## Homework 0

Solutions

- 1. (Projections)
  - (a) False. This only holds if the vectors in the basis are orthogonal. Take

$$b = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \quad b_2 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}. \tag{1}$$

This is obviously a basis of  $\mathbb{R}^2$ . However

$$\mathcal{P}_{\mathbb{R}^2} b_1 = b_1 \neq \sum_{i=1}^m \langle b_1, b_i \rangle b_i$$
$$= \begin{bmatrix} 0 \\ 1 \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$
$$= \begin{bmatrix} 1 \\ 2 \end{bmatrix}.$$

(b) True. We will prove that each set includes the other set, which implies that they are equal.

 $S \subseteq (S^{\perp})^{\perp}$ . If  $x \in S$  then for any  $v \in S^{\perp}$   $x \perp v$  by the definition of orthogonal complement, so  $x \in (S^{\perp})^{\perp}$ .

 $(\mathcal{S}^{\perp})^{\perp} \subseteq \mathcal{S}$ . Let  $x \in (\mathcal{S}^{\perp})^{\perp}$ . Let us assume  $\mathcal{S}$  has dimension d. Let  $b_1, \ldots, b_d$  be an orthonormal basis of  $\mathcal{S}$ , and  $b_{d+1}, \ldots, b_n$  a basis of  $\mathcal{S}^{\perp}$ . The set  $b_1, \ldots, b_n$  is an orthonormal basis for all of  $\mathbb{R}^n$  (for  $i \leq d$  and  $j > d \langle b_i, b_j \rangle = 0$  because  $b_i \in \mathcal{S}$  and  $b_i \in \mathcal{S}^{\perp}$ ), so

$$x = \sum_{i=1}^{n} \langle b_i, x \rangle b_i. \tag{2}$$

However x is orthogonal to  $S^{\perp}$  so  $\langle b_i, x \rangle = 0$  for  $d+1 \leq i \leq n$ , which implies that x is in the span of  $b_1, \ldots, b_d$  and consequently belongs to S.

(c) For any  $x \in \mathbb{R}^n$ ,

$$\begin{bmatrix} \frac{1}{n} \sum_{i=1}^{n} x[i] \\ \cdots \\ \frac{1}{n} \sum_{i=1}^{n} x[i] \end{bmatrix} = \left\langle \frac{1}{\sqrt{n}} \vec{1}, x \right\rangle \frac{1}{\sqrt{n}} \vec{1}, \tag{3}$$

where  $\vec{1}$  is the vector of ones. Since  $\|\vec{1}\|_2^2 = n$ ,  $\frac{1}{\sqrt{n}}\vec{1}$  is a unit norm vector, so this is a projection onto its span.

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2. (Eigendecomposition) Using the eigendecomposition of the matrix corresponding to the system of equations, we obtain that the population of deer and wolfs at time n is given by

$$= \frac{1}{4^n} \left( \begin{bmatrix} 3 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 4 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 3 & 1 \\ 1 & 1 \end{bmatrix}^{-1} \right)^n \begin{bmatrix} d_0 \\ w_0 \end{bmatrix}$$
 (5)

$$= \frac{1}{4^n} \begin{bmatrix} 3 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 4 & 0 \\ 0 & 1 \end{bmatrix}^n \begin{bmatrix} 3 & 1 \\ 1 & 1 \end{bmatrix}^{-1} \begin{bmatrix} d_0 \\ w_0 \end{bmatrix}$$
 (6)

$$= \begin{bmatrix} 3 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & \frac{1}{4^n} \end{bmatrix} \begin{bmatrix} 0.5 & -0.5 \\ -0.5 & 1.5 \end{bmatrix} \begin{bmatrix} d_0 \\ w_0 \end{bmatrix}.$$
 (7)

Taking the limit as  $n \to \infty$  yields

$$\lim_{n \to \infty} \begin{bmatrix} d_n \\ w_n \end{bmatrix} = \frac{d_0 - w_0}{2} \begin{bmatrix} 3 \\ 1 \end{bmatrix}. \tag{8}$$

There will be three times more deer than wolfs, as long as  $d_0 > w_0$ .

- 3. (Function approximation)
  - (a) Let  $u_1, u_2, u_3 \in P_2$  denote the orthonormal basis produced by Gram-Schmidt. Then

$$u_1 = \frac{1}{\|1\|} = \frac{1}{\sqrt{2}} \approx 0.7071 \tag{9}$$

$$\langle x, u_1 \rangle = \frac{1}{\sqrt{2}} \int_{-1}^{1} x \, dx = 0 \tag{10}$$

$$x - \langle x, u_1 \rangle u_1 = x \tag{11}$$

$$u_2 = \frac{x}{\|x\|} = \sqrt{\frac{3}{2}}x \approx 1.22474x \tag{12}$$

$$\langle x^2, u_1 \rangle = \frac{1}{\sqrt{2}} \int_{-1}^1 x^2 \, dx = \frac{\sqrt{2}}{3}$$
 (13)

$$\langle x^2, u_2 \rangle = \sqrt{\frac{3}{2}} \int_{-1}^1 x^3 \, dx = 0$$
 (14)

$$x^{2} - \langle x^{2}, u_{1} \rangle u_{1} - \langle x^{2}, u_{2} \rangle u_{2} = x^{2} - 1/3$$
(15)

$$u_3 = \frac{x^2 - 1/3}{\|x^2 - 1/3\|} = \sqrt{\frac{45}{8}}(x^2 - 1/3)$$
 (16)

$$\approx -0.7906 + 2.3717x^2. \tag{17}$$

(b) We have

$$\langle f, u_1 \rangle = \frac{2\sqrt{2}}{\pi} \approx 0.9003 \tag{18}$$

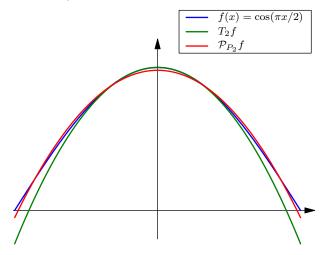
$$\langle f, u_2 \rangle = 0 \tag{19}$$

$$\langle f, u_3 \rangle = \frac{2\sqrt{10} (\pi^2 - 12)}{\pi^3} \approx -0.4346$$
 (20)

$$\mathcal{P}_{P_2} f = \sum_{i=1}^{3} \langle u_i, f \rangle u_i \tag{21}$$

$$= \frac{15(\pi^2 - 12)(x^2 - \frac{1}{3})}{\pi^3} + \frac{2}{\pi} \approx 0.9802 - 1.0306x^2.$$
 (22)

(c) We have  $T_2 f(x) = 1 - \pi^2 x^2 / 8$ .



- (d) The projection is the best approximator in the norm induced by the inner product, so in particular  $||f \mathcal{P}_{P_2} f|| < ||f T_2 f||$ . The Taylor expansion provides a local approximation, which is arbitrarily close to the function as we approach 0, but can deviate significantly in other regions.
- 4. (Scalar linear estimation)
  - (a) By Lemma 2.1, if we fix a the optimal b equals  $E(\tilde{y} a\tilde{x}) = \mu_{\tilde{y}} a\mu_{\tilde{x}}$ . Plugging this in we have

$$\min_{b \in \mathbb{R}} E[(a\tilde{x} + b - \tilde{y})^2] = E[(a(\tilde{x} - \mu_{\tilde{x}}) - (\tilde{y} - \mu_y))^2]$$
(23)

$$= a^{2} \operatorname{Var}(\tilde{x}) + \operatorname{Var}(\tilde{y}) - 2a \operatorname{Cov}(\tilde{x}\tilde{y}).$$
 (24)

This is a convex quadratic function with respect to a, so we can set the derivative to zero to find the minimum:

$$a_{\text{opt}} = \frac{\text{Cov}(\tilde{x}\tilde{y})}{\text{Var}(\tilde{x})} \tag{25}$$

$$=\frac{\sigma_{\tilde{y}}\rho_{\tilde{x},\tilde{y}}}{\sigma_{\tilde{x}}},\tag{26}$$

SO

$$b_{\text{opt}} = \mu_{\tilde{y}} - \frac{\sigma_{\tilde{y}} \rho_{\tilde{x}, \tilde{y}} \mu_{\tilde{x}}}{\sigma_{\tilde{x}}}.$$
 (27)

(b) By independence,

$$E(\tilde{x}\tilde{y}) = E(\tilde{z})E(\tilde{y}^2)$$
(28)

$$=0. (29)$$

The estimate equals

$$a_{\text{opt}}\tilde{x} + b_{\text{opt}} = \mu_{\tilde{y}}. (30)$$

(c) Set  $\tilde{z} = 1$  with probability 1/2, and  $\tilde{z} = -1$  with probability 1/2. Then if  $\tilde{x} > 0$ , we set the estimate to  $\tilde{x}$ , and if  $\tilde{x} < 0$ , we set the estimate to  $-\tilde{x}$ .

## 5. (Gradients)

(a)

$$\frac{\partial f(x)}{\partial x[i]} = \frac{\partial \sum_{j=1}^{n} b[j]x[j]}{\partial x[i]}$$
(31)

$$=b[i], (32)$$

so the gradient equals b.

(b)

$$\frac{\partial f(x)}{\partial x[i]} = \frac{\partial \sum_{j=1}^{n} \sum_{k=1}^{n} A[j,k]x[j]x[k]}{\partial x[i]}$$
(33)

$$= \sum_{j=1}^{n} A[i,j]x[j] + \sum_{j=1}^{n} A[j,i]x[j],$$
 (34)

so the gradient equals  $Ax + A^Tx$ .