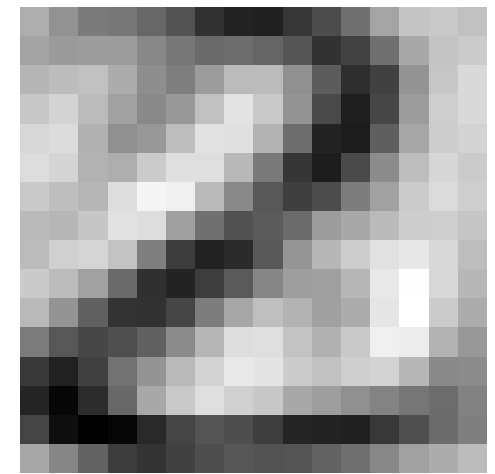
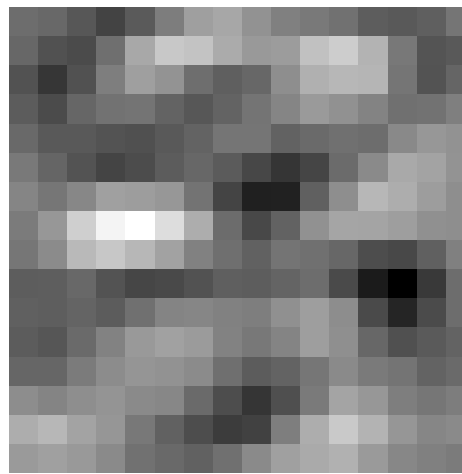
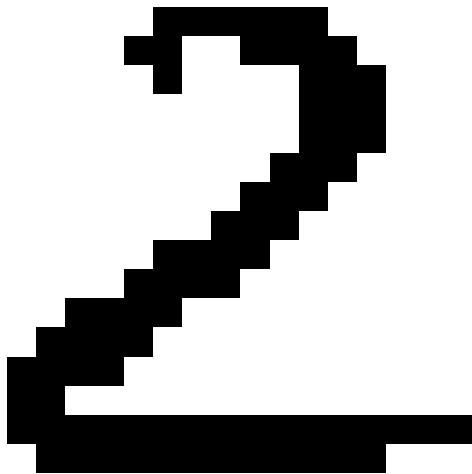


Advanced Machine Learning

Principal Component Analysis (PCA)

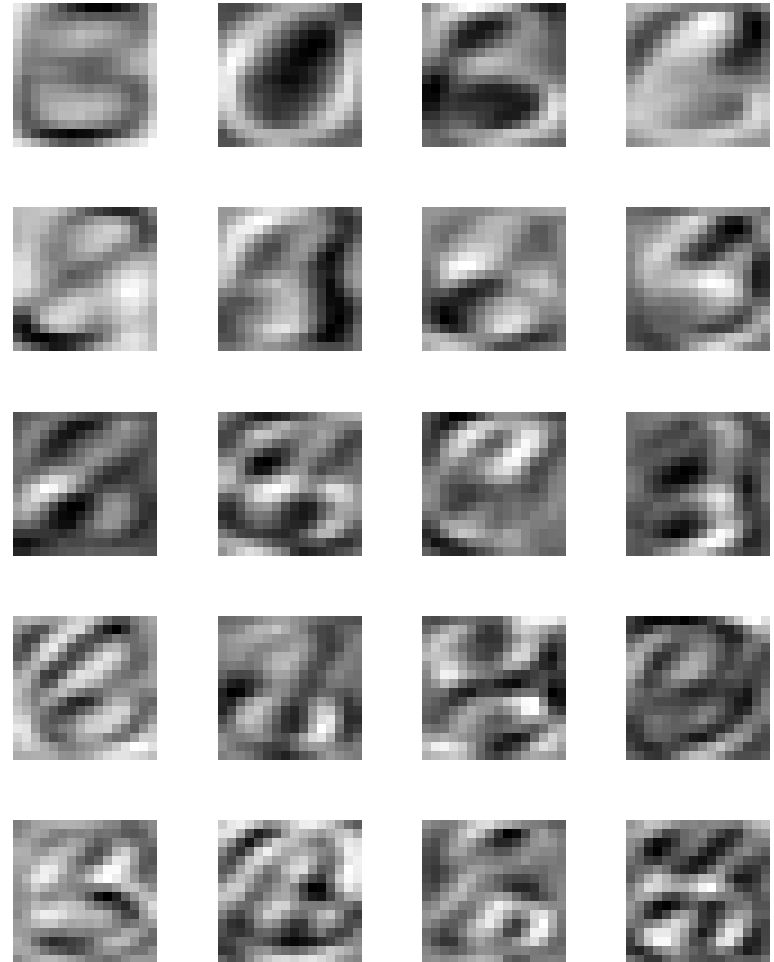
1.6 -1.1 -1.6 2.1 -0.52 2.8 0.72 0.7 -0.68 -0.41 -1.4 -1.5 -0.54 -0.62 1.3 -1.4 -0.27 0.74 0.77 -1



Covariance matrices, dimensionality reduction, PCA, Duality

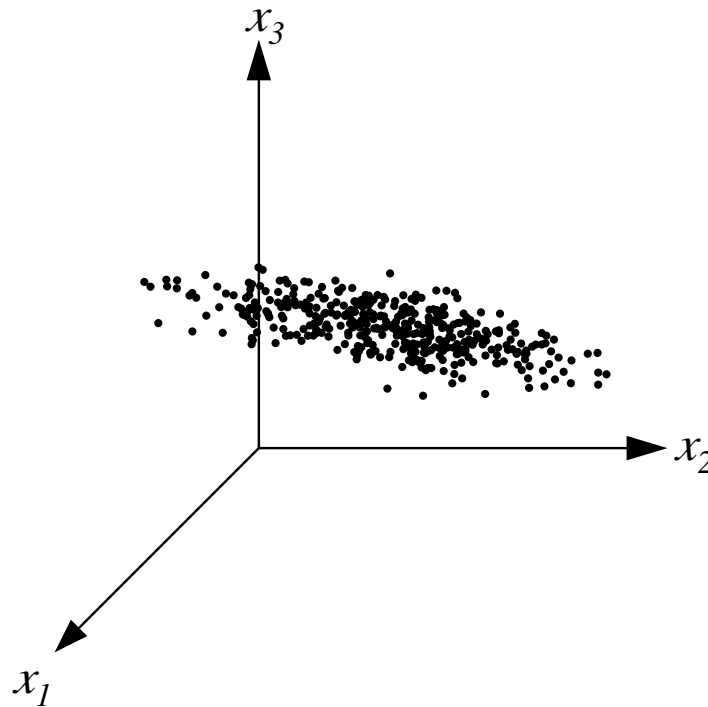
Outline

1. **Covariance Matrices**
2. Principal Component Analysis
3. Duality



Spread of Data

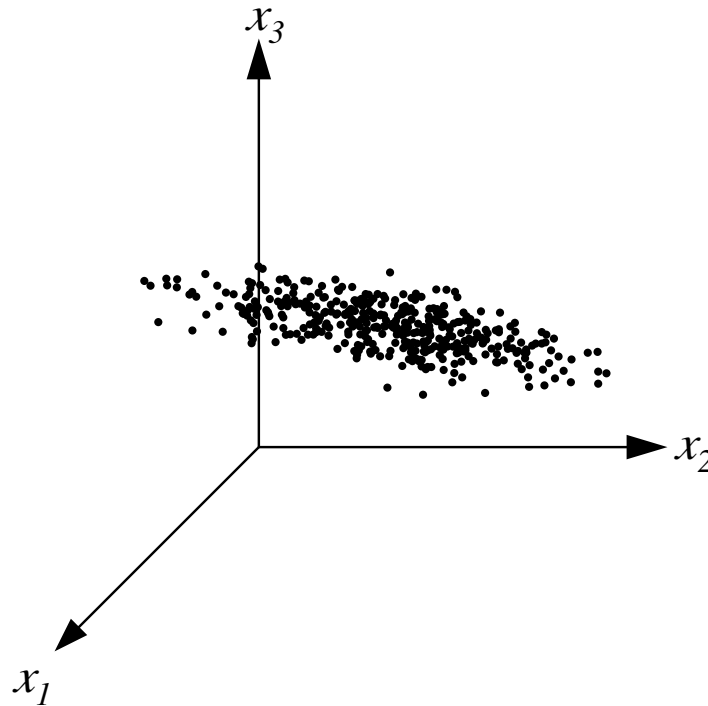
- Often data varies significantly in only some directions



- Reduce dimensions by projecting onto low dimensional subspace with maximum variation

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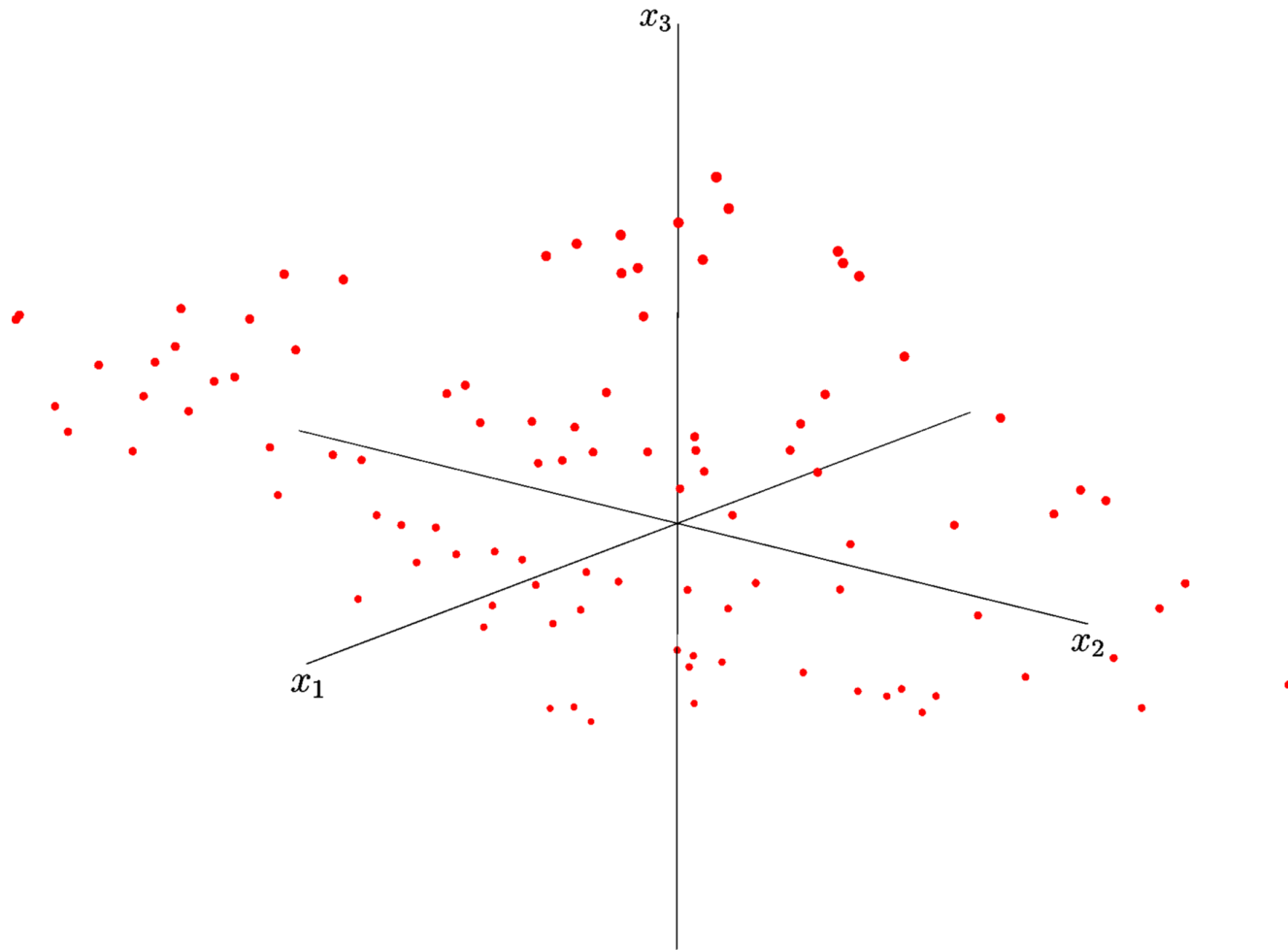
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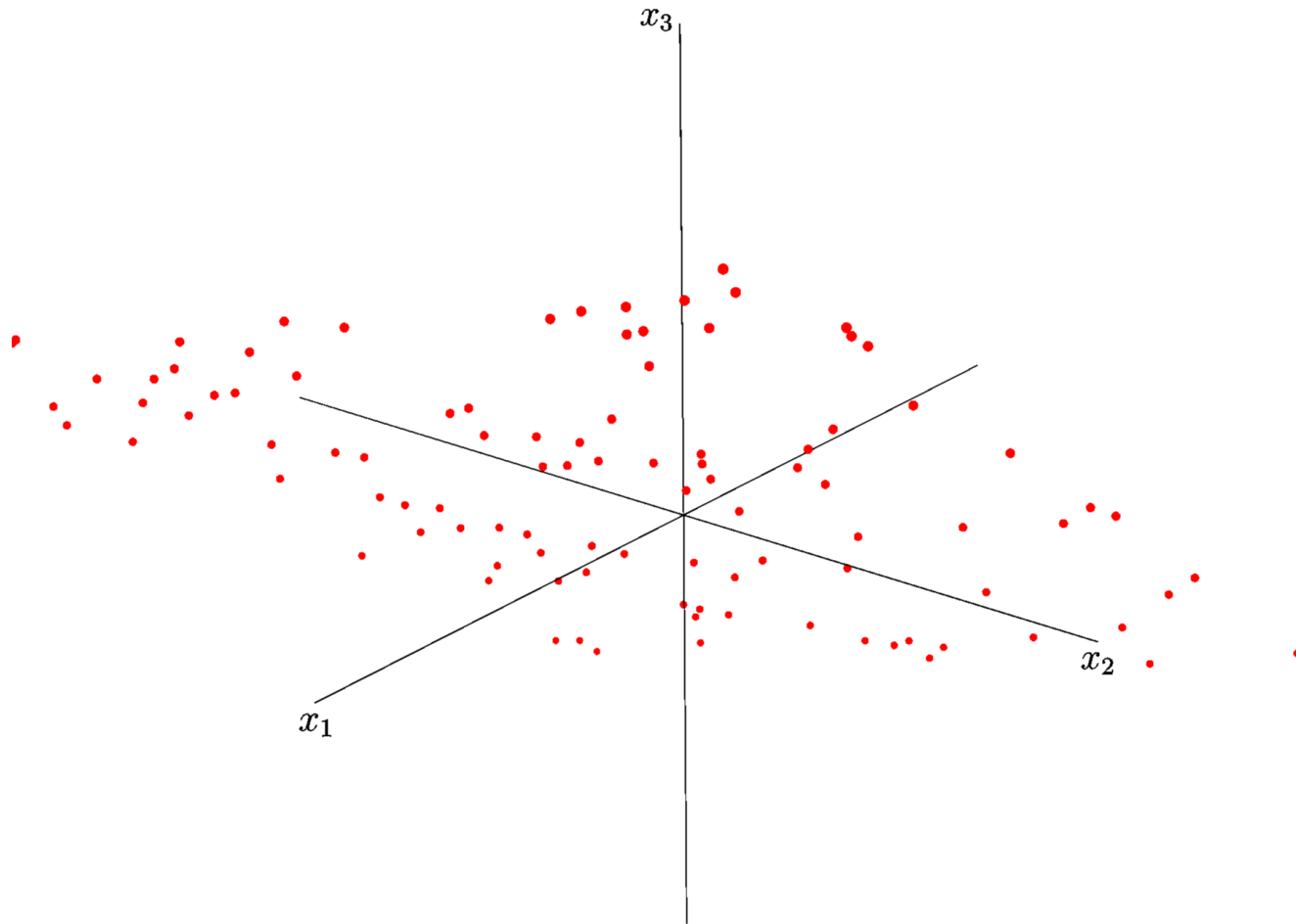
Looking is not Enough

Can't spot low dimensional data by looking at numbers



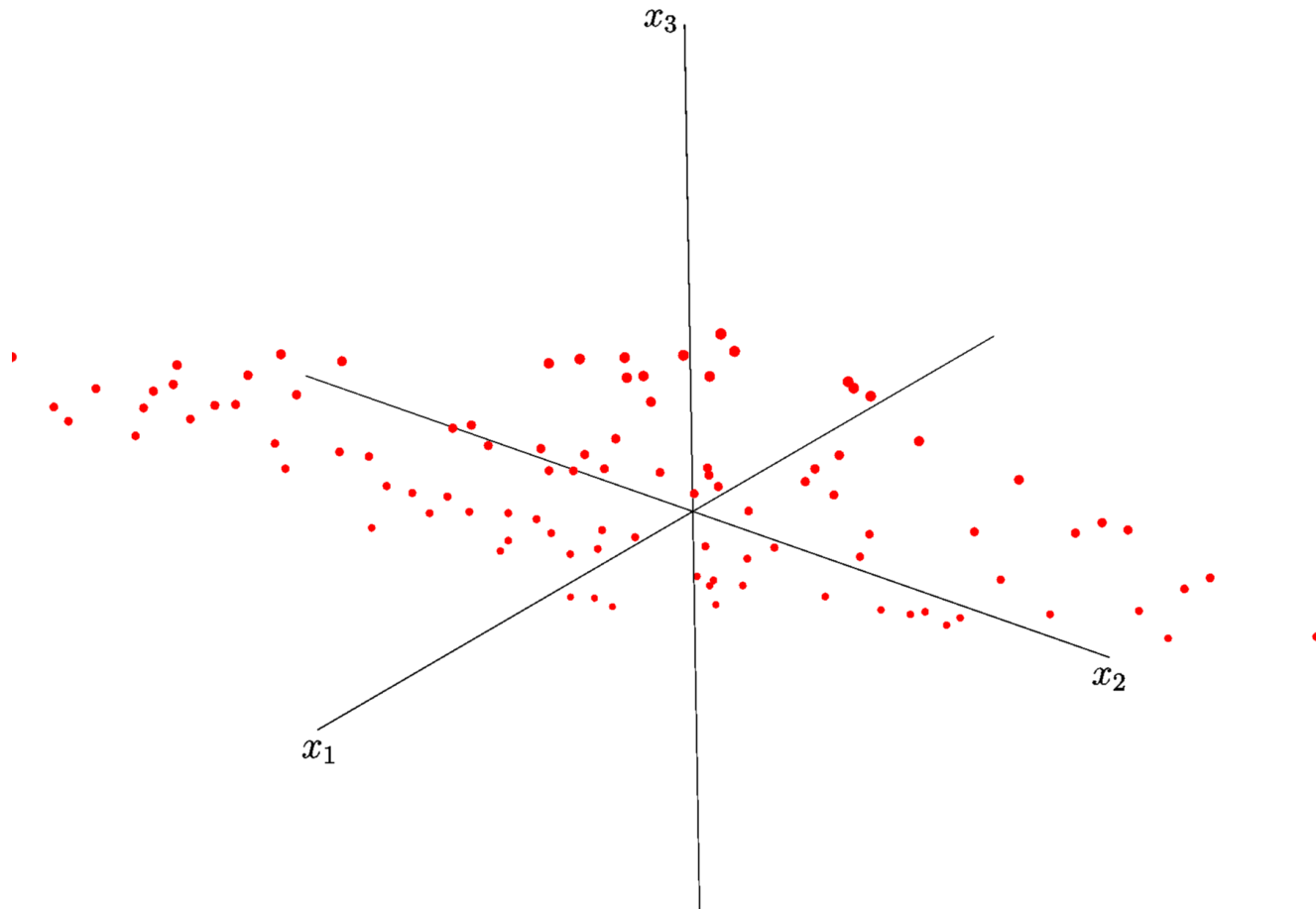
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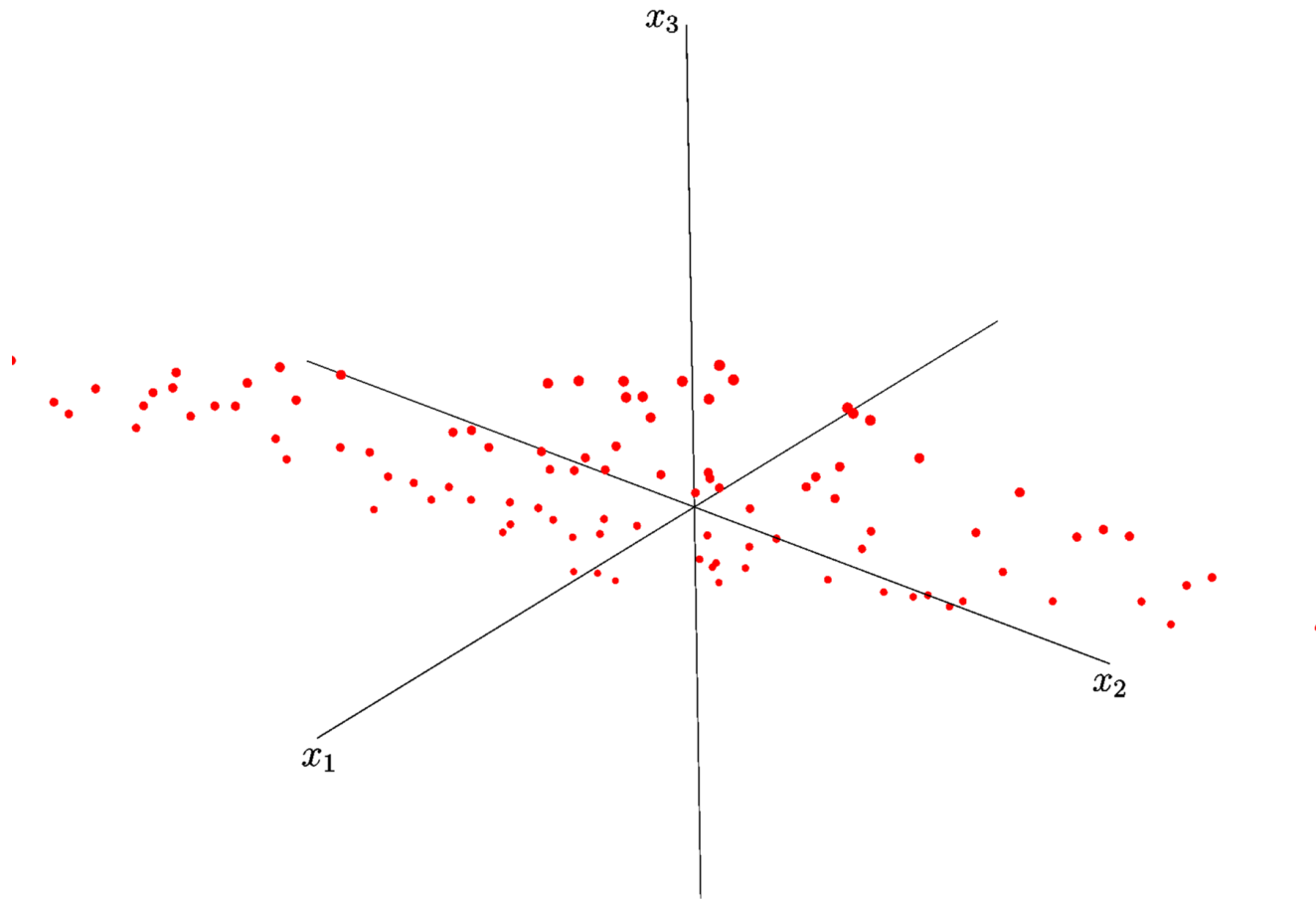
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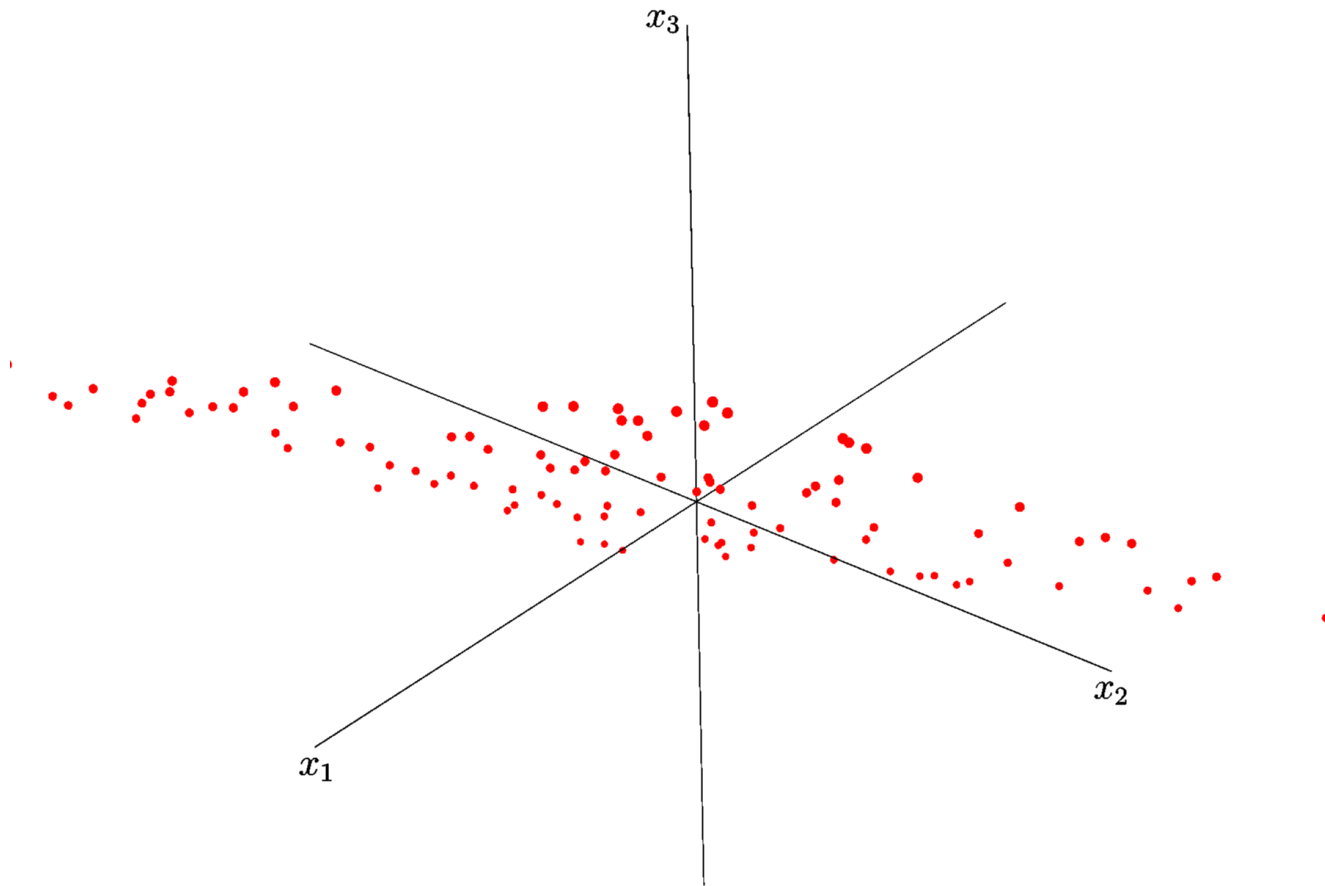
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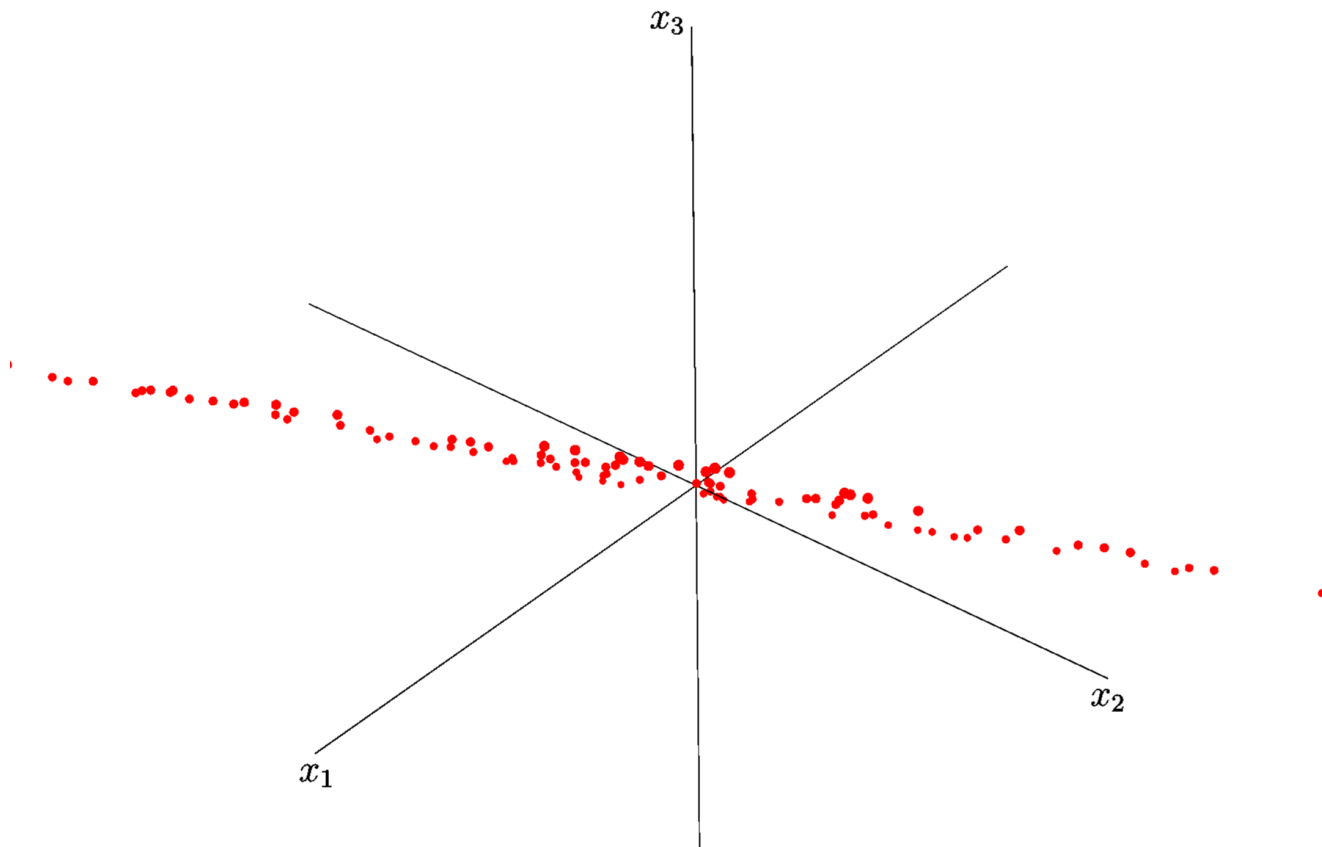
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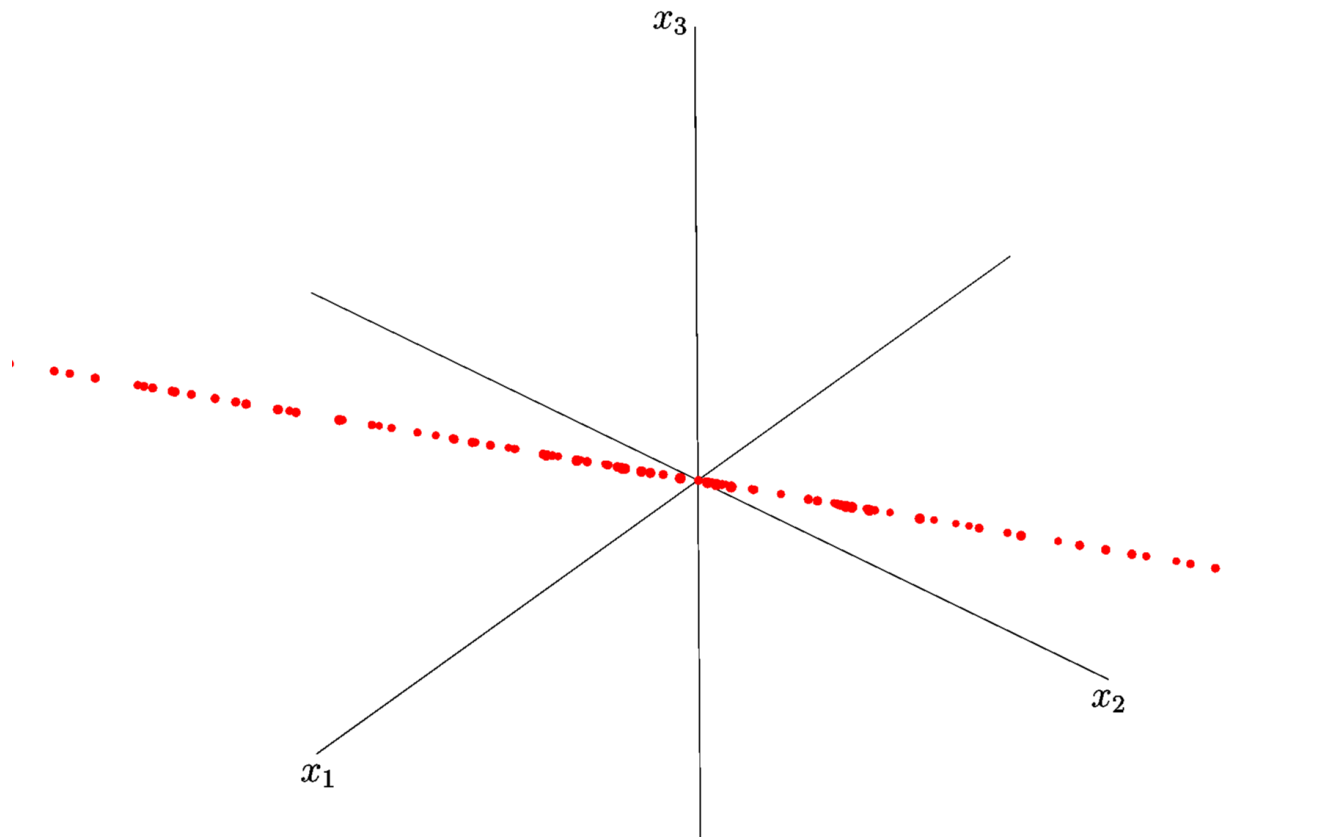
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Dimensionality Reduction

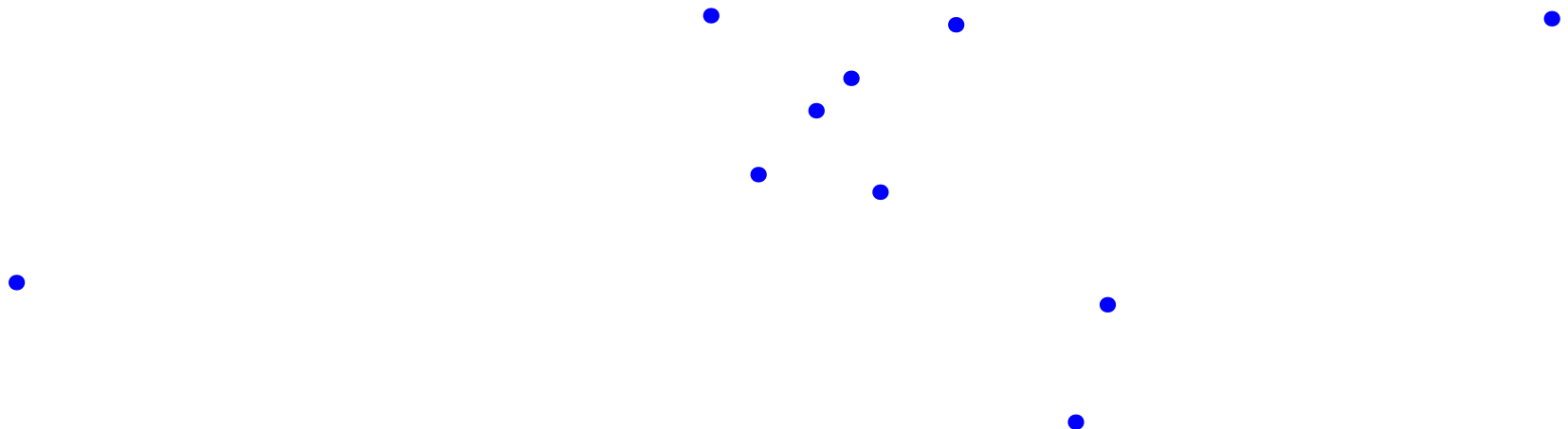
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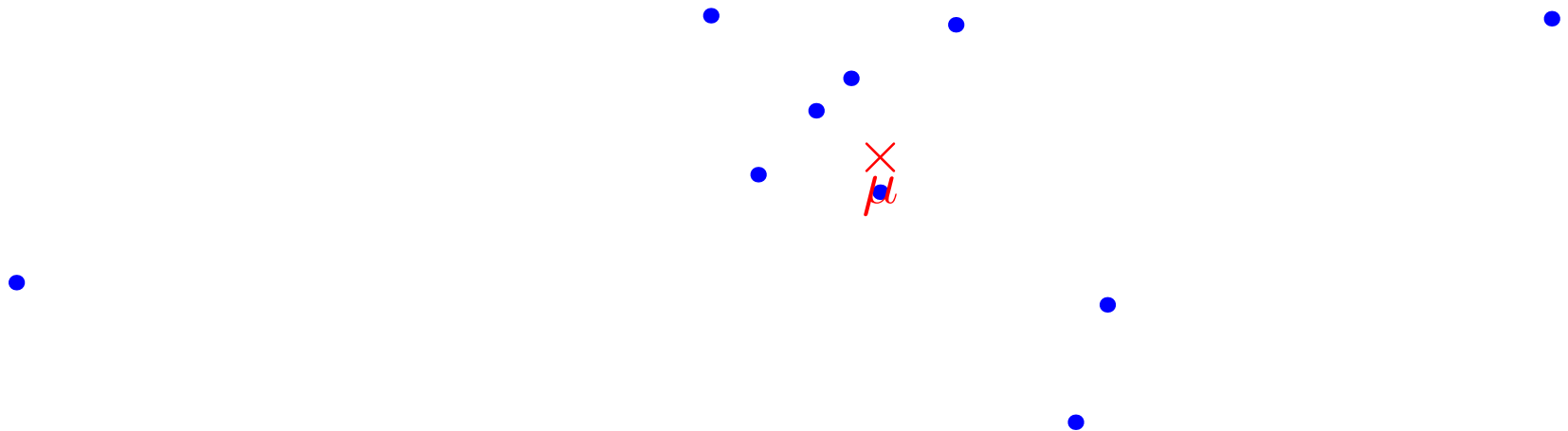
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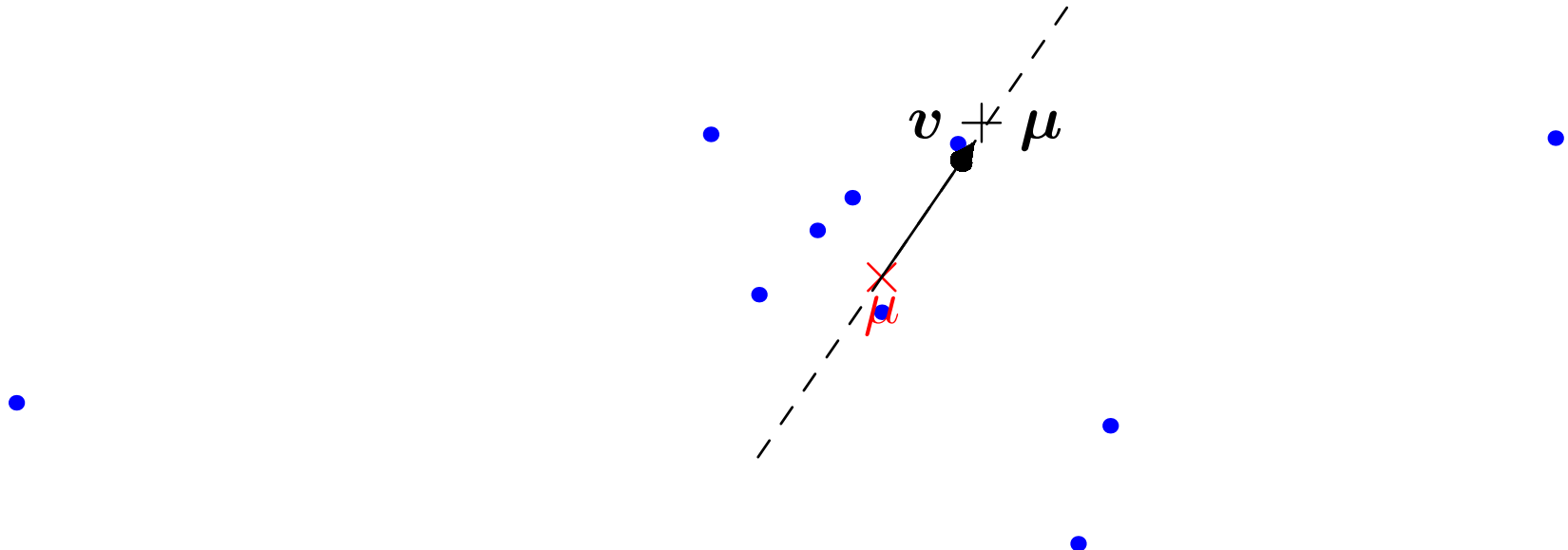
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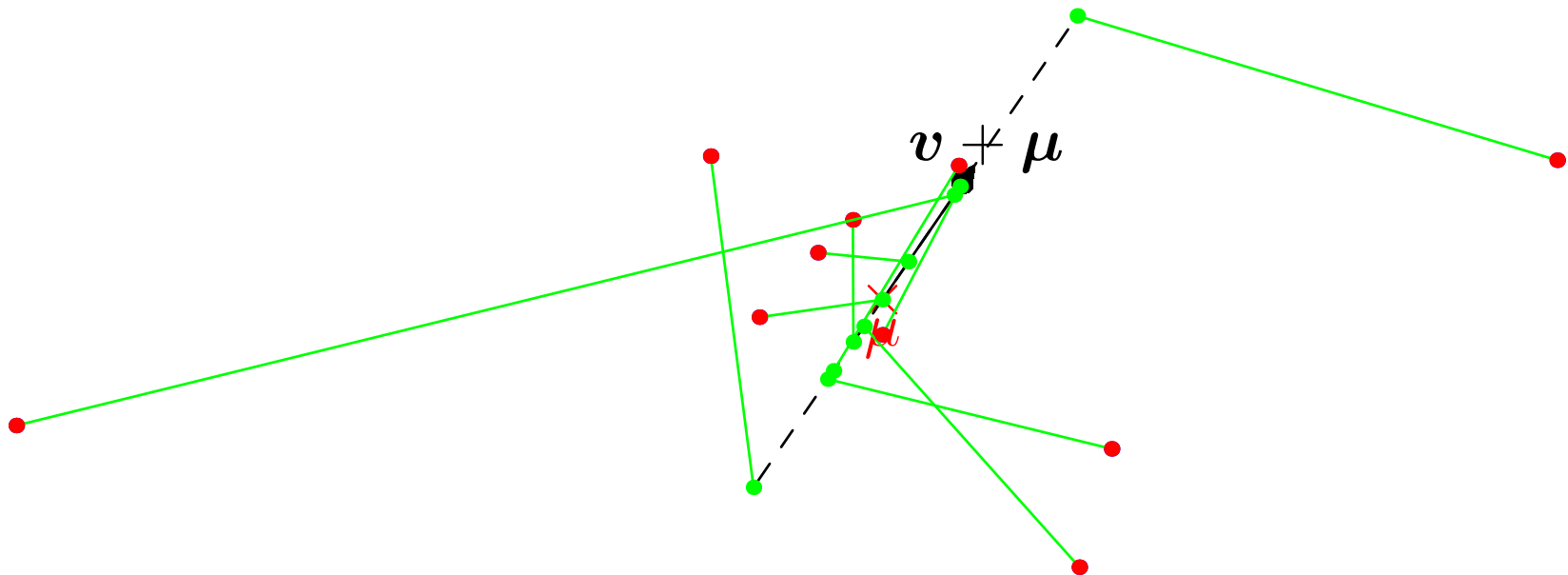
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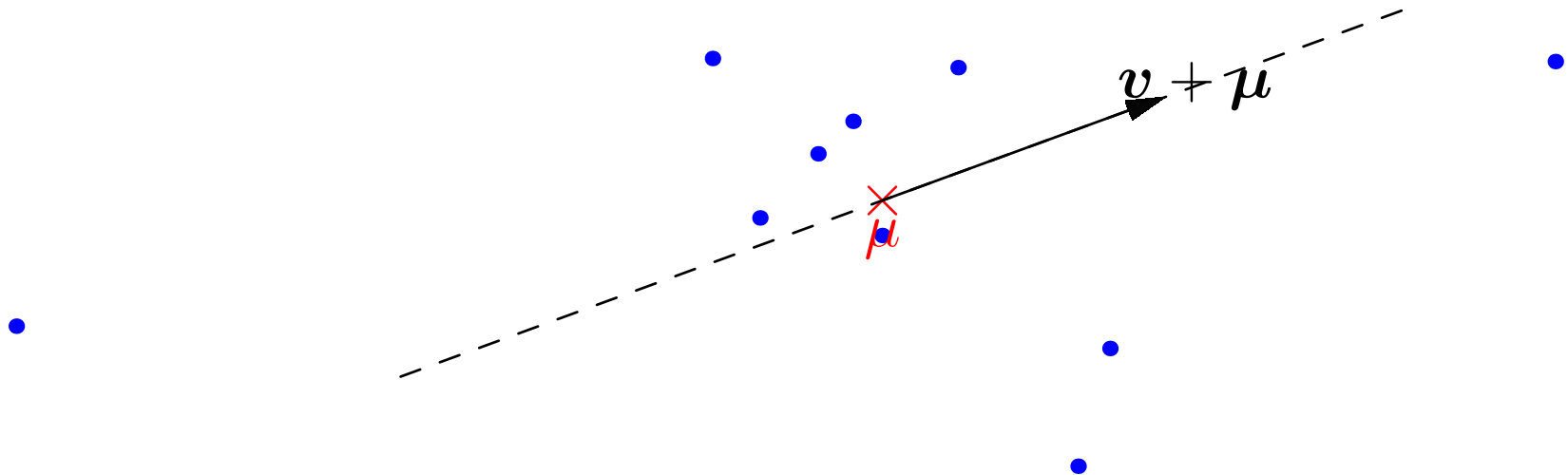
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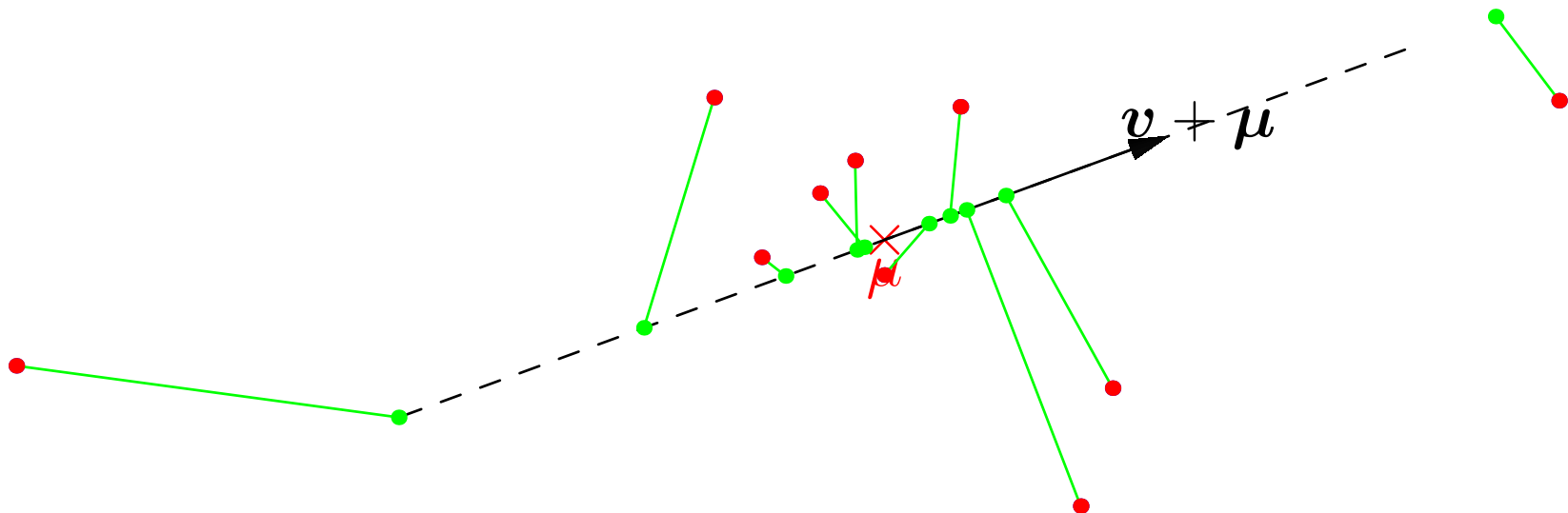
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Direction of Maximum Variation

- Look for the vector \mathbf{v} with $\|\mathbf{v}\|^2 = 1$ to maximise

$$\sigma^2 = \frac{1}{m-1} \sum_{i=1}^m (\mathbf{v}^\top (\mathbf{x}_i - \boldsymbol{\mu}))^2$$

- This is a constrained optimisation problem
- Solve by maximising Lagrangian

$$\mathcal{L} = \frac{1}{m-1} \sum_{k=1}^m (\mathbf{v}^\top (\mathbf{x}_k - \boldsymbol{\mu}))^2 - \lambda (\|\mathbf{v}\|^2 - 1)$$

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$$\begin{aligned}\mathcal{L} &= \frac{1}{m-1} \sum_{k=1}^m \left(\mathbf{v}^\top (\mathbf{x}_k - \boldsymbol{\mu}) \right)^2 - \lambda (\|\mathbf{v}\|^2 - 1) \\ &= \frac{1}{m-1} \sum_{k=1}^m \left(\mathbf{v}^\top (\mathbf{x}_k - \boldsymbol{\mu}) (\mathbf{x}_k - \boldsymbol{\mu})^\top \mathbf{v} \right) - \lambda (\|\mathbf{v}\|^2 - 1) \\ &= \mathbf{v}^\top \left(\frac{1}{m-1} \sum_{k=1}^m (\mathbf{x}_k - \boldsymbol{\mu}) (\mathbf{x}_k - \boldsymbol{\mu})^\top \right) \mathbf{v} - \lambda (\|\mathbf{v}\|^2 - 1) \\ &= \mathbf{v}^\top \mathbf{C} \mathbf{v} - \lambda (\mathbf{v}^\top \mathbf{v} - 1)\end{aligned}$$

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$$\nabla \mathcal{L} = 2(\mathbf{C} \mathbf{v} - \lambda \mathbf{v}) = 0 \quad \Rightarrow \quad \mathbf{C} \mathbf{v} = \lambda \mathbf{v}$$

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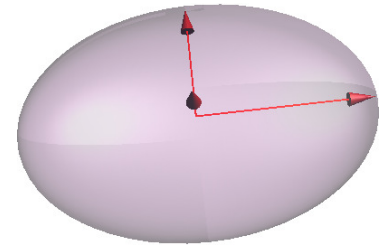
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Direction of Maximum Variation

- The eigenvectors are directions that are extrema of the variance



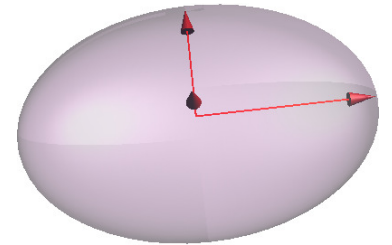
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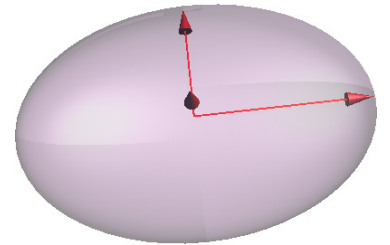
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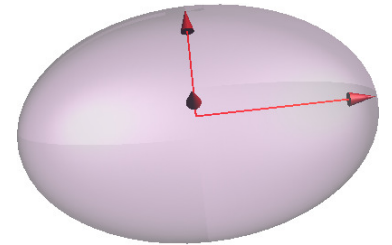
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Covariance Matrix

- The **covariance matrix** is defined as

$$\mathbf{C} = \frac{1}{m-1} \sum_{k=1}^m (\mathbf{x}_k - \boldsymbol{\mu})(\mathbf{x}_k - \boldsymbol{\mu})^\top$$

- The components C_{ij} measure how the i^{th} and j^{th} components co-vary

$$C_{ij} = \frac{1}{m-1} \sum_{k=1}^m (x_{ik} - \mu_i)(x_{jk} - \mu_j)$$

- C.f. covariance of random variables

$$\text{Cov}(X, Y) = \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])]$$

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Outer Product

- Remember that the outer-product of two vectors is defined as

$$\mathbf{x}\mathbf{y}^\top = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} (y_1 \quad y_2 \quad \cdots \quad y_n) = \begin{pmatrix} x_1 y_1 & x_1 y_2 & \cdots & x_1 y_n \\ x_2 y_1 & x_2 y_2 & \cdots & x_2 y_n \\ \vdots & \vdots & \ddots & \vdots \\ x_n y_1 & x_n y_2 & \cdots & x_n y_n \end{pmatrix}$$

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- Define the matrix

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Properties of Covariance Matrix

- The **quadratic form** of a vector and matrix is defined as

$$\mathbf{v}^T \mathbf{M} \mathbf{v}$$

- The quadratic form of a covariance matrix is non-negative for any vector

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Properties of Covariance Matrix

- The **quadratic form** of a vector and matrix is defined as

$$\mathbf{v}^T \mathbf{M} \mathbf{v}$$

- The quadratic form of a covariance matrix is non-negative for any vector

$$\mathbf{v}^T \mathbf{C} \mathbf{v} = \mathbf{v}^T \mathbf{X} \mathbf{X}^T \mathbf{v} = \mathbf{u}^T \mathbf{u} = \|\mathbf{u}\|^2 \geq 0$$

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Eigenvalue Decomposition

- The eigenvectors of \mathbf{C} with the largest eigenvalues are known as the **principal components**
- The eigenvalues are all greater than or equal to zero
- Recall an eigenvector \mathbf{v} satisfies the equation

$$\mathbf{C}\mathbf{v} = \lambda\mathbf{v}$$

- Multiplying both sides by \mathbf{v}^\top

$$\mathbf{v}^\top \mathbf{C}\mathbf{v} = \lambda \mathbf{v}^\top \mathbf{v} = \lambda \|\mathbf{v}\|^2$$

but $\mathbf{v}^\top \mathbf{C}\mathbf{v} \geq 0$ and $\|\mathbf{v}\|^2 > 0$ so

$$\lambda = \frac{\mathbf{v}^\top \mathbf{C}\mathbf{v}}{\|\mathbf{v}\|^2} \geq 0$$

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Surface Defined by Matrix

- The set of vectors x such that

$$x^T C^{-1} x = 1$$

defines a surface

- The surface is an ellipsoid, \mathcal{E}
- The eigenvectors point in the direction of the principal axes of the ellipsoid
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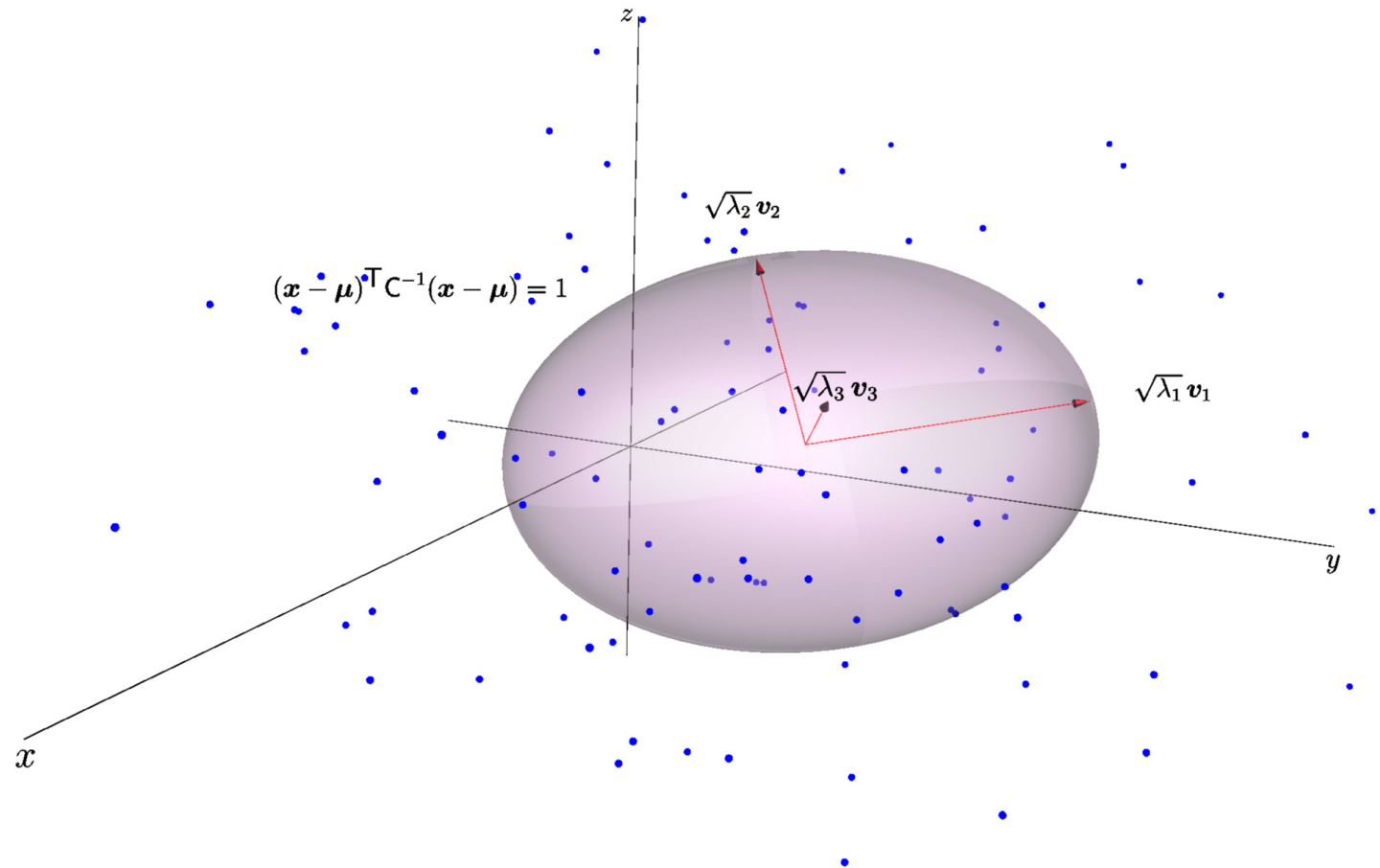
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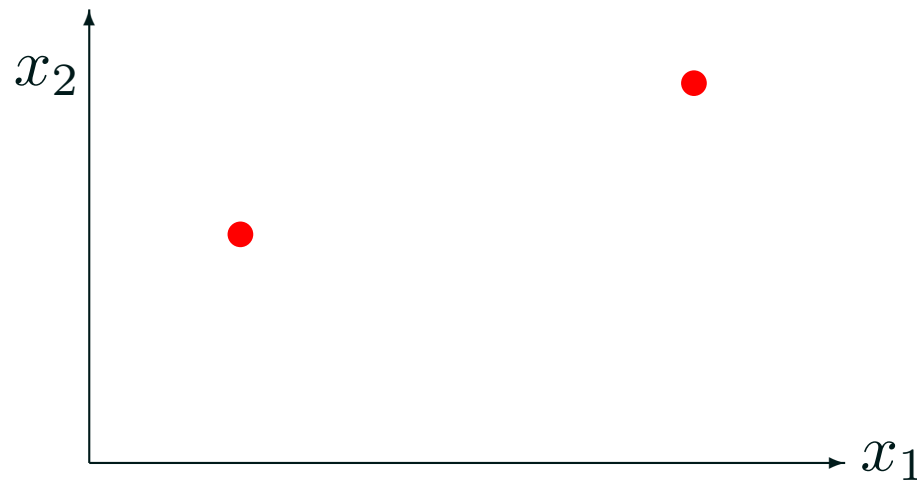
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Ellipsoid and Eigen Space



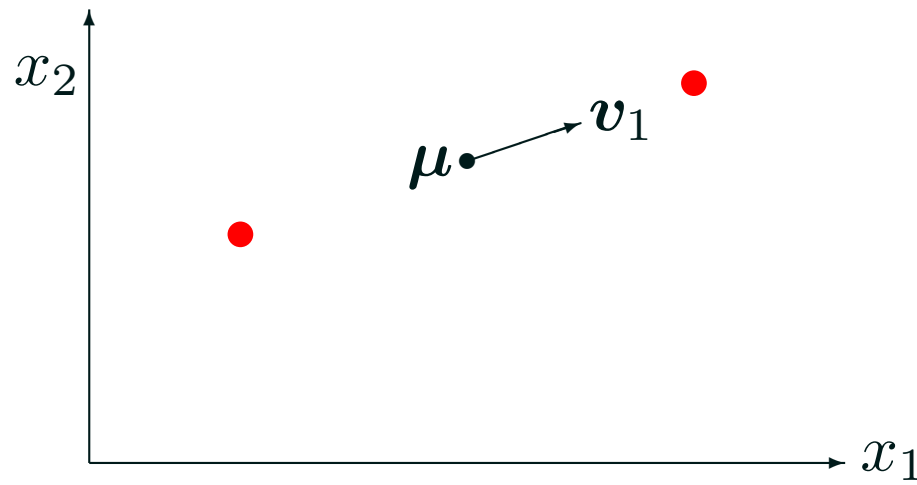
Spanning Input Space

- A covariance matrix will have a zero eigenvalue only if there is no variation in the direction of the corresponding eigenvector
- A covariance matrix will have zero eigenvalues if the number of patterns are less than or equal to the number of dimensions



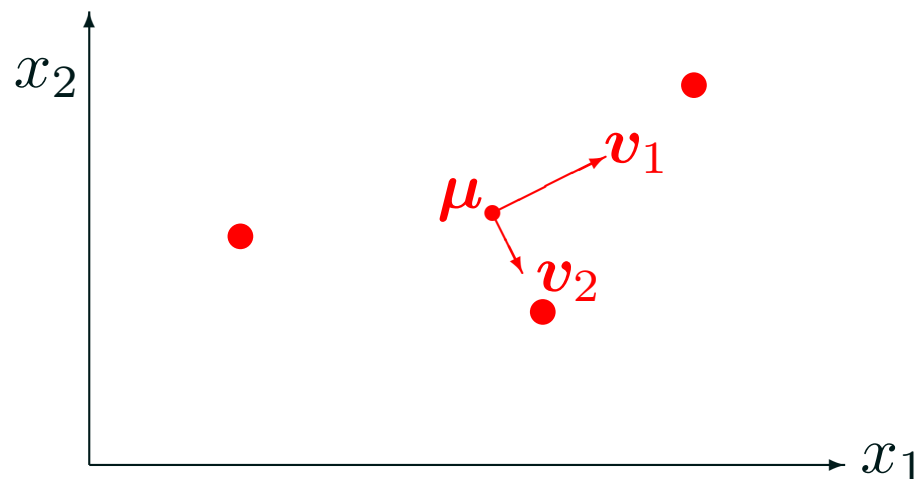
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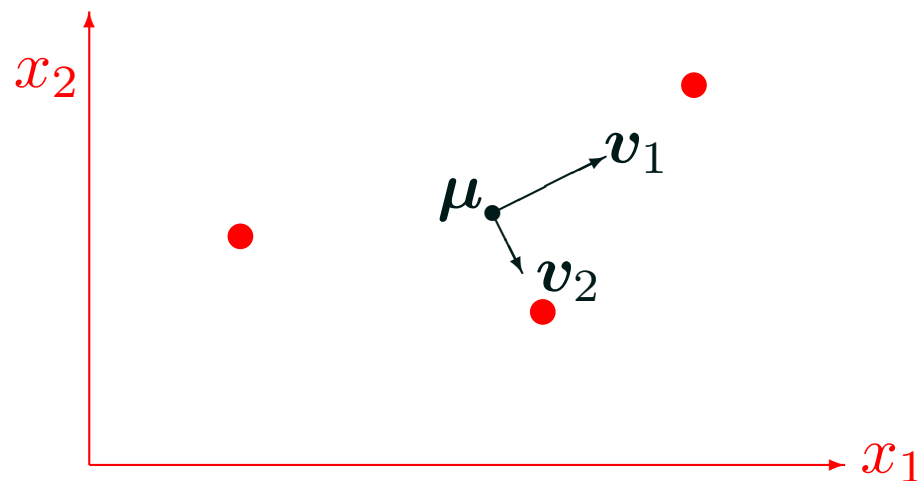
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Positive Definite

- Matrices with no zero eigenvalues are called **full rank** matrices (as opposed to rank deficient)
- Full rank matrices are invertible, rank deficient matrices are singular and non-invertible
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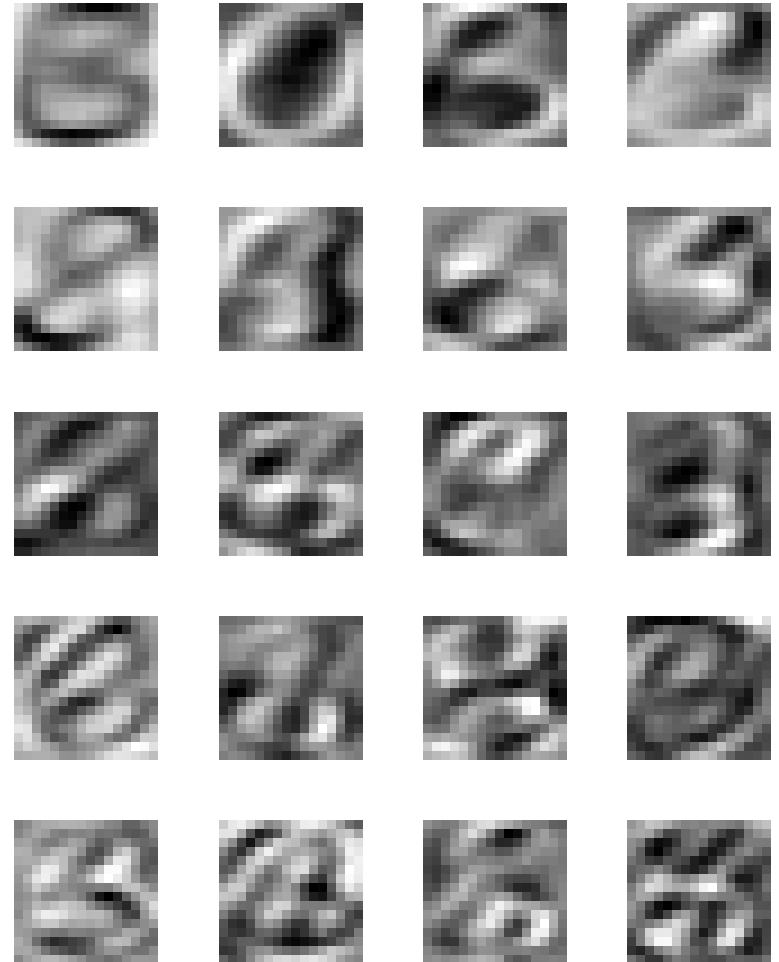
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Outline

1. Covariance Matrices
2. **Principal Component Analysis**
3. Duality



Principal Component Analysis

- PCA occurs as follows
 - ★ Construct the covariance matrix
 - ★ Find the eigenvalues and eigenvectors
 - ★ Keep the eigenvectors with the largest eigenvalues (principal components)
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Projection Matrix

- To project the inputs construct the projection matrix

$$\mathbf{P} = \begin{pmatrix} \mathbf{v}_1^T \\ \mathbf{v}_2^T \\ \vdots \\ \mathbf{v}_k^T \end{pmatrix}$$

- $k < p$ is the number of principal components we keep
- Given a p -dimensional input pattern \mathbf{x} we can construct a k -dimensional representation \mathbf{z}

$$\mathbf{z} = \mathbf{P}(\mathbf{x} - \boldsymbol{\mu})$$

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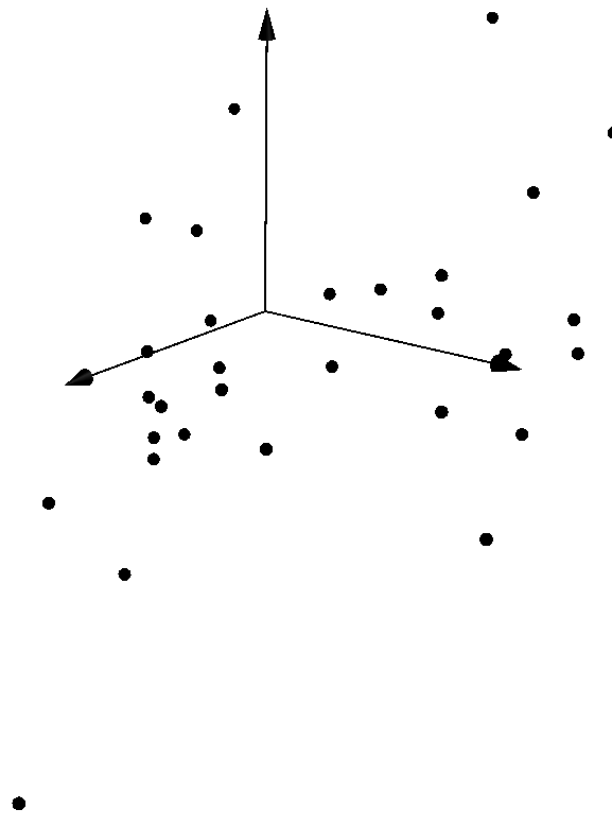
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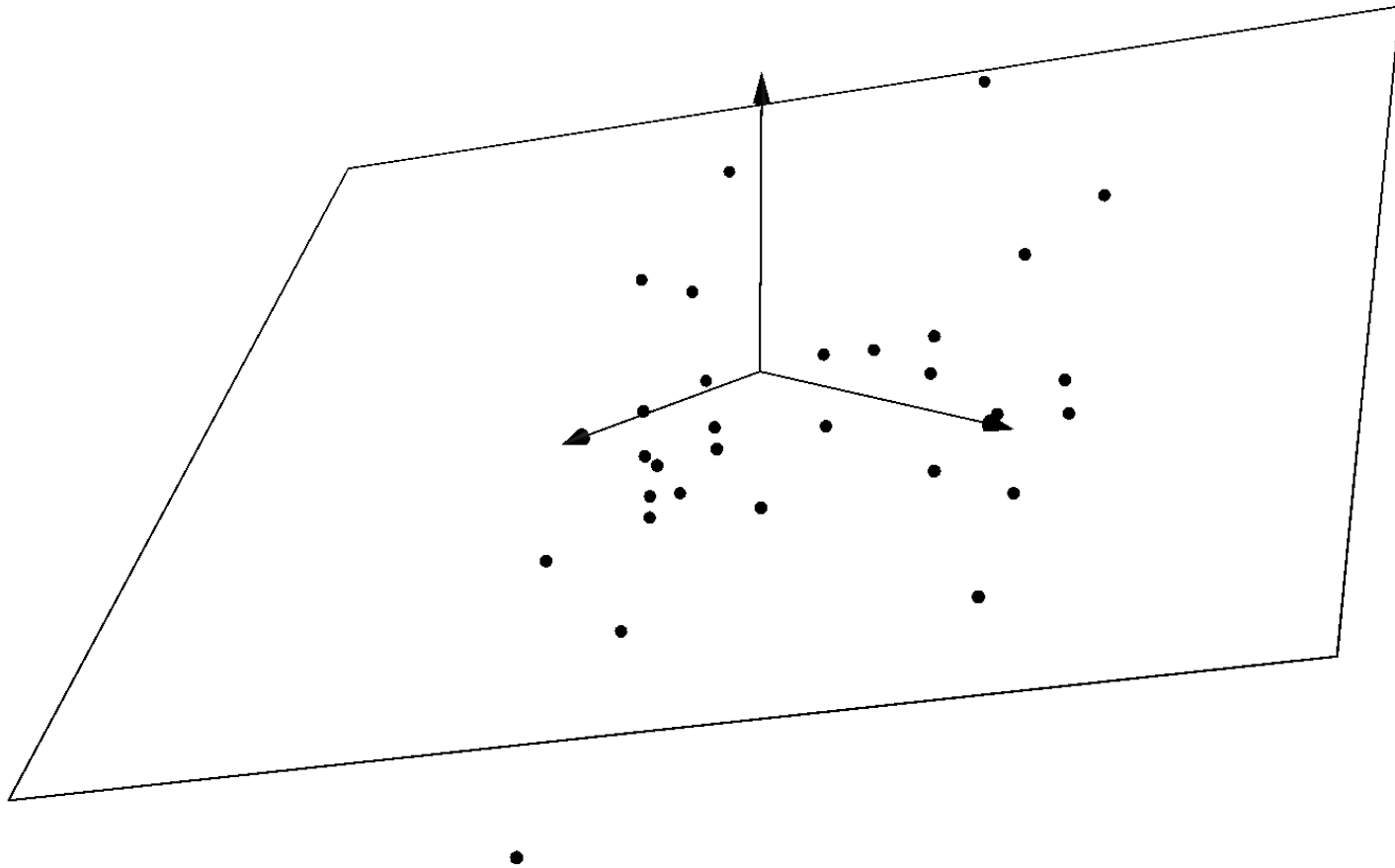
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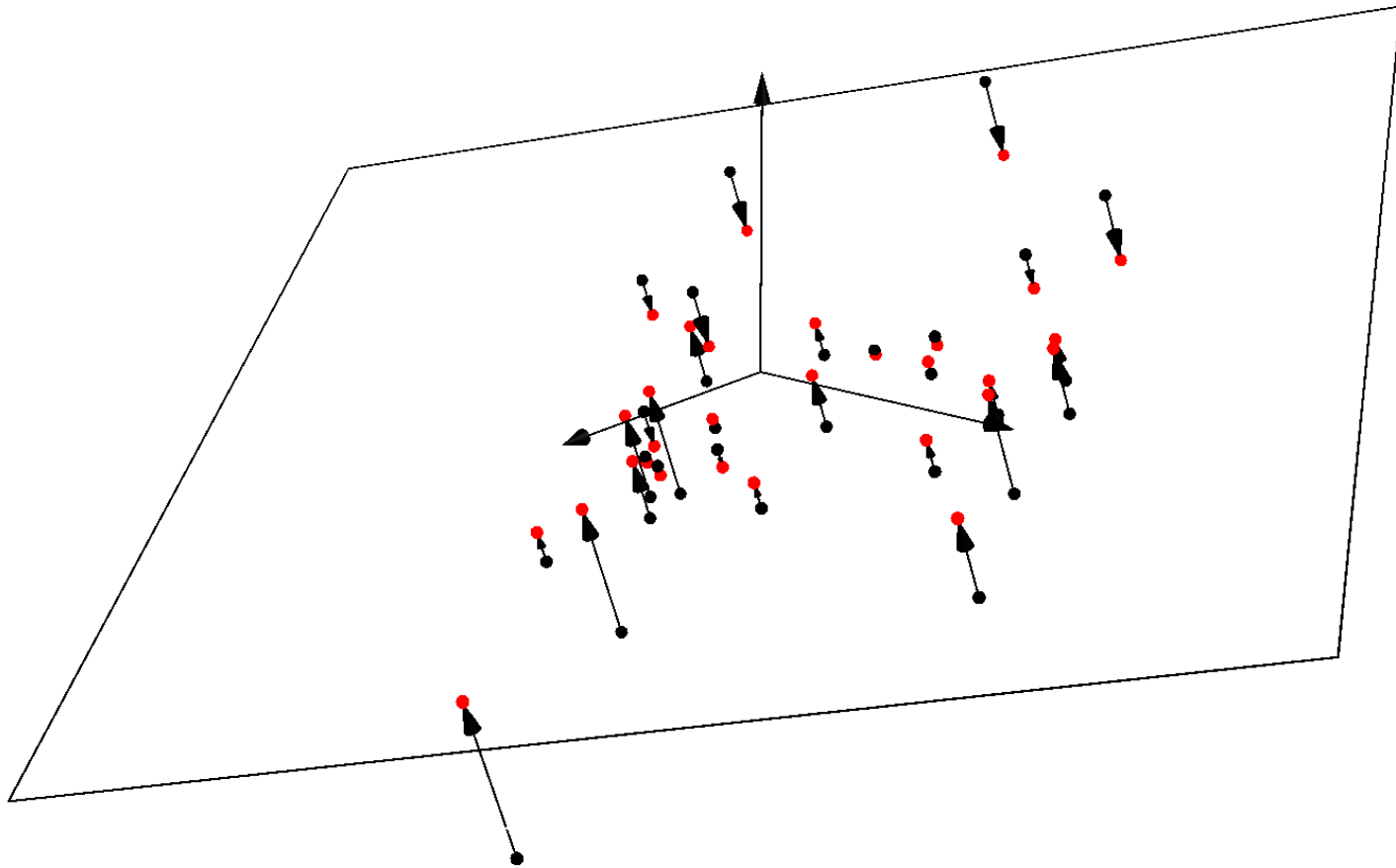
Subspace Projection



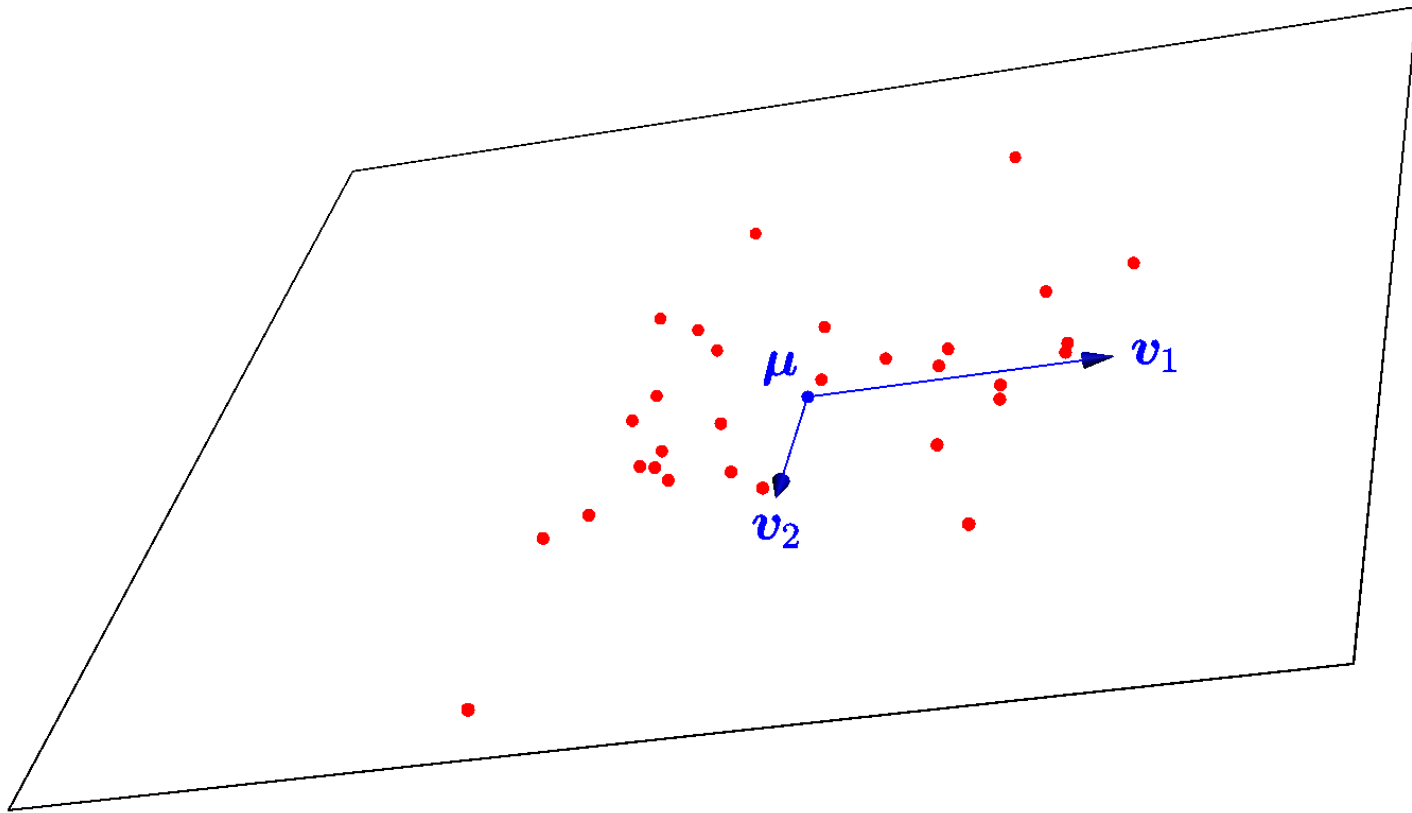
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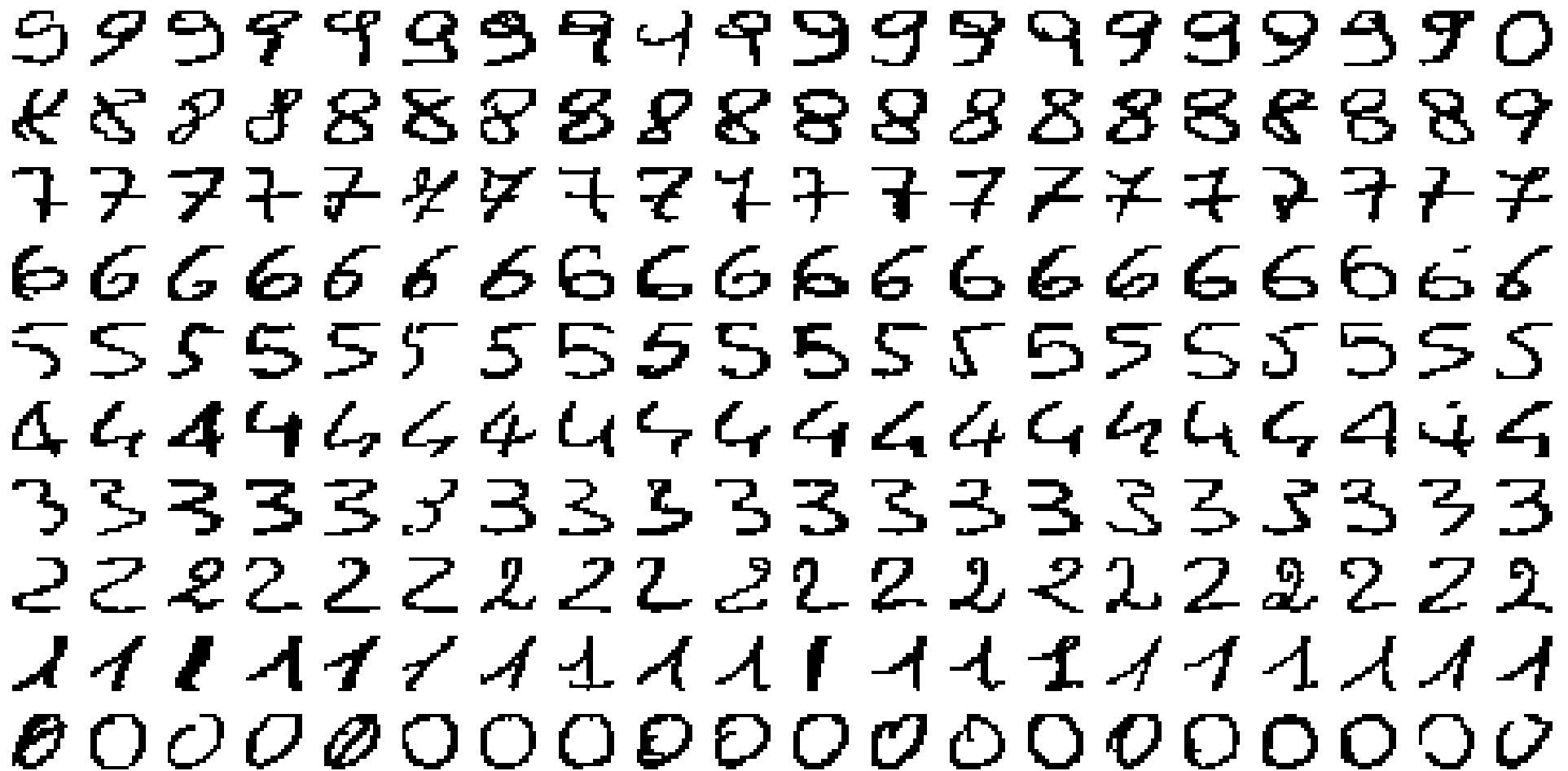
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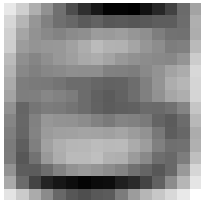
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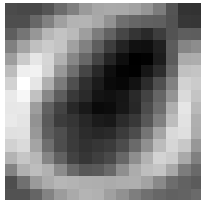
Hand Written Digits



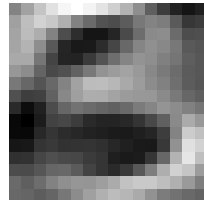
Eigenvectors



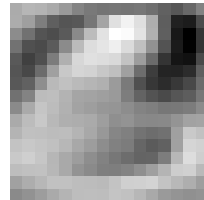
μ



v_1



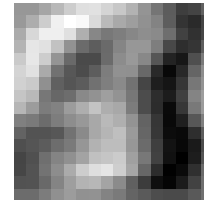
v_2



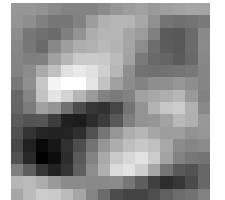
v_3



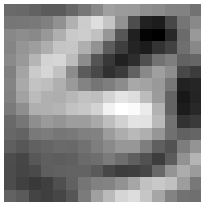
v_4



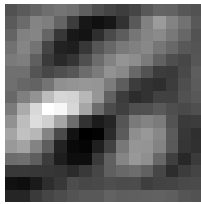
v_5



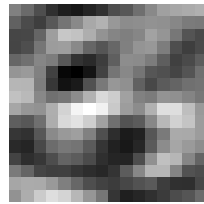
v_6



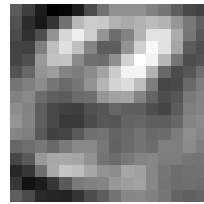
v_7



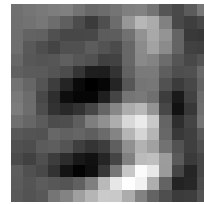
v_8



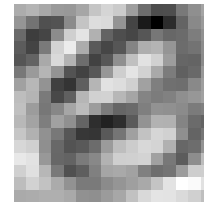
v_9



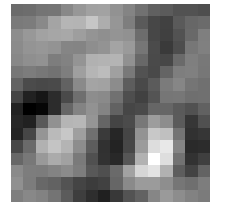
v_{10}



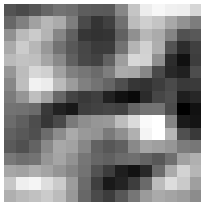
v_{11}



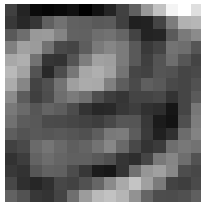
v_{12}



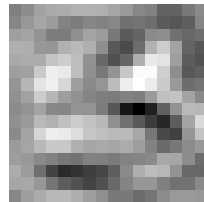
v_{13}



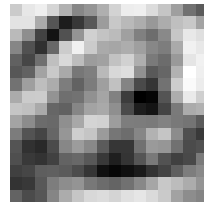
v_{14}



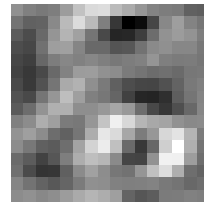
v_{15}



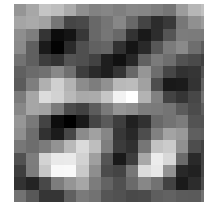
v_{16}



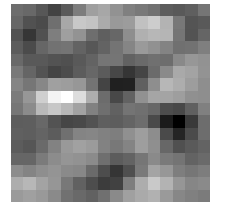
v_{17}



v_{18}



v_{19}



v_{20}

Reconstruction

- Projecting into a subspace of eigenvectors can be seen as approximating the inputs by

$$\hat{\mathbf{x}}_i = \boldsymbol{\mu} + \sum_{j=1}^k z_j^i \mathbf{v}_j, \quad z_j^i = \mathbf{v}_j^\top (\mathbf{x}_i - \boldsymbol{\mu}), \quad \|\mathbf{v}_j\| = 1$$

- Principle component analysis projects the data into a subspace of size m with the minimal approximation error $\mathbb{E}[\|\hat{\mathbf{x}}_i - \mathbf{x}_i\|^2]$
- The loss of “energy” (or squared error) is equal to the sum of the eigenvalues in the directions that are ignored

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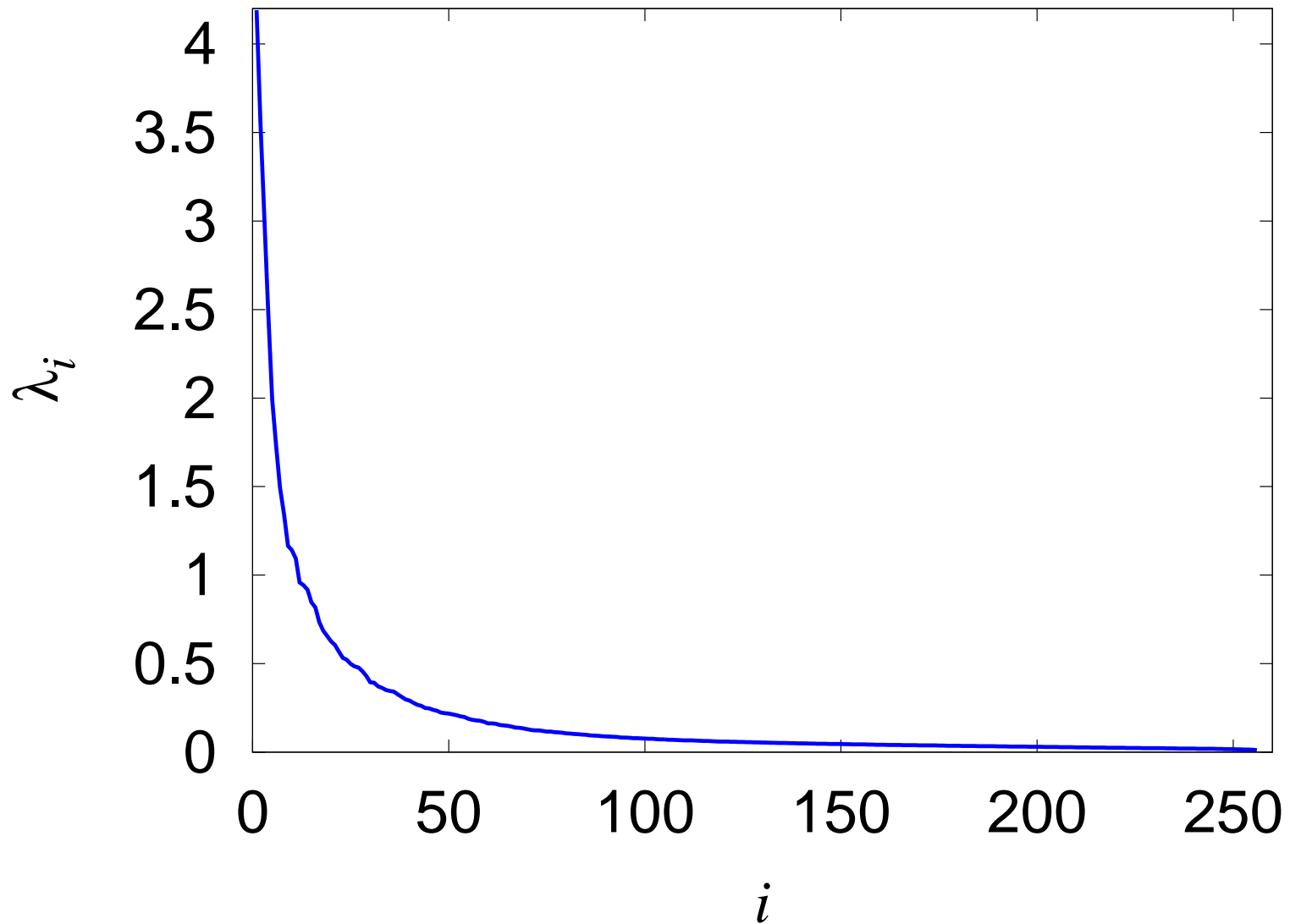
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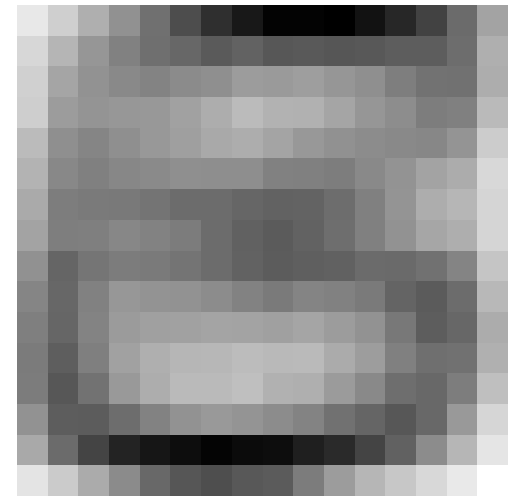
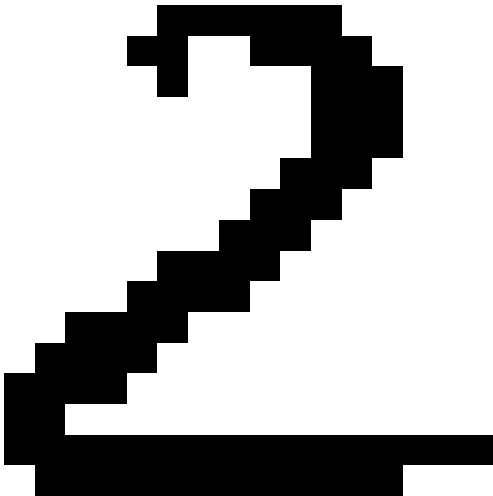
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Eigenvalues for Digits



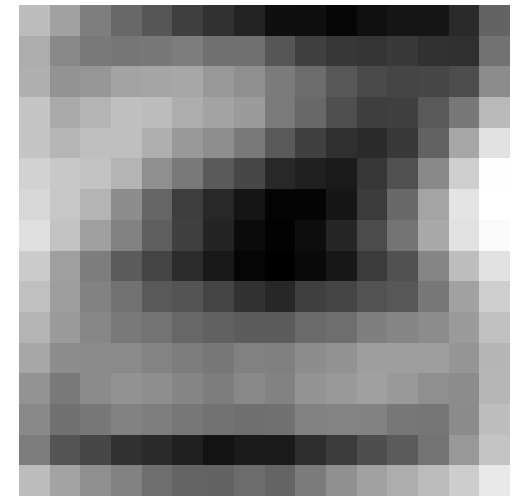
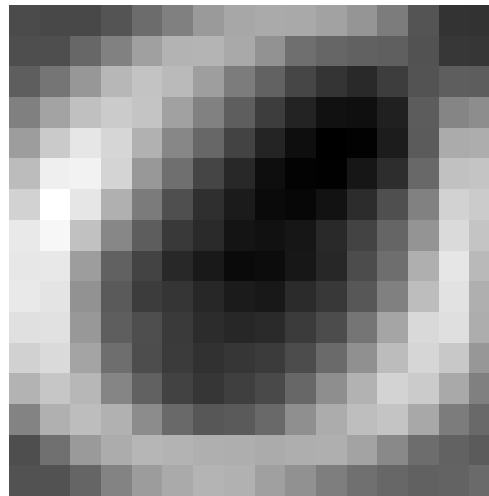
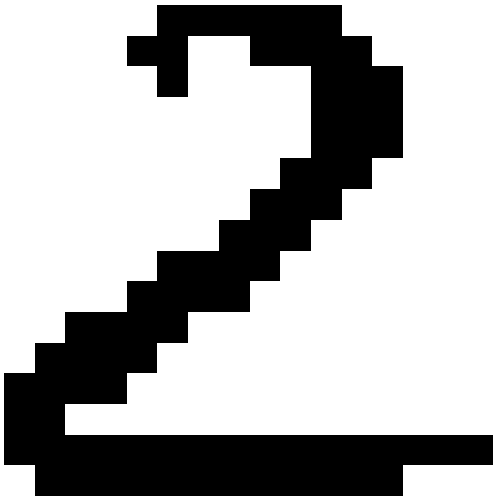
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1.6 -1.1 -1.6 2.1 -0.52 2.8 0.72 0.7 -0.68 -0.41 -1.4 -1.5 -0.54 -0.62 1.3 -1.4 -0.27 0.74 0.77 -1



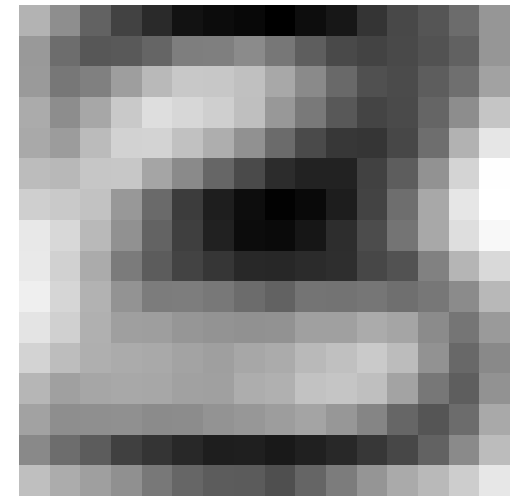
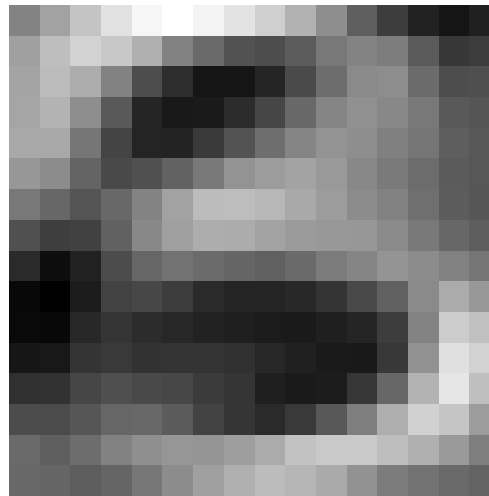
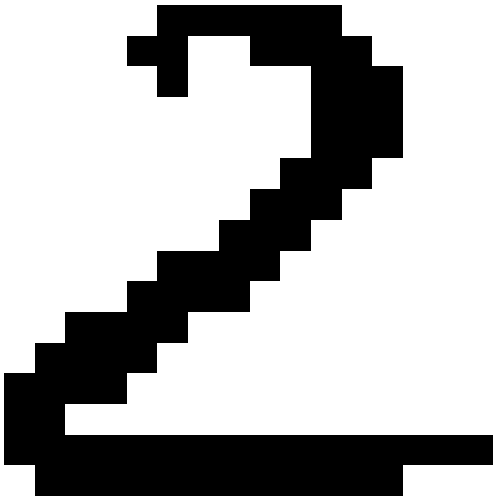
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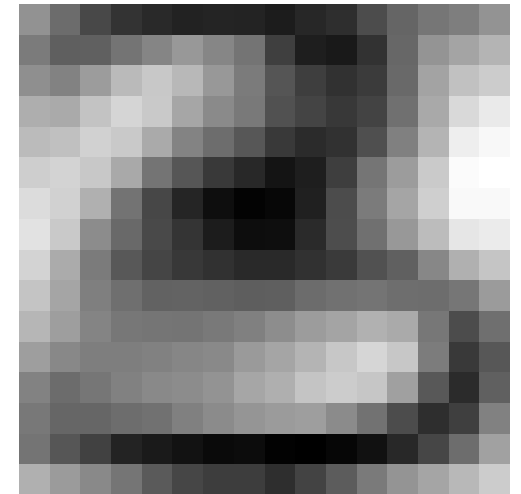
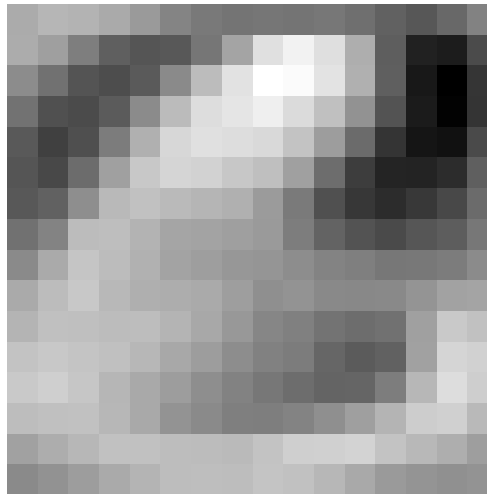
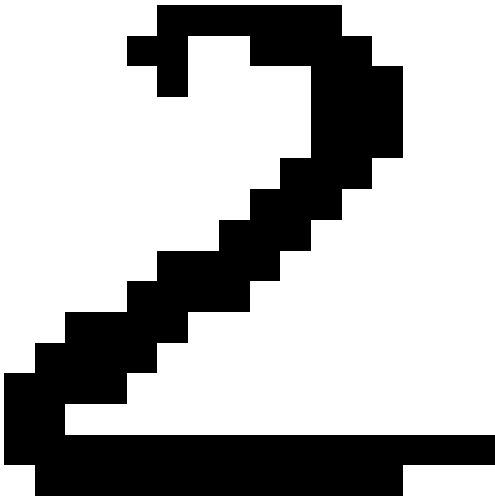
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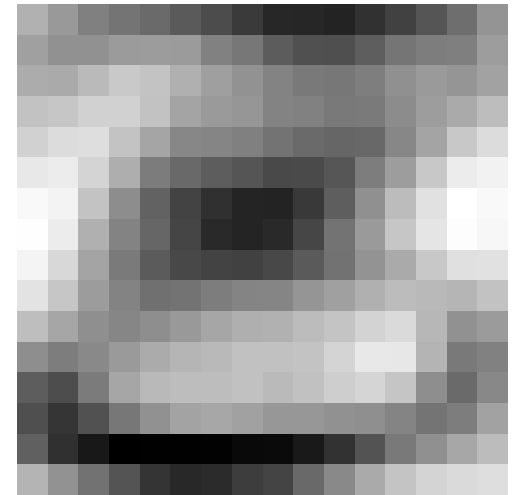
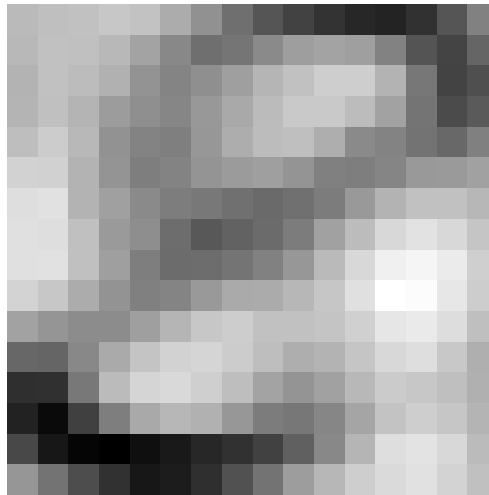
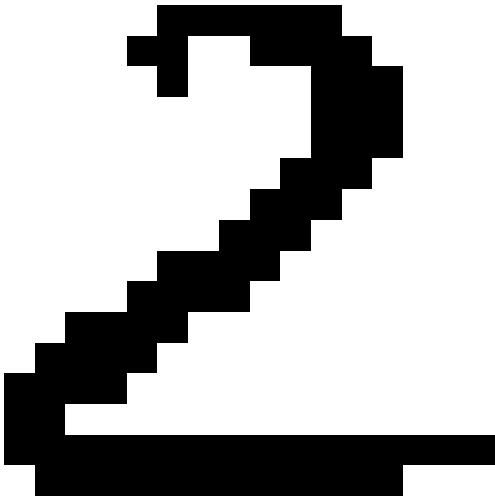
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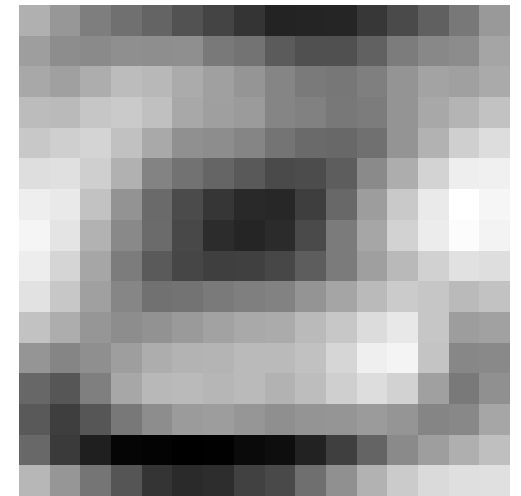
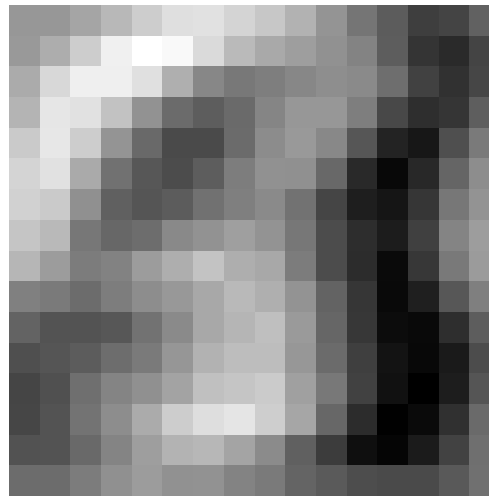
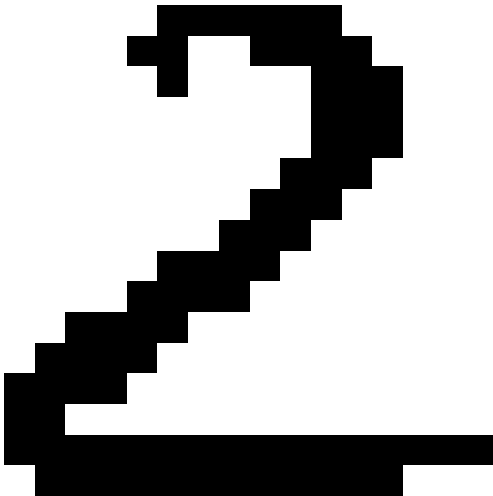
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1.6 -1.1 -1.6 **2.1** -0.52 2.8 0.72 0.7 -0.68 -0.41 -1.4 -1.5 -0.54 -0.62 1.3 -1.4 -0.27 0.74 0.77 -1



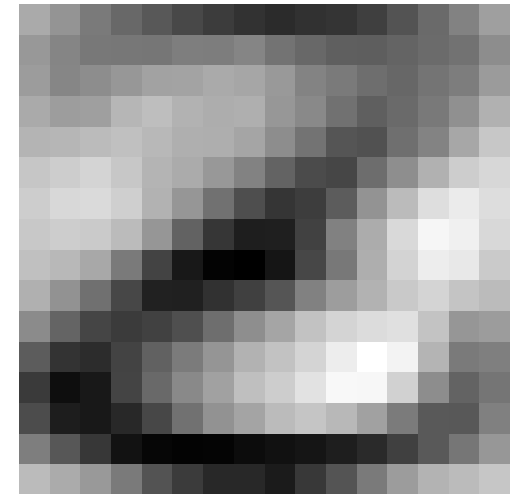
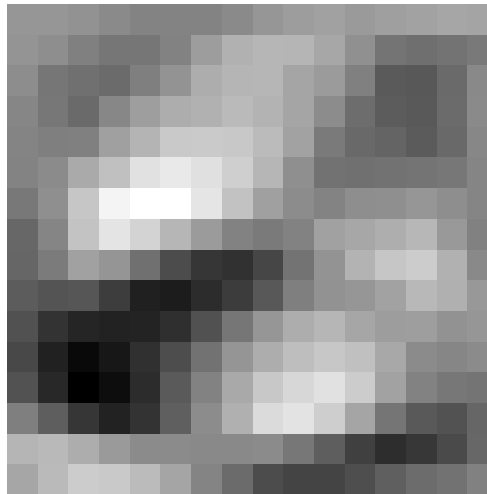
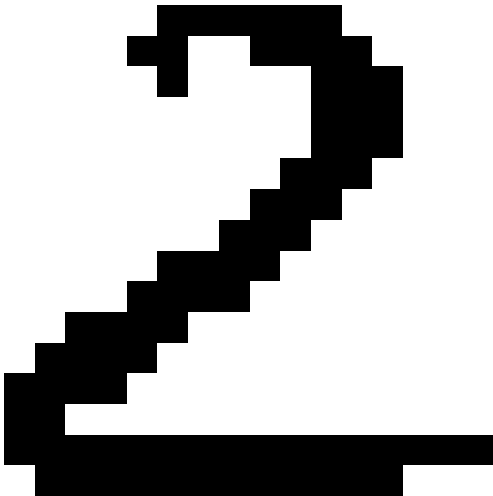
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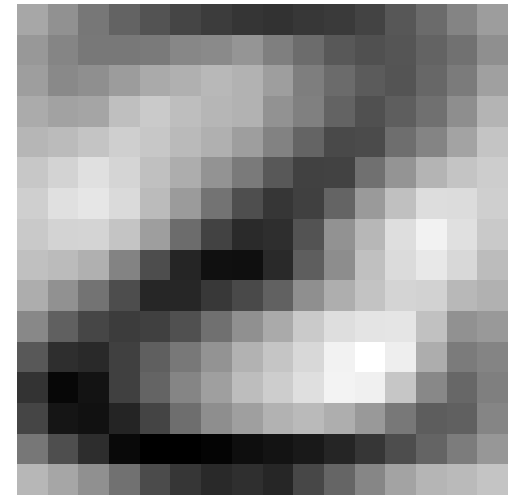
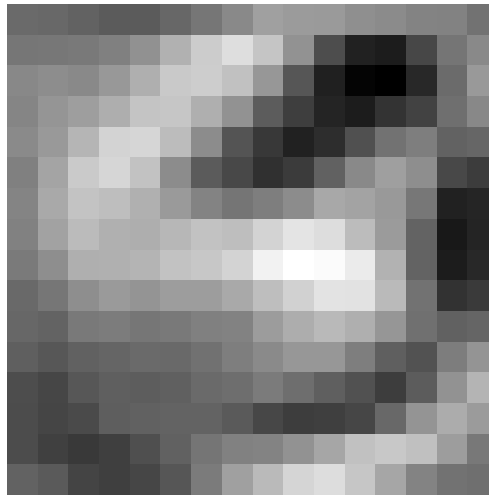
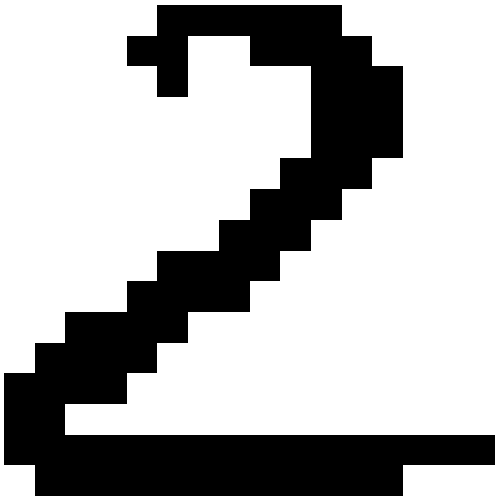
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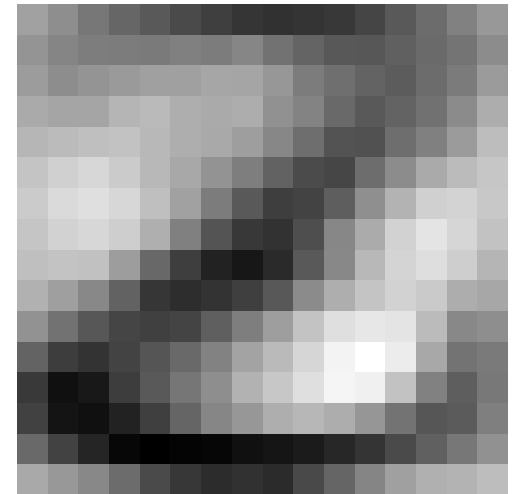
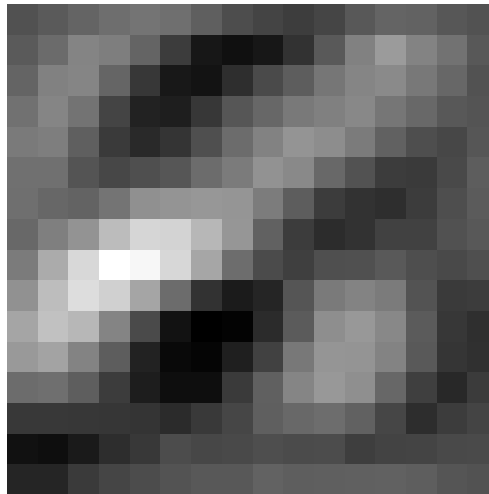
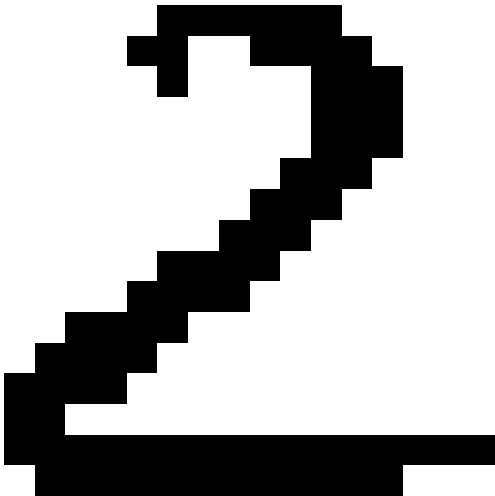
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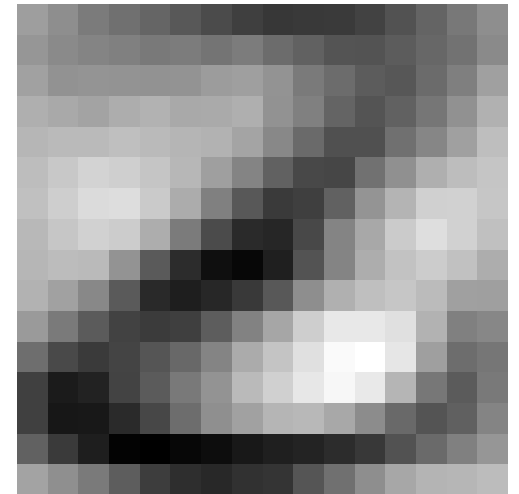
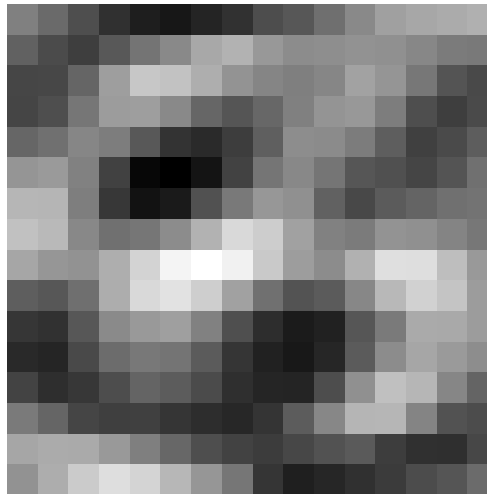
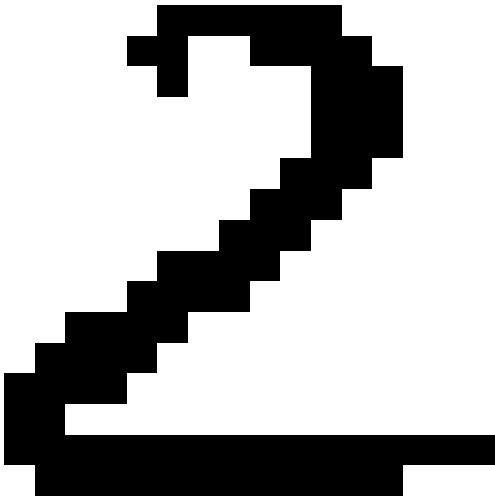
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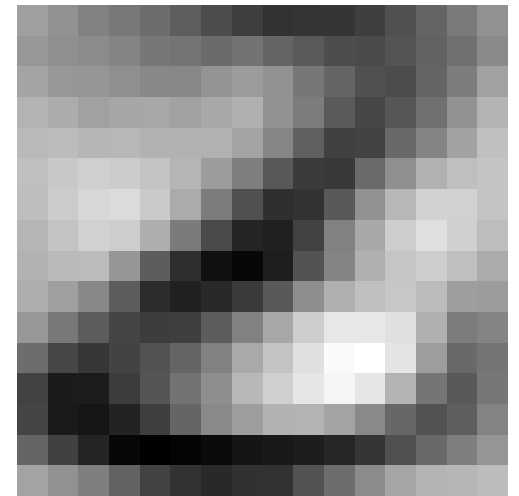
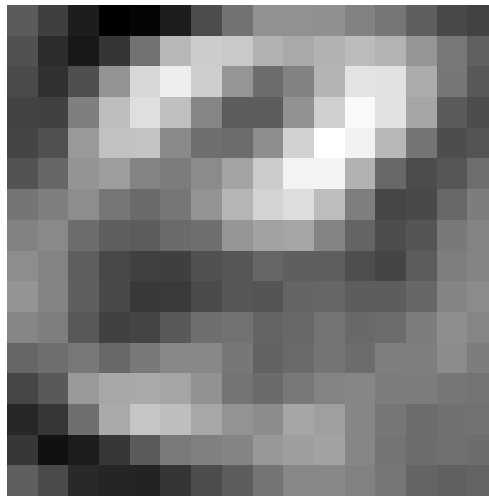
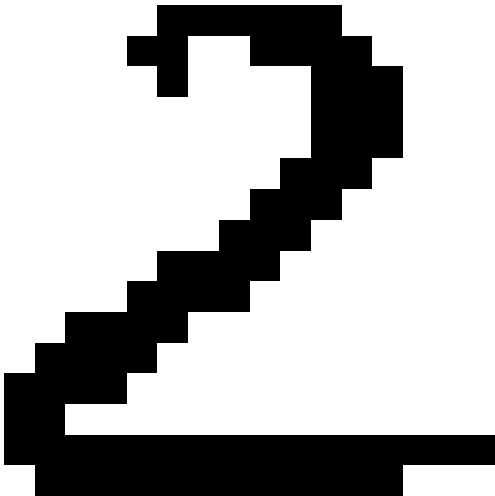
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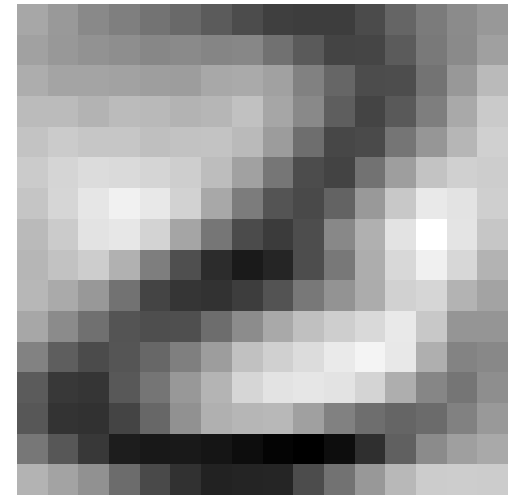
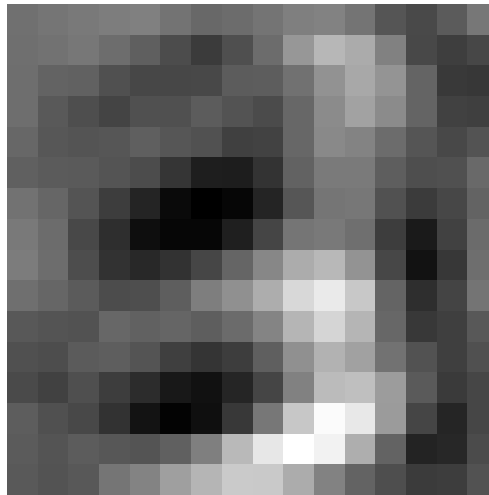
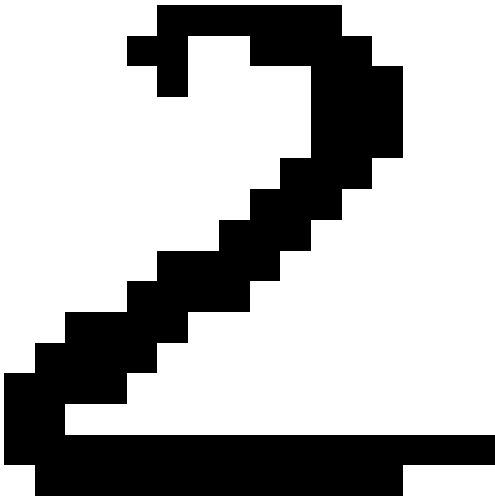
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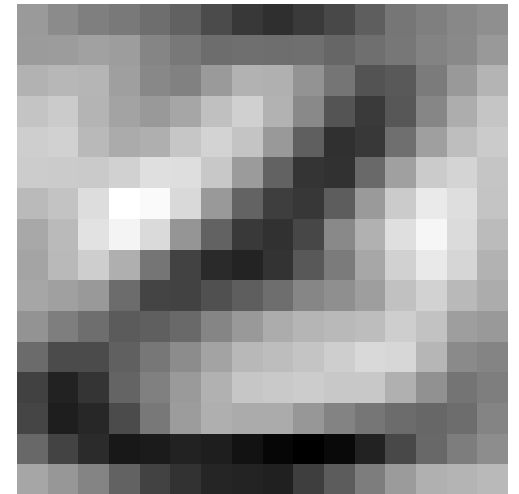
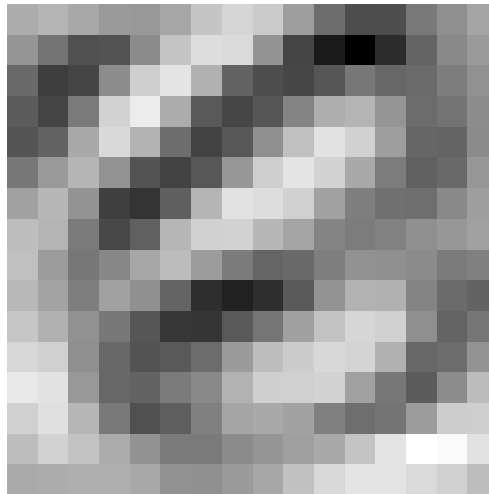
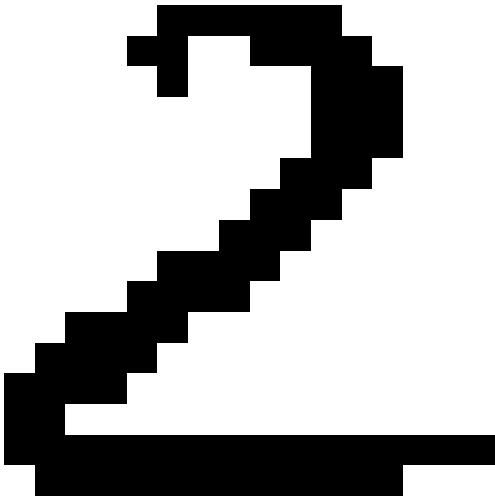
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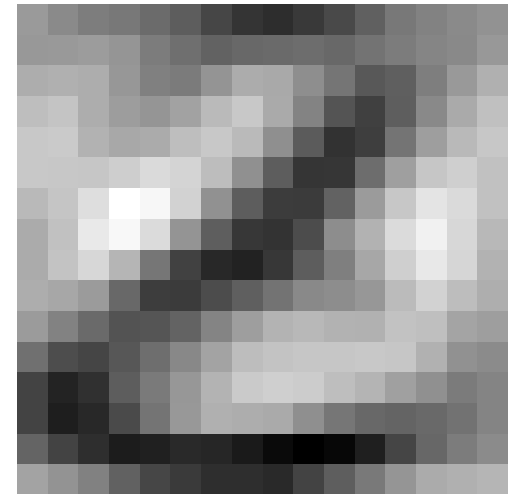
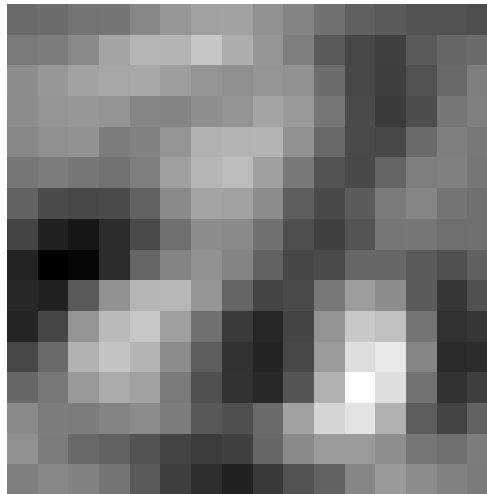
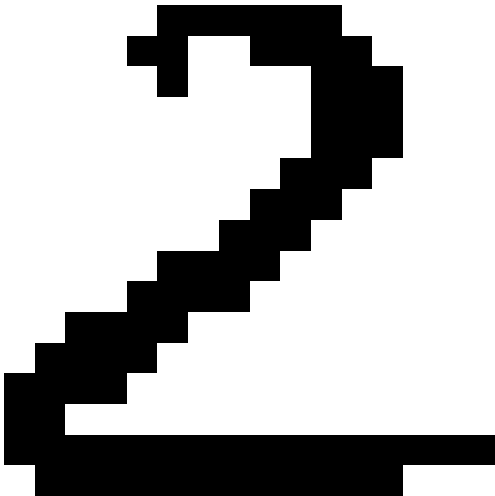
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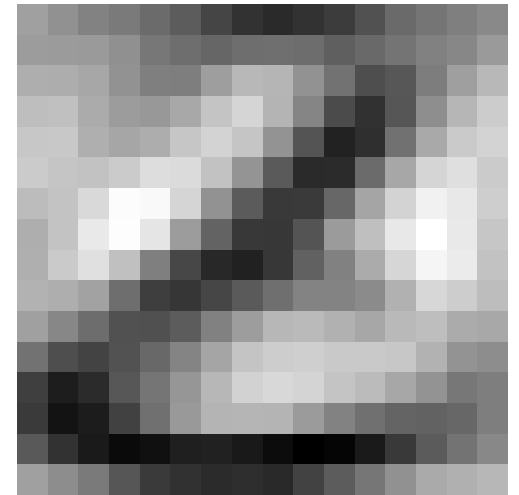
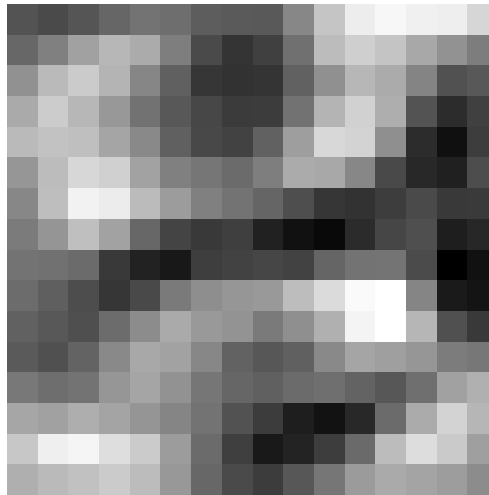
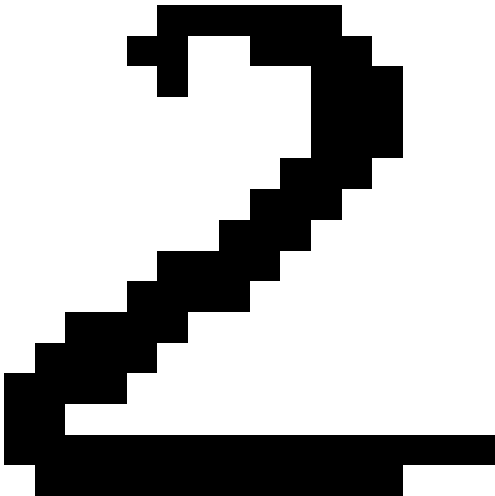
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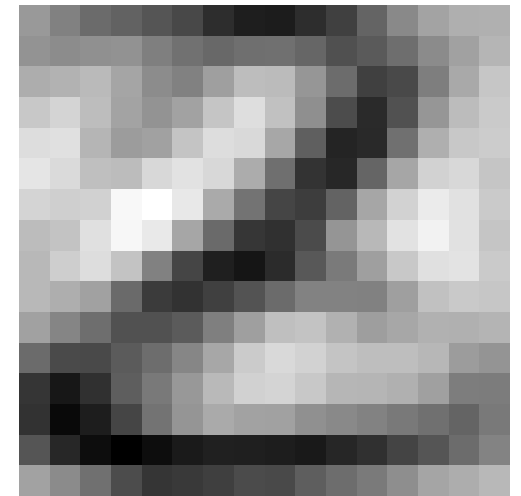
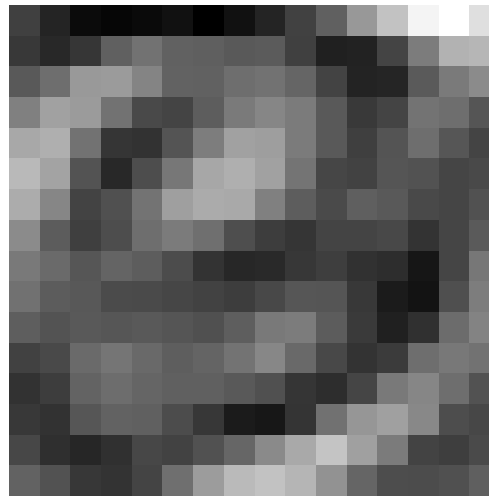
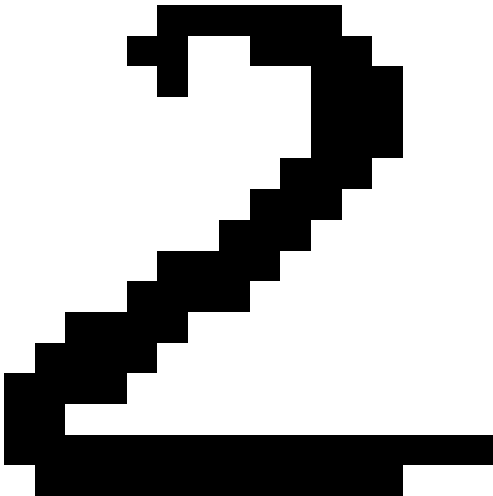
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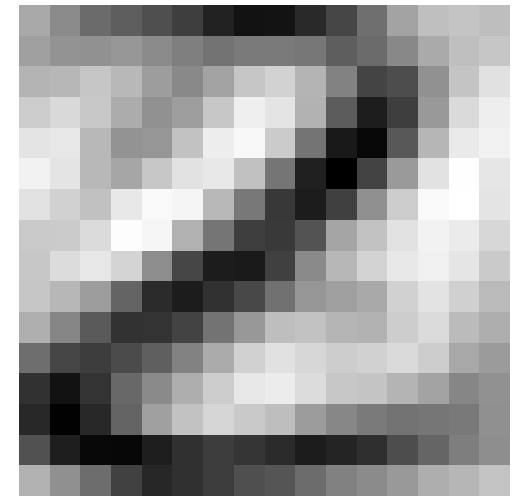
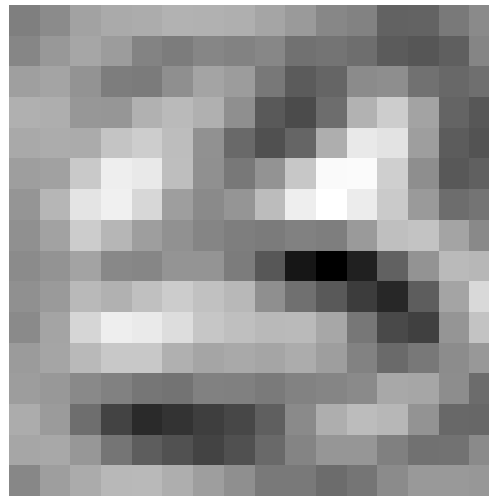
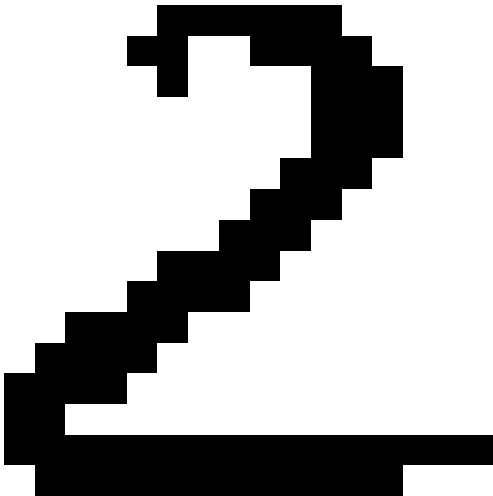
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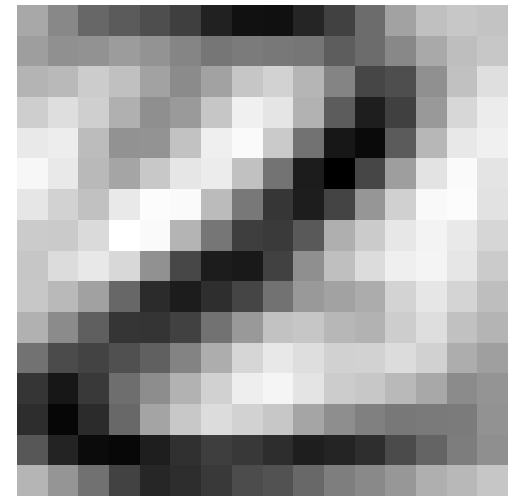
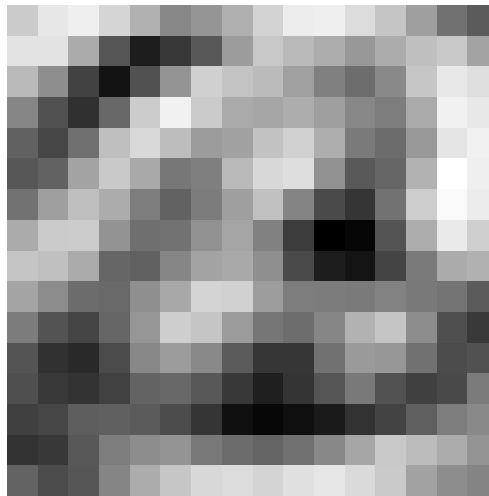
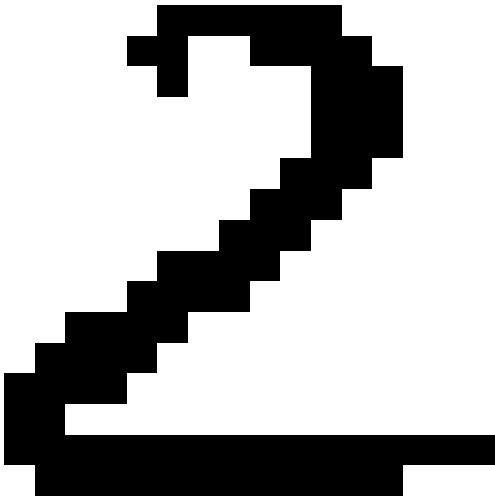
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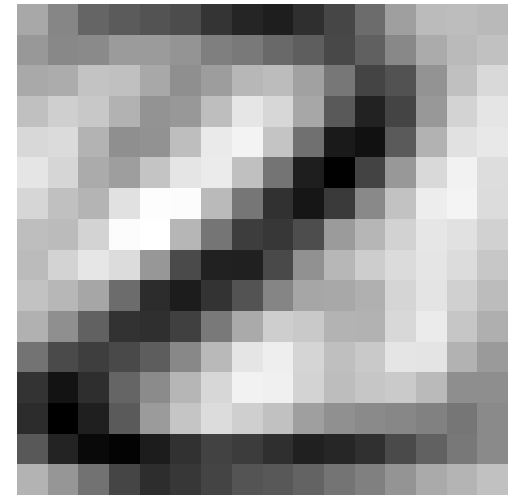
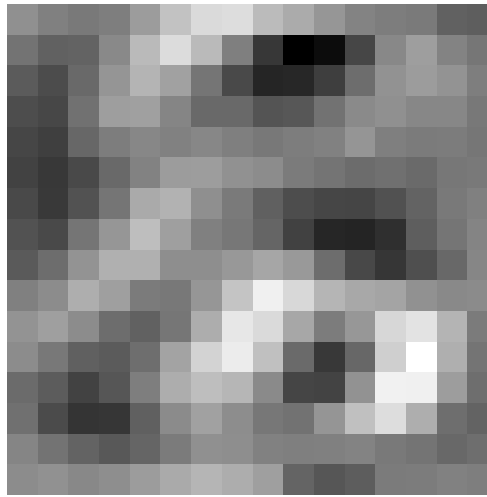
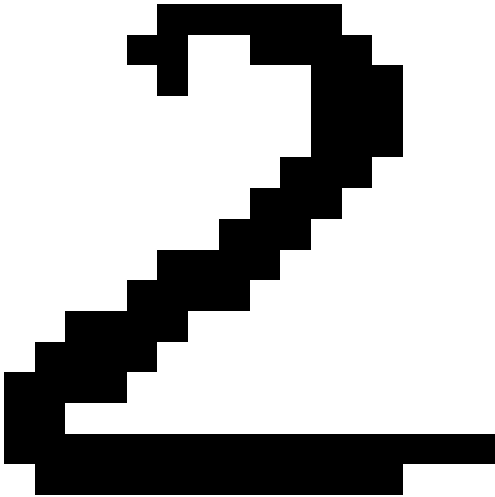
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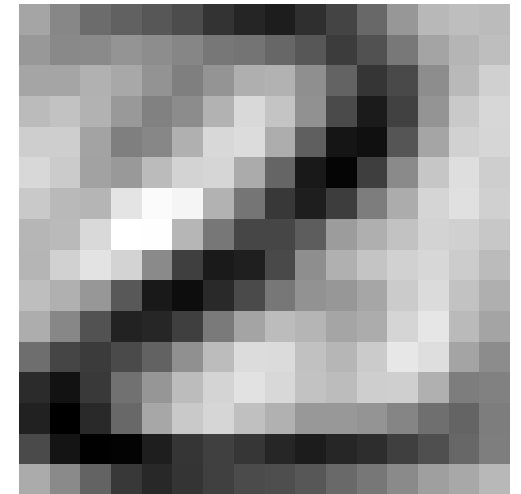
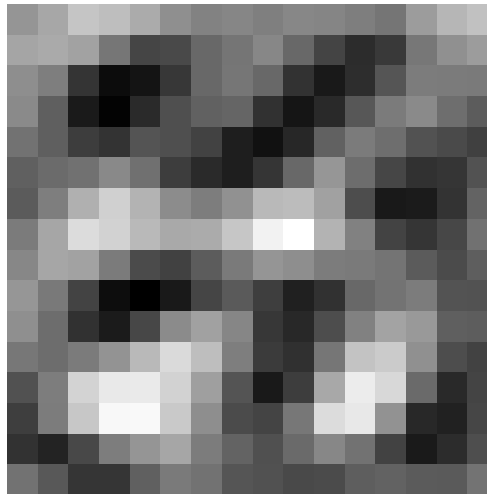
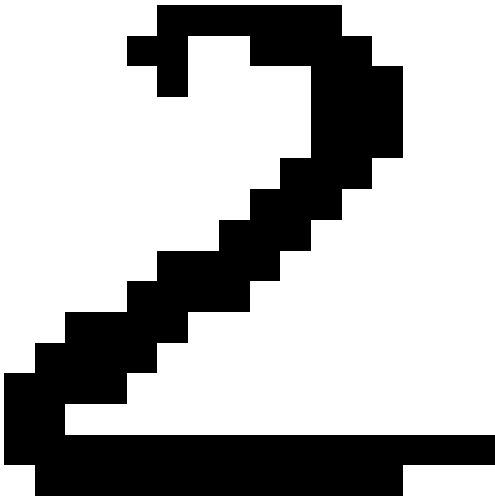
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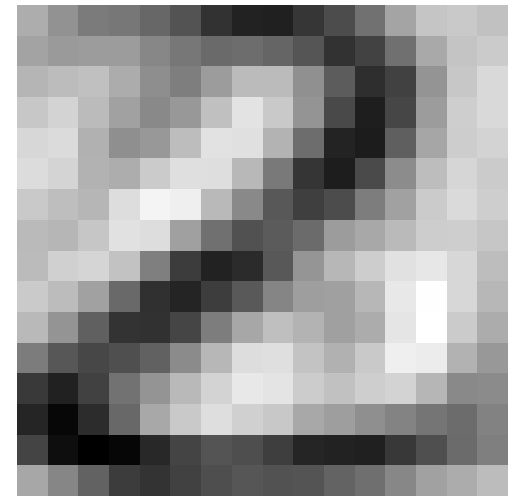
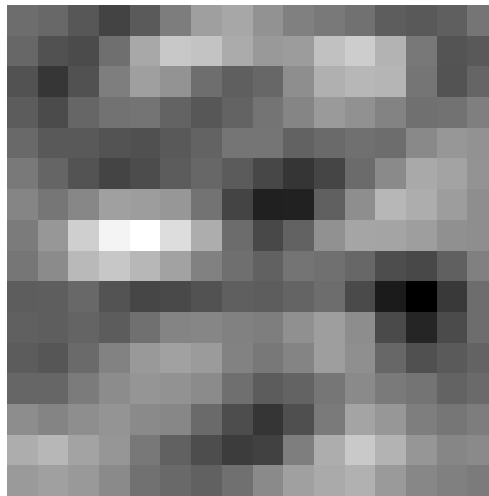
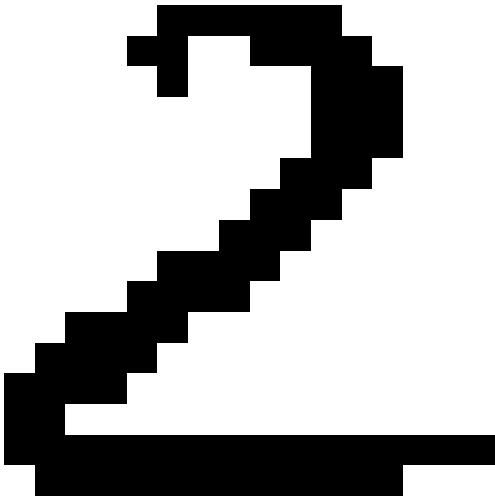
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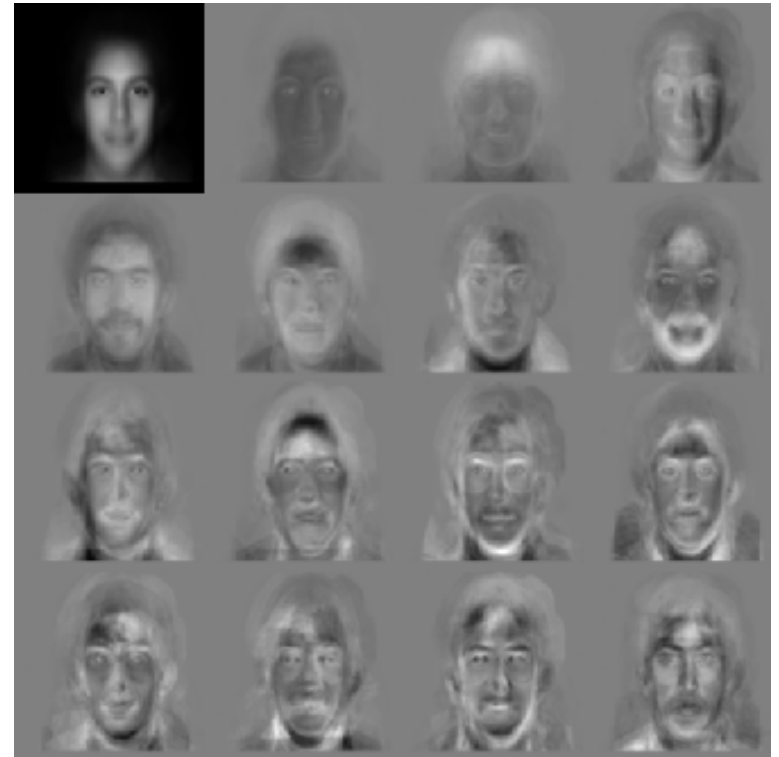
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Outline

1. Covariance Matrices
2. Principal Component Analysis
3. **Duality**



PCA for Images

- An image often contains around $p = 256 \times 256 = 64k$ pixels
- In standard PCA we would create an $p \times p$ matrix with over 4×10^9 elements
- This is intractable
- m images span at most a $m - 1$ dimensional subspace
- Usually this subspace will be much smaller than the space of all images $m \ll p$

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Dual Matrix

- The covariance $\mathbf{C} = \mathbf{X}\mathbf{X}^\top$ is a $p \times p$ matrix
- Consider the $m \times m$ matrix $\mathbf{D} = \mathbf{X}^\top \mathbf{X}$
- Suppose \mathbf{v} is an eigenvector of \mathbf{D}

$$\mathbf{D}\mathbf{v} = \lambda\mathbf{v}$$

$$\mathbf{X}^\top \mathbf{X}\mathbf{v} = \lambda\mathbf{v}$$

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- $\mathbf{u} = \mathbf{X} \mathbf{v}$

Dual Matrix

- The covariance $\mathbf{C} = \mathbf{X}\mathbf{X}^\top$ is a $p \times p$ matrix
- Consider the $m \times m$ matrix $\mathbf{D} = \mathbf{X}^\top \mathbf{X}$
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- Matrices $\mathbf{C} = \mathbf{X}\mathbf{X}^\top$ and $\mathbf{D} = \mathbf{X}^\top\mathbf{X}$ have the same eigenvalues
- Can use the dual $m \times m$ matrix \mathbf{D} to find eigenvalues and eigenvectors of \mathbf{C}
- Note that $\mathbf{D} = \mathbf{X}^\top\mathbf{X}$ has components $D_{kl} \propto (\mathbf{x}_k - \boldsymbol{\mu})^\top(\mathbf{x}_l - \boldsymbol{\mu})$
- Takes $O(p \times m \times m)$ time to construct \mathbf{D}
- We work in a “dual space” which is the space spanned by the examples

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What Does a Subspace Look Like?

- Consider $\mathbf{y}^1 = \begin{pmatrix} 2 \\ 4 \\ 4 \end{pmatrix}$, $\mathbf{y}^2 = \begin{pmatrix} 8 \\ 6 \\ 2 \end{pmatrix}$ with mean $\boldsymbol{\mu} = \begin{pmatrix} 5 \\ 5 \\ 3 \end{pmatrix}$
- Subtracting the mean $\mathbf{x}^i = \mathbf{y}^i - \boldsymbol{\mu}$ we can construct matrix

$$\mathbf{X} = \begin{pmatrix} x_1^1 & x_1^2 \\ x_2^1 & x_2^2 \\ x_3^1 & x_3^2 \end{pmatrix} = \begin{pmatrix} -3 & 3 \\ -1 & 1 \\ 2 & -2 \end{pmatrix}$$

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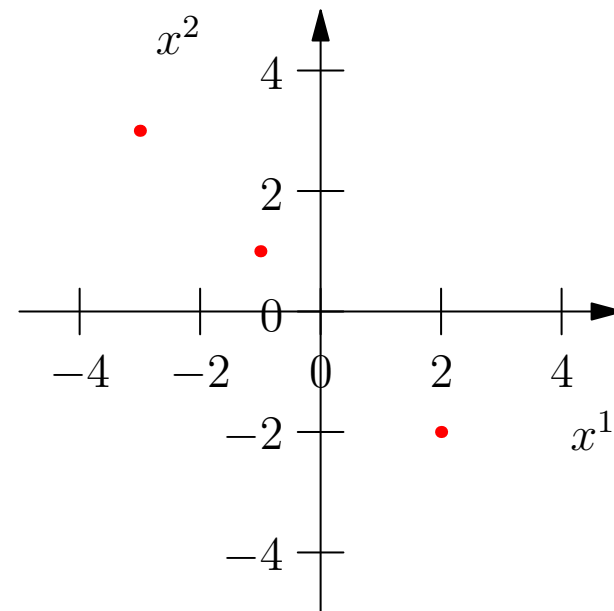
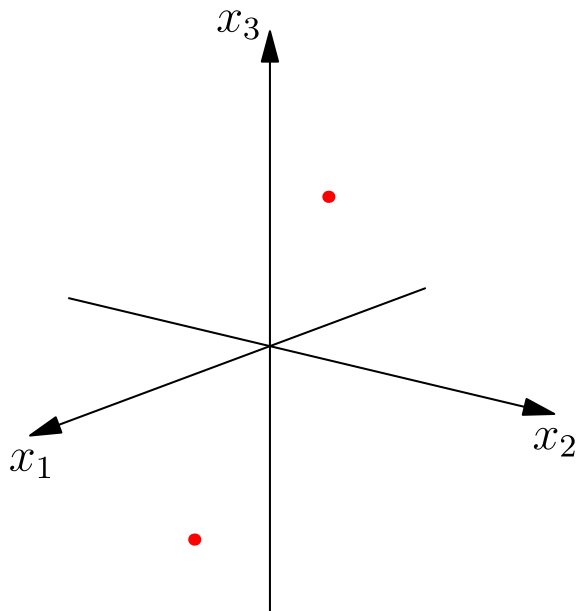
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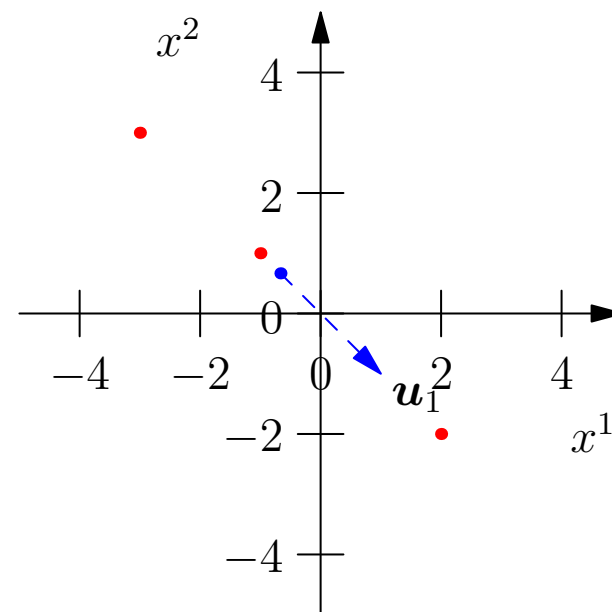
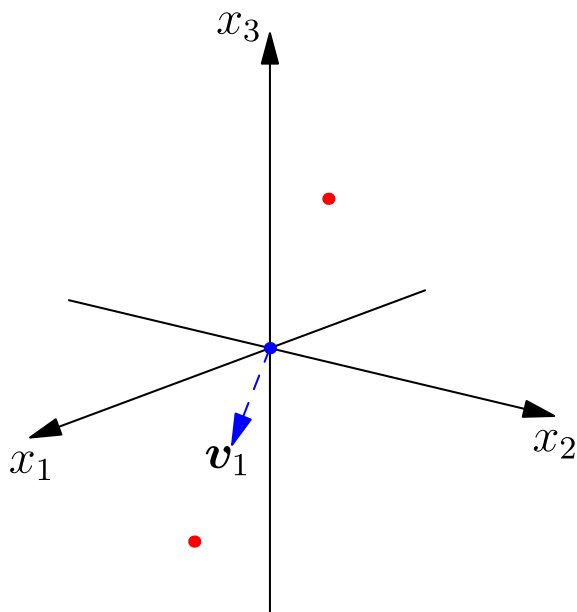
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Summary

- PCA allows us to reduce the dimensionality of the inputs
- We project the inputs into a sub-space where the data varies the most
- We can work in either the original space ($\mathbf{X}\mathbf{X}^T$) or the dual space ($\mathbf{X}^T\mathbf{X}$)
- When we have many more features than examples (i.e. $p \gg m$) then it is more efficient working in the dual space

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- We will see examples of dual spaces again when we look at SVMs