1. Principal component analysis (PCA). Assume that we represent given data (row vectors) $\mathbf{x}_{1}^{\top}, \mathbf{x}_{2}^{\top}, \ldots, \mathbf{x}_{n}^{\top}$ as rows of a matrix

$$
X=\left[\begin{array}{c}
\mathbf{x}_{1}^{\top} \\
\mathbf{x}_{2}^{\top} \\
\vdots \\
\mathbf{x}_{n}^{\top}
\end{array}\right] \in \mathbb{R}^{n \times d} .
$$

We view components of vectors $\mathbf{x}_{i}^{\top}$ as various features of observed objects. Columns $\mathbf{c}_{j}$ of the matrix $X=\left[\mathbf{c}_{1}, \mathbf{c}_{2}, \ldots, \mathbf{c}_{d}\right]$ are often called feature vectors.
The objective of this task is to find so-called principal components $\mathbf{y}_{1}, \ldots, \mathbf{y}_{d} \in \mathbb{R}^{n}$ which are uncorrelated projections of data $\mathbf{x}_{i}^{\top}$ onto unit vectors $\mathbf{v}_{1}^{\top}, \ldots, \mathbf{v}_{d}^{\top}$, such that the variances $\operatorname{var}\left(\mathbf{y}_{i}\right)$ are maximized. Some anchor points:

- Centralization of data: Subtract the mean value from each column of $X$ to obtain

$$
\bar{X}:=X-\left[\mu_{1}, \mu_{2}, \ldots, \mu_{d}\right]
$$

where $\mu_{j}=\mu_{j}[1, \ldots, 1]^{\top}$ and $\mu_{j}$ is the average value of components of the feature vector $\mathbf{c}_{j}$.

- Evaluation of the singular value decomposition of $\bar{X}: \bar{X}=U S V^{\top}$ where $U=$ $\left[\mathbf{u}_{1}, \ldots, \mathbf{u}_{n}\right] \in \mathbb{R}^{n \times n}, V=\left[\mathbf{v}_{1}, \ldots, \mathbf{v}_{d}\right] \in \mathbb{R}^{d \times d}$, and $S \in \mathbb{R}^{n \times d}$ is a diagonal matrix with singular values $\sigma_{1} \geq \sigma_{2} \geq \cdots \geq \sigma_{d}$ on the diagonal.
- Principal components of $X$ are $\mathbf{y}_{1}, \ldots, \mathbf{y}_{d} \in \mathbb{R}^{n}$ obtained as

$$
\mathbf{y}_{j}=\bar{X} \mathbf{v}_{j}=\sigma_{j} \mathbf{u}_{j} .
$$

Answer questions below.
(a) Let $\Sigma=\frac{1}{n-1} \bar{X}^{\top} \bar{X}$. Show that for any $\mathbf{v}, \mathbf{w} \in \mathbb{R}^{d}$ we have $\operatorname{cov}(X \mathbf{v}, X \mathbf{w})=\mathbf{v}^{\top} \Sigma \mathbf{w}$.
(b) How can $\operatorname{var}\left(\mathbf{y}_{j}\right):=\operatorname{cov}\left(\mathbf{y}_{j}, \mathbf{y}_{j}\right)$ be expressed with singular values of $\bar{X}$ ?
(c) Evaluate $\operatorname{cov}\left(\mathbf{y}_{j}, \mathbf{y}_{k}\right)$ za $j \neq k$.

Write these three Octave functions:

- [mu, Vk, Uk, Dk]=pca(X, k) which for a given data matrix $X$ and an integer $k, 0 \leq k \leq \min (n, d)$, returns averages mu, matrices Vk and Uk containing first $k$ left/right principal directions, and a vector Dk with first $k$ variances $\operatorname{var}\left(\mathbf{y}_{j}\right)$,
- Z=proj(X) which for a given data matrix $X$ returns the projection of $\mathbf{x}_{i}^{\top}-$ [ $\mu_{i 1}, \ldots, \mu_{i d}$ ] onto largest two principal directions and draws a picture of both principal directions and projections of data,
- $r=$ threshold $(X, p)$ which for a data matrix $X$ and a number $p \in[0,1]$ returns the smallest integer $r$, such that

$$
\frac{\operatorname{var}\left(\mathbf{y}_{1}\right)+\cdots+\operatorname{var}\left(\mathbf{y}_{r}\right)}{\operatorname{var}\left(\mathbf{y}_{1}\right)+\cdots+\operatorname{var}\left(\mathbf{y}_{d}\right)} \geq p
$$

holds.

