ARTIFICIAL NEURAL NETWORK

Chinmayananda A.
Department of Electronics and Communication Engineering

OUTLINE

- ***Self Organization***
  - Intuitive Principles of Self-Organization
  - Self-Organized Feature Analysis
  - Feature Selection / Extraction
- ***Principal Component Analysis***
  - Introduction
  - Eigenvalue Decomposition

Chinmayananda A.
Department of Electronics and Communication Engineering

SELF ORGANIZATION

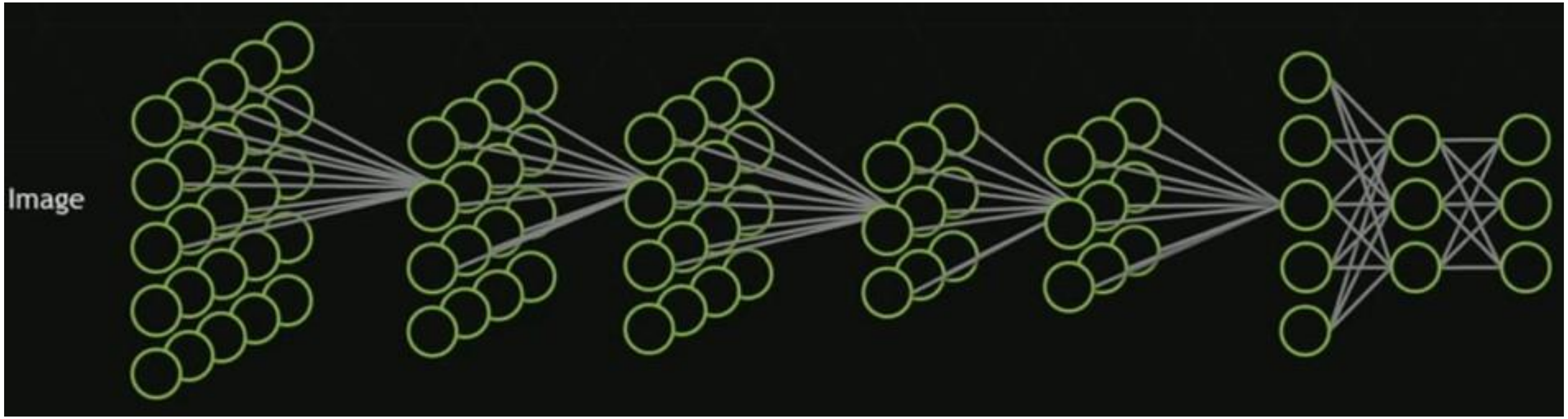
Chinmayananda A.
Department of Electronics and Communication Engineering

Introduction to Self-Organization

- Self-organization is same as unsupervised learning.
  - Modelling of network structures for self-organization tends to follow neurobiological structures.
- Algorithms want to discover significant patterns / features in the input data, without a teacher.
  - Examples :
    - Image Processing – Blobs of the same colour , Edges.
    - Speech Processing – Phonemes, Syllables.

Intuition for Self-Organization

- Algorithms for self-organization are provided with a set of rules of a “local” nature.
  - Locality ⇒ change applied to a synaptic weight of a neuron is confined to immediate neighbourhood of the neuron.



Intuition for Self-Organization (Continued)

- Locality enables to compute an input-output mapping with specific desirable properties.
- Key reason - “Global order can arise from local interactions.”
- Weights are modified until a final configuration develops.
- Network organisation occurs at two levels in a feedback loop.
  - Activity - activity patterns are produced due to inputs.
  - Connectivity - synaptic weights are modified due to neuronal signals in the activity patterns, because of synaptic plasticity
  - Plasticity permits neurons to adapt to the environment.

INTUITIVE PRINCIPLES OF SELF ORGANISATION

Principle I

- Principle I. ``Modifications in weights tend to self-amplify.''
  - Due to self-reinforcement and locality.
  - Feedback between changes in weights and changes in activity patterns must be positive to achieve self-organisation.
  - Strong synapse implies coincidence of presynaptic and postsynaptic signals.
  - The synapse has increased strength by such a coincidence.
  - This is same as Hebb's postulate.

INTUITIVE PRINCIPLES OF SELF ORGANISATION

Principle II

- Principle II. Limitation of resources leads to competition among synapses, in turn leading to selection of fittest synapses at the expense of others.
- For stability, there must be contention for limited resources
  - (Examples : number of inputs, energy resources).
- An increase in the strength of some synapses must be compensated by a decrease in others.
- Only successful synapses can grow, while the less successful get weaker and may also disappear. This is possible due to synaptic plasticity (adjustability of weights).

INTUITIVE PRINCIPLES OF SELF ORGANISATION

Principle III

- <u>Principle III.</u> Modifications in synaptic weights tend to cooperate.
- A synapse on its own cannot efficiently produce favourable events.
- We need cooperation among synapses converging onto a neuron.
- They must carry coincident signals strong enough to activate it.
- The presence of a vigorous synapse can enhance the fitness of other synapses in spite of the overall competition in the network.
- This can occur due to synaptic plasticity or due to simultaneous stimulations of presynaptic neurons from the external environment.
- All 3 Principles are related to the network, not to the environment.

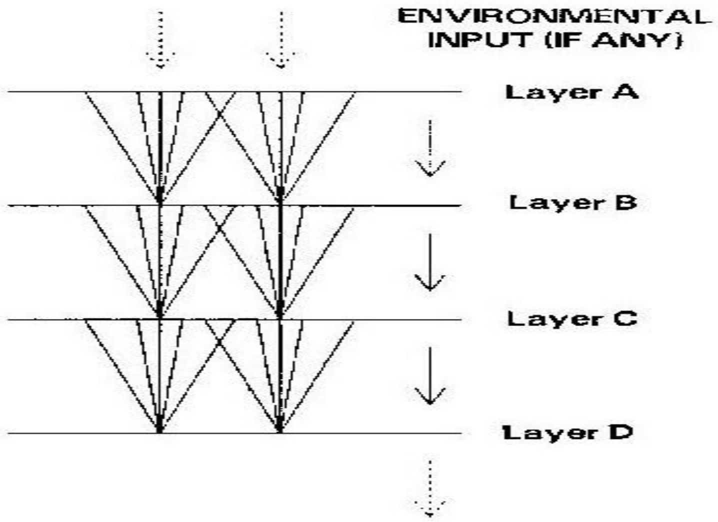
Principle IV

- Principle IV. Order and structure in activation patterns represent redundant information acquired by the network as knowledge.
- For self-organisation, redundancy in the activation patterns supplied by the environment is required.
- Knowledge is obtained by observations of statistical parameters such as mean, variance and correlation matrix of the input data.
- These principles provide the neurobiological basis for the adaptive algorithms for principal component analysis.

SELF-ORGANIZED FEATURE ANALYSIS

An Example

- Linsker's model of mammalian visual system processes information in different stages.
- Initial stages analyse simple features like contrast and edge orientation. Complex features are analysed later.
- Local feedforward connections from one layer to the next.



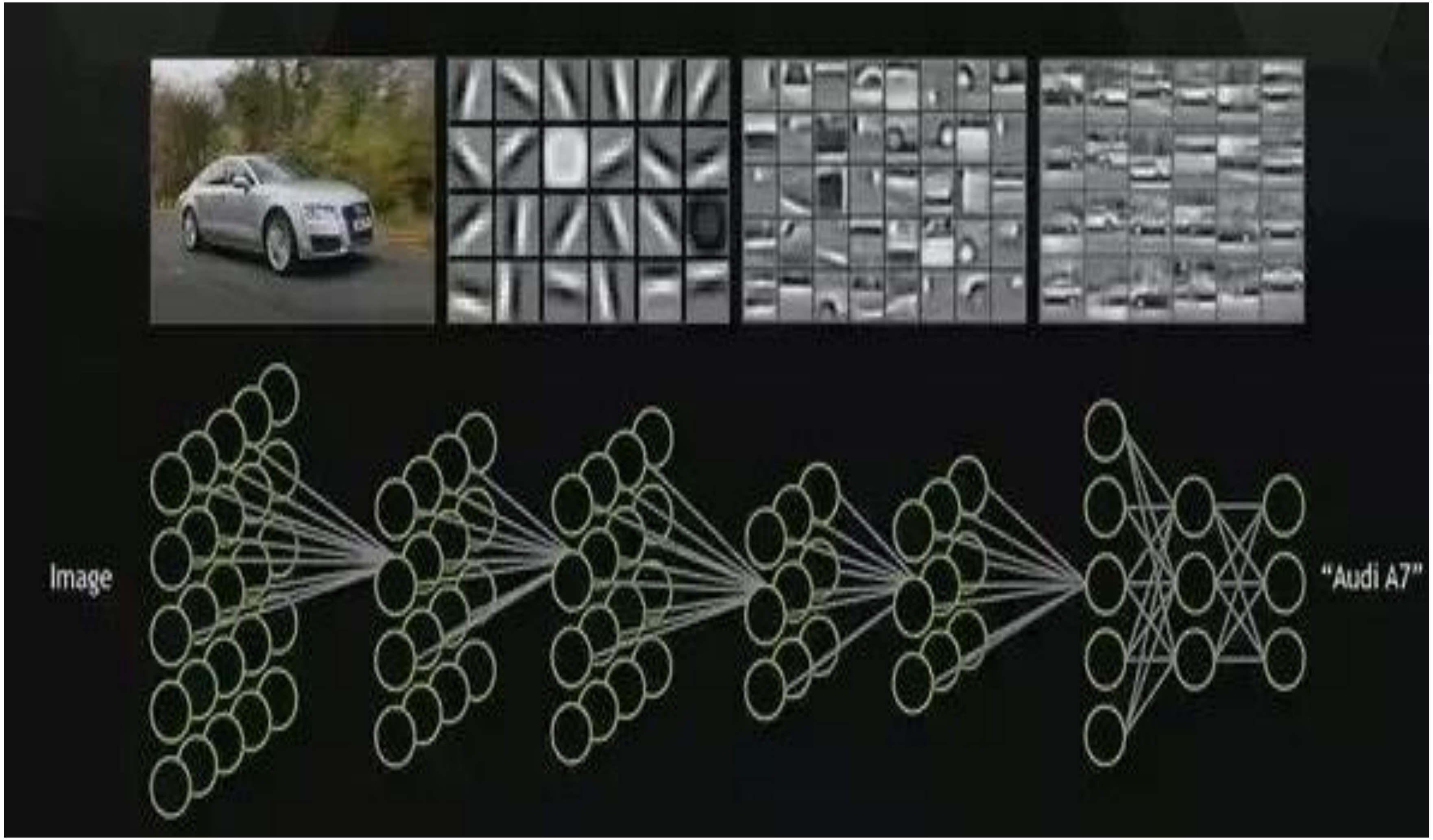
SELF-ORGANIZED FEATURE ANALYSIS

An Example (Continued)

- All inputs from previous layer are not connected to the next layer.
- Neurons in one layer capture spatial correlations in the previous layer.
- Two assumptions are made regarding the structural nature –
    - Positions of synaptic connections are fixed for the entire neuronal development process once they have been chosen.
    - Each neuron acts as a linear combiner.
- Combines aspects of Hebbian learning with cooperative and competitive learning, such that self-organized feature analysing properties are developed fully before proceeding to the next layer.

SELF-ORGANIZED FEATURE ANALYSIS

A Visual Example



Need For Feature Selection / Feature Extraction

- Input variables are pre-processed to transform them into some new space of variables where, it is hoped that supervised / unsupervised learning will be easier to solve computationally.
- In digit recognition, the images are translated and scaled so that each digit is contained within a box of a fixed size.
- This reduces the variability within each digit class, as the location and scale of all the digits are now the same.
- Makes easier for an algorithm to distinguish between classes.
- Such pre-processing stage is also called feature extraction.

Need For Feature Selection / Feature Extraction

- Feature Extraction is also performed to speed up computation.
- For real-time face detection (high-resolution video stream), the computer must handle huge numbers of pixels per second.
- Employing a learning algorithm may be computationally infeasible. Hence, one should extract features preserving useful information enabling faces to be distinguished from non-faces.
- For instance, the average value of the image intensity over a rectangular subregion can be evaluated extremely efficiently.
- Hence, # features < # pixels, implying dimensionality reduction.

PRINCIPLE COMPONENT ANALYSIS

Chinmayananda A.
Department of Electronics and Communication Engineering

PRINCIPAL COMPONENT ANALYSIS (PCA)

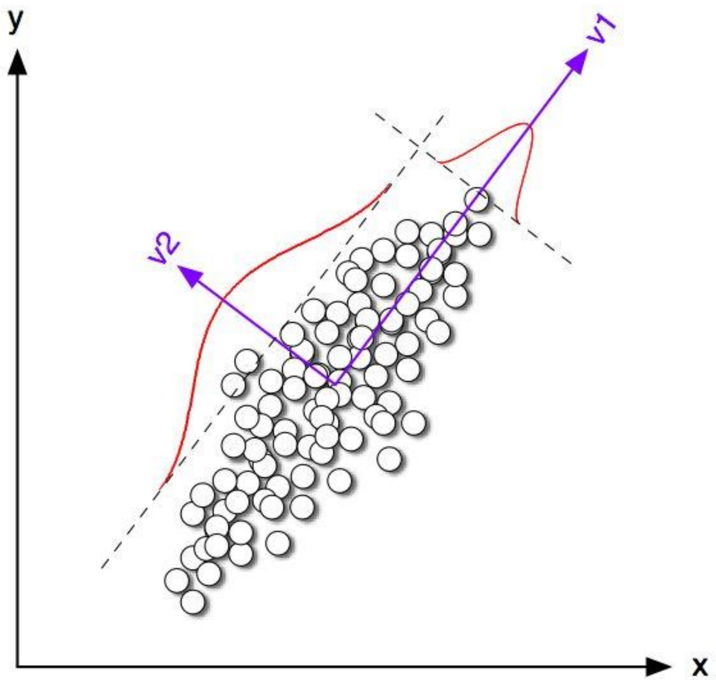
Introduction to PCA

- PCA is used in applications like dimensionality reduction, lossy data compression and data visualization.
- Data space is transformed to a feature space such that the data set (represented as a vector x) is represented by less number of effective features while retaining most of the intrinsic information.
- Truncating some components of the data set incurs loss of significant information if they are providing lot of information.
- We want to find a linear transformation T such that truncating $T(x)$ is optimum in the mean squared error sense. This implies that some components (truncated) of $T(x)$ must have very low variance.

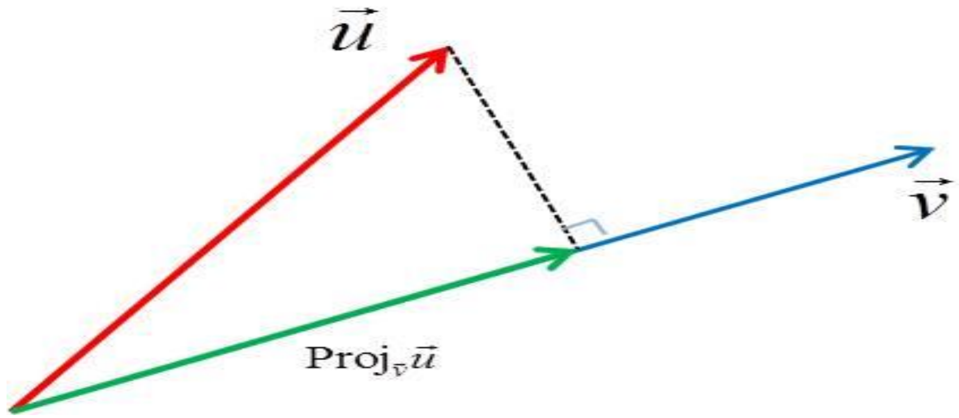
PRINCIPAL COMPONENT ANALYSIS (PCA)

Intuition

- The given data set has an original coordinate system.
- Important features or clusters in the data set can be seen when the original coordinate system is transformed into another appropriate coordinate system.



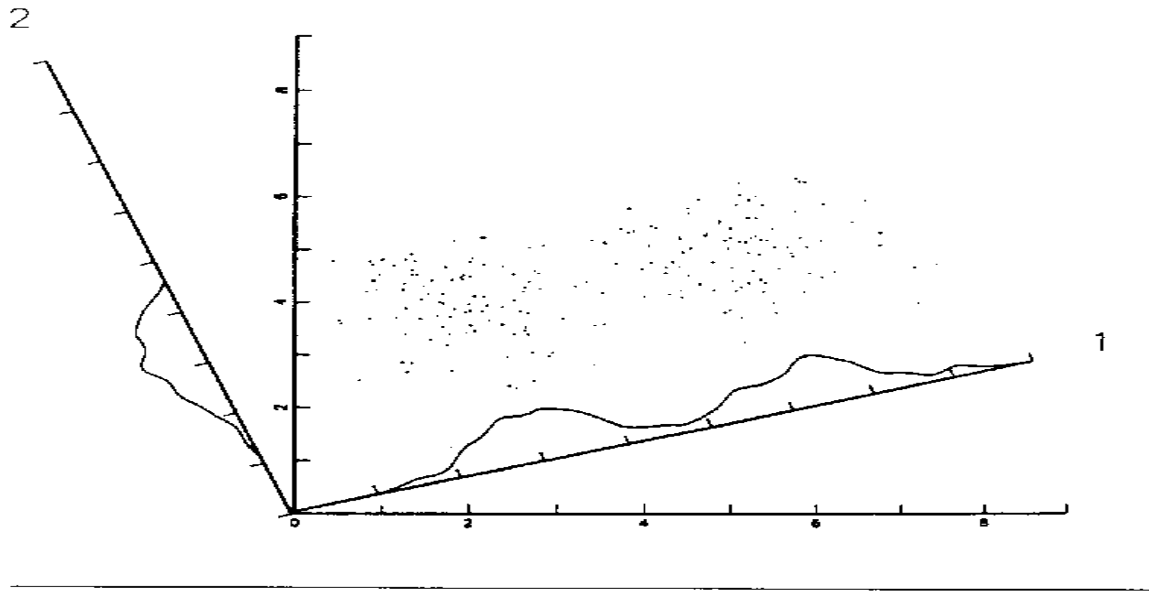
Significant ``projections’’ of the data over the ``right’’ coordinate system are called principal components.



PRINCIPAL COMPONENT ANALYSIS (PCA)

A Motivating Example

- The horizontal and vertical axes represent the natural coordinates.



- Axis `1’ represents first principal component. Projecting the data set onto axis `1’ clearly shows that the data set has two distinct clusters.
- This is not seen from projection on axis `2’. Projection onto axis `1’ has maximum variance.

Eigenvalue Decomposition : Introduction

- For a given matrix R, λ is an eigenvalue if a vector q exists such that $Rq = \lambda$q, and q is called an eigenvector of the matrix R corresponding to the eigenvalue λ.
- Eigenvalue decomposition is a representation of the given matrix in terms of eigenvalues and eigenvectors (spectral decomposition).
- Eigenvalue decomposition is valid only for diagonalizable matrices.
- A matrix R is diagonalizable if an invertible matrix P exists such that R $= PDP^{-1}$, where D is a diagonal matrix.

PRINCIPLE COMPONENT ANALYSIS (PCA)

Eigenvalue Decomposition of a Correlation matrix

- Correlation matrix of a random vector X is given by $R = E[XX^T]$.
    - $E[\ ]$ is the statistical expectation operator.
    - If X is an $m \times 1$ vector, then R is an $m \times m$ matrix.
- Known properties :
    - Any symmetric matrix is diagonalizable.
    - Any correlation matrix R has real and non-negative eigenvalues.
    - If eigenvalues are distinct, so are the associated eigenvectors.
- For an $m \times m$ correlation matrix R, assume that the eigenvalues are ordered as $\lambda_1 > \lambda_2 > \ \dots > \lambda_m$, with the corresponding eigenvectors $q_1, q_2, \dots, q_m$.

PRINCIPLE COMPONENT ANALYSIS (PCA)

Eigenvalue Decomposition (Continued)

- Let $Q = [q_1, q_2, \dots, q_j, \dots q_m]$, and $\Lambda = diag[\lambda_1, \lambda_2, \dots, \lambda_j, \dots \lambda_m]$.
- The m equations $Rq_j = \lambda_j q_j$ can be written as $RQ = Q\Lambda$.
- Eigenvectors of a symmetric matrix are orthonormal.
- $\Rightarrow Q$ is orthonormal $\Rightarrow q_i^T q_j = 0$ for $i \neq j$, and $q_i^T q_j = 1$ for $i = j$.
- $\Rightarrow Q^T Q = I \Rightarrow Q^T = Q^{-1}$.
- $\Rightarrow RQ = Q\Lambda$ is same as $Q^{-1}RQ = \Lambda \Rightarrow Q^T RQ = \Lambda$.
- $\Rightarrow q_j^T \, Rq_k = \lambda_j$, if $k = j$, and $q_j^T Rq_k = 0$ otherwise.
- Note that $Q^T RQ = \Lambda \Rightarrow R = Q\Lambda Q^T$.
- $\Rightarrow R = \sum_{i=1}^{m} \lambda_i \, q_i \, q_i^T$

THANK YOU

Chinmayananda A.
Department of Electronics and Communication Engineering

chinmay@pes.edu

+91 8197254535