S223696915
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Correlation Analysis Documentation

Objective

The objective of this analysis is to explore and identify correlations between multiple time-series sensor readings (s1, s2, and s3) using statistical and visualization techniques. We aim to uncover any temporal relationships and synchronization patterns among these signals.

Tools and Libraries Used

- Python 3.x
- Pandas – for data manipulation
- NumPy – for numerical computations
- Matplotlib – for plotting
- Seaborn – for advanced statistical visualization

Dataset Overview

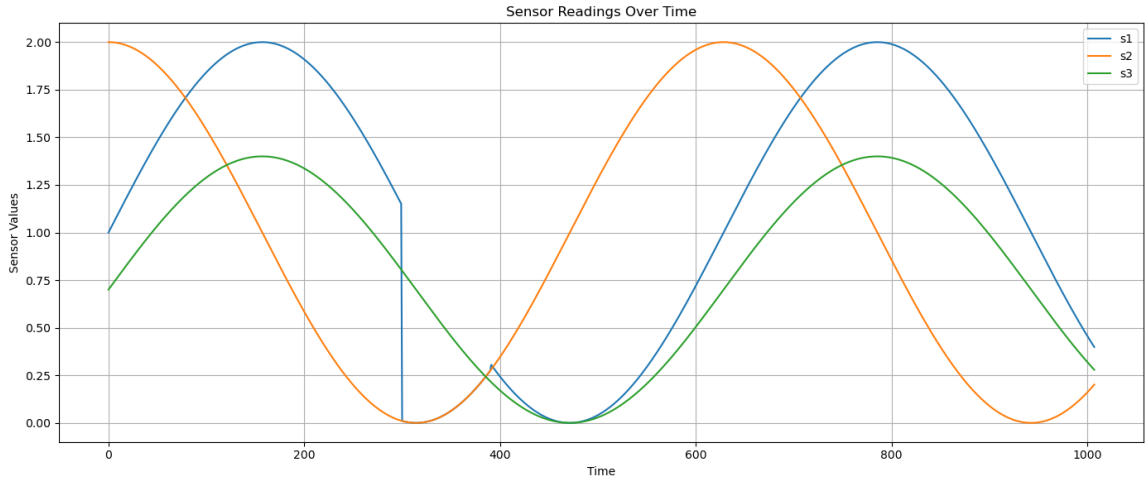
- File: complex.csv
- Shape: 1008 rows × 4 columns
- Columns: time, s1, s2, s3
- Missing Values: None
- Data Types:
  - time: int64
  - s1, s2, s3: float64

Data Cleaning

- Stripped any leading/trailing whitespaces from column names.
- Confirmed absence of missing values using df.isnull().sum().

Visual Exploration

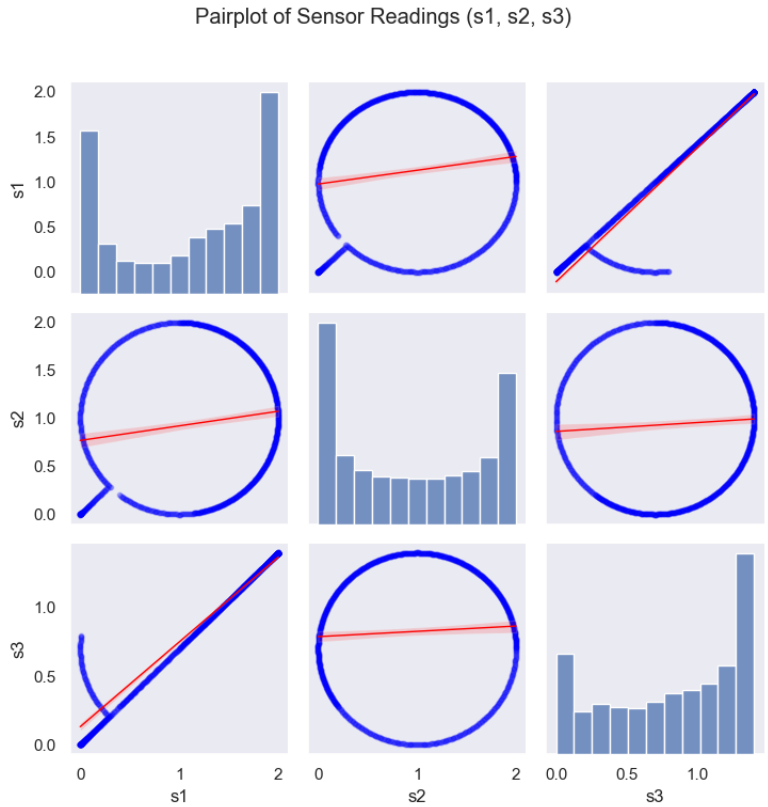
1. Line Plot of Sensor Readings Over Time
   - Each of the sensors (s1, s2, s3) was plotted against the time column to observe their temporal behavior.



s2 remains nearly constant, while s1 and s3 exhibit dynamic and upward-trending patterns respectively.

2. Pairplot

- Used seaborn.pairplot to explore relationships and correlations between the three sensor readings.



- Strong linear correlation between s1 and s3.

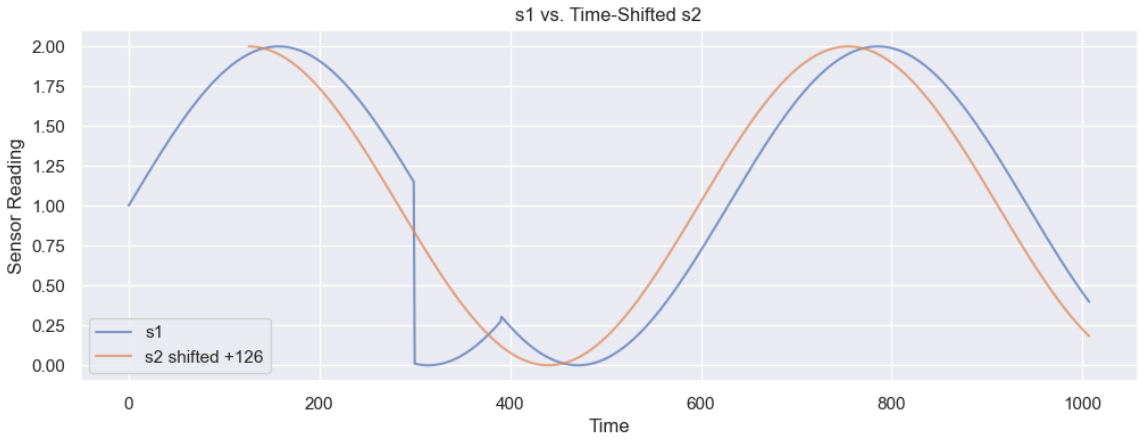
- Circular/elliptical patterns between s1 vs s2 and s2 vs s3, suggesting phase-shifted signals.
- Diagonal histograms show:
    - s1 and s2: Possibly bimodal due to oscillatory nature.
    - s3: Right-skewed, aligning with its cumulative trend.

Cross-Correlation Analysis

• Purpose: To identify the lag (time shift) where two signals (s1 and s2) are most strongly correlated.
• Process:
- Centered the signals by subtracting the mean.
- Used np.correlate() with mode='full'.
- Found max correlation at lag = 126.

Shifted Plot Comparison

• s2 was shifted by +126 time units.
• Visual inspection confirmed the alignment with s1, validating the computed lag.



Heatmap of Correlation Coefficients

• Correlation matrix computed and visualized using seaborn heatmap.
• s1 vs s2: Strong positive correlation
• s1 vs s3, s2 vs s3: Lower or moderate correlation

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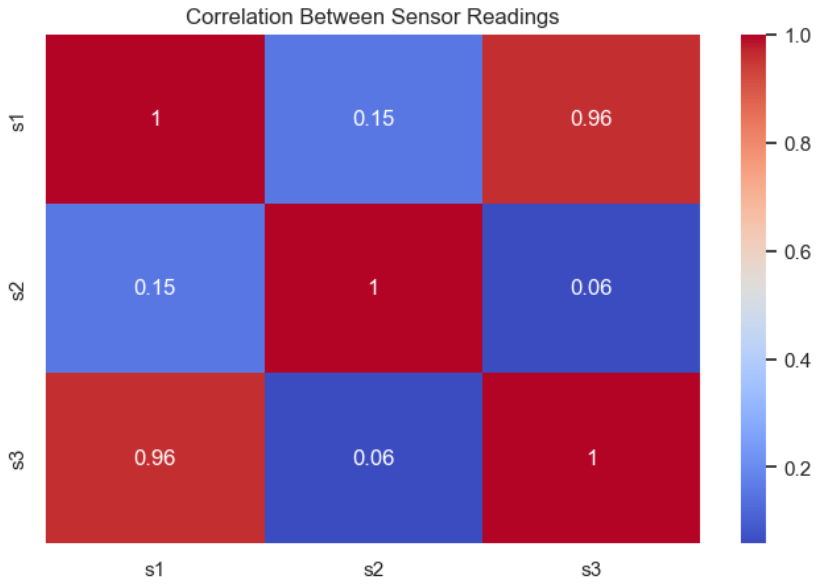


Key Findings

- No missing values or anomalies.
- s1 and s2 show a strong correlation with a time lag of 126
- Correlation heatmap supports the finding.
- s1: Shows periodic behavior
- s3: Cumulative or trending behavior
- s2: Likely a reference signal, flat and independent
- High correlation between s1 and s3, potential causality or shared origin
- s2 may be a phase-shifted version or control for comparison

Correlation Analysis

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```
df=pd.read_csv(r"D:\iot\complex.csv")
df.head()
```

[2]:

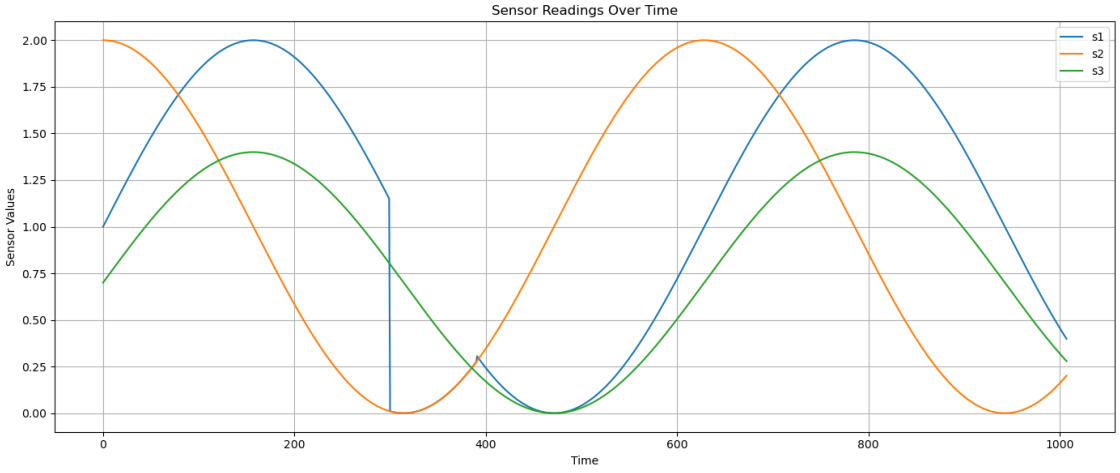
	time	s1	s2	s3
0	0	1.000000	2.00000	0.700000
1	1	1.010000	1.99995	0.707000
2	2	1.019999	1.99980	0.713999
3	3	1.029996	1.99955	0.720997
4	4	1.039989	1.99920	0.727993

[3]:
```
print("Data Overview:")
print(df.info())
print("\nMissing Values:")
print(df.isnull().sum())
```

```
Data Overview:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1008 entries, 0 to 1007
Data columns (total 4 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   time    1008 non-null   int64
 1    s1     1008 non-null   float64
 2    s2     1008 non-null   float64
 3    s3     1008 non-null   float64
dtypes: float64(3), int64(1)
memory usage: 31.6 KB
None

Missing Values:
time    0
 s1     0
 s2     0
```

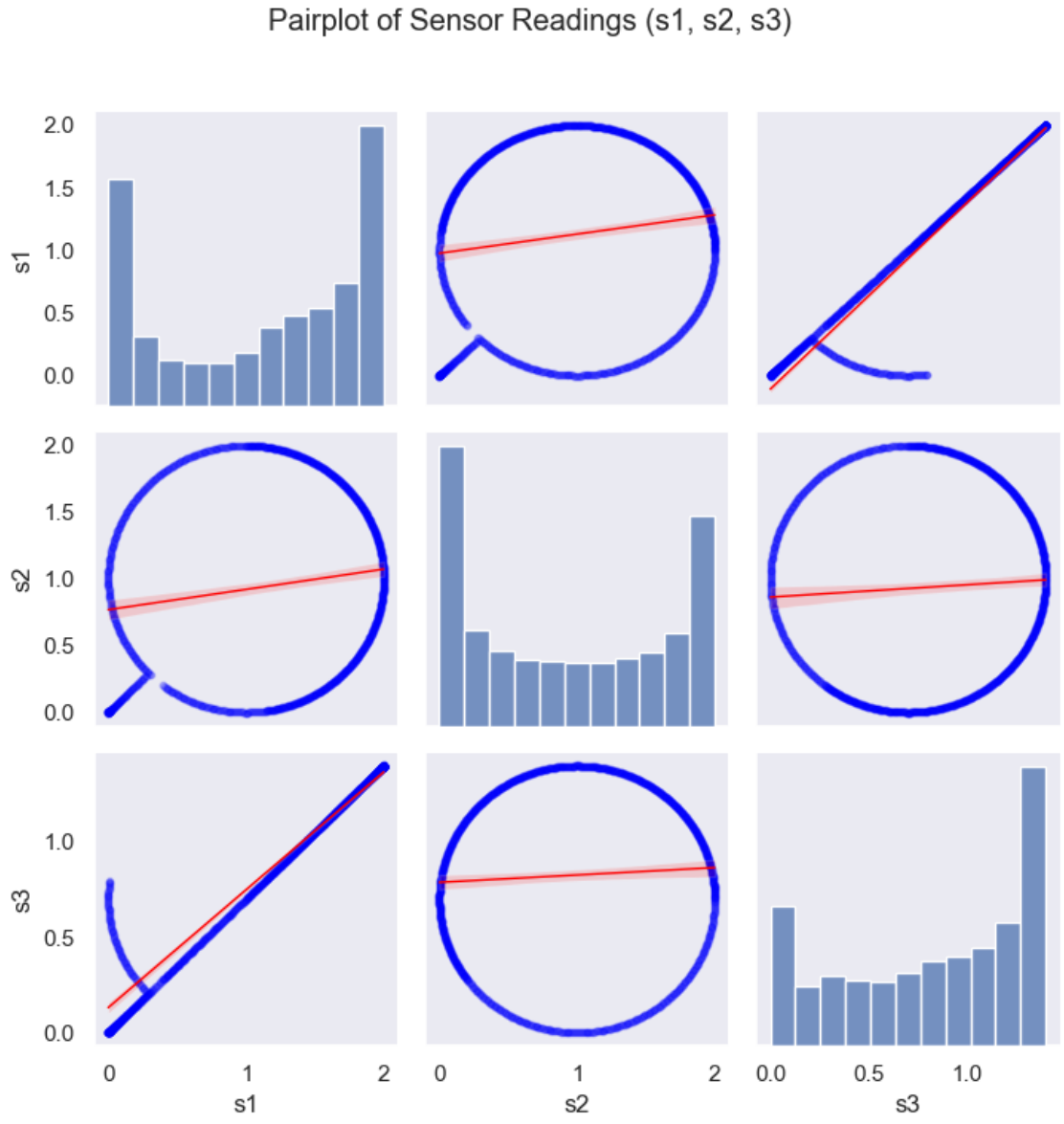
```
 s3     0
dtype: int64
```

[4]:
```
# Remove any leading/trailing whitespace from column names
df.columns = df.columns.str.strip()

# Plot sensor readings over time
plt.figure(figsize=(14, 6))

# List of columns to plot
sensor_cols = ['s1', 's2', 's3']

# Plot each sensor column if it exists in the DataFrame
for col in sensor_cols:
    if col in df.columns:
        plt.plot(df['time'], df[col], label=col)
    else:
        print(f"Column '{col}' not found in DataFrame.")

# Add plot details
plt.legend()
plt.title("Sensor Readings Over Time")
plt.xlabel("Time")
plt.ylabel("Sensor Values")
plt.grid(True)
plt.tight_layout()
plt.show()
```



[5]:
```
# Set seaborn theme
sns.set_theme(style="dark")
```

```python
# Define columns to plot
sensor_cols = ['s1', 's2', 's3']

# Create pairplot
g = sns.pairplot(
    df[sensor_cols],
    kind='reg',
    diag_kind='auto',
    plot_kws={
        'scatter_kws': {'s': 10, 'alpha': 0.2, 'color': 'blue'},
        'line_kws': {'color': 'red', 'linewidth': 1}
    }
)

# Add title
g.fig.suptitle("Pairplot of Sensor Readings (s1, s2, s3)", y=1.02)
plt.tight_layout()
plt.show()
```

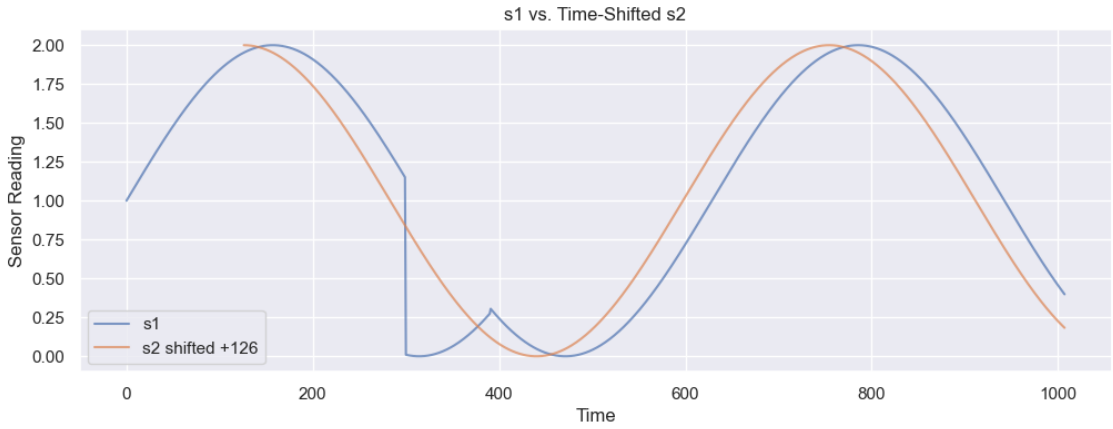


[6]:
```
# Ensure 's1' and 's2' exist and are numeric
x = df['s1'] - df['s1'].mean()
y = df['s2'] - df['s2'].mean()

# Compute full cross-correlation
corr = np.correlate(x, y, mode='full')

# Create lags array
lags = np.arange(-len(x) + 1, len(x))

# Find lag where correlation is maximum
```

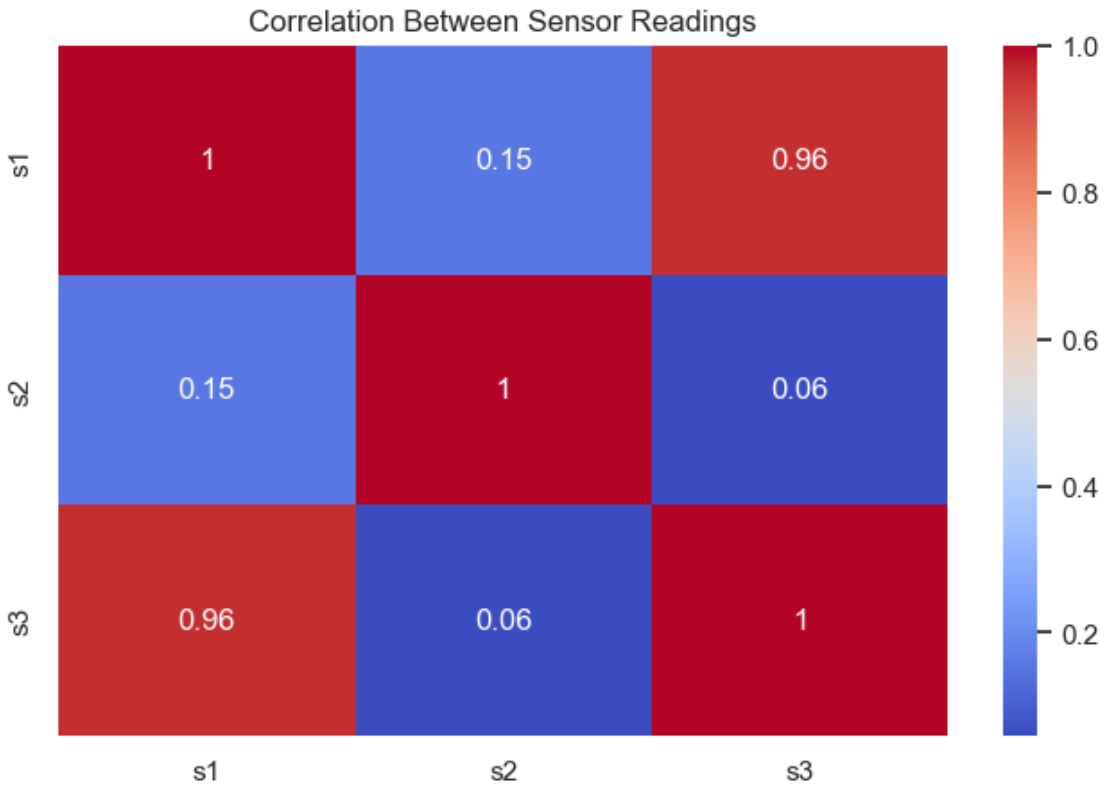
```
lag = lags[np.argmax(corr)]

print(f"Max correlation occurs at lag = {lag}")
```

```
Max correlation occurs at lag = 126
```

[7]:
```
plt.figure(figsize=(12, 4))

# Plot s1
plt.plot(df['s1'], label='s1', alpha=0.7)

# Plot s2 shifted by +126
plt.plot(df['s2'].shift(126), label='s2 shifted +126', alpha=0.7)

# Add plot details
plt.legend()
plt.title('s1 vs. Time-Shifted s2')
plt.xlabel('Time')
plt.ylabel('Sensor Reading')
plt.grid(True)
plt.show()
```



[8]:
```
# Correlation heatmap
plt.figure(figsize=(8, 5))
sns.heatmap(df[['s1', 's2', 's3']].corr(), annot=True, cmap='coolwarm')
plt.title("Correlation Between Sensor Readings")
plt.show()
```


Correlation Between Sensor Readings
s1
s2
s3
1
0.15
0.96
0.15
1
0.06
0.96
0.06
1
s1
s2
s3
1.0
0.8
0.6
0.4
0.2