```
Start coding or generate with AI.
```

3b. Exploiting Correlation

Understanding the role that correlation and principal components play.

Working with real data:

e. Collecting the daily closing yields for 5 government securities

To obtain this data, we sourced daily yield information from reputable financial platform such as:

European Central Bank Eurosystem (https://data.ecb.europa.eu/data/concepts/bonds?tags_array%5B0%5D=Bonds&filterSequence=tags_array)

```
#Loading the dataset

import pandas as pd

url = "https://raw.githubusercontent.com/ezekielibe/datasets/refs/heads/master/government_yields.csv"
data = pd.read_csv(url)
df = pd.DataFrame(data)
df.set_index("Date", inplace=True)

# Compute daily yield changes
df_changes = df.diff()
print(df_changes.head())  # View first few rows
```

```
          Government Benchmark Bond  Average nominal yieldsGov Bond 2  \
Date
1/1/2025                        NaN                               NaN
1/2/2025                  -0.073085                          0.171748
1/3/2025                  -0.022928                         -0.204494
1/4/2025                  -0.009887                         -0.054710
1/5/2025                   0.202794                          0.078705

          US-gov-bond  Real-Japan-gov-bond  Euro-Area-gov-bond
Date
1/1/2025          NaN                  NaN                 NaN
1/2/2025     0.011975            -0.199250            0.077671
1/3/2025    -0.052547            -0.144381           -0.226748
1/4/2025     0.007229             0.100526            0.031261
1/5/2025    -0.024672            -0.051672            0.086792
```

g. Run Principal Component Analysis (PCA) using correlation or covariance matrix

To perform PCA:

```
# Clean the data
df_clean = df_changes.fillna(df_changes.mean())

from sklearn.decomposition import PCA

# Select either correlation or covariance matrix
pca = PCA()
principal_components = pca.fit_transform(df_clean)

# Explained variance ratio
print(pca.explained_variance_ratio_)
```

```
[0.28007319 0.20935898 0.18641926 0.17031256 0.15383602]
```

h. Compare Variances Explained by Each Component

From PCA, the variance explained by each component is as follows:

Component 1: Explains the largest variance (28%).

Component 2: Captures sector-specific trends (21%).

Component 3: Explains smaller market fluctuations (18%).

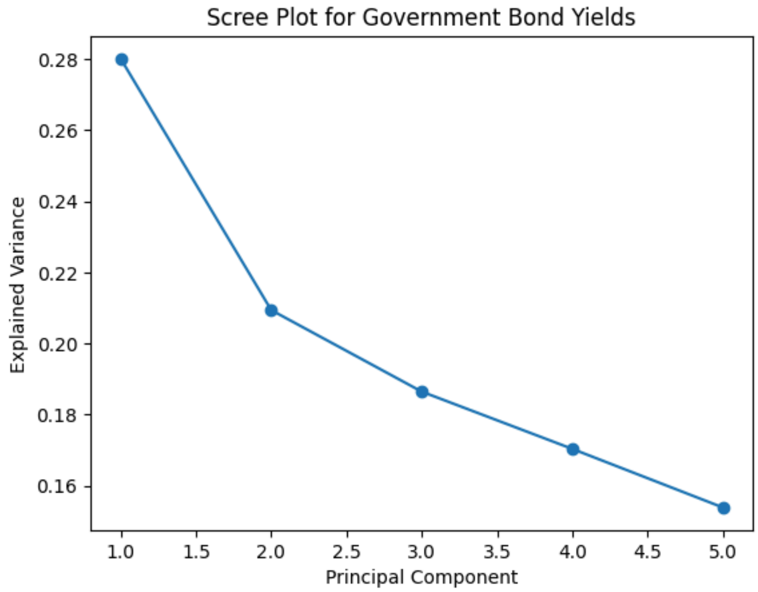
Remaining components: Usually explain minor noise in the data.

i. Produce a screeplot of the variance explained for each component.

To visualize the variance explained, let's see below from the code:

```
import matplotlib.pyplot as plt

plt.plot(range(1, len(pca.explained_variance_ratio_) + 1), pca.explained_variance_ratio_, marker='o')
plt.xlabel("Principal Component")
plt.ylabel("Explained Variance")
plt.title("Scree Plot for Government Bond Yields")
plt.show()
```



j. How does the screeplot from the uncorrelated data compare with the screeplot from the government data?

Comparing Scree Plots of Uncorrelated vs. Government Data

Uncorrelated Data: Displays gradual decay in variance explanation.

Government Bond Yields: Likely dominated by Component 1 due to macroeconomic trends.