

Fabian Figueroa

Professor Stephen Pena

Applied Linear Algebra

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Project 1

Part 1:

For the creation of a random time series with noise, the provided code by professor was utilised.

```
t = np.arange(0, np.pi + 0.1, 0.1)
clean_signal = np.cos(np.pi * t) * t
noise_level = np.std(clean_signal) / np.random.rand()
x = clean_signal + noise_level * np.random.randn(len(t))
x_interp = interp1d(t, x, kind='linear', bounds_error=False, fill_value="extrap")
```

Utilisation of given code to generate a random time series

Part 2:

For the implementation of the integral calculation, the NumPy trapez function was leveraged. This function utilizes the *Trapezoid Rule* to calculate an integral.

$$\text{Trapezoidal Rule for Numerical Integration } \int_a^b f(x) dx \approx \frac{b-a}{2n} \sum_{k=0}^n (f(x_k) + f(x_{k+1}))$$

```
# Compute Gram matrix A (G) (6x6) and vector b (6x1)
G = np.zeros((6, 6))
b = np.zeros(6)

for i in range(6):
    for j in range(6):
        # Inner product: A[i,j] = ∫ u_i(t) u_j(t) dt
        integrand = lambda t: basis_funcs(t, i) * basis_funcs(t, j)
        G[i, j] = np.trapez(integrand(t), t)

    # Projection: b[i] = ∫ x_interp(t) u_i(t) dt
    integrand_b = lambda t: x_interp(t) * basis_funcs(t, i)
    b[i] = np.trapez(integrand_b(t), t)

# Solve Ac = b for coefficients (required for projection)
coefficients = np.linalg.solve(G, b)

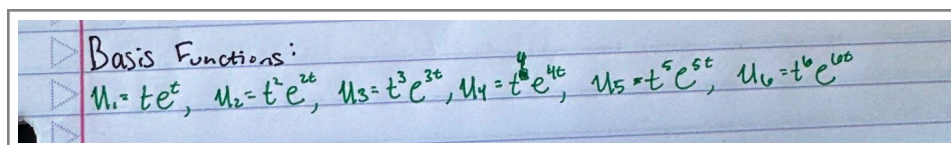
# Reconstruct approximation
approximation = np.zeros_like(t)
for i in range(6):
    approximation += coefficients[i] * basis_funcs(t, i)
```

NumPy's trapez function being utilised within the matrix calculation

Part 3:

For my basis functions, I chose to use the following:

$$u_n(t) = t^n \cdot e^{nt}, n \in \{1, 2, 3, 4, 5, 6\}$$



Basis Functions:
 $u_1 = te^t, u_2 = t^2e^{2t}, u_3 = t^3e^{3t}, u_4 = t^4e^{4t}, u_5 = t^5e^{5t}, u_6 = t^6e^{6t}$

Written portion of basis functions chosen

```

# Define new basis functions {t·et, t2·e2t, ..., t6·e6t}
def basis_funcs(t, index):
    n = index + 1 # n = 1, 2, ..., 6
    return (t ** n) * np.exp(n * t)

```

Code snapshot of implementation for chosen basis functions

Part 5:

To formulate the linear system of the chosen basis functions I set up a matrix that receives the inner products of $\langle u_i, u_j \rangle$, $i, j \in \{1, 2, 3, 4, 5, 6\}$, for each element of the 6x6 matrix.

$$\begin{bmatrix}
 \langle u_1, u_1 \rangle & \langle u_1, u_2 \rangle & \langle u_1, u_3 \rangle & \langle u_1, u_4 \rangle & \langle u_1, u_5 \rangle & \langle u_1, u_6 \rangle \\
 \langle u_2, u_1 \rangle & \langle u_2, u_2 \rangle & \langle u_2, u_3 \rangle & \langle u_2, u_4 \rangle & \langle u_2, u_5 \rangle & \langle u_2, u_6 \rangle \\
 \langle u_3, u_1 \rangle & \langle u_3, u_2 \rangle & \langle u_3, u_3 \rangle & \langle u_3, u_4 \rangle & \langle u_3, u_5 \rangle & \langle u_3, u_6 \rangle \\
 \langle u_4, u_1 \rangle & \langle u_4, u_2 \rangle & \langle u_4, u_3 \rangle & \langle u_4, u_4 \rangle & \langle u_4, u_5 \rangle & \langle u_4, u_6 \rangle \\
 \langle u_5, u_1 \rangle & \langle u_5, u_2 \rangle & \langle u_5, u_3 \rangle & \langle u_5, u_4 \rangle & \langle u_5, u_5 \rangle & \langle u_5, u_6 \rangle \\
 \langle u_6, u_1 \rangle & \langle u_6, u_2 \rangle & \langle u_6, u_3 \rangle & \langle u_6, u_4 \rangle & \langle u_6, u_5 \rangle & \langle u_6, u_6 \rangle
 \end{bmatrix}$$

Latex implementation of written matrix for clarity

Example computation of an inner product:
 Choosing u_2 and u_3 to compute inner product, we have:
 $\langle u_2, u_3 \rangle = \int_a^b u_2(t) u_3(t) dt$, where u_2 and u_3 are two integrable functions on $[a, b]$ and $\int_a^b u_2(t) u_3(t) dt$ is an inner product equating to $\int_a^b t^2 e^{it} \cdot t^3 e^{3it} dt$

Formulating a linear system:
 To formulate the linear system of the chosen basis functions you will set up a matrix that takes the inner product of $\langle u_i, u_j \rangle$ for each element:

$\langle u_1, u_1 \rangle$	$\langle u_1, u_2 \rangle$	$\langle u_1, u_3 \rangle$	$\langle u_1, u_4 \rangle$	$\langle u_1, u_5 \rangle$	$\langle u_1, u_6 \rangle$
$\langle u_2, u_1 \rangle$	$\langle u_2, u_2 \rangle$	$\langle u_2, u_3 \rangle$	$\langle u_2, u_4 \rangle$	$\langle u_2, u_5 \rangle$	$\langle u_2, u_6 \rangle$
$\langle u_3, u_1 \rangle$	$\langle u_3, u_2 \rangle$	$\langle u_3, u_3 \rangle$	$\langle u_3, u_4 \rangle$	$\langle u_3, u_5 \rangle$	$\langle u_3, u_6 \rangle$
$\langle u_4, u_1 \rangle$	$\langle u_4, u_2 \rangle$	$\langle u_4, u_3 \rangle$	$\langle u_4, u_4 \rangle$	$\langle u_4, u_5 \rangle$	$\langle u_4, u_6 \rangle$
$\langle u_5, u_1 \rangle$	$\langle u_5, u_2 \rangle$	$\langle u_5, u_3 \rangle$	$\langle u_5, u_4 \rangle$	$\langle u_5, u_5 \rangle$	$\langle u_5, u_6 \rangle$
$\langle u_6, u_1 \rangle$	$\langle u_6, u_2 \rangle$	$\langle u_6, u_3 \rangle$	$\langle u_6, u_4 \rangle$	$\langle u_6, u_5 \rangle$	$\langle u_6, u_6 \rangle$

Written 6x6 matrix and example computation for the inner products of $\langle u_i, u_j \rangle$

```
G = np.zeros((6, 6))
b = np.zeros(6)

for i in range(6):
    for j in range(6):
        # Inner product: G[i,j] = ∫ u_i(t) u_j(t) dt
        integrand = lambda t: basis_funcs(t, i) * basis_funcs(t, j)
        G[i, j] = np.trapz(integrand(t), t)

    # Projection: b[i] = ∫ x_interp(t) u_i(t) dt
    integrand_b = lambda t: x_interp(t) * basis_funcs(t, i)
    b[i] = np.trapz(integrand_b(t), t)

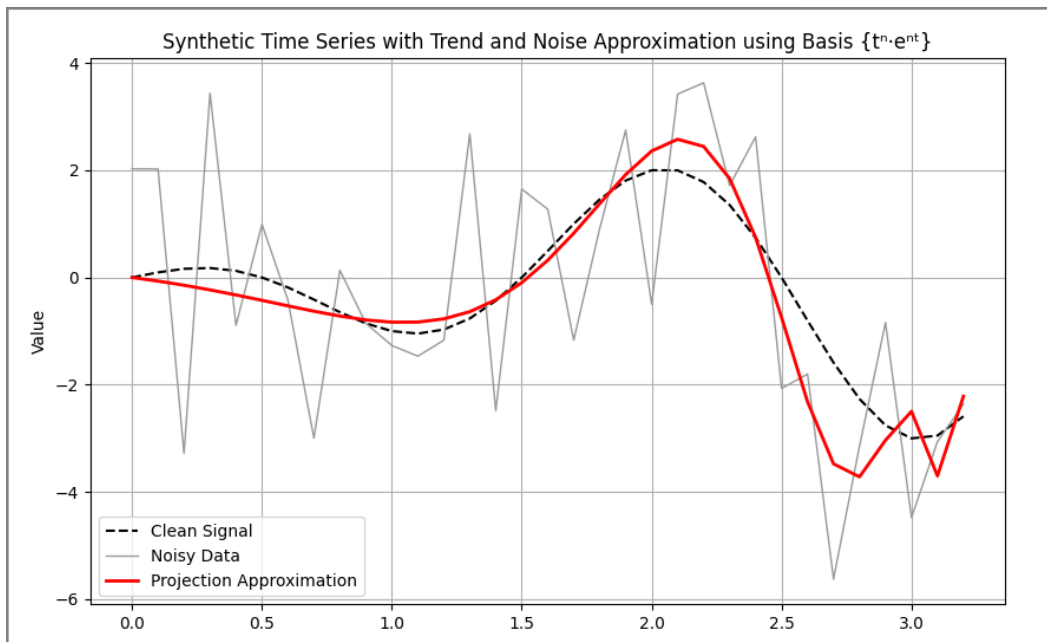
# Solve Gc = b for coefficients (required for projection)
coefficients = np.linalg.solve(G, b)
```

Code snapshot of the implementation and calculation of matrix and inner products for each element

Part 6:

For the approximation of the randomly generated time series the inner product of each element was calculated and then used to solve $Ax = b$ for coefficients.

Programme Output



Synthetic time series approximation using 6 basis functions; $u_n(t) = t^n \cdot e^{nt}$, $n \in \{1, 2, 3, 4, 5, 6\}$

```
# Compute Gram matrix A (G) (6x6) and vector b (6x1)
G = np.zeros((6, 6))
b = np.zeros(6)

for i in range(6):
    for j in range(6):
        # Inner product: A[i,j] = ∫ u_i(t) u_j(t) dt
        integrand = lambda t: basis_funcs(t, i) * basis_funcs(t, j)
        G[i, j] = np.trapz(integrand(t), t)

    # Projection: b[i] = ∫ x_interp(t) u_i(t) dt
    integrand_b = lambda t: x_interp(t) * basis_funcs(t, i)
    b[i] = np.trapz(integrand_b(t), t)

# Solve Ac = b for coefficients (required for projection)
coefficients = np.linalg.solve(G, b)

# Reconstruct approximation
approximation = np.zeros_like(t)
for i in range(6):
    approximation += coefficients[i] * basis_funcs(t, i)
```

Code snapshot showing implementation of coefficient calculation

Whole Programme:

```

import numpy as np
import matplotlib.pyplot as plt
from scipy.interpolate import interp1d

# Define basis functions  $\{t \cdot e^t, t^2 \cdot e^{2t}, \dots, t^6 \cdot e^{6t}\}$ 
def basis_funcs(t, index):
    n = index + 1 # n = 1, 2, ..., 6
    return (t ** n) * np.exp(n * t)

# Generate noisy data (identical to original)
t = np.arange(0, np.pi + 0.1, 0.1)
clean_signal = np.cos(np.pi * t) * t
noise_level = np.std(clean_signal) / np.random.rand()
x = clean_signal + noise_level * np.random.randn(len(t))
x_interp = interp1d(t, x, kind='linear', bounds_error=False, fill_value="extrap")

# Compute Gram matrix A (G) (6x6) and vector b (6x1)
G = np.zeros((6, 6))
b = np.zeros(6)

for i in range(6):
    for j in range(6):
        # Inner product:  $A[i,j] = \int u_i(t) u_j(t) dt$ 
        integrand = lambda t: basis_funcs(t, i) * basis_funcs(t, j)
        G[i, j] = np.trapz(integrand(t), t)

    # Projection:  $b[i] = \int x\_interp(t) u_i(t) dt$ 
    integrand_b = lambda t: x_interp(t) * basis_funcs(t, i)
    b[i] = np.trapz(integrand_b(t), t)

# Solve  $Ac = b$  for coefficients (required for projection)
coefficients = np.linalg.solve(G, b)

# Reconstruct approximation
approximation = np.zeros_like(t)
for i in range(6):
    approximation += coefficients[i] * basis_funcs(t, i)

# Plot results (same as original)
plt.figure(figsize=(10, 6))
plt.grid(True)
plt.plot(t, clean_signal, 'k--', linewidth=1.5, label='Clean Signal')
plt.plot(t, x, color=[0.6, 0.6, 0.6], linewidth=1, label='Noisy Data')
plt.plot(t, approximation, 'r-', linewidth=2, label='Projection Approximation')
plt.title('Synthetic Time Series with Trend and Noise Approximation using Basis  $\{t^n \cdot e^{nt}\}$ ')
plt.xlabel('Time (t)')
plt.ylabel('Value')
plt.legend(loc='best')
plt.show()

```