Advanced Methods Homework 1

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1 Vector spaces and inner products

1. *Proof.* Denote $\{\mathbf{a}_1, \mathbf{a}_2, \cdots, \mathbf{a}_k\}$ be a basis of W. And we can expand them to a basis of $\mathbb{R}^n$ as $\{\mathbf{a}_1, \mathbf{a}_2, \cdots, \mathbf{a}_k, \mathbf{a}_{k+1}, \cdots, \mathbf{a}_n\}$. Then we do Gram-Schmidt orthogonalization to the basis and get $\{\mathbf{b}_1, \mathbf{b}_2, \cdots, \mathbf{b}_k, \mathbf{b}_{k+1}, \cdots, \mathbf{b}_n\}$. It's easy to see that $\{\mathbf{b}_1, \mathbf{b}_2, \cdots, \mathbf{b}_k\}$ become an othogonal basis of W (they are othogonal, hence linear independent, and k is the dimension of W). Now we assert that $V = \mathbf{span}\{\mathbf{b}_{k+1}, \cdots, \mathbf{b}_n\}$ will be $W^\perp$.

   First, for every vector $\mathbf{x}$ in $W^\perp$, it has a representation $\mathbf{x} = \sum_{i=1}^n \omega_i \mathbf{b}_i$ for some $\omega_i \in \mathbb{R}^n$. Since $\mathbf{x} \in W^\perp$, we have $\langle \mathbf{x}, \mathbf{b}_j \rangle = 0$, for all $j = 1, 2, \cdots, k$. Therefore $\omega_j = 0$ for $1 \leq j \leq k$, which means $\mathbf{x} \in V$ and $W^\perp \subset V$.

   In the other side, for every vector $\mathbf{y} = \sum_{t=k+1}^n \gamma_t \mathbf{b}_t \in V$, it's quite direct to see that $\langle \mathbf{y}, \mathbf{b}_j \rangle = 0$, for all $j = 1, 2, \cdots, k$, hence $\langle \mathbf{y}, \mathbf{w} \rangle = 0$, for all $\mathbf{w} \in W$. Therefore $\mathbf{y} \in W^\perp$ and $W^\perp \subset V$.

   Now we get $W^\perp = V$, hence $\dim(W^\perp) = n - k$. Also we can see that $W^\perp$ is unique. If not, we can merge the two different $W^\perp$ and get a higher dimensional subspace Z that is orthogonal to W. Then $Z \oplus W \subset \mathbb{R}^n$ but $\dim(Z \oplus W) \geq n + 1 > n$, a contradiction. □

2. (a) *Proof.* According to Cauchy inequality, $(\sum u_i v_i)^2 \leq \sum u_i^2 \sum v_i^2$. It's equivalent here that $|\langle \mathbf{u}, \mathbf{v} \rangle| \leq ||\mathbf{u}||||\mathbf{v}||$. □

   (b) *Proof.*

$$
\begin{aligned}
||\mathbf{u} + \mathbf{v}||^2 + ||\mathbf{u} - \mathbf{v}||^2 &= (\mathbf{u} + \mathbf{v})'(\mathbf{u} + \mathbf{v}) + (\mathbf{u} - \mathbf{v})'(\mathbf{u} - \mathbf{v}) &(1)\\
&= \mathbf{u}'\mathbf{u} + 2\mathbf{u}'\mathbf{v} + \mathbf{v}'\mathbf{v} + \mathbf{u}'\mathbf{u} - 2\mathbf{u}'\mathbf{v} + \mathbf{v}'\mathbf{v} &(2)\\
&= 2\mathbf{u}'\mathbf{u} + 2\mathbf{v}'\mathbf{v} = 2||\mathbf{u}||^2 + 2||\mathbf{v}||^2 &(3)
\end{aligned}
$$

□

3. In the definition of projection in Lecture 2, **y - Π(y—x)** should be orthogonal to $\mathbf{x}$. So there is nothing need to be proved. Maybe we should changed the definition here that (suppose $\mathbf{x} \neq \mathbf{0}$, or there is no meaningful projection)

$$\Pi(\mathbf{y}—\mathbf{x}) \triangleq \underset{\mathbf{u} \in \mathrm{span}\{\mathbf{x}\}}{\mathrm{argmin}} ||\mathbf{y} \text{ - } \mathbf{u}||^2$$

   Proof. (This proof contains the part to assert that projection above is well defined) Suppose $\mathbf{u} = b\mathbf{x}$, then $||\mathbf{y} - \mathbf{u}||^2 = \mathbf{y}'\mathbf{y} - 2b\mathbf{x}'\mathbf{y} + b^2\mathbf{x}'\mathbf{x}$. It's a quadratic function with highest coefficient $\mathbf{x}'\mathbf{x} > 0$, therefore have a unique minimizer. Differentiate it with b, let it be zero and we get the normal equation $\mathbf{x}'\mathbf{y} = b\mathbf{x}'\mathbf{x}$, which means (since $\Pi(\mathbf{y}—\mathbf{x}) = b\mathbf{x}$) : $\langle \Pi(\mathbf{y}—\mathbf{x}), x\rangle = \langle \mathbf{y}, x\rangle$ and therefore $\mathbf{y} - \Pi(\mathbf{y}—\mathbf{x}) \perp \mathbf{x}$. □

2 Regression

1. Slope $\hat{\beta}_{yx}$ of regressing $\mathbf{y}$ on $\mathbf{x}$ is $\hat{\rho}_{xy}\, \frac{\hat{\sigma}_y}{\hat{\sigma}_x}$, where $\hat{\rho}_{xy}$ is the sample correlation coefficient and $\hat{\sigma}_y, \hat{\sigma}_x$ are the sample standard deviation of y and x. So, slope $\hat{\beta}_{xy}$ of $\mathbf{x}$ on $\mathbf{y}$ is $\hat{\rho}_{yx}\, \frac{\hat{\sigma}_x}{\hat{\sigma}_y}$. We have that $\hat{\rho}_{xy} = \hat{\rho}_{yx}$, so $\hat{\beta}_{xy}\hat{\beta}_{yx} = \hat{\rho}^2_{xy}$.

2. *Proof.* In the setting of mean only regression of $\mathbf{y}$, we have $\hat{\mu} = \overline{\mathbf{y}} = \sum_{i=1}^n y_i/n$. And the residual is $\mathbf{r} = \mathbf{y} - \overline{\mathbf{y}}\mathbf{J}_n$, therefore sum of residual is $\sum r_i = \sum_1^n y_i - n \cdot \sum_1^n y_i/n = 0$. □

3. *Proof.* In the setting of mean only regression of $\mathbf{y}$ on $\mathbf{x}$, we have $\hat{\beta} = \frac{\langle \mathbf{y},\mathbf{x}\rangle}{\langle \mathbf{x},\mathbf{x}\rangle}$. Therefore residual is $\mathbf{r} = \mathbf{y} - \frac{\langle \mathbf{y},\mathbf{x}\rangle}{\langle \mathbf{x},\mathbf{x}\rangle}\mathbf{x}$, therefore $\langle \mathbf{r}, \mathbf{x}\rangle = \langle \mathbf{y}, \mathbf{x}\rangle - \frac{\langle \mathbf{y},\mathbf{x}\rangle}{\langle \mathbf{x},\mathbf{x}\rangle} \cdot \langle \mathbf{x}, \mathbf{x}\rangle = 0$, $\mathbf{r}\perp\mathbf{x}$. □

4. Notation as above, when $\mathbf{y}\perp\mathbf{x}$, we find that the residual $\mathbf{r} = \mathbf{y}$, which of course need not sum to zero.

5. *Proof.* In this setting of regressing $\mathbf{y}$ on $\mathbf{x}$, we get the normal equation that:

$$\begin{aligned} \mathbf{J}_n'\mathbf{y} &= \hat{\beta}_0\mathbf{J}_n'\mathbf{J}_n + \hat{\beta}_1\mathbf{J}_n'\mathbf{x} && (4)\\ \mathbf{x}'\mathbf{y} &= \hat{\beta}_0\mathbf{x}'\mathbf{J}_n + \hat{\beta}_1\mathbf{x}'\mathbf{x} && (5) \end{aligned}$$

and also the residual $\mathbf{r} = \mathbf{y} - \hat{\beta}_0\mathbf{J}_n - \hat{\beta}_1\mathbf{x}$. Then:

$$\langle \mathbf{r}, \mathbf{J}_n\rangle = \mathbf{J}_n'\mathbf{y} - \hat{\beta}_0\mathbf{J}_n'\mathbf{J}_n + \hat{\beta}_1\mathbf{J}_n'\mathbf{x} = 0$$

and

$$\langle \mathbf{r}, \mathbf{x}\rangle = \mathbf{x}'\mathbf{y} - \hat{\beta}_0\mathbf{x}'\mathbf{J}_n + \hat{\beta}_1\mathbf{x}'\mathbf{x} = 0$$

So we get the residual $\mathbf{r}\perp\mathbf{J}_n$ and $\mathbf{r}\perp\mathbf{x}$. □

3 Least squares

1. *Proof.* Given $\mathbf{H}^2 = \mathbf{H}$, then $(\mathbf{I - H})^2 = \mathbf{I}^2 - 2\mathbf{H} + \mathbf{H}^2 = \mathbf{I} - 2\mathbf{H} + \mathbf{H} = \mathbf{I - H}$. □

2. After calculating, I think the method mentioned to estimate β_2 in this question is:

   - First, regressing $\mathbf{y}$ on $\mathbf{x}_1$ through origin and get the residual $\mathbf{r}_1$.
   - Second, regressing $\mathbf{x}_2$ on $\mathbf{x}_1$ through origin and get the residual $\mathbf{r}_2$.
   - Finally, regressing $\mathbf{r}_1$ on $\mathbf{r}_2$ through origin and get the estimation $\hat{\beta}_2$.

   Proof. To minimize $||\mathbf{y} - \beta_1\mathbf{x}_1 - \beta_2\mathbf{x}_2||^2$, we can first suppose β_2 be a constant and minimize through β_1(it will be a function of β_2), and then minimize through β_2 to get the estimation. So the goal is firstly to find the $\operatorname{argmin}_{\beta_1} ||(\mathbf{y} - \beta_2\mathbf{x}_2) - \beta_1\mathbf{x}_1||^2$. This is simply a regression through origin and we can get that $\beta_1^{min} = \frac{\langle \mathbf{y}-\beta_2\mathbf{x}_2,\mathbf{x}_1\rangle}{\langle \mathbf{x}_1,\mathbf{x}_2\rangle}$.

Therefore, the second step is to find the argmin of:

$$||\mathbf{y} - \beta_2\mathbf{x}_2 - \frac{\langle \mathbf{y} - \beta_2\mathbf{x}_2, \mathbf{x}_1\rangle}{\langle \mathbf{x}_1, \mathbf{x}_2\rangle}\mathbf{x}_1||^2 = ||(\mathbf{y} - \frac{\langle \mathbf{y}, \mathbf{x}_1\rangle}{\langle \mathbf{x}_1, \mathbf{x}_1\rangle}\mathbf{x}_1) - \beta_2(\mathbf{x}_2 - \frac{\langle \mathbf{x}_2, \mathbf{x}_1\rangle}{\langle \mathbf{x}_1, \mathbf{x}_1\rangle}\mathbf{x}_1)||^2$$

Also, we can find that:

$$\mathbf{r}_1 = \mathbf{y} - \frac{\langle \mathbf{y}, \mathbf{x}_1\rangle}{\langle \mathbf{x}_1, \mathbf{x}_1\rangle}\mathbf{x}_1 \tag{6}$$

$$\mathbf{r}_2 = \mathbf{x}_2 - \frac{\langle \mathbf{x}_2, \mathbf{x}_1\rangle}{\langle \mathbf{x}_1, \mathbf{x}_1\rangle}\mathbf{x}_1 \tag{7}$$

Therefore, $\hat{\beta}_2$ comes from minimizing $||\mathbf{r}_1 - \beta_2\mathbf{r}_2||^2$, which is just doing regression through origin of $\mathbf{r}_1$ on $\mathbf{r}_2$. Then we finish the proof that the procedure described in the question is valid. □

3. *Proof.* Suppose that $\mathbf{X}$ is of size $m \times n$, where $m \leq n$ (or we replace $\mathbf{X}$ by $\mathbf{X}'$, and we just need to prove the same thing). Then consider the singular value decomposition of $\mathbf{X}$ is $\mathbf{X} = \mathbf{USV}$, where $\mathbf{U}, \mathbf{V}$ are orthogonal matrices and $\mathbf{S} = (diag\{\lambda_1, \lambda_2, \cdots, \lambda_r, 0, \cdots, 0\}, \mathbf{0}) : \lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \cdots \geq \lambda_r > 0$. Here $r = rank(\mathbf{X})$. Now consider the svd of $\mathbf{X}', \mathbf{X}'\mathbf{X}, \mathbf{X}\mathbf{X}'$, we have:

$$\mathbf{X}' = \mathbf{V}'\mathbf{S}'\mathbf{U}' \tag{8}$$

$$\mathbf{X}'\mathbf{X} = \mathbf{V}'\begin{pmatrix} diag\{\lambda_1^2, \lambda_2^2, \cdots, \lambda_r^2, 0, \cdots, 0\} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{pmatrix}\mathbf{V} \tag{9}$$

$$\mathbf{X}\mathbf{X}' = \mathbf{U}\ diag\{\lambda_1^2, \lambda_2^2, \cdots, \lambda_r^2, 0, \cdots, 0\}\ \mathbf{U}' \tag{10}$$

Therefore we can see that the three matrices above all have and only have r nonzero singular values, which means they are all of rank r. Then we get $rank(\mathbf{X}) = rank(\mathbf{X}') = rank(\mathbf{X}'\mathbf{X}) = rank(\mathbf{X}\mathbf{X}')$. □

4. If the design matrix is orthogonal, then we have:

$$\mathbf{J} = ||\mathbf{y} - \mathbf{X}\boldsymbol{\beta}||^2 = \mathbf{y}'\mathbf{y} - 2\mathbf{y}'\mathbf{X}\boldsymbol{\beta} + \boldsymbol{\beta}'\mathbf{X}'\mathbf{X}\boldsymbol{\beta} = \mathbf{y}'\mathbf{y} - 2\mathbf{y}'\mathbf{X}\boldsymbol{\beta} + \boldsymbol{\beta}'\boldsymbol{\beta}$$

And then we get the normal equation as:

$$\frac{\partial \mathbf{J}}{\partial \boldsymbol{\beta}} = 2\boldsymbol{\beta} - 2\mathbf{X}'\mathbf{y} = 0$$

So we have $\hat{\boldsymbol{\beta}} = \mathbf{X}'\mathbf{y}$.

4 Computing and analysis

Code is shown below and we simulate the data ourselves and test the L_1 norm of the differences of $\hat{\beta}$, fitted_value and residuals from two results.

1.

```
mylm <- function(y,X){
    D = cbind(1,X)
    beta = solve(t(D) %*% D) %*% t(D) %*% y
    fitted = D %*% beta
    residuals = y - fitted
    result = list(beta = beta,
                  fitted = fitted,
                  residuals = residuals)
    return(result)
}
```

2.

```
test.X = cbind(sample(1:100),sample(1:100),sample(1:100))
beta = c(5,-1,4,2)
test.y = cbind(1,test.X) %*% beta + rnorm(100)
model = lm(test.y~test.X)
mymodel = mylm(test.y,test.X)
c(sum(abs(model$coefficients - mymodel$beta)),
  sum(abs(model$fitted.values - mymodel$fitted)),
  sum(abs(model$residuals - mymodel$residuals))
 )
```

```
## [1] 1.096900e-13 2.499334e-11 2.488536e-11
```