Dimension reduction

From modelling to visualization

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Farnoosh Khodakarami

Webinar outline

Introduction

1) Why do we need dimension reduction?
2) What are the widely-used dimension reduction methods

Dimension reduction in practice

1) Implementation in Python
2) Assumptions and parameters

DataSets

Features(Attribute/variable)

Data records (samples)

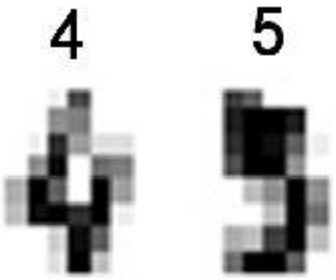
ID	Address	# Bed	#Bath	...	School Score	Year Build	Crime Rate
				...			
				...			

 # Features = Dimension of dataset

Number of dimensions in images

Number of dimensions (features) is equal to number of pixels if we use them directly as features of our models.

8*8=64 → 2048*1536=3,145,728



UCI ML hand-written digits

Why do we need to reduce number of dimensions?

- **May help to eliminate irrelevant features or reduce noise**

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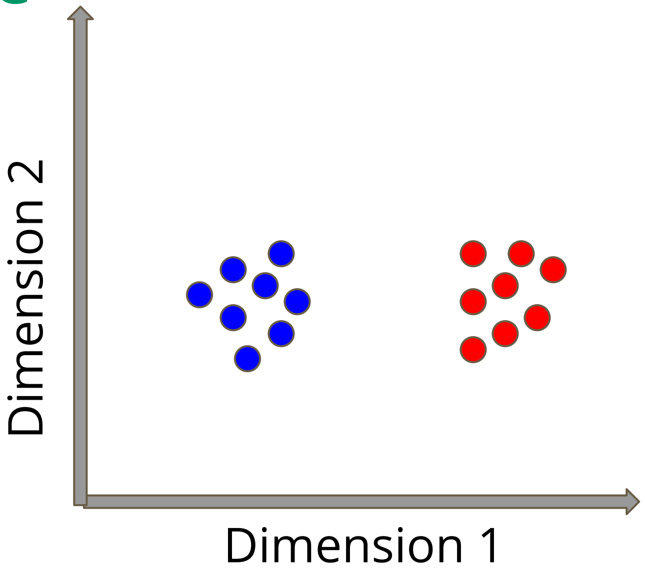

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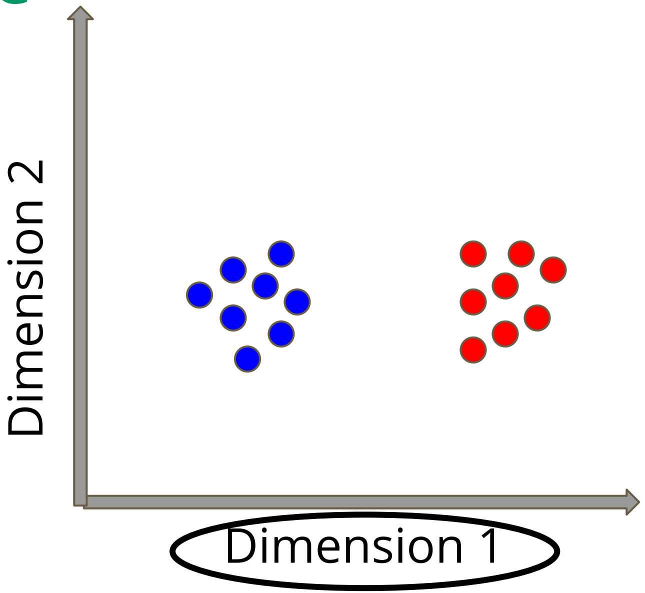
- **May help to eliminate irrelevant features or reduce noise**



Why do we need to reduce number of dimensions?

- May help to eliminate irrelevant features or reduce noise
- Reduce Time and Memory in computations

Why do we need to reduce number of dimensions?

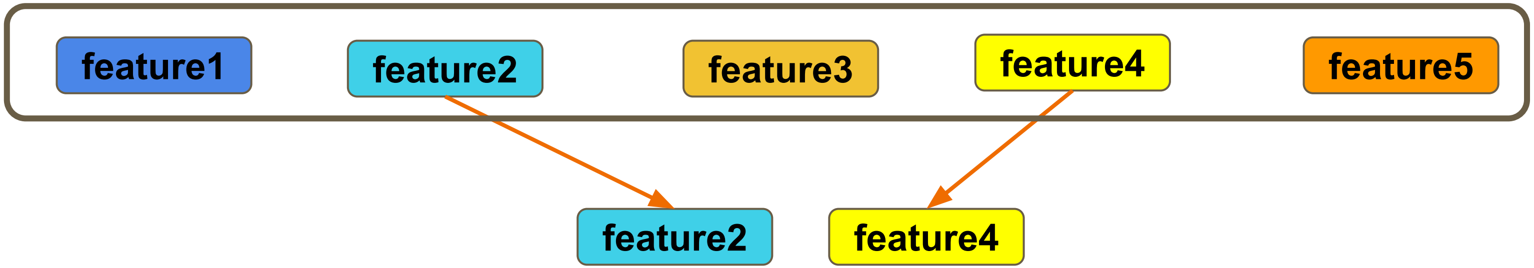
- **May help to eliminate irrelevant features or reduce noise**
- **Reduce Time and Memory in computations**
- **Allow data to be more easily visualized**

We can imagine things in 3D.

We can visualize, in an easy to interpret way, up to 2D.

Dimensionality Reduction

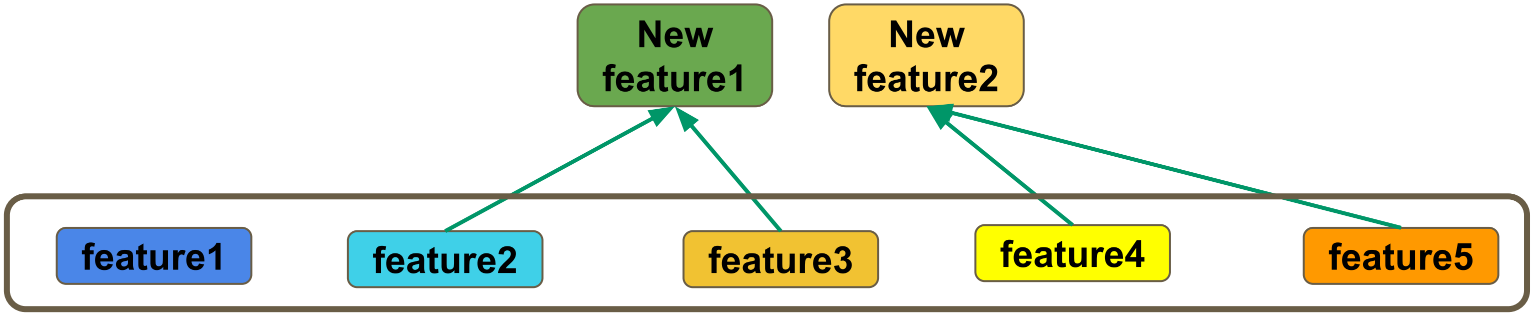
Dimensionality Reduction



Feature Selection

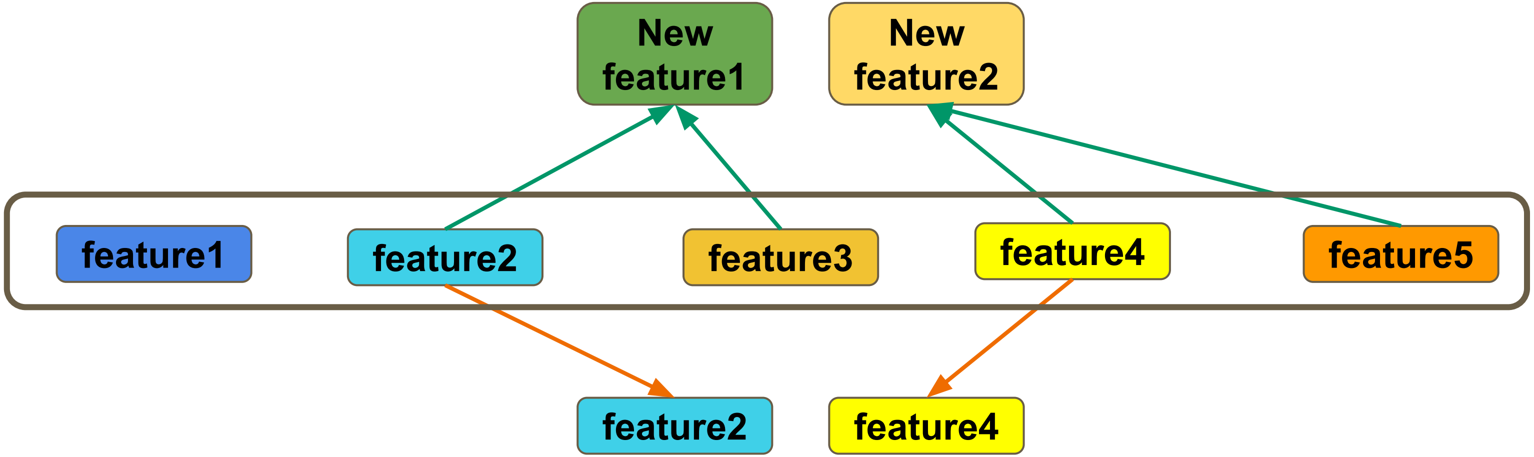
Dimensionality Reduction

Feature Extraction



Dimensionality Reduction

Feature Extraction



Feature Selection

Example of Feature Extraction

Risk of Diabetes

	Weight(lb)	**Hight(ft)**
Joe	170	6’
James	150	5’3’’

Example of Feature Extraction

Risk of Type 2 Diabetes

	Weight(lb)	**Hight(ft)**
Joe	170	6’
James	150	5’3’’

Is risk of type 2 diabetes higher for Joe?

Example of Feature Extraction

Risk of Type 2 Diabetes

	Weight(lb)	Hight(ft)
Joe	170	6’
James	150	5’3’’

	BMI
Joe	23.1
James	26.6

$$BMI = \frac{Weight\,(kg)}{[Height(m)]^2}$$

Example of Feature Extraction

Risk of Type 2 Diabetes

	BMI
Joe	23.1
James	26.6

Risk of type 2 diabetes is higher for James

Ganz, Michael L., et al. "The association of body mass index with the risk of type 2 diabetes: a case–control study nested in an electronic health records system in the United States." *Diabetology & metabolic syndrome* 6.1 (2014): 50.

Feature Extraction

1 Principal Component Analysis (PCA)

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Review

Cite this article: Jolliffe IT, Cadima J. 2016 Principal component analysis: a review and recent developments. *Phil. Trans. R. Soc. A* **374**: 20150202.
http://dx.doi.org/10.1098/rsta.2015.0202

Principal component analysis: a review and recent developments

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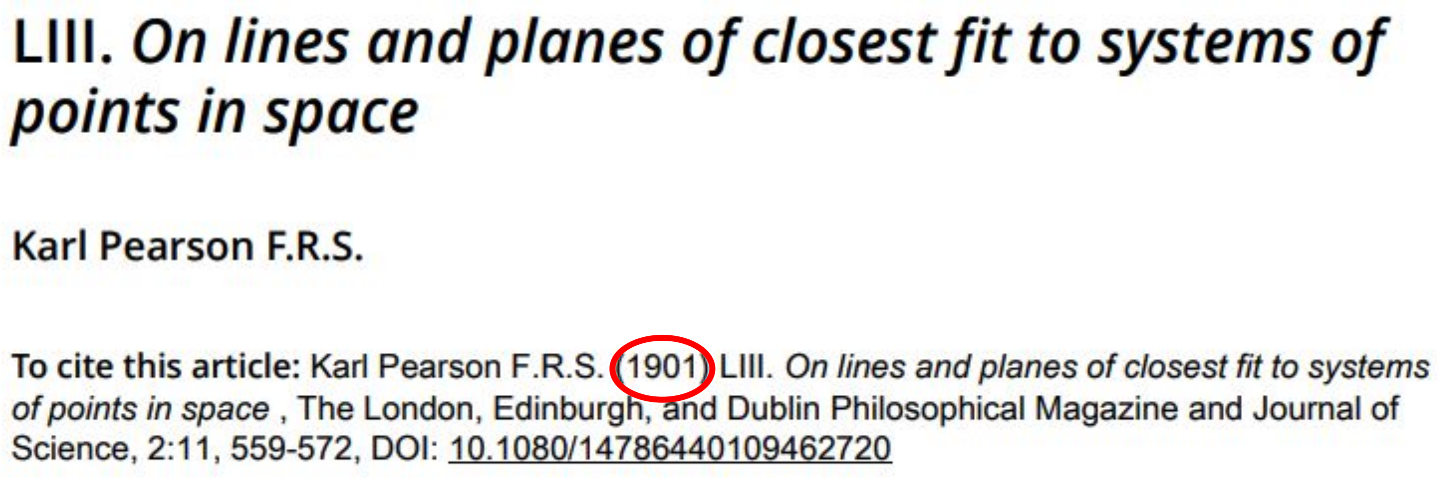
Feature Extraction

1 Principal Component Analysis (PCA)

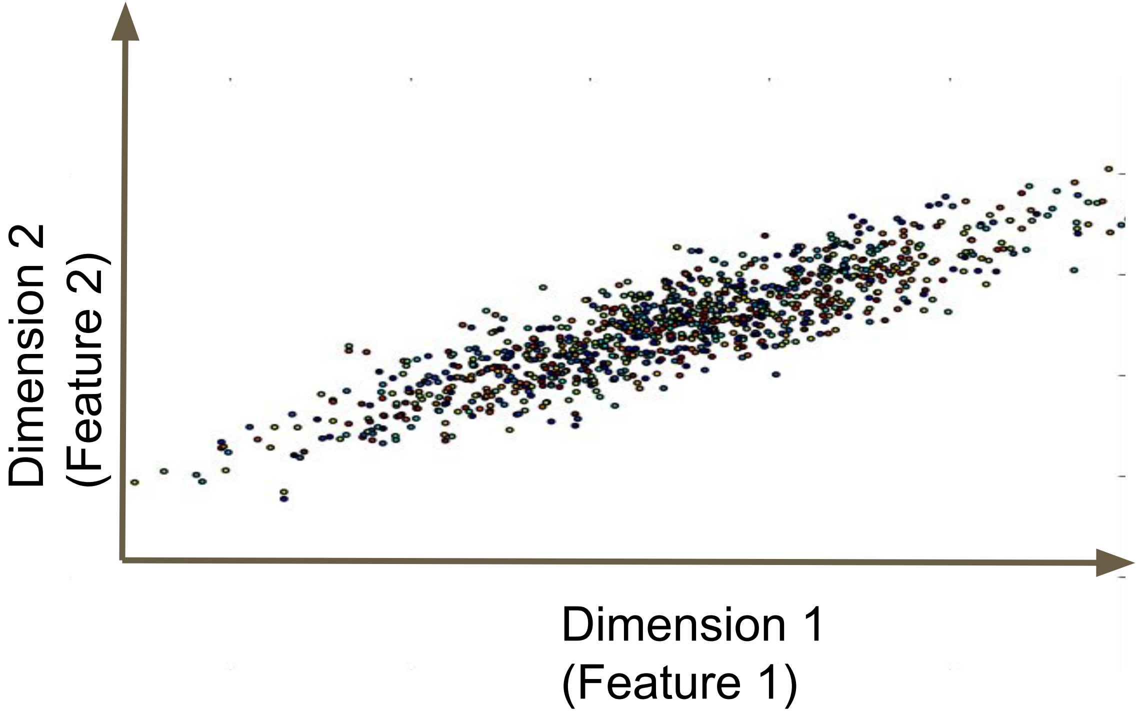

LIII. *On lines and planes of closest fit to systems of points in space*

Karl Pearson F.R.S.

To cite this article: Karl Pearson F.R.S. (1901) LIII. *On lines and planes of closest fit to systems of points in space* , The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science, 2:11, 559-572, DOI: 10.1080/14786440109462720

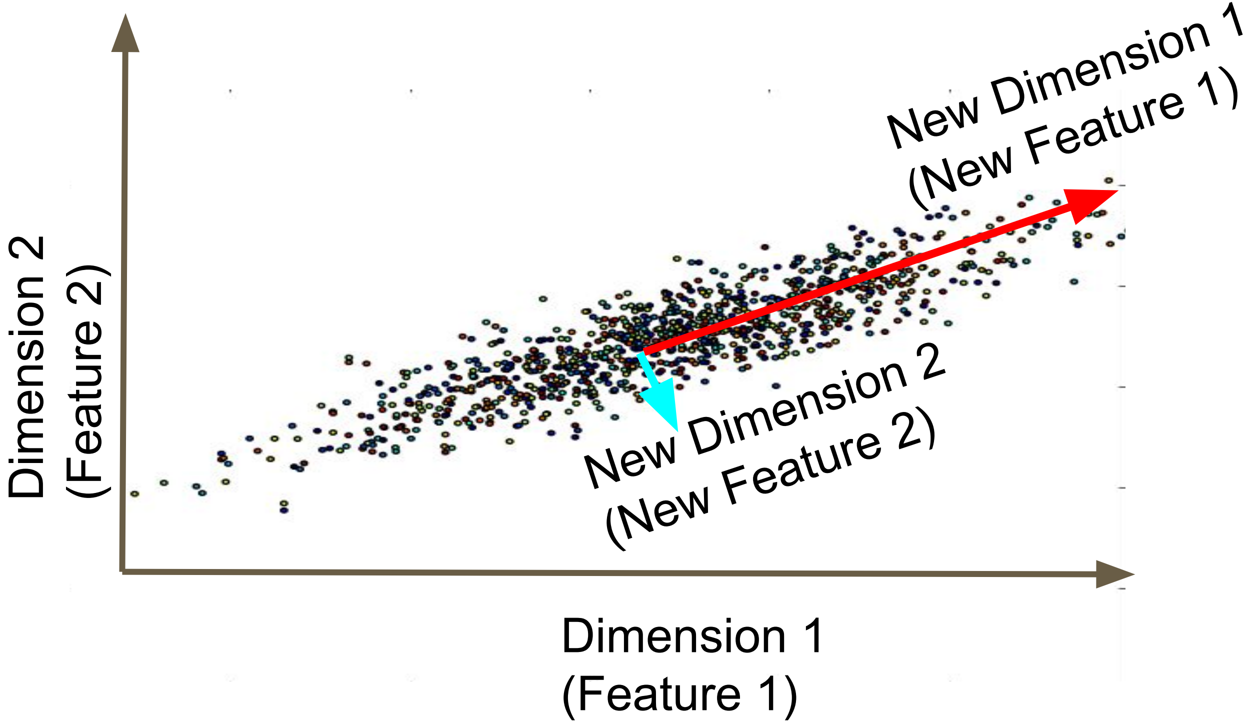
Feature Extraction

1 **Principal Component Analysis (PCA)**

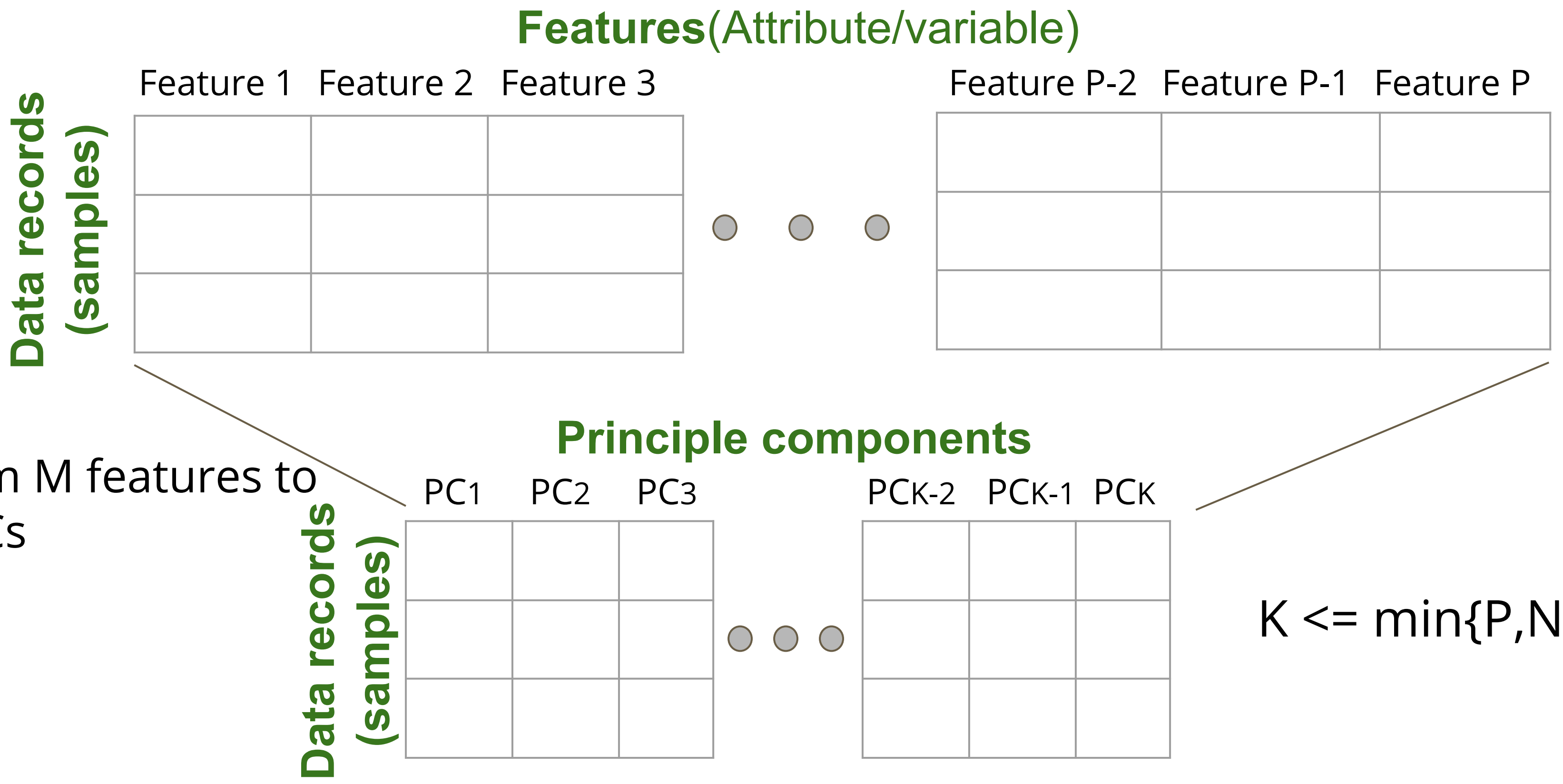


Feature Extraction

1 **PCA: Principal Component Analysis**



PCA: Principal Component Analysis



From M features to K PCs

K <= min{P,N}

Feature Extraction

2

t-SNE: t-Distributed Stochastic Neighbor Embedding

Journal of Machine Learning Research 9 (2008) 2579-2605 Submitted 5/08; Revised 9/08; Published 11/08

Visualizing Data using t-SNE

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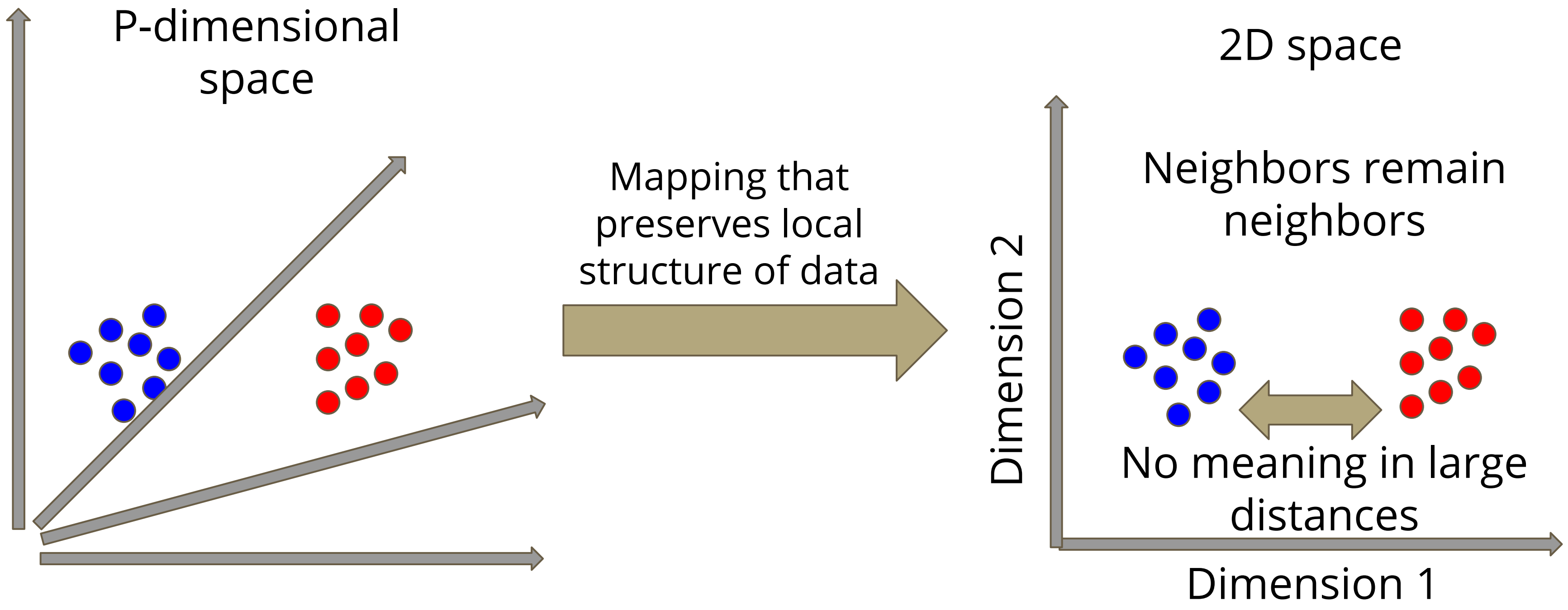
Editor: Yoshua Bengio

Amazing GitHub page

https://lvdmaaten.github.io/tsne/

t-SNE: t-Distributed Stochastic Neighbor Embedding



The embedding does not preserve global structure of data

Feature Extraction

3

UMAP: Uniform Manifold Approximation and Projection

UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction

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December 7, 2018

Amazing GitHub repository

https://github.com/lmcinnes/umap

Feature Extraction

1. PCA: Principal Component Analysis
2. t-SNE: t-Distributed Stochastic Neighbor Embedding
3. UMAP: Uniform Manifold Approximation and Projection