An introduction to PCA

Weekly AI pills

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Summary

- The aim of Principal Component Analysis
- Derivation
    1. A Geometrical idea
    2. A statistical Derivation
    3. Singolar Value Decomposition
- PCA from Encoder Decoder NN
- Dummy examples

Let $X \in \mathbb{R}^{N \times n}$ be a dataset of N **observation** within n **variables**.

$$X = \begin{bmatrix} x_1^T \\ \vdots \\ x_N^T \end{bmatrix} = \begin{bmatrix} x^{(1)} & \Big| & \cdots & \Big| & x^{(n)} \end{bmatrix} \tag{1}$$

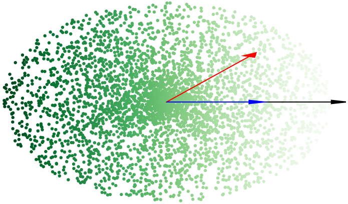
Notations:

- $x_i \in \mathbb{R}^n$ represents a single **observation**, i.e a **sample** in the feature space.
- $x^{(i)} \in \mathbb{R}^N$ represents the single **variable**, i.e a **column** of the dataset.
- The object $\mathbb{1}_n \in \mathbb{R}^n$ is the unitary columnar vector of length n $\mathbb{1}_n = [1, \cdots, 1]$.

Geometrical Introduction: Finding a principal direction.

1. Scalar product measures the projection of x_j along the direction w.
2. We are only interested on module.
3. Summation over samples to get the global projection's contribute.
4. Searching for w which maximizes projection.
5. Adding constraint to avoid $w \to \infty$ solution.

$$w_1 \in \underset{||w||_2=1}{\operatorname{argmax}} \sum_{j=1}^{N} \left(w \cdot x_j\right)^2$$



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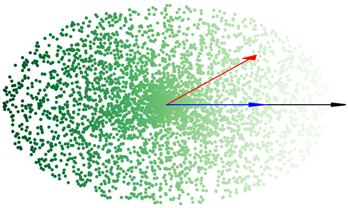

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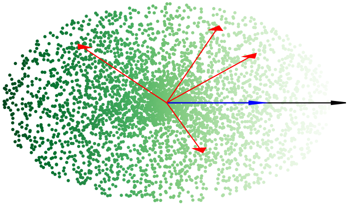

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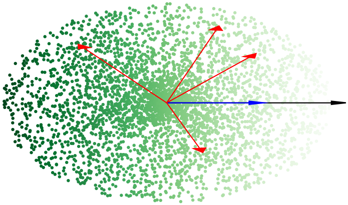

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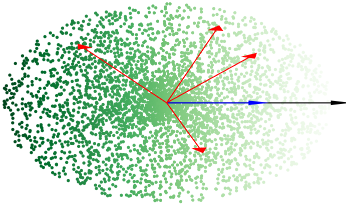

Geometrical Introduction: Finding other directions

We search for other orthogonal directions which maximize projections.

$$w_1 \in \underset{\|w\|_2=1}{\operatorname{argmax}} \sum_{j=1}^{N} (w \cdot x)^2$$

$$w_2 \in \underset{\|w\|_2=1}{\operatorname{argmax}} \sum_{j=1}^{N} (w \cdot x)^2 \quad \text{and} \quad w_2 \perp w_1$$

$$\vdots$$

$$w_n \in \underset{\|w\|_2=1}{\operatorname{argmax}} \sum_{j=1}^{N} (w \cdot x)^2 \quad \text{and} \quad w_2 \perp \{w_1, \ldots, w_{n-1}\}$$

Example

Geometrical Introduction: Direction Selection

Let us define $V(w) = \sum_j (w \cdot x_j)^2$ as **momentum along** w.
If w_1, w_2, w_3 orthogonal that maximizes V in the 3D example, then

1. $V(w_1) = 3181.20$ $\approx 82.5\%$
2. $V(w_2) = 646.25$ $\approx 17.0\%$
3. $V(w_3) = 19.23$ $\approx 0.5\ \%$

What if we forget the last direction?

Observation

- $x_j = \alpha_{1j} w_1 + \alpha_{2j} w_2 + \alpha_{3j} w_3$ (where $\alpha_{ij} = w_i \cdot x_j$).
- $\tilde{x}_j = \alpha_{1j} w_1 + \alpha_{2j} w_2$.

$$\frac{1}{N} \sum_j \|x_j - \tilde{x}_j\|^2 = \frac{V(w_3)}{N} \approx 4.8\, 10^{-3} \qquad \text{(MSE)}$$

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