samples:**

"Stocks fell as interest rates rose in the US." → Finance

"The central bank plans to increase interest rates again." → Finance

"The team won the championship after a thrilling final." → Sports

"The coach praised the players for their defense." → Sports

"New smartphone released with advanced AI camera features." → Technology

"Tech companies compete to release faster chips." → Technology

#### **Testing Samples:**

"Investors are worried about inflation and market volatility."  $\rightarrow$  ???

"Oil prices climbed after new trade restrictions."  $\rightarrow$  ???

"The new season starts next month with tough rivalries."  $\rightarrow$  ???



#### **Step 2. Dictionary Learning Outcome**

The algorithm learns latent "atoms" that roughly align with our labels:

- Atom 1 (Finance) ≈ words about stocks, interest rates, bank, investors
- Atom 2 (Sports) ≈ words about team, coach, championship
- Atom 3 (Technology) ≈ words about smartphone, Al, chips, tech



#### **Step 3. Sparse Representation of New Data**

When a new article comes in, dictionary learning represents it as a mixture of atoms rather than a single cluster.

#### Example:

"Investors worry as <u>tech</u> stocks plunge after poor earnings reports with the new <u>AI</u> chips."

= 60% Finance Atom + 40% <u>Technology Atom</u> → Finance-Tech hybrid label



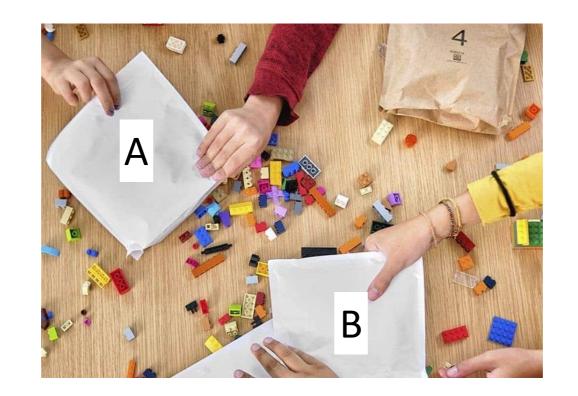
house plane











		big house		big plane	
Small house		Small plane			
Pack A	Γ1	2	2	47	
Pack B	1	2	1	2	
Pack C	1	2	2	4	
Pack D	L1	2	1	2	

Column	Model	Interpretation (feature counts)
1	Small house	1 pack A, 1 pack B, 1 pack C, 1 pack D
2	Big house	2 pack A, 2 pack B, 2 pack C, 2 pack D
3	Small airplane	2 pack A, 1 pack B, 2 pack C, 1 pack D
4	Big airplane	4 pack A, 2 pack B, 4 pack C, 2 pack D

What is a dictionary in machine learning?

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 2 & 4 \\ 1 & 2 & 1 & 2 \\ 1 & 2 & 2 & 4 \\ 1 & 2 & 1 & 2 \end{bmatrix} = \begin{bmatrix} 1 & 2 \\ 1 & 1 \\ 1 & 2 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 0 & 0 \\ 1 & 2 & 0 & 0 \\ 1 & 2 & 1 & 2 \end{bmatrix}$$

Lego Set 1={A,B,C,D}  
Lego Set 2={A,A,B,C,C,D}
$$\begin{bmatrix} 1 & 2 \\ 1 & 1 \\ 1 & 2 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = a \times \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} + b \times \begin{bmatrix} 2 \\ 1 \\ 2 \end{bmatrix}$$

What is a dictionary in machine learning?

Let 
$$x \in \mathbb{R}^d$$
,  $D \in \mathbb{R}^{d \times k}$  
$$\alpha^* = \arg\min_{\alpha \in \mathbb{R}^k} \|x - D\alpha\|^2.$$

Note that  $||x|| = \sqrt{x^{\top}x}$  is the ell 2 norm.

Given  $x_1, \ldots, x_n \in \mathbb{R}^d$ 

$$\{D^*, \alpha_1^*, \dots, \alpha_n^*\} = \arg \min_{D \in \mathbb{R}^{d \times k}, \alpha_1, \dots, \alpha_n \in \mathbb{R}^k} \frac{1}{n} \sum_{i=1}^n ||x_i - D\alpha_i||^2.$$



$$X = egin{bmatrix} 1 & 2 & 2 & 4 \ 1 & 2 & 1 & 2 \ 1 & 2 & 2 & 4 \ 1 & 2 & 1 & 2 \end{bmatrix}$$

$$D = egin{bmatrix} 1 & 2 \ 1 & 1 \ 1 & 2 \ 1 & 1 \end{bmatrix}, \qquad A = egin{bmatrix} 1 & 2 & 0 & 0 \ 0 & 0 & 1 & 2 \end{bmatrix}$$



$$X = egin{bmatrix} 1 & 2 & 2 & 4 \ 1 & 2 & 1 & 2 \ 1 & 2 & 2 & 4 \ 1 & 2 & 1 & 2 \end{bmatrix}$$

$$D = egin{bmatrix} 1 & 2 \ 1 & 1 \ 1 & 2 \ 1 & 1 \end{bmatrix}, \qquad A = egin{bmatrix} 1 & 2 & 0 & 0 \ 0 & 0 & 1 & 2 \end{bmatrix}$$

$$\sqrt{(1-1)^2 + (1-1)^2 + (1-1)^2 + (1-1)^2} = 0$$



$$X = egin{bmatrix} 1 & 2 & 2 & 4 \ 1 & 2 & 1 & 2 \ 1 & 2 & 2 & 4 \ 1 & 2 & 1 & 2 \end{bmatrix}$$

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$$D = egin{bmatrix} 1 & 2 \ 1 & 1 \ 1 & 2 \ 2 & 1 \end{bmatrix}, \qquad A = egin{bmatrix} 1 & 2 & 0 & 0 \ 0 & 0 & 1 & 2 \end{bmatrix}$$

$$\sqrt{(1-1)^2 + (1-1)^2 + (1-1)^2 + (1-2)^2} = 1$$

#### Note that

$$\frac{1}{n} \sum_{i=1}^{n} \|x_i - D\alpha_i\|^2 = \frac{1}{n} \|X - DR\|_F^2,$$

where 
$$X = [x_1, x_2, \dots, x_n] \in \mathbb{R}^{d \times n}$$
,

$$R = [\alpha_1, \alpha_2, \dots, \alpha_n] \in \mathbb{R}^{k \times n},$$

$$||X||_F = \sqrt{\operatorname{trace}(X^\top X)} = \sqrt{\sum_{i=1}^d \sum_{j=1}^n X_{i,j}^2}$$
 is the Frobenius norm of X.

$$X = egin{bmatrix} 1 & 2 & 2 & 4 \ 1 & 2 & 1 & 2 \ 1 & 2 & 2 & 4 \ 1 & 2 & 1 & 2 \end{bmatrix}$$



$$D = egin{bmatrix} 1 & 2 \ 1 & 1 \ 1 & 2 \ 1 & 1 \end{bmatrix}, \quad A = egin{bmatrix} 1 & 2 & 0 & 0 \ 0 & 0 & 1 & 2 \end{bmatrix}$$

$$E = X - DA = 0$$

$$||E||_F = 0$$

$$X = egin{bmatrix} 1 & 2 & 2 & 4 \ 1 & 2 & 1 & 2 \ 1 & 2 & 2 & 4 \ 1 & 2 & 1 & 2 \end{bmatrix}$$

$$X = egin{bmatrix} 1 & 2 & 2 & 4 \ 1 & 2 & 1 & 2 \ 1 & 2 & 2 & 4 \ 1 & 2 & 1 & 2 \end{bmatrix} \hspace{0.5cm} D = egin{bmatrix} 1 \ 1 \ 1 \ 1 \end{bmatrix}, \quad A = egin{bmatrix} 1 & 2 & 2 & 4 \ 1 \end{bmatrix}$$

$$X' = DA = egin{bmatrix} 1 & 2 & 2 & 4 \ 1 & 2 & 2 & 4 \ 1 & 2 & 2 & 4 \ 1 & 2 & 2 & 4 \ 1 & 2 & 2 & 4 \ \end{bmatrix}$$

$$E=X-X'=egin{bmatrix} 0 & 0 & 0 & 0 \ 0 & 0 & -1 & -2 \ 0 & 0 & 0 & 0 \ 0 & 0 & -1 & -2 \ \end{bmatrix}$$

$$\|E\|_F = \sqrt{0^2 + \dots + (-2)^2 + (-1)^2 + \dots} = \sqrt{10} \approx 3.16$$
  $\|X\|_F \approx 8.37$ 

Note that

$$\arg\min_{D\in\mathcal{D},R\in\mathcal{R}}\|X-DR\|_F^2,$$

where  $\mathcal{D}$  and  $\mathcal{R}$  are some specific domains for D and R.

## Optimisation

#### Objective:

$$\min_{D \in \mathcal{D}, R \in \mathcal{R}} \|X - DR\|_F^2$$

The objective is convex with respect to either R or D but not to both.

Fix R, solve for D

$$\min_{D \in \mathcal{D}} \|X - DR\|_F^2$$

Fix D, solve for R

$$\min_{R \in \mathcal{R}} \|X - DR\|_F^2$$

Engan, Kjersti, Sven Ole Aase, and J. Hakon Husoy. "Method of optimal directions for frame design." Acoustics, Speech, and Signal Processing, 1999. Proceedings., 1999 IEEE International Conference on. Vol. 5. IEEE, 1999.

## Optimisation

#### Objective:

$$\min_{D \in \mathcal{D}, R \in \mathcal{R}} \|X - DR\|_F^2$$

The objective is convex with respect to either D or R but not to both.

Suppose  $D^*$  and  $R^*$  are the local minimisers for the objective, we have

$$X \cong D^*R^* = (D^*A)(A^{-1}R^*).$$

Normalisation (optional):

$$D_{:,i} \leftarrow D_{:,i} / \|D_{:,i}\|$$

#### **Scaling Ambiguity**



$$Q=egin{bmatrix} 2 & 0 \ 0 & 0.5 \end{bmatrix}, \qquad Q^{-1}=egin{bmatrix} 0.5 & 0 \ 0 & 2 \end{bmatrix}.$$

$$D' = DQ, \qquad A' = Q^{-1}A.$$

$$D' = egin{bmatrix} 2 & 1 \ 2 & 0.5 \ 2 & 1 \ 2 & 0.5 \end{bmatrix}, \qquad A' = egin{bmatrix} 0.5 & 1 & 0 & 0 \ 0 & 0 & 2 & 4 \end{bmatrix}.$$

#### **Scaling Ambiguity**



#### Solution 1

$$X = egin{bmatrix} 1 & 2 & 2 & 4 \ 1 & 2 & 1 & 2 \ 1 & 2 & 2 & 4 \ 1 & 2 & 1 & 2 \end{bmatrix}$$

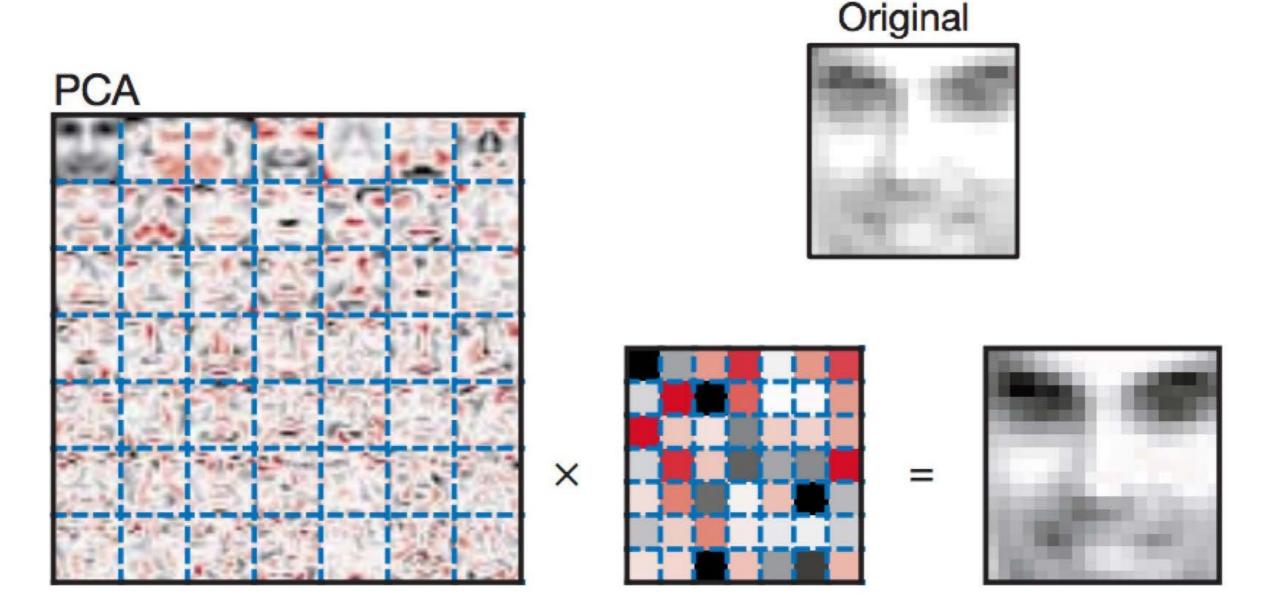
$$D = egin{bmatrix} 1 & 2 \ 1 & 1 \ 1 & 2 \ 1 & 1 \end{bmatrix}, \qquad A = egin{bmatrix} 1 & 2 & 0 & 0 \ 0 & 0 & 1 & 2 \end{bmatrix}$$

#### Solution 2

$$D' = egin{bmatrix} 2 & 1 \ 2 & 0.5 \ 2 & 1 \ 2 & 0.5 \end{bmatrix}, \qquad A' = egin{bmatrix} 0.5 & 1 & 0 & 0 \ 0 & 0 & 2 & 4 \end{bmatrix}$$

PCA: 
$$A = U\Lambda U^T$$

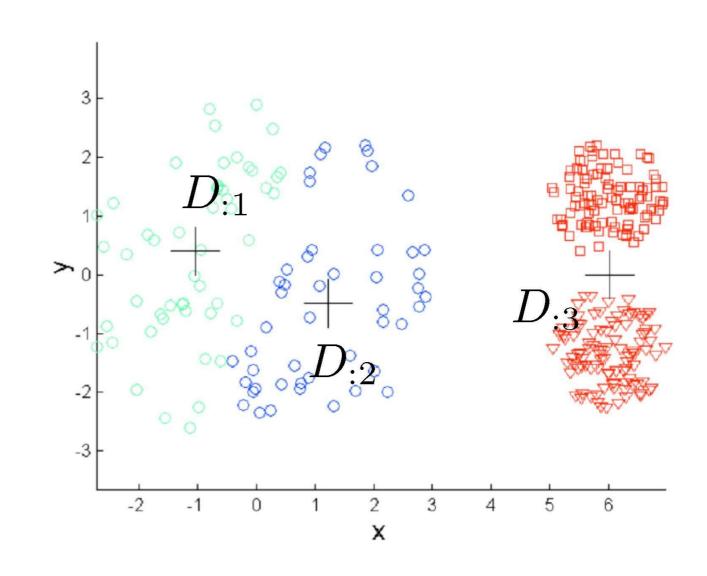
$$\alpha^* = \arg\min_{\alpha \in \mathbb{R}^k} \|x - D\alpha\|^2.$$



Lee, Daniel D., and H. Sebastian Seung. "Learning the parts of objects by non-negative matrix factorization." Nature 401.6755 (1999): 788.

K-means clustering:

$$\min_{D \in \mathcal{D}, R \in \mathcal{R}} \|X - DR\|_F^2$$



Special requirement: each column of R only one have entry equals to one, the other entries are all zeros.

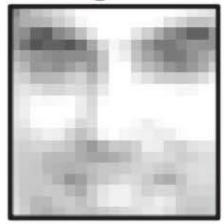
K-means clustering:

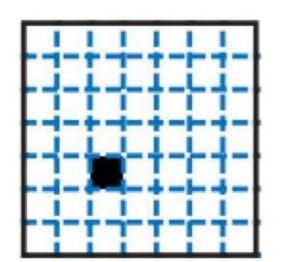
$$\alpha^* = \arg\min_{\alpha \in \mathbb{R}^k} \|x - D\alpha\|^2.$$

#### K-means centroids



#### Original







Lee, Daniel D., and H. Sebastian Seung. "Learning the parts of objects by non-negative matrix factorization." Nature 401.6755 (1999): 788.

X



# Dictionary Matrix or Code Matrix may have negative values which may not to explain in real-world applications such as use Lego pack N but remove pack M

$$DA = egin{bmatrix} 1 & 1 \ 1 & -1 \ 1 & 1 \ 1 & -1 \end{bmatrix} \cdot egin{bmatrix} 1 & 2 & 3 & 4 \ 1 & 2 & 3 & 4 \end{bmatrix} = egin{bmatrix} 2 & 4 & 6 & 8 \ 0 & 0 & 0 & 0 \ 2 & 4 & 6 & 8 \ 0 & 0 & 0 & 0 \end{bmatrix}$$

## Non-negative matrix factorisation



#### • Why non-negativity of data?

Data is often nonnegative by nature Image intensities
Movie ratings
Document-term counts
Microarray data
Stock market values

## Non-negative matrix factorisation

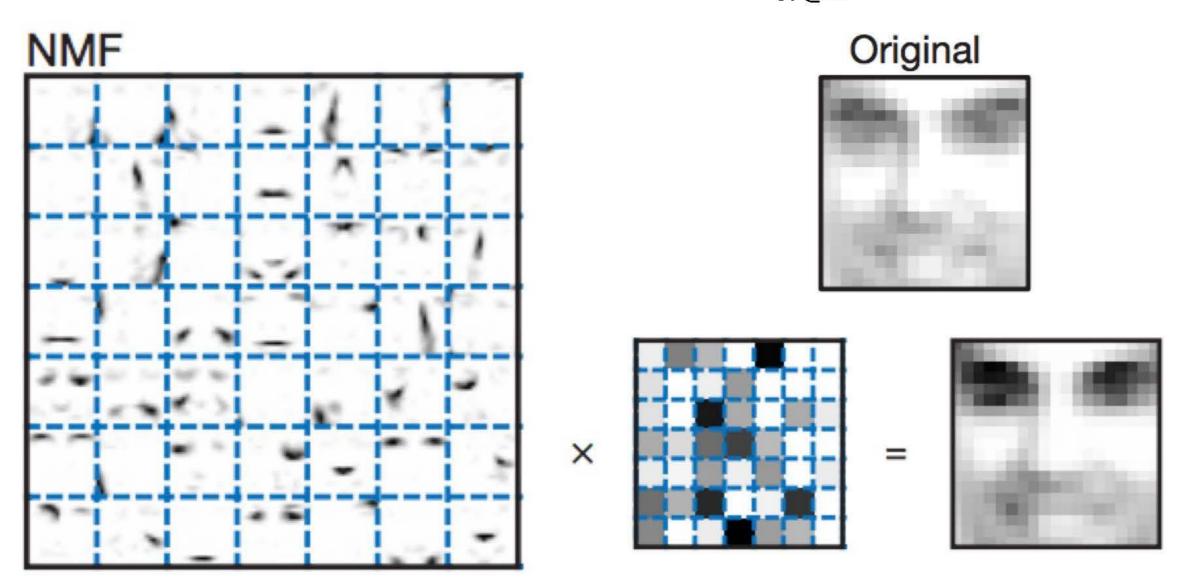


$$\min_{D \in \mathcal{D}, R \in \mathcal{R}} \|X - DR\|_F^2$$

Special requirement:  $\mathcal{D} = \mathbb{R}_+^{d imes k}, \quad \mathcal{R} = \mathbb{R}_+^{k imes n}.$ 

# Non-negative matrix factorisation

$$\alpha^* = \arg\min_{\alpha \in \mathbb{R}^k} \|x - D\alpha\|^2.$$



Lee, Daniel D., and H. Sebastian Seung. "Learning the parts of objects by non-negative matrix factorization." Nature 401.6755 (1999): 788.

## NMF optimisation

MUR (Multiplicative Update Rules):

$$\min_{D \in \mathcal{D}, R \in \mathcal{R}} \|X - DR\|_F^2$$

Fix D, solve for R

$$\frac{\partial \|X - DR\|_F^2}{\partial R} = -2D^\top X + 2D^\top DR$$

The Matrix Cookbook: <a href="https://www.math.uwaterloo.ca/">https://www.math.uwaterloo.ca/</a> ~hwolkowi/matrixcookbook.pdf

Online helping tool: http://www.matrixcalculus.org/

$$||X - DR||_F^2 = \text{trace}((X - DR)^\top (X - DR))$$



- Dictionary Learning
- Non-negative Matrix Factorisation