

## Support vector machines unit:

- ▶ What PCA is (Monday)
- ▶ Applications of PCA (Wednesday, in lab)
- ▶ The math of PCA (**Today**)
- ▶ PCA algorithms (next week Monday)

## Today:

- ▶ Follow-up from yesterday's lab
- ▶ Maximum-variance view
  - ▶ Finding the first (or zeroth) principal component
  - ▶ Finding more principal components
- ▶ Minimum-information-loss view

The most important source for all of this was Deisenroth et al, *Mathematics for Machine Learning*, 2020, 286–293.

(Available on Canvas)

## Coming up:

### **Due Fri, Mar 28:**

*Textbook reading from Chapter 10 (see Canvas)*

### **Due Mon, Mar 31:**

*Take PCA quiz*

### **Due Fri, Apr 4:**

*Implement PCA*

### **Sometime between Mar 31 and Apr 17:**

*Make an office-hours appointment for project check-in  
(Originally the deadline was Apr 11)*

*(There will be an ethics reading thrown in here sometime)*

Let  $\mathbf{W} = \begin{pmatrix} \mathbf{v}_0 \\ \vdots \\ \mathbf{v}_{M-1} \end{pmatrix} \in \mathbb{R}^{M \times D}$  be a set of orthonormal basis vectors.

Let  $\mathbf{z}_n = \mathbf{W}\mathbf{x}_n$  be the projection of  $\mathbf{x}_n$  in the vector space defined by these basis vectors.

Let  $\mathbf{U} = \mathbf{W}^T$ . We can project  $\mathbf{z}_n$  back into the original space with  $\tilde{\mathbf{x}}_n = \mathbf{U}\mathbf{z}_n$ .

Let  $\mathbf{v}_0 \in \mathbb{R}^D$  be the zeroth (“first”) principal component (which we want to find).

Let  $z_{0,n} = \mathbf{v}_0^T \mathbf{x}_n$  be the zeroth coordinate in the projection of  $\mathbf{x}_n$ .

Let  $z_0$  be a random variable modeling the value of the zeroth coordinate. Assume data is centered, that is,  $\mathbb{E}[z_0] = 0$ . Then

$$\begin{aligned}\text{Var}[z_0] &= \frac{1}{N} \sum_{n=0}^{N-1} (z_{0,n} - 0)^2 \\ &= \frac{1}{N} \sum_{n=0}^{N-1} (\mathbf{v}_0^T \mathbf{x}_n)^2 \\ &= \frac{1}{N} \sum_{n=0}^{N-1} (\mathbf{v}_0^T \mathbf{x}_n \mathbf{x}_n^T \mathbf{v}_0) \\ &= \mathbf{v}_0^T \left( \frac{1}{N} \sum_{n=0}^{N-1} \mathbf{x}_n \mathbf{x}_n^T \right) \mathbf{v}_0\end{aligned}$$

Let  $\mathbf{v}_0 \in \mathbb{R}^D$  be the zeroth (“first”) principal component (which we want to find).

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Let  $z_0$  be a random variable modeling the value of the zeroth coordinate. Assume data is centered, that is,  $\mathbb{E}[z_0] = 0$ .

Let  $\mathbf{C} = \frac{1}{N} \sum_{n=0}^{N-1} \mathbf{x}_n \mathbf{x}_n^T$  be the data covariance matrix. Then

$$\begin{aligned} \text{Var}[z_0] &= \frac{1}{N} \sum_{n=0}^{N-1} (z_{0,n} - 0)^2 \\ &= \frac{1}{N} \sum_{n=0}^{N-1} (\mathbf{v}_0^T \mathbf{x}_n)^2 \\ &= \frac{1}{N} \sum_{n=0}^{N-1} (\mathbf{v}_0^T \mathbf{x}_n \mathbf{x}_n^T \mathbf{v}_0)^2 \\ &= \mathbf{v}_0^T \left( \frac{1}{N} \sum_{n=0}^{N-1} \mathbf{x}_n \mathbf{x}_n^T \right) \mathbf{v}_0 \\ &= \mathbf{v}_0^T \mathbf{C} \mathbf{v}_0 \end{aligned}$$

which we want to maximize subject to  $\|\mathbf{v}_0\|^2 = 1$

Optimization problem as a Lagrangian:

$$\mathcal{L}(\mathbf{v}_0, \lambda_0) = \mathbf{v}_0 \mathbf{C} \mathbf{v}_0 + \lambda_0(1 - \mathbf{v}_0^T \mathbf{v}_0)$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_0} = 1 - \mathbf{v}_0^T \mathbf{v}_0$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{v}_0} = 2\mathbf{v}_0^T \mathbf{C} - 2\lambda_0 \mathbf{v}_0^T = 0$$

$$\mathbf{v}_0^T \mathbf{C} = \lambda_0 \mathbf{v}_0^T$$

Plug that into our formula for the variance:

$$\text{Var}[z_0] = \mathbf{v}_0^T \mathbf{C} \mathbf{v}_0$$

$$= \lambda_0 \mathbf{v}_0^T \mathbf{v}_0 = \lambda_0$$

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