# Homework \#5 solution key 

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## Problem 8.5.

Solution. For the matched filter considered in Example 2, it is given that the random vector $\mathbf{X}=\mathbf{s}+\mathbf{V}$, where the signal component is represented by $\mathbf{s}$ has a fixed Euclidean norm of one, i.e., $\sqrt{\mathbf{s}^{\mathrm{T}} \mathbf{s}}=1 \Longrightarrow \mathbf{s}^{\mathrm{T}} \mathbf{s}=1$.
The random vector $\mathbf{V}$, represents the additive noise component and has zero mean and covariance matrix $\sigma^{2} \mathbf{I}$. The correlation matrix of $\mathbf{X}$ is given by $\mathbf{R}=\mathbf{s s}^{\mathrm{T}}+\sigma^{2} \mathbf{I}$.
The largest eigenvalue of the correlation matrix $\mathbf{R}$ and the corresponding eigenvector are $\lambda_{1}=1+\sigma^{2}$ and $\mathbf{q}_{1}=\mathbf{s}$ respectively. Let us post multiply the correlation matrix by the eigenvector $\mathbf{q}_{1}$.

$$
\begin{aligned}
\mathbf{R q}_{1} & =\left(\mathbf{s s}^{\mathrm{T}}+\sigma^{2} \mathbf{I}\right) \mathbf{q}_{1} \\
& =\left(\mathbf{s s}^{\mathrm{T}}+\sigma^{2} \mathbf{I}\right) \mathbf{s} \\
& =\mathbf{s s}^{\mathrm{T}} \mathbf{s}+\sigma^{2} \mathbf{s} \\
& =\mathbf{s}+\sigma^{2} \mathbf{s} \quad\left(\text { since } \mathbf{s}^{\mathrm{T}} \mathbf{s}=1\right) \\
& =\left(1+\sigma^{2}\right) \mathbf{s} \\
& =\lambda_{1} \mathbf{s} \\
& =\lambda_{1} \mathbf{q}_{1}
\end{aligned}
$$

Therefore the given parameters satisfy the basic relation of $\mathbf{R} \mathbf{q}_{1}=\lambda_{1} \mathbf{q}_{1}$.
Problem 8.15.
Solution. Let the total number of inputs be $N$. The data $\mathbf{x}_{i}$ is projected using a kernel to get the projected data set $\phi\left(\mathbf{x}_{i}\right)$. Let $\tilde{\phi}\left(\mathbf{x}_{i}\right)$ be the projected data points after centralizing the data as given below

$$
\tilde{\phi}\left(\mathbf{x}_{i}\right)=\phi\left(\mathbf{x}_{i}\right)-\frac{1}{N} \sum_{l=1}^{N} \phi\left(\mathbf{x}_{l}\right) .
$$

We can get the corresponding elements of the gram matrix $\tilde{K}$ as below:

$$
\begin{aligned}
\tilde{k}_{i j} & =\tilde{\phi}^{\mathrm{T}}\left(\mathbf{x}_{i}\right) \tilde{\phi}\left(\mathbf{x}_{j}\right) \\
& =\left(\phi\left(\mathbf{x}_{i}\right)-\frac{1}{N} \sum_{m=1}^{N} \phi\left(\mathbf{x}_{m}\right)\right)^{\mathrm{T}}\left(\phi\left(\mathbf{x}_{j}\right)-\frac{1}{N} \sum_{n=1}^{N} \phi\left(\mathbf{x}_{n}\right)\right) \\
& =\phi\left(\mathbf{x}_{i}\right)^{\mathrm{T}} \phi\left(\mathbf{x}_{j}\right)-\frac{1}{N} \sum_{m=1}^{N} \phi^{\mathrm{T}}\left(\mathbf{x}_{m}\right) \phi\left(\mathbf{x}_{j}\right)-\frac{1}{N} \sum_{n=1}^{N} \phi^{\mathrm{T}}\left(\mathbf{x}_{i}\right) \phi\left(\mathbf{x}_{n}\right)+-\frac{1}{N^{2}} \sum_{m=1}^{N} \sum_{n=1}^{N} \phi^{\mathrm{T}}\left(\mathbf{x}_{m}\right) \phi\left(\mathbf{x}_{n}\right) \\
& =k_{i j}-\frac{1}{N} \sum_{m=1}^{N} k_{m j}-\frac{1}{N} \sum_{n=1}^{N} k_{i n}+-\frac{1}{N^{2}} \sum_{m=1}^{N} \sum_{n=1}^{N} k_{m n}
\end{aligned}
$$

A compact representation of the above in the matrix form is given by

$$
\tilde{\mathbf{K}}=\mathbf{K}-\mathbf{N K}-\mathbf{K N}+\mathbf{N K N}
$$

where $\mathbf{N}$ is an $N \times N$ matrix with all entries as $\frac{1}{N}$.
Problem 8.16.
Solution. It is given that the eigenvector $\tilde{q}$ of the correlation matrix $\tilde{\mathbf{R}}$ is normalized to unit length, that is,

$$
\begin{equation*}
\tilde{q}_{k}^{\mathrm{T}} \tilde{q}_{k}=1 \text { for } k=1,2, \ldots, l \tag{1}
\end{equation*}
$$

where it is assumed that the eigenvalues of $\mathbf{K}$ are arranged in descending order with $\lambda_{l}$ being the smallest nonzero eigenvalue of the Gram matrix $\mathbf{K}$. We know that

$$
\begin{align*}
\tilde{q} & =\sum_{j=1}^{N} \alpha_{j} \phi\left(x_{j}\right)  \tag{2}\\
K \alpha & =\lambda \alpha \tag{3}
\end{align*}
$$

Using (2) in (1) and upon simplifying, we get

$$
\begin{aligned}
1 & =\tilde{q}_{k}^{\mathrm{T}} \tilde{q}_{k} \\
& =\sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_{k i}^{\mathrm{T}} \alpha_{k j} \phi\left(x_{i}\right)^{\mathrm{T}} \phi\left(x_{j}\right) \\
& =\alpha_{k}^{\mathrm{T}} K \alpha_{k} \\
& =\alpha_{k}^{\mathrm{T}} \lambda_{k} \alpha_{k} \quad(\text { Using }(3)) \\
& =\lambda_{k} \alpha_{k}^{\mathrm{T}} \alpha_{k} \\
\frac{1}{\lambda_{k}} & =\alpha_{k}^{\mathrm{T}} \alpha_{k} \text { for } k=1,2, \ldots, l .
\end{aligned}
$$

Therefore, we see that normalization of the eigenvector $\alpha$ of the Gram matrix $\mathbf{K}$ is equivalent to the requirement of $\mathrm{Eq}(8.109)$ to be satisfied.

