

EEE424 HW2 FALL 2024-25

Q1)

$$\phi_k[n] = e^{j2\pi \frac{kn}{N}}, k=0, \dots, N-1, \phi_\ell[n] = e^{j2\pi \frac{\ell n}{N}}$$

$$\phi_\ell^*[n] = e^{-j2\pi \frac{\ell n}{N}}, \sum_{n=0}^{N-1} e^{j2\pi \frac{k}{N}n} \cdot e^{-j2\pi \frac{\ell}{N}n} = \sum_{n=0}^{N-1} \left(e^{j2\pi \frac{(k-\ell)}{N}n} \right)$$

$$= \frac{1 - e^{j2\pi (k-\ell)}}{1 - e^{j2\pi \frac{(k-\ell)}{N}}}, \sum_{n=0}^{N-1} \phi_k[n] \phi_\ell^*[n] = \begin{cases} N, & k=\ell \\ 0, & k \neq \ell \end{cases}$$

Hence, $\sum_{n=0}^{N-1} \phi_k[n] \phi_\ell^*[n] = 0$ for $k \neq \ell$.

Q2)

$$\sin(mt) \sin(nt) = \frac{1}{2} (\cos((m-n)t) - \cos((m+n)t))$$

$$\int_{t_0}^{t_0+T} \sin(mt) \sin(nt) dt = \frac{1}{2} \int_{t_0}^{t_0+T} \cos((m-n)t) dt - \frac{1}{2} \int_{t_0}^{t_0+T} \cos((m+n)t) dt$$

if $m \neq n$ the integral becomes $\frac{1}{2} \int_{t_0}^{t_0+T} \cos(k_1 t) dt - \frac{1}{2} \int_{t_0}^{t_0+T} \cos(k_2 t) dt$

where $\{k_1, k_2\} \in \mathbb{Z}$. For any $k \in \mathbb{Z}$ $\int_{t_0}^{t_0+T} \cos(kt) dt = 0$, hence,

$$\int_{t_0}^{t_0+T} \sin(mt) \sin(nt) dt = 0 \text{ if } m \neq n, \quad m=n \Rightarrow \frac{1}{2} \int_{t_0}^{t_0+T} \cos((m-n)t) dt = \frac{1}{2} \int_{t_0}^{t_0+T} 1 dt = \frac{T}{2}$$

$$\int_{t_0}^{t_0+T} \sin(mt) \sin(nt) dt = \frac{T}{2} \text{ if } m=n. \text{ Similarly,}$$

$$\cos(mt) \cos(nt) = \frac{1}{2} (\cos((m+n)t) + \cos((m-n)t))$$

$$\int_{t_0}^{t_0+T} \cos(mt) \cos(nt) dt = \frac{1}{2} \int_{t_0}^{t_0+T} \cos((m+n)t) dt + \frac{1}{2} \int_{t_0}^{t_0+T} \cos((m-n)t) dt \text{ Again let}$$

$m+n=k_1, m-n=k_2, \{k_1, k_2\} \in \mathbb{Z}$, for any $k \in \mathbb{Z}$ $\int_{t_0}^{t_0+T} \cos(kt) dt = 0$ hence,

$$\int_{t_0}^{t_0+T} \cos(mt) \cos(nt) dt = 0 \text{ if } m \neq n, \quad m=n \Rightarrow \frac{1}{2} \int_{t_0}^{t_0+T} \cos((m-n)t) dt = \frac{1}{2} \int_{t_0}^{t_0+T} 1 dt = \frac{T}{2}$$

$$\int_{t_0}^{t_0+T} \cos(mt) \cos(nt) dt = \frac{T}{2} \text{ if } m=n.$$

$$Q3) \quad x_i = \langle x, \phi_i \rangle, \quad x = \sum_{i=0}^{n-1} x_i \phi_i, \quad \beta_i = \langle x, \phi_i \rangle$$

$$\beta_i = \langle x_i \phi_i, \phi_i \rangle, \quad \text{Let } \underline{\Phi} \text{ matrix be } [\phi_0 \phi_1 \phi_2 \dots \phi_{k-1}]$$

As matrix vector multiplication $\underline{\beta}$ can be expressed as

$$\underline{\beta} = \underline{\Phi}^H \underline{\Phi} \underline{x}, \quad \langle \phi_i, \phi_j \rangle = \begin{cases} \delta_{ij}, & i=j \\ 0, & i \neq j \end{cases} \quad \text{hence, } \underline{\Phi}^H \underline{\Phi} = \underline{I}$$

$$\underline{\beta} = \underline{I} \cdot \underline{x} = \underline{x}, \quad \text{hence, } \beta_i = x_i \text{ for } i=0, 1, \dots, k-1$$

$$\|x - \hat{x}\| = \sqrt{x_0^2 \|\phi_0\|^2 + \dots + x_{n-1}^2 \|\phi_{n-1}\|^2 - (\beta_0 \|\phi_0\|^2 + \dots + \beta_{k-1} \|\phi_{k-1}\|^2)}$$

$$\|\phi_i\|^2 = 1 \text{ due to orthonormality. hence } \|x - \hat{x}\| = \sqrt{\sum_{i=0}^{k-1} (x_i^2 - \beta_i^2) + c_1}$$

$$\text{where } c_1 \text{ is a constant, } c_1 = \sum_{i=0}^{n-1} x_i^2, \quad \|x - \hat{x}\| = \sqrt{\sum_{i=0}^{k-1} (x_i - \beta_i)(x_i + \beta_i) + c_1}$$

$$\|x - \hat{x}\| \text{ is minimized if } \left| \sum_{i=0}^{k-1} (x_i - \beta_i)(x_i + \beta_i) \right| \text{ is minimized}$$

$$\text{the minimum value can be obtained when } x_i = \beta_i, \quad \left| \sum_{i=0}^{k-1} (x_i - \beta_i)(x_i + \beta_i) \right| = 0$$

$$\text{which results } \|x - \hat{x}\| = \sqrt{c_1}.$$

Q4) a)

$$(i) \quad \text{we want } \arg \min_{\hat{y}} \sum_{i=1}^N (y_i - \hat{y}_i)^2 = \|y - \hat{y}\|^2, \quad \text{Let } y - \hat{y} = \underline{\varepsilon}$$

$$\|\underline{\varepsilon}\| \text{ is minimized if } \langle \underline{\varepsilon}, p_i \rangle = 0, \quad \text{Since } \text{basis}(S_2) = \{p_1, p_2, \dots, p_M\}$$

$$\underline{\varepsilon} \perp S_2 \quad \text{hence, } y - \hat{y} \perp S_2$$

$$(ii) \quad \text{in part (i) it is shown that } \langle \underline{\varepsilon}, p_i \rangle = 0, \quad \text{Since } \{p_1, p_2, \dots, p_M\} \text{ is basis for } S_2, \quad \hat{y} = \sum_{i=1}^M \beta_i p_i, \text{ for } \beta_i \text{ constants.}$$

$$\langle \underline{\varepsilon}, \hat{y} \rangle = \langle \underline{\varepsilon}, \beta_i p_i \rangle = \beta_i \langle \underline{\varepsilon}, p_i \rangle = 0 \quad \text{hence } y - \hat{y} \perp \hat{y}$$

$$(iii) \quad p_3 \text{ vectors form a basis for } S_2. \quad y - \hat{y} \perp S_2 \text{ implies}$$

$$\text{that } \langle y - \hat{y}, p_j \rangle = 0 \text{ due to the fact that } p_j \text{'s form a basis for } S_2 \text{ hence } y - \hat{y} \perp p_j \text{ for } j=1, \dots, M.$$

b) From part (a) it is known that $\langle y - \hat{y}, p_j \rangle = 0$ for $j \in [1, m]$
 substitute $\hat{y} = \sum_{i=1}^m c_i p_i$ to inner product, $\langle y - \sum_{i=1}^m c_i p_i, p_j \rangle = 0$

$$\langle y, p_j \rangle - \sum_{i=1}^m c_i \langle p_i, p_j \rangle = 0, \quad \boxed{\sum_{i=1}^m c_i \langle p_i, p_j \rangle = \langle y, p_j \rangle}$$

c) $\hat{x} = \operatorname{argmin}_x (\|y - Ax\|^2)$, $\|y - Ax\|^2 = (y - Ax)^T (y - Ax)$

$$f(x) = y^T y - \underbrace{y^T Ax}_{\substack{y^T Ax = x^T A^T y}} - (Ax)^T y + x^T A^T Ax, \quad \nabla_x f(x) = \nabla_x (-2y^T Ax) + \nabla_x (x^T A^T Ax)$$

$$\nabla_x f(x) = -2A^T y + 2A^T Ax, \text{ equate to zero for } \hat{x}, -2A^T y + 2A^T Ax = 0$$

$$A^T Ax = A^T y, \quad \boxed{\hat{x} = (A^T A)^{-1} A^T y \text{ where } (A^T A)^{-1} A^T = A_{ps}}$$

① $\hat{x} = (A^T A)^{-1} A^T y$, $A = \begin{bmatrix} 1 & -1 \\ -2 & 1 \\ 1 & 1 \end{bmatrix}_{3 \times 2}$, $y = \begin{bmatrix} 4 \\ -1 \\ 1 \end{bmatrix}_{3 \times 1}$

$$A^T A = \begin{bmatrix} 1 & -2 & 1 \\ -1 & 1 & 1 \end{bmatrix}_{2 \times 3} \begin{bmatrix} 1 & -1 \\ -2 & 1 \\ 1 & 1 \end{bmatrix}_{3 \times 2} = \begin{bmatrix} 6 & -2 \\ -2 & 3 \end{bmatrix}, \det(A^T A) = 14$$

$$(A^T A)^{-1} = \frac{1}{14} \begin{bmatrix} 3 & 2 \\ 2 & 6 \end{bmatrix}, (A^T A)^{-1} A^T = \frac{1}{14} \begin{bmatrix} 3 & 2 \\ 2 & 6 \end{bmatrix}_{2 \times 2} \begin{bmatrix} 1 & -2 & 1 \\ -1 & 1 & 1 \end{bmatrix}_{2 \times 3}$$

$$= \frac{1}{14} \begin{bmatrix} 1 & -4 & 5 \\ -4 & 2 & 8 \end{bmatrix}, (A^T A)^{-1} A^T y = \frac{1}{14} \begin{bmatrix} 1 & -4 & 5 \\ -4 & 2 & 8 \end{bmatrix} \begin{bmatrix} 4 \\ -1 \\ 1 \end{bmatrix} = \frac{1}{14} \begin{bmatrix} 13 \\ -10 \end{bmatrix}$$

$$\boxed{\hat{x} = \frac{1}{14} \begin{bmatrix} 13 \\ -10 \end{bmatrix}}$$

② $\hat{y} = A\hat{x} = \frac{1}{14} \begin{bmatrix} 1 & -1 \\ -2 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 13 \\ -10 \end{bmatrix} = \frac{1}{14} \begin{bmatrix} 23 \\ -36 \\ 3 \end{bmatrix}$

$$y - \hat{y} = \begin{bmatrix} 4 - \frac{23}{14} \\ -1 + \frac{36}{14} \\ 1 - \frac{3}{14} \end{bmatrix} = \begin{bmatrix} \frac{33}{14} \\ \frac{22}{14} \\ \frac{11}{14} \end{bmatrix}$$

$$\langle y - \hat{y}, \hat{y} \rangle = \begin{bmatrix} \frac{23}{14} & -\frac{36}{14} & \frac{3}{14} \end{bmatrix} \begin{bmatrix} \frac{33}{14} \\ \frac{22}{14} \\ \frac{11}{14} \end{bmatrix} = 0 \text{ hence } y - \hat{y} \perp \hat{y}.$$

Q5)

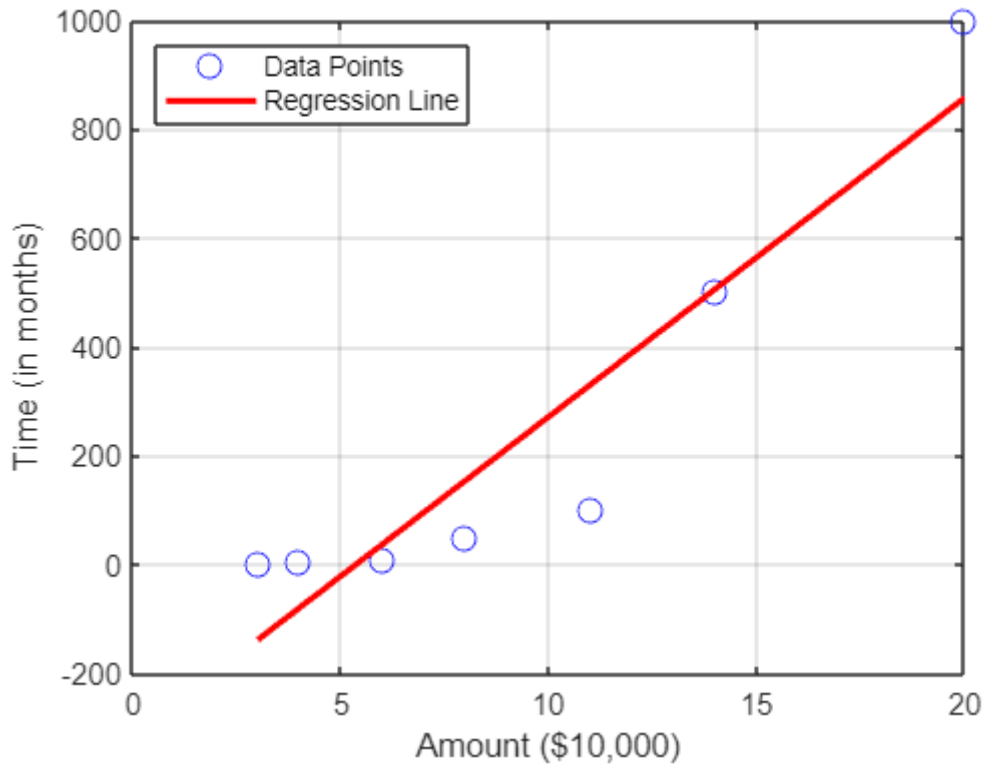


Figure 1 The amount of time for approval vs amount of fund with linear regression model and original data

MATLAB code :

```
x= [3 ;4; 6; 8; 11; 14; 20];
y = [1; 5; 10; 50; 100; 500; 1000];
A = [ones(length(x), 1), x]; % design matrix
R = transpose(A) * A;
R1 = inv(R);
q = transpose(A) * y;
c = (R1)* q;
B0 =c(1); % B0
B1= c(2); % B1
y_predict = B0 + B1*x; % testprediction
figure;
plot(x, y, 'o', 'MarkerSize', 8, 'MarkerEdgeColor', 'b', 'DisplayName', 'Data Points');
hold on;
x_line = linspace(min(x), max(x), 100);
y_line = B0 + B1 * x_line;
plot(x_line, y_line, '-r', 'LineWidth', 2, 'DisplayName', 'Regression Line');
xlabel('Amount ($10,000)');
ylabel('Time (in months)');
legend('Location', 'NorthWest');
grid on;
hold off;
```

Q6)

	1
1	0.0020
2	0.0039
3	1.2732
4	0.0039
5	-6.2958e-06
6	0.0039
7	0.4244
8	0.0039
9	-1.2592e-05
10	0.0039
11	0.2546
12	0.0039
13	-1.8888e-05
14	0.0039
15	0.1819
16	0.0039
17	-2.5184e-05
18	0.0039
19	0.1415
20	0.0039
21	-3.1481e-05

Figure 2 The Fourier coefficients for 10 harmonics

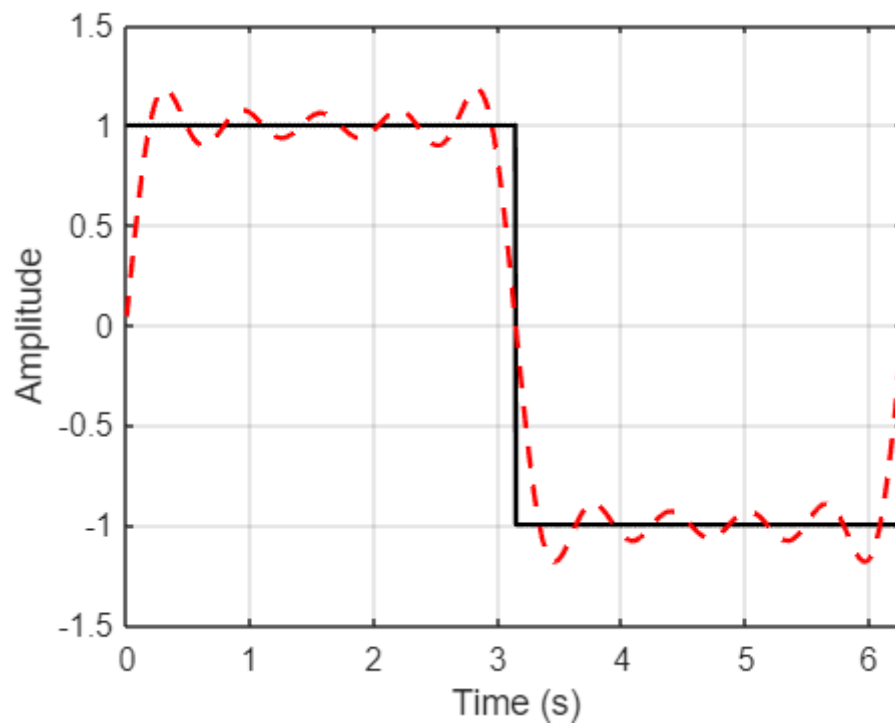


Figure 3 Approximation of the square wave with 10 harmonics

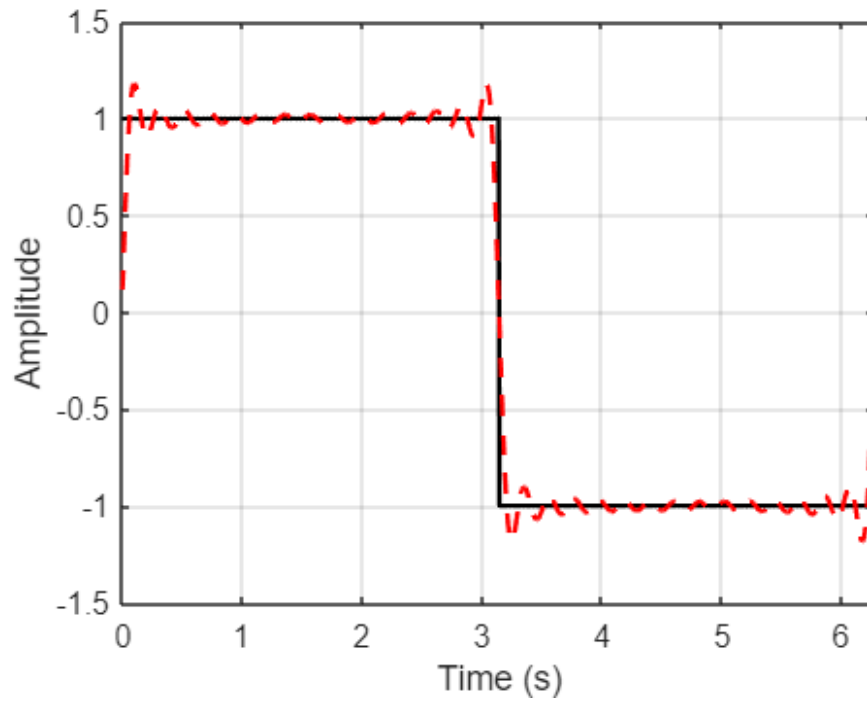


Figure 4 Approximation of the square wave with 30 harmonics

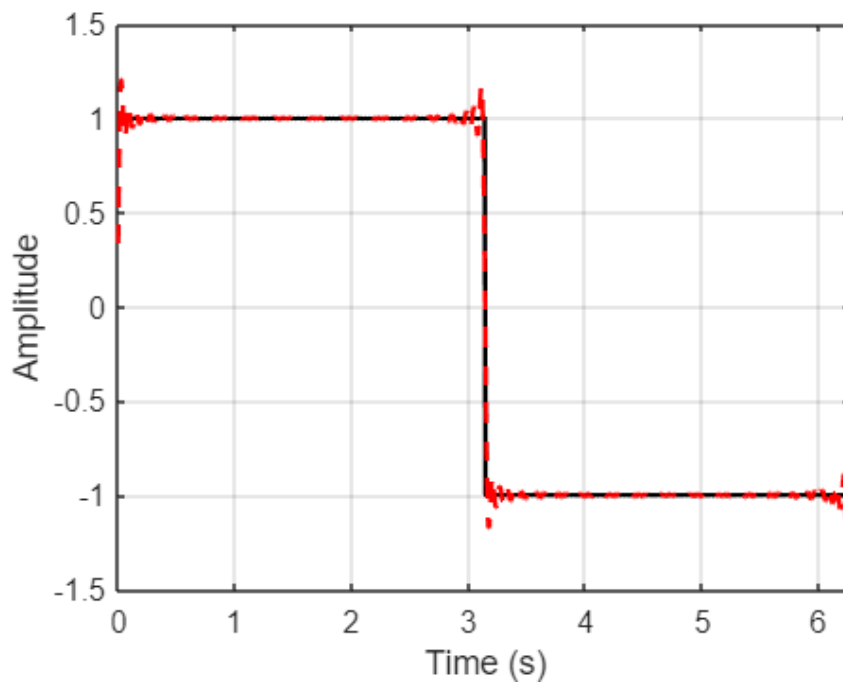


Figure 5 Approximation of the square wave with 100 harmonics

Three different figures are provided above in which 10, 30, and, 100 harmonics are used respectively in order to approximate the square wave periodic with 2π and with a ranging amplitude from -1 to 1. It is clearly observable from the figures that, as number of harmonics increases the the approximation fits better to the square wave. To explain this, think the design matrix A as the feature matrix where each of the harmonics represent a feature which are independent from each other. As the number of features increase the model is more likely to fit to the features of the desired square wave shape in a logical sense. Hence, as we increase the number of harmonics the approximation becomes more accurate.

MATLAB code :

```
T = 2 * pi;
omega = 2 * pi / T;
t = linspace(0, T, 1000);
num_coeff = 100;
square_wave = zeros(size(t));
for i = 1:length(t)
    if mod(t(i), T) < T/2
        square_wave(i) = 1;
    else
        square_wave(i) = -1;
    end
end
A = ones(length(t), 2 * num_coeff + 1);
for k = 1:num_coeff
    A(:, 2*k) = cos(k * omega * t);
    A(:, 2*k + 1) = sin(k * omega * t);
end
R = transpose(A) * A;
R1 = inv(R);
q = transpose(A) * transpose(square_wave);
coeff = (R1) * q;
approx = A * coeff;
plot(t, square_wave, 'k', 'LineWidth', 1.5, 'DisplayName', 'Original Square Wave');
hold on;
plot(t, approx, 'r--', 'LineWidth', 1.5, 'DisplayName', sprintf('Approximation with %d Harmonics', num_coeff));
xlabel('Time (s)');
ylabel('Amplitude');
grid on;
hold off;
```