

ECE 269 - Solution to Homework 3

Fall 2021

Problem 1 It is given that \mathcal{V} is a subspace of \mathbb{R}^n , $\mathcal{V}^\perp = \{\mathbf{x} \in \mathbb{R}^n : \mathbf{x}^T \mathbf{y} = 0, \forall \mathbf{y} \in \mathcal{V}\}$.

- (a) Consider $\alpha, \beta \in \mathbb{R}$, $\mathbf{v}_1, \mathbf{v}_2 \in \mathcal{V}^\perp$. So $\forall \mathbf{u} \in \mathcal{V}$:
 $(\alpha \mathbf{v}_1 + \beta \mathbf{v}_2)^T \mathbf{u} = \alpha \mathbf{v}_1^T \mathbf{u} + \beta \mathbf{v}_2^T \mathbf{u} = 0$ since $\mathbf{v}_1^T \mathbf{u} = 0 = \mathbf{v}_2^T \mathbf{u}$.
 Also, $\mathbf{0} \in \mathcal{V}^\perp$ since $\mathbf{0}^T \mathbf{u} = 0, \forall \mathbf{u} \in \mathcal{V}$. Thus, \mathcal{V}^\perp is a subspace of \mathbb{R}^n .
- (b) Using the given matrix \mathbf{A} , notice that:
 $\mathcal{V} = \{\sum_{i=1}^k x_i \mathbf{v}_i : x_1, \dots, x_k \in \mathbb{R}\} =$
 $\{\mathbf{A} \cdot (x_1, \dots, x_k)^T : x_1, \dots, x_k \in \mathbb{R}\} =$
 $\{\mathbf{A} \mathbf{x} : \mathbf{x} \in \mathbb{R}^k\} = \mathcal{R}(\mathbf{A})$. Meaning \mathcal{V} is the range space of \mathbf{A} .
 Similarly:
 $\mathcal{V}^\perp = \{\mathbf{y} \in \mathbb{R}^n : \mathbf{y}^T \sum_{i=1}^k x_i \mathbf{v}_i = 0, \forall x_1, \dots, x_k \in \mathbb{R}\}$
 $= \{\mathbf{y} \in \mathbb{R}^n : (\sum_{i=1}^k x_i \mathbf{v}_i^T) \mathbf{y} = 0, \forall x_1, \dots, x_k \in \mathbb{R}\}$
 $= \{\mathbf{y} \in \mathbb{R}^n : \mathbf{x}^T \mathbf{A}^T \mathbf{y} = 0, \forall \mathbf{x} \in \mathbb{R}^k\}$
 $= \{\mathbf{y} \in \mathbb{R}^n : \mathbf{A}^T \mathbf{y} = \mathbf{0}\}$
 $= \mathcal{N}(\mathbf{A}^T)$.
 Meaning the orthogonal complement of the range space is the null space of the transpose.
- (c) Consider $\mathbf{x} \in \mathcal{V}$. By definition of the orthogonal subspace $\mathbf{x}^T \mathbf{y} = 0, \forall \mathbf{y} \in \mathcal{V}^\perp \rightarrow \mathbf{x} \in (\mathcal{V}^\perp)^\perp$. Thus, $\mathcal{V} \subseteq (\mathcal{V}^\perp)^\perp$. Using the result of section (d), $\dim(\mathcal{V}) + \dim(\mathcal{V}^\perp) = n \rightarrow \dim(\mathcal{V}^\perp) + \dim((\mathcal{V}^\perp)^\perp) = n \rightarrow \dim((\mathcal{V}^\perp)^\perp) = \dim(\mathcal{V}) \rightarrow \mathcal{V} = (\mathcal{V}^\perp)^\perp$.
- (d) Using section (b), we get that
 $\dim(\mathcal{V}) = \dim(\mathcal{R}(\mathbf{A})) = \text{rank}(\mathbf{A}) = \text{rank}(\mathbf{A}^T)$. And,
 $\dim(\mathcal{V}^\perp) = \dim(\mathcal{N}(\mathbf{A}^T))$.
 Using the rank nullity theorem and the fact that $\mathbf{A}^T \in \mathbb{R}^{k \times n}$:
 $n = \text{rank}(\mathbf{A}^T) + \dim(\mathcal{N}(\mathbf{A}^T)) = \dim(\mathcal{V}) + \dim(\mathcal{V}^\perp)$.
- (e) Assuming $\mathcal{V} \subseteq \mathcal{W}$ implies:
 $\forall \mathbf{v} \in \mathcal{V} \rightarrow \mathbf{v} \in \mathcal{W}$, so taking $\mathbf{u} \in \mathcal{W}^\perp$:
 $\mathbf{u}^T \mathbf{v} = 0, \forall \mathbf{v} \in \mathcal{V} \rightarrow \mathbf{u}^T \mathbf{v} = 0, \forall \mathbf{v} \in \mathcal{V} \rightarrow \mathbf{u} \in \mathcal{V}^\perp \rightarrow \mathcal{W}^\perp \subseteq \mathcal{V}^\perp$.
- (f) We know that if \mathbf{v} is a projection of \mathbf{x} on \mathcal{V} , the $\mathbf{v}^\perp = \mathbf{x} - \mathbf{v}$ is orthogonal to all vectors in \mathcal{V} , meaning $\mathbf{v}^\perp \in \mathcal{V}^\perp$. Let us assume $\exists \mathbf{v} \neq \mathbf{u}, \mathbf{u} \in \mathcal{V}$ and $\mathbf{v}^\perp, \mathbf{u}^\perp \in \mathcal{V}^\perp$ such that $\mathbf{x} = \mathbf{v} + \mathbf{v}^\perp = \mathbf{u} + \mathbf{u}^\perp$. So $\mathbf{v} - \mathbf{u} = \mathbf{u}^\perp - \mathbf{v}^\perp$. However, since $\mathcal{V}, \mathcal{V}^\perp$ are subspaces, we get

that $\mathbf{v} - \mathbf{u} \in \mathcal{V}$, $\mathbf{u}^\perp - \mathbf{v}^\perp \in \mathcal{V}^\perp$, so $\mathbf{v} - \mathbf{u} \in \mathcal{V} \cap \mathcal{V}^\perp = \mathbf{0} \rightarrow \mathbf{v} = \mathbf{u}$ in contradiction to the assumption. Thus, the representation is unique.

Problem 2 A symmetric matrix $\mathbf{P} = \mathbf{P}^T \in \mathbb{R}^{n \times n}$ is said to be a projection matrix if $\mathbf{P} = \mathbf{P}^2$.

- (a) $(\mathbf{I} - \mathbf{P})^T = \mathbf{I} - \mathbf{P}^T = \mathbf{I} - \mathbf{P}$ and so $\mathbf{I} - \mathbf{P}$ is symmetric. Also, $(\mathbf{I} - \mathbf{P})^2 = (\mathbf{I} - \mathbf{P})(\mathbf{I} - \mathbf{P}) = \mathbf{I} - \mathbf{P} - \mathbf{P} + \mathbf{P}^2 = \mathbf{I} - 2\mathbf{P} + \mathbf{P} = \mathbf{I} - \mathbf{P}$. Hence, $\mathbf{I} - \mathbf{P}$ is symmetric and $\mathbf{I} - \mathbf{P} = (\mathbf{I} - \mathbf{P})^2$, and thus it is a projection matrix.
- (b) Notice that $(\mathbf{U}\mathbf{U}^T)^T = (\mathbf{U}^T)^T\mathbf{U}^T = \mathbf{U}\mathbf{U}^T$ and $(\mathbf{U}\mathbf{U}^T)^2 = \mathbf{U}\mathbf{U}^T\mathbf{U}\mathbf{U}^T = \mathbf{U}\mathbf{I}\mathbf{U}^T = \mathbf{U}\mathbf{U}^T$.
- (c) First of all, $\mathbf{A}^T\mathbf{A}$ is invertible for a full-rank tall matrix $\mathbf{A} \in \mathbb{R}^{n \times k}$ (To see this $\mathbf{A}^T\mathbf{A}\mathbf{x} = \mathbf{0} \implies \mathbf{x}^T\mathbf{A}^T\mathbf{A}\mathbf{x} = \mathbf{0} \implies \mathbf{A}\mathbf{x} = \mathbf{0} \implies \mathbf{x} = \mathbf{0}$). For symmetry, consider $(\mathbf{A}(\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T)^T = (\mathbf{A}^T)^T((\mathbf{A}^T\mathbf{A})^{-1})^T\mathbf{A}^T = \mathbf{A}((\mathbf{A}^T\mathbf{A})^{-1})^T\mathbf{A}^T = \mathbf{A}((\mathbf{A}^T\mathbf{A})^T)^{-1}\mathbf{A}^T = \mathbf{A}(\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T$. Also, consider $(\mathbf{A}(\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T)^2 = \mathbf{A}(\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T\mathbf{A}(\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T = \mathbf{A}(\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T$.
- (d) It suffices to show that $\|\mathbf{x} - \mathbf{v}\|$ is minimized over all $\mathbf{v} \in \mathcal{R}(\mathbf{P})$ by $\mathbf{v}^* = \mathbf{P}\mathbf{x}$. For any $\mathbf{v} \in \mathcal{R}(\mathbf{P})$:

$$\begin{aligned} \|\mathbf{x} - \mathbf{v}\|^2 &= \|\mathbf{x} - \mathbf{P}\mathbf{x} + \mathbf{P}\mathbf{x} - \mathbf{v}\|^2 = \|\mathbf{x} - \mathbf{P}\mathbf{x}\|^2 + \|\mathbf{P}\mathbf{x} - \mathbf{v}\|^2 + 2(\mathbf{x} - \mathbf{P}\mathbf{x})^T(\mathbf{P}\mathbf{x} - \mathbf{v}) \\ &= \|\mathbf{x} - \mathbf{P}\mathbf{x}\|^2 + \|\mathbf{P}\mathbf{x} - \mathbf{v}\|^2 + 2(\mathbf{x}^T - \mathbf{x}^T\mathbf{P})(\mathbf{P}\mathbf{x} - \mathbf{v}) \\ &= \|\mathbf{x} - \mathbf{P}\mathbf{x}\|^2 + \|\mathbf{P}\mathbf{x} - \mathbf{v}\|^2 + 2(\mathbf{x}^T\mathbf{P}\mathbf{x} - \mathbf{x}^T\mathbf{v} - \mathbf{x}^T\mathbf{P}^2\mathbf{x} + \mathbf{x}^T\mathbf{P}\mathbf{v}) \\ &= \|\mathbf{x} - \mathbf{P}\mathbf{x}\|^2 + \|\mathbf{P}\mathbf{x} - \mathbf{v}\|^2 + 2(\mathbf{x}^T\mathbf{P}\mathbf{x} - \mathbf{x}^T\mathbf{v} - \mathbf{x}^T\mathbf{P}\mathbf{x} + \mathbf{x}^T\mathbf{v}) \\ &= \|\mathbf{x} - \mathbf{P}\mathbf{x}\|^2 + \|\mathbf{P}\mathbf{x} - \mathbf{v}\|^2 \geq \|\mathbf{x} - \mathbf{P}\mathbf{x}\|^2. \end{aligned}$$
Where we used $\mathbf{P} = \mathbf{P}^2$ and $\mathbf{P}\mathbf{v} = \mathbf{v}, \forall \mathbf{v} \in \mathcal{R}(\mathbf{P})$ ($\mathbf{v} = \mathbf{P}\mathbf{x} = \mathbf{P}^2\mathbf{x} = \mathbf{P}\mathbf{v}$). To achieve equality in the last inequality, we need $\|\mathbf{P}\mathbf{x} - \mathbf{v}\| = 0 \rightarrow \mathbf{v} = \mathbf{P}\mathbf{x}$. Thus, $\argmin_{\mathbf{v} \in \mathcal{R}(\mathbf{P})} \|\mathbf{x} - \mathbf{v}\| = \mathbf{P}\mathbf{x}$.
- (e) Consider $\mathbf{P} = \mathbf{u}\mathbf{u}^T$. Since $\mathbf{P} = \mathbf{P}^T$ and $\mathbf{P} = \mathbf{P}^2$, \mathbf{P} is a projection matrix. Since $\mathcal{R}(\mathbf{P}) = \text{span}(\mathbf{u})$, using part (d) $\mathbf{P}\mathbf{x}$ is the projection of \mathbf{x} onto $\text{span}(\mathbf{u})$. This can also be directly verified since $(\mathbf{u}^T\mathbf{x})\mathbf{u} = \mathbf{u}\mathbf{u}^T\mathbf{x} = \mathbf{P}\mathbf{x}$ is the component of \mathbf{x} in the direction for the unit vector \mathbf{u} .