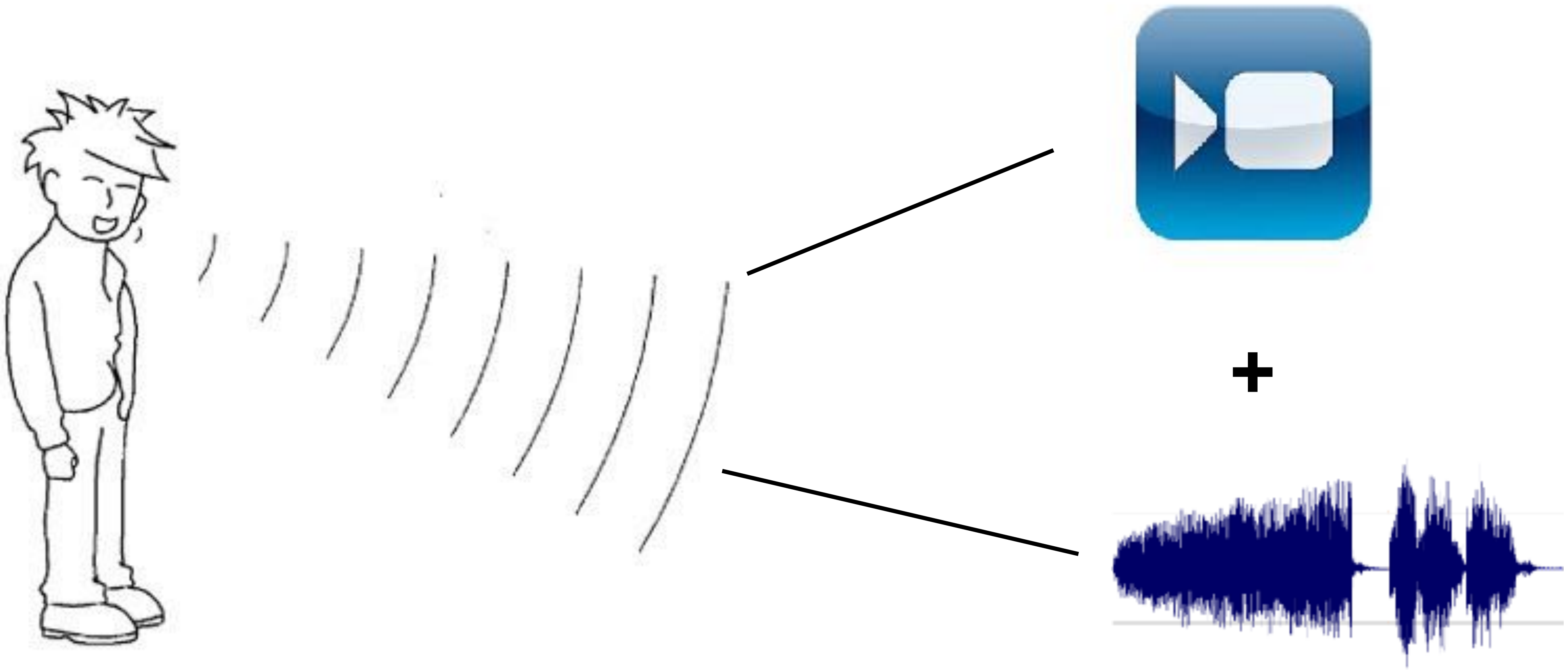
Machine Learning for Data Science (CS4786)
Lecture 6

Canonical Correlation Analysis
+
Kernel PCA

Example I: Speech Recognition



- Audio might have background sounds uncorrelated with video
- Video might have lighting changes uncorrelated with audio
- Redundant information between two views: the speech

Example II: Combining Feature Extractions

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EXAMPLE II: COMBINING FEATURE EXTRACTIONS

- Method A and Method B are both equally good feature extraction techniques
- Concatenating the two features blindly yields large dimensional feature vector with redundancy
- Applying techniques like CCA extracts the key information between the two methods
- Removes extra unwanted information

Canonical Correlation Analysis

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Age

\+ Gender

Candies per week

Favorite Cartoon

Two View Dimensionality Reduction

- Data comes in pairs $(\mathbf{x}_1, \mathbf{x}_1'), \ldots, (\mathbf{x}_n, \mathbf{x}_n')$ where $\mathbf{x}_t$'s are d dimensional and $\mathbf{x}_t'$'s are d' dimensional

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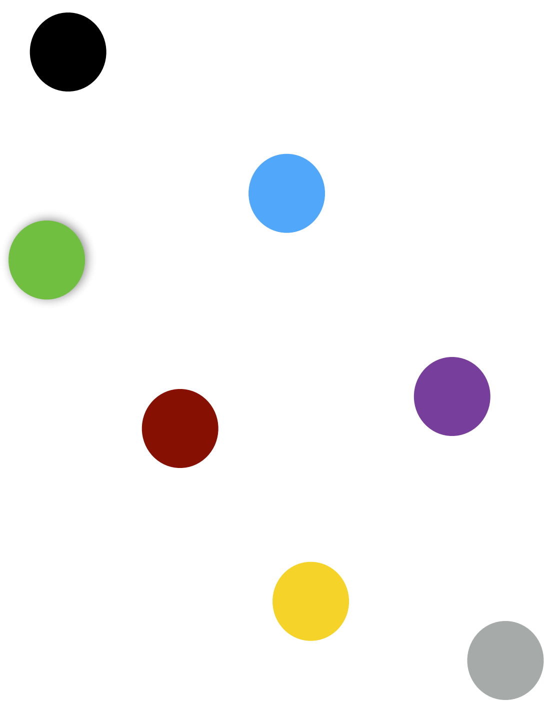
- Goal: Compress say view one into $\mathbf{y}_1, \ldots, \mathbf{y}_n$, that are K dimensional vectors

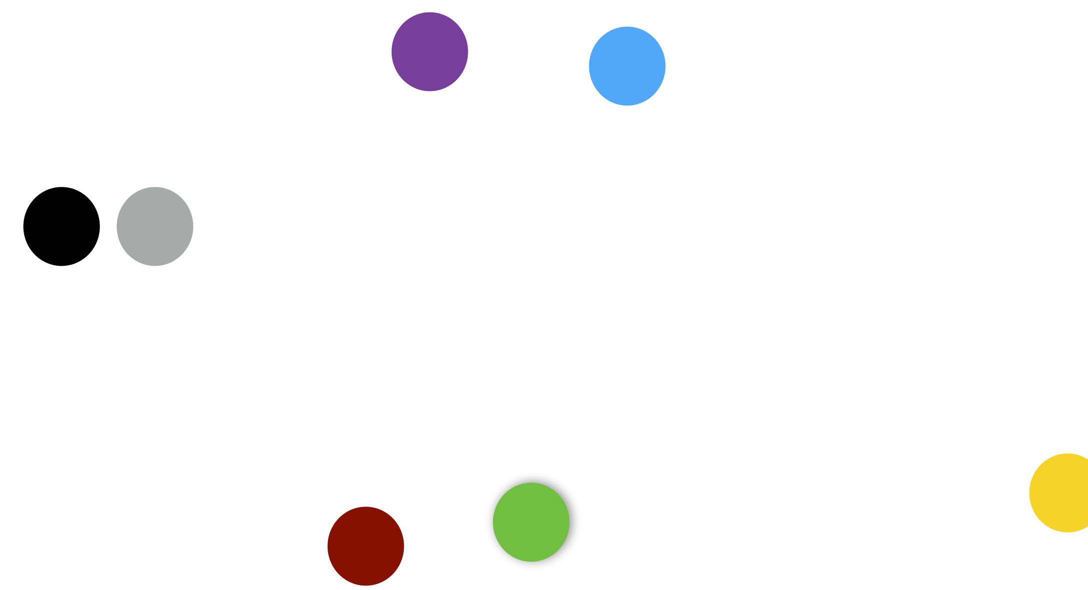
  - Retain information redundant between the two views

  - Eliminate "noise" specific to only one of the views

Which Direction to Pick?



View I



View II

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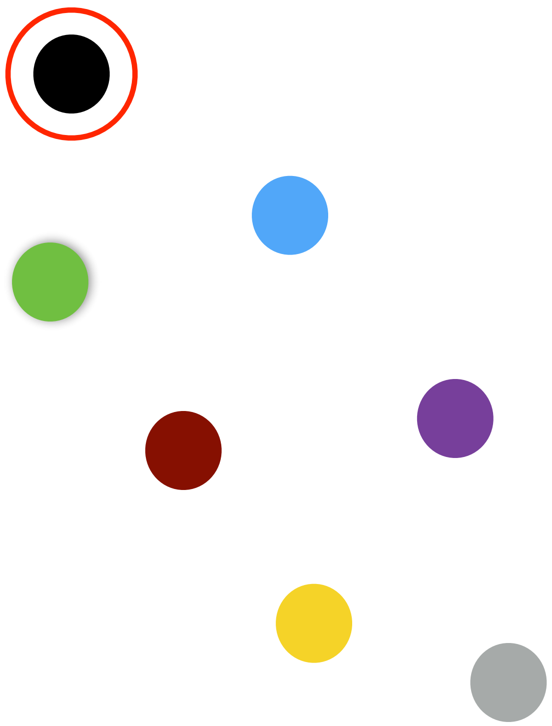

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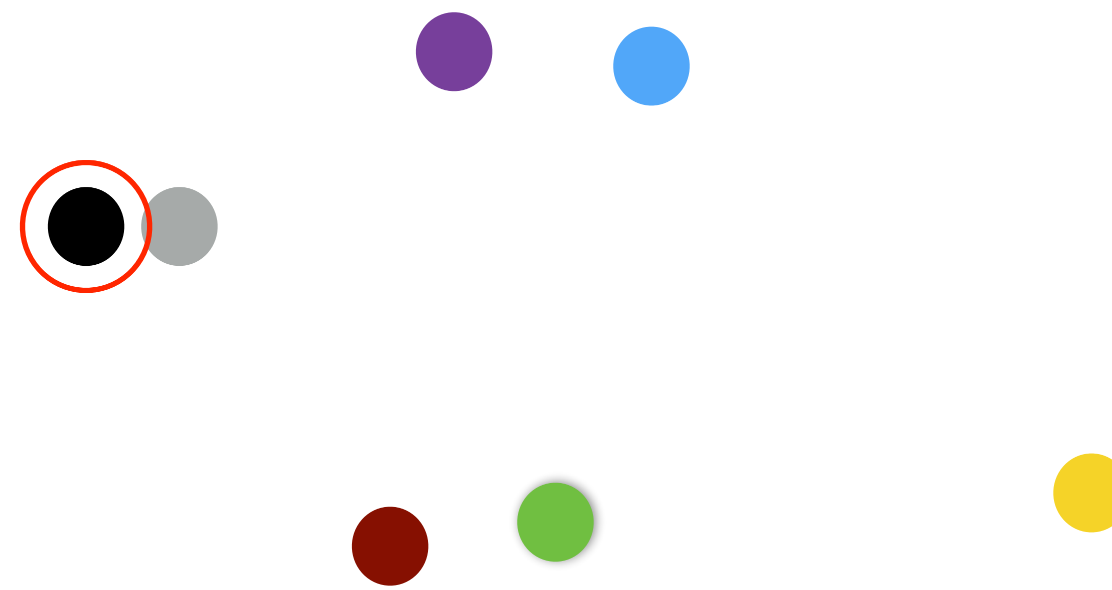

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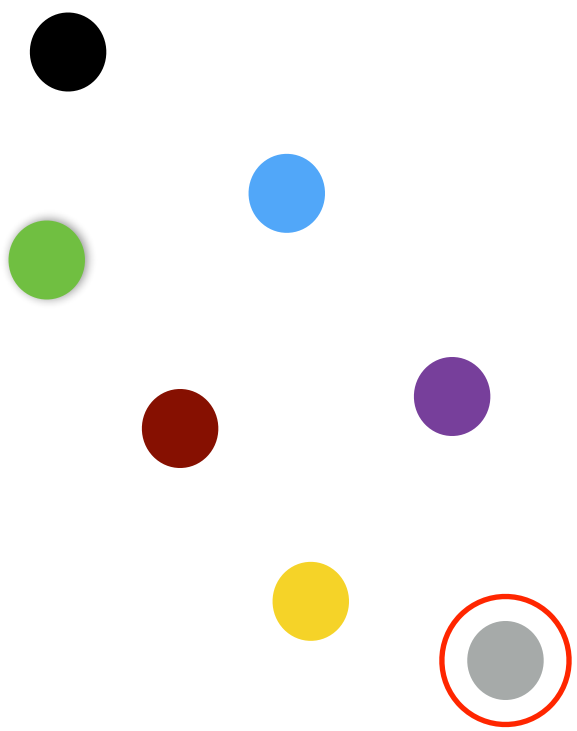

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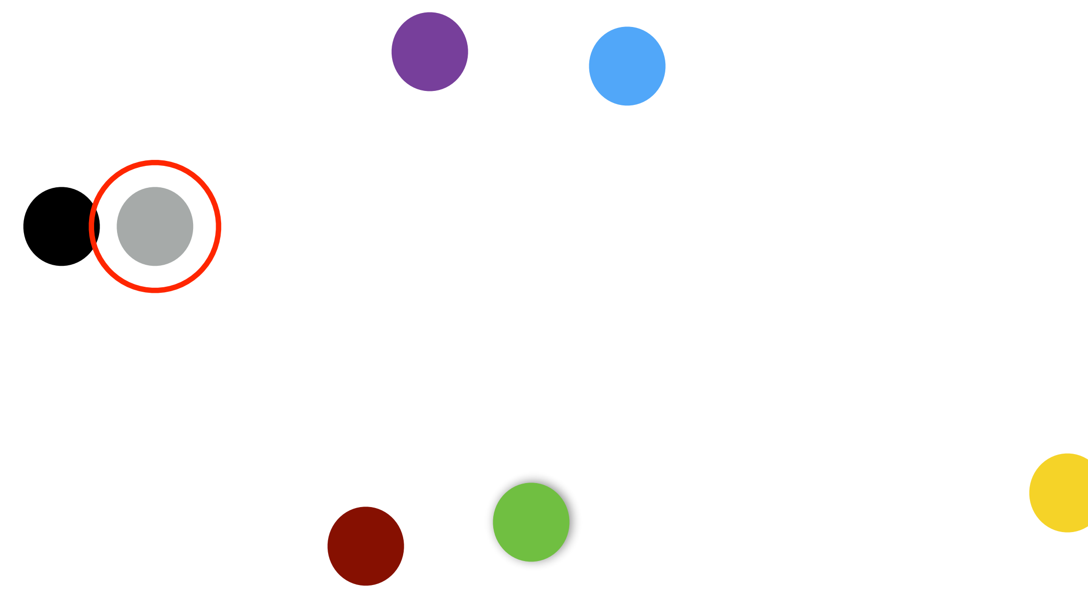

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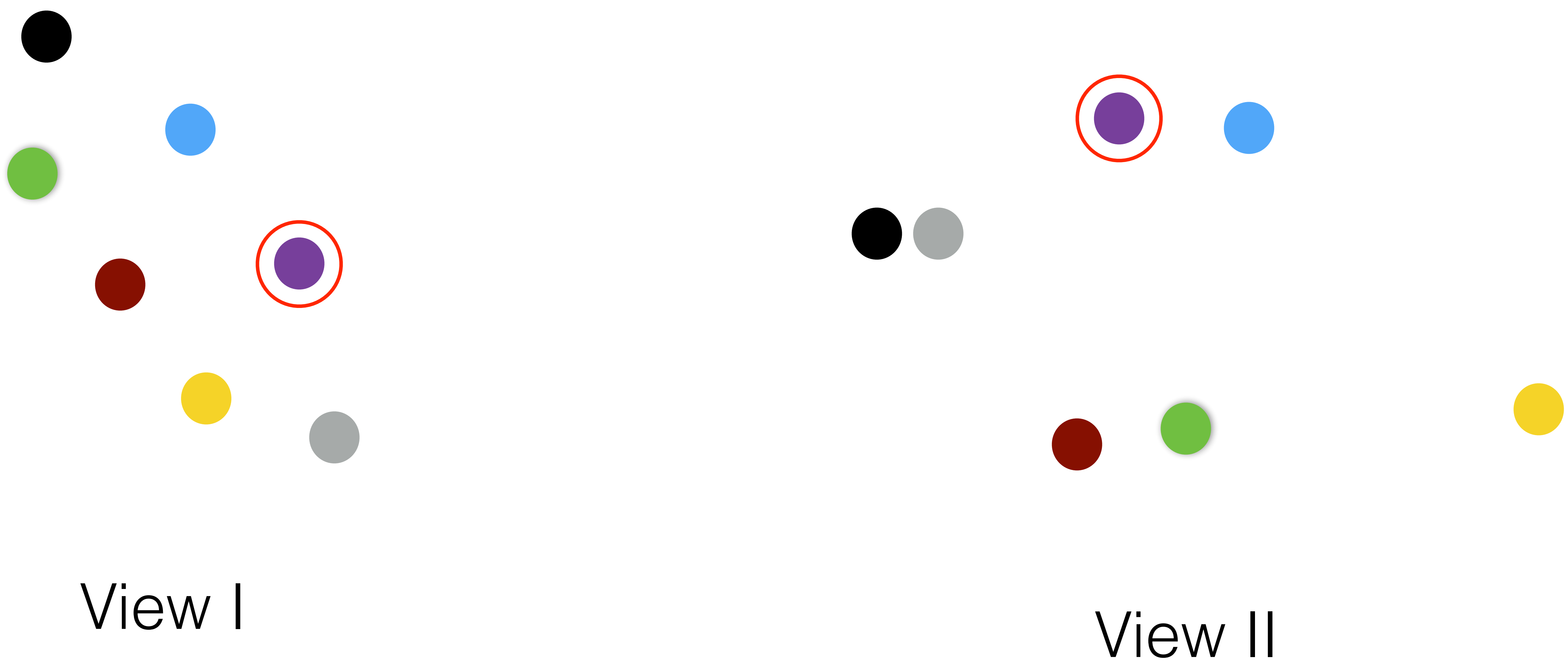

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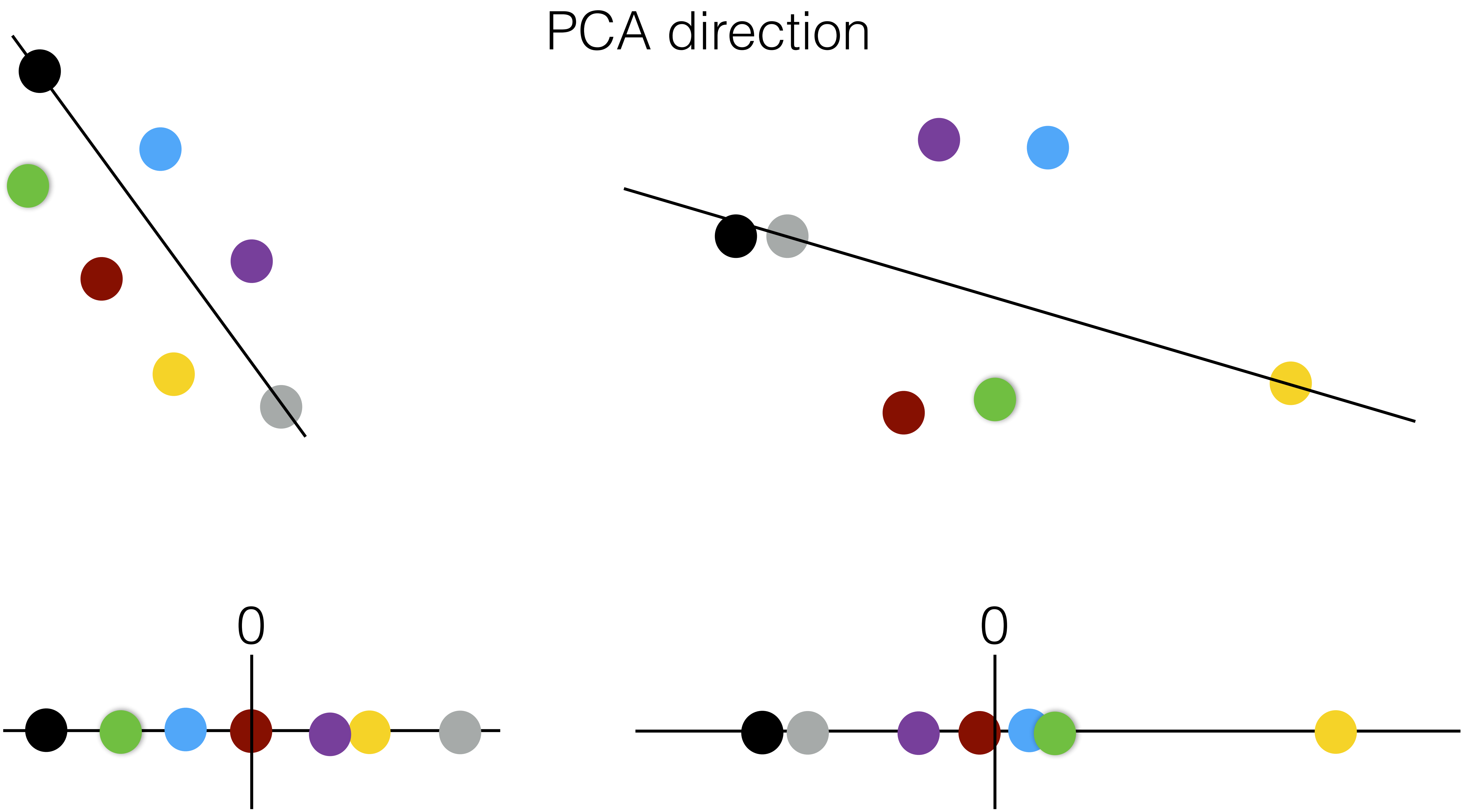

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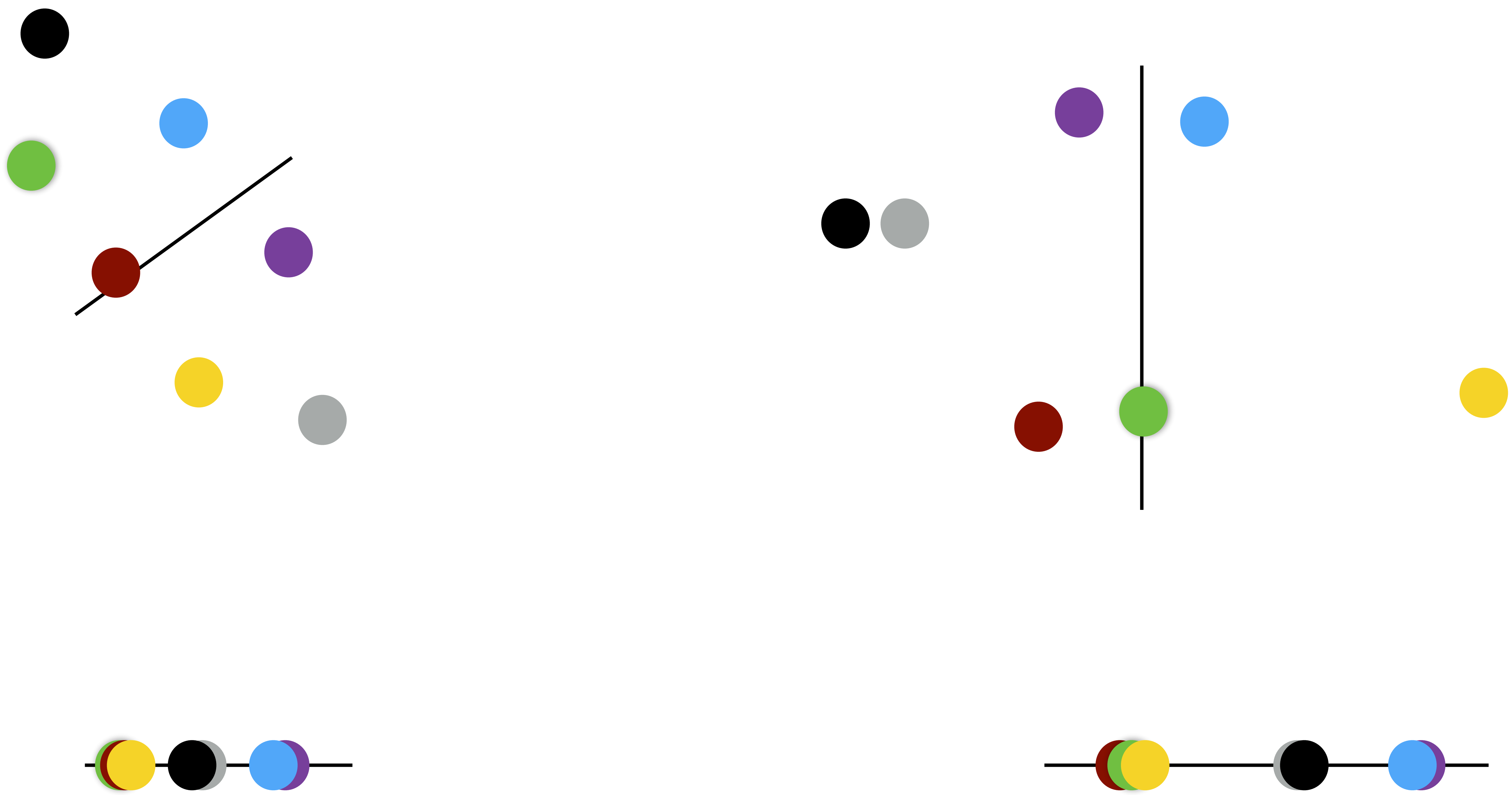

Direction has large covariance

Maximizing Correlation Coefficient

- Say $\mathbf{w}_1$ and $\mathbf{v}_1$ are the directions we choose to project in views 1 and 2 respectively we want these directions to maximize,

$$\frac{\frac{1}{n}\sum_{t=1}^{n}\left(\mathbf{y}_t[1] - \frac{1}{n}\sum_{t=1}^{n}\mathbf{y}_t[1]\right)\cdot\left(\mathbf{y}'_t[1] - \frac{1}{n}\sum_{t=1}^{n}\mathbf{y}'_t[1]\right)}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\mathbf{y}_t[1] - \frac{1}{n}\sum_{t=1}^{n}\mathbf{y}_t[1]\right)^2}\sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\mathbf{y}'_t[1] - \frac{1}{n}\sum_{t=1}^{n}\mathbf{y}'_t[1]\right)}}$$

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where $\mathbf{y}_t[1]=\mathbf{w}_1^\top\mathbf{x}_t$ and $\mathbf{y}'_t[1]=\mathbf{v}_1^\top\mathbf{x}'_t$

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$$\text{s.t. } \frac{1}{n}\sum_{t=1}^{n}\left(\mathbf{y}_t[1] - \frac{1}{n}\sum_{t=1}^{n}\mathbf{y}_t[1]\right)^2 = \frac{1}{n}\sum_{t=1}^{n}\left(\mathbf{y}'_t[1] - \frac{1}{n}\sum_{t=1}^{n}\mathbf{y}'_t[1]\right) = 1$$

where $\mathbf{y}_t[1] = \mathbf{w}_1^\top \mathbf{x}_t$ and $\mathbf{y}'_t[1] = \mathbf{v}_1^\top \mathbf{x}'_t$

Canonical Correlation Analysis

- Hence we want to solve for projection vectors $\mathbf{w}_1$ and $\mathbf{v}_1$ that

$$\text{maximize } \frac{1}{n}\sum_{t=1}^{n} \mathbf{w}_1^\top(\mathbf{x}_t - \mu) \cdot \mathbf{v}_1^\top(\mathbf{x}'_t - \mu')$$

$$\text{subject to } \frac{1}{n}\sum_{t=1}^{n} (\mathbf{w}_1^\top(\mathbf{x}_t - \mu))^2 = \frac{1}{n}\sum_{t=1}^{n} (\mathbf{v}_1^\top(\mathbf{x}'_t - \mu'))^2 = 1$$

where $\mu = \frac{1}{n}\sum_{t=1}^{n} \mathbf{x}_t$ and $\mu' = \frac{1}{n}\sum_{t=1}^{n} \mathbf{x}'_t$

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- Hence we want to solve for projection vectors $\mathbf{w}_1$ and $\mathbf{v}_1$ that

$$\text{maximize } \mathbf{w}_1^\top \Sigma_{1,2} \mathbf{v}_1$$
$$\text{subject to } \mathbf{w}_1^\top \Sigma_{1,1} \mathbf{w}_1 = \mathbf{v}_1^\top \Sigma_{2,2} \mathbf{v}_1 = 1$$

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$$\Sigma = \begin{matrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{matrix} = \mathrm{cov}\left(X \; X' \right)$$

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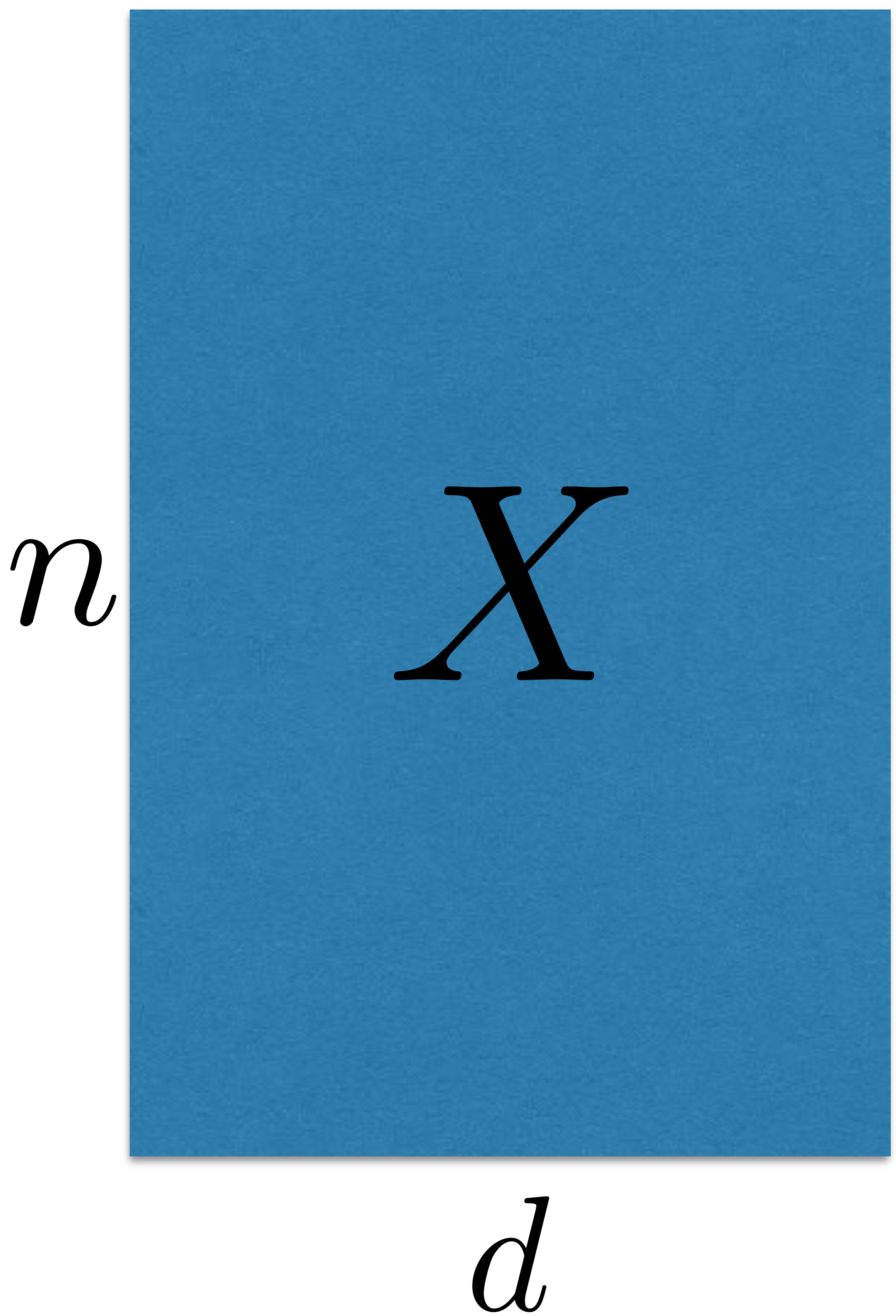
3. $W = \text{eigs}\left(\Sigma_{11}^{-1}\Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}, K \right)$

4. $Y_1 = X_1 - \mu_1 \times W$

CCA Demo

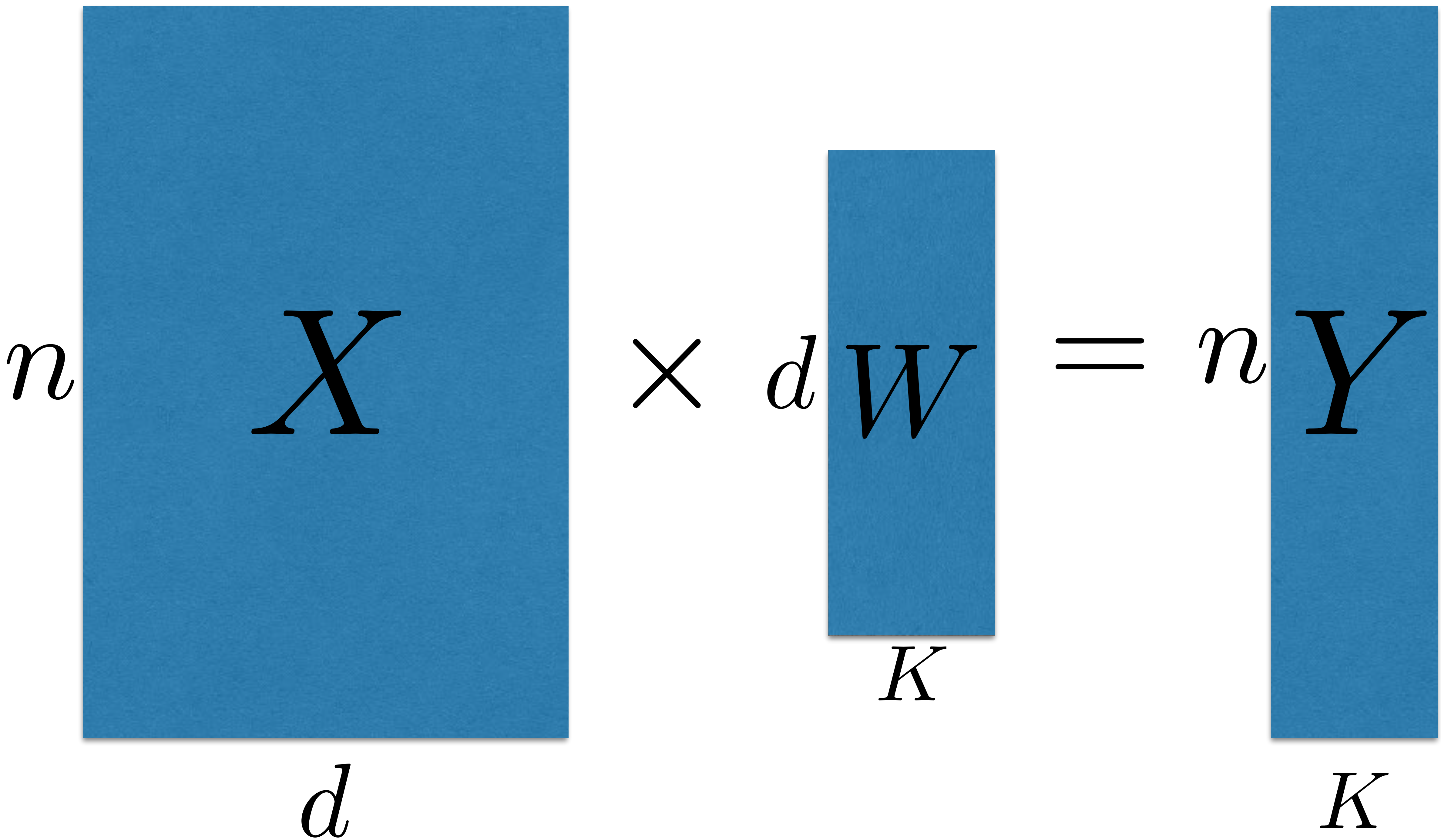
Linear Projections

Linear Projections



LINEAR PROJECTIONS

Linear Projections



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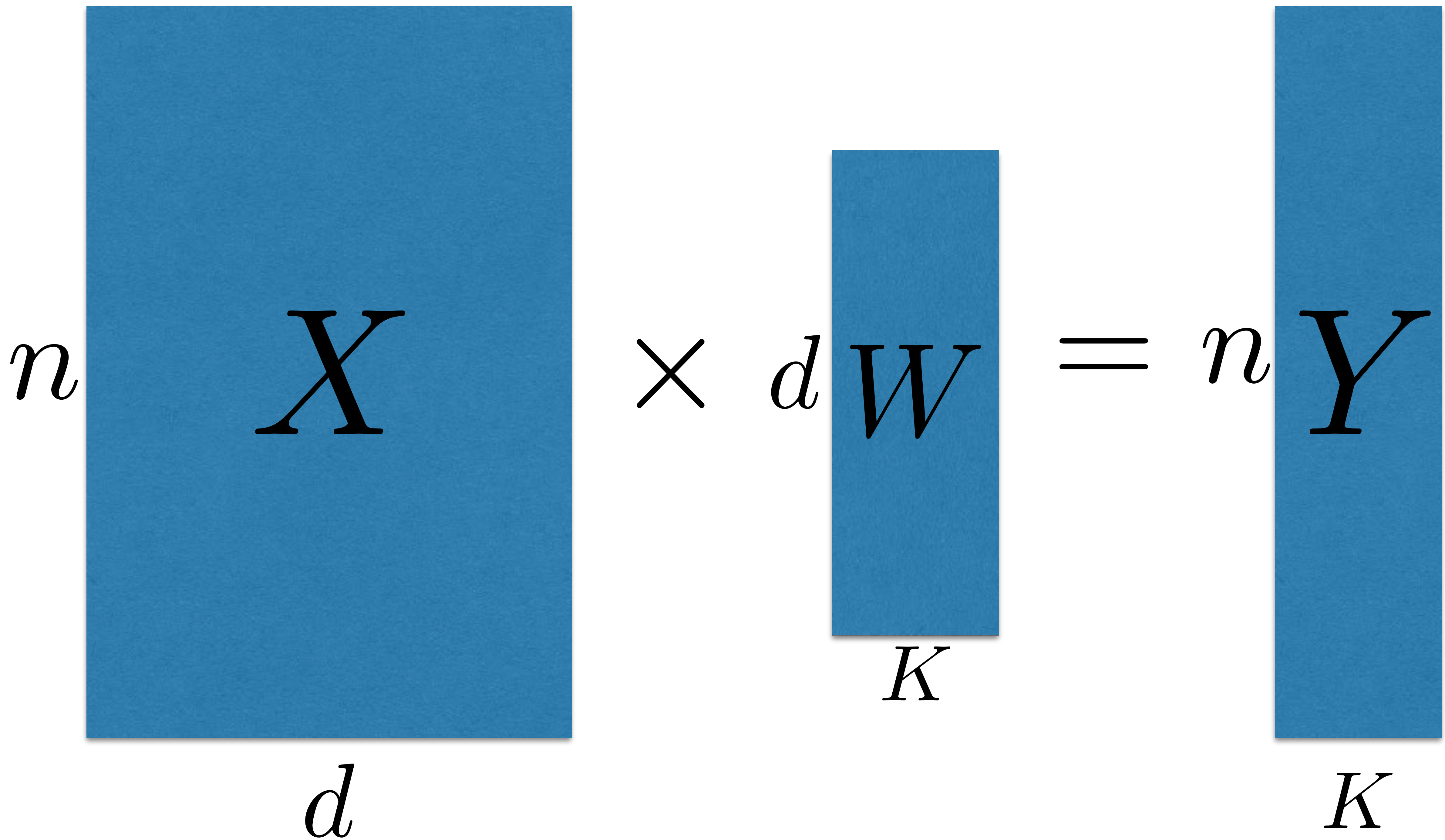
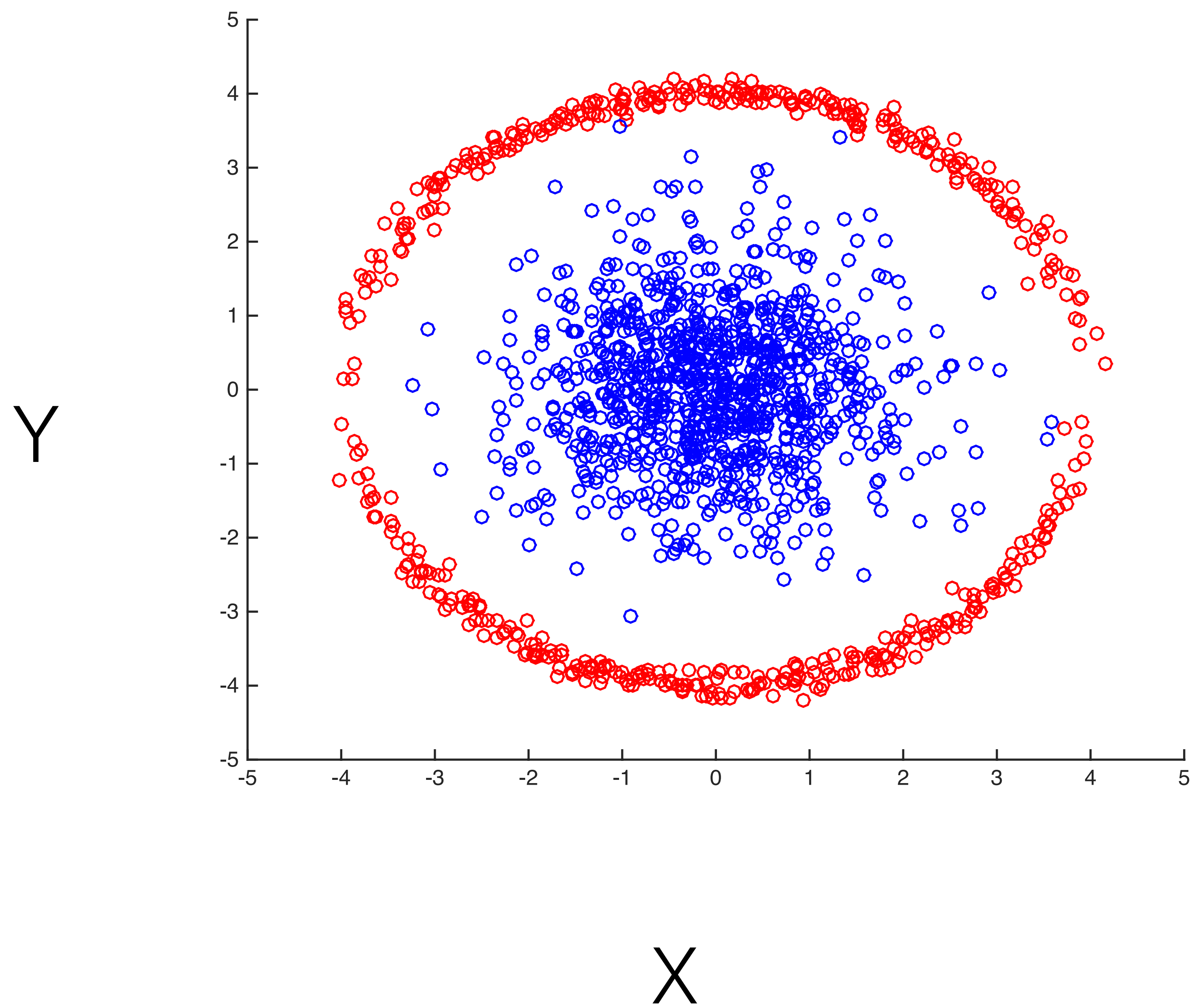


Works when data lies in a low dimensional linear sub-space

EXAMPLE



Linear Projections (Right Co-ordinates)

Demo

Kernel Trick

- Lift to higher dimensions to introduce non-linearity
  - Linear in high dim = non-linear in lower dim
- Project to lower dimension using PCA

A First Cut

- Given $\mathbf{x}_t \in \mathbb{R}^d$, the feature space vector is given by mapping

$$\Phi(\mathbf{x}_t) = (\mathbf{x}_t[1], \ldots, \mathbf{x}_t[d], \mathbf{x}_t[1] \cdot \mathbf{x}_t[1], \mathbf{x}_t[1] \cdot \mathbf{x}_t[2], \ldots, \mathbf{x}_t[d] \cdot \mathbf{x}_t[d], \ldots)^\top$$

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- However dimension blows up as d^K
- Is there a way to do this without enumerating Φ?

Kernel Trick

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  - **If** we can write down an algorithm only in terms of $\Phi(\mathbf{x}_t)^\top \Phi(\mathbf{x}_s)$ for data points $\mathbf{x}_t$ and $\mathbf{x}_s$

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- Kernel function measures similarity between points.

Kernel Trick

$(\mathbf{x}_t^\top \mathbf{y}_t)^p$

Kernel Trick

$$(\mathbf{x}_t^\top \mathbf{y}_t)^p = \sum_{k_1+k_2+\ldots+k_d=p} \binom{c}{k_1, k_2, \ldots, k_d} \prod_{j=1}^{d} (x_t[j] y_t[j])^{k_j}$$

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$$
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\Phi(\mathbf{x})^\top = \left(\ldots, \sqrt{\binom{c}{k_1, k_2, \ldots, k_d}} \prod_{j=1}^{d} x_t[j]^{k_t}, \ldots \right)_{k_1+k_2+\ldots+k_d=p}
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$$\lambda_k W_k = \frac{1}{n}\left(\sum_{t=1}^{n} \mathbf{x}_t \mathbf{x}_t^\top\right) W_k = \frac{1}{n}\sum_{t=1}^{n}\left(\mathbf{x}_t^\top W_k\right)\mathbf{x}_t$$

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$$\begin{aligned}\mathbf{y}_s[k] &= W_k^\top \mathbf{x}_s \\ &= \frac{1}{\lambda_k}\left(\frac{1}{n}\sum_{t=1}^{n} \mathbf{y}_t[k]\mathbf{x}_t\right)^\top \mathbf{x}_s\end{aligned}$$

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Where $\tilde{K}_{s,t} = \mathbf{x}_t^\top \mathbf{x}_s$ is the kernel matrix for centered data

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- Hence, the k'th column on Y matrix is such that

$$\mathbf{y}[k] = \frac{1}{n\lambda_k}\mathbf{y}[k]\tilde{K}$$

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$$= \frac{1}{\lambda_k^2 n^2}\mathbf{y}[k]\tilde{K}\mathbf{y}[k]^\top = \frac{1}{n\lambda_k}\|\mathbf{y}[k]\|^2$$

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$$\mathbf{y}[k] = \frac{1}{n\lambda_k}\mathbf{y}[k]\tilde{K}$$

Also we have, $1 = \|W_k\|^2 = \frac{1}{\lambda_k^2 n^2}\left(\sum_{t=1}^{n}\mathbf{y}_t[k]\mathbf{x}_t\right)^\top\left(\sum_{s=1}^{n}\mathbf{y}_s[k]\mathbf{x}_s\right)$

$$= \frac{1}{\lambda_k^2 n^2}\sum_{t=1}^{n}\sum_{s=1}^{n}\mathbf{y}_s[k]\mathbf{x}_s^\top\mathbf{x}_t\ \mathbf{y}_t[k]$$

$$= \frac{1}{\lambda_k^2 n^2}\mathbf{y}[k]\tilde{K}\mathbf{y}[k]^\top = \frac{1}{n\lambda_k}\|\mathbf{y}[k]\|^2$$

Hence $P_k = \mathbf{y}[k]/\sqrt{n\lambda_k}$ is an eigenvector of $\tilde{K}$ with eigen value $\gamma_k = n\lambda_k$

Rewritting PCA

- We assumed centered data, what if its not,

$$\begin{aligned}
\tilde{K}_{s,t} &= \left(\mathbf{x}_t - \frac{1}{n}\sum_{u=1}^{n}\mathbf{x}_u)\right)^\top \left(\mathbf{x}_s - \frac{1}{n}\sum_{u=1}^{n}\mathbf{x}_u\right) \\
&= \mathbf{x}_t^\top \mathbf{x}_s - \left(\frac{1}{n}\sum_{u=1}^{n}\mathbf{x}_u\right)^\top \mathbf{x}_s - \left(\frac{1}{n}\sum_{u=1}^{n}\mathbf{x}_u\right)^\top \mathbf{x}_t \\
&\quad + \frac{1}{n^2}\left(\sum_{u=1}^{n}\mathbf{x}_u\right)^\top \left(\sum_{v=1}^{n}\mathbf{x}_v\right) \\
&= \mathbf{x}_t^\top \mathbf{x}_s - \frac{1}{n}\sum_{u=1}^{n}\mathbf{x}_u^\top \mathbf{x}_s - \frac{1}{n}\sum_{u=1}^{n}\mathbf{x}_u^\top \mathbf{x}_t + \frac{1}{n^2}\sum_{u=1}^{n}\sum_{v=1}^{n}\mathbf{x}_u^\top \mathbf{x}_v
\end{aligned}$$

Rewriting PCA

- Equivalently, if Kern is the matrix ($\text{Kern}_{t,s} = x_t^\top x_s$),

$$\tilde{K} = \text{Kern} - \frac{(\mathbf{1}_{n\times n} \times \text{Kern})}{n} - \frac{(\text{Kern} \times \mathbf{1}_{n\times n})}{n} + \frac{(\mathbf{1}_{n\times n} \times \text{Kern} \times \mathbf{1}_{n\times n})}{n^2}$$

KERNEL PCA

KERNEL PCA

All we need to be able to compute, to perform PCA are $\mathbf{x}_t^\top \mathbf{x}_s$

Kernel PCA

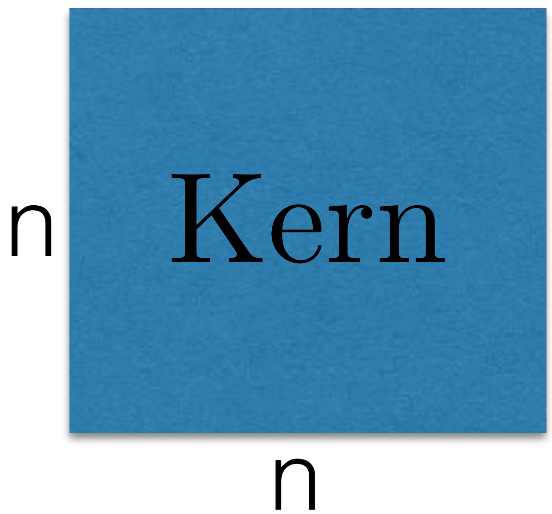
All we need to be able to compute, to perform PCA are $\mathbf{x}_t^\top \mathbf{x}_s$

Replace $\mathbf{x}_t^\top \mathbf{x}_s$ with $\Phi(\mathbf{x}_t)^\top \Phi(\mathbf{x}_s) = k(x_t, x_s)$ to perform PCA in feature space

Kernel PCA

Kernel PCA

1.



$$
= \begin{bmatrix}
k(x_1, x_1) & k(x_1, x_2) & \dots & k(x_1, x_n) \\
k(x_2, x_1) & k(x_2, x_2) & \dots & k(x_2, x_n) \\
. & . & . & . \\
. & . & . & . \\
. & . & . & . \\
k(x_{n-1}, x_1) & k(x_{n-1}, x_2) & \dots & k(x_{n-1}, x_n) \\
k(x_n, x_1) & k(x_n, x_2) & \dots & k(x_n, x_n)
\end{bmatrix}
$$

Kernel PCA

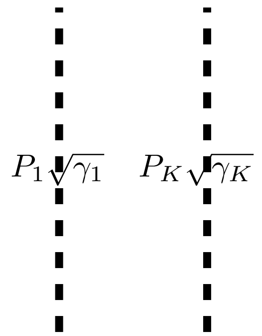
1.

$$\underbrace{\text{Kern}}_{n \times n} = \begin{bmatrix} k(x_1,x_1) & k(x_1,x_2) & \dots & k(x_1,x_n) \\ k(x_2,x_1) & k(x_2,x_2) & \dots & k(x_2,x_n) \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ k(x_{n-1},x_1) & k(x_{n-1},x_2) & \dots & k(x_{n-1},x_n) \\ k(x_n,x_1) & k(x_n,x_2) & \dots & k(x_n,x_n) \end{bmatrix}$$

2.

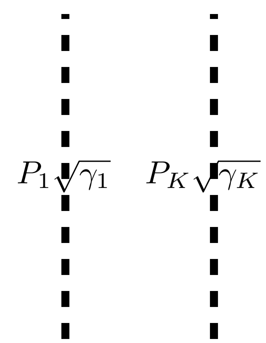
$$\underbrace{\tilde{K}}_{n \times n} = \text{Kern} - \frac{1}{n}\left(\mathbf{1}\ \text{Kern} + \text{Kern}\ \mathbf{1}\right) + \frac{1}{n^2}\mathbf{1}\ \text{Kern}\ \mathbf{1}$$

Kernel PCA



Kernel PCA

3. $\left[{}^{n}\underset{K}{P}, \gamma \right] = \text{eigs}\left(\tilde{K}, K \right)$



3. $\left[P, \gamma \right] = \text{eigs}\left(\tilde{K}, K \right)$

n, K

4. $Y = \left[P_1\sqrt{\gamma_1} \;\cdots\; P_K\sqrt{\gamma_K} \right]$

n, K, K