

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
```

```
In [2]: # Define column names (First 6 columns are metadata, rest are genotypic data)
col_names = ["Family_ID", "Individual_ID", "Paternal_ID", "Maternal_ID", "Sex", "Phenotype"]

# Loads only first 6 metadata columns
df_metadata = pd.read_csv("donors.ped", delim_whitespace=True, names=col_names, usecols=range(6))

# Display first few rows
print(df_metadata.head())
```

	Family_ID	Individual_ID	Paternal_ID	Maternal_ID	Sex	Phenotype
0	1	4023	0	0	0	-9
1	1	4313	0	0	0	-9
2	1	4054	0	0	0	-9
3	1	4165	0	0	0	-9
4	1	4373	0	0	0	-9

```
In [3]: df_full = pd.read_csv("donors.ped", delim_whitespace=True, header=None)

# Assign column names (first 6 are metadata, rest are SNPs)
metadata_cols = ["Family_ID", "Individual_ID", "Paternal_ID", "Maternal_ID", "Sex", "Phenotype"]
snps_cols = [f"SNP_{i}" for i in range(1, len(df_full.columns) - 5)] # SNPs start from column 7
df_full.columns = metadata_cols + snps_cols

# Display first few rows
print(df_full.head())
```

	Family_ID	Individual_ID	Paternal_ID	Maternal_ID	Sex	Phenotype	SNP_1	\
0	1	4023	0	0	0	-9	G	
1	1	4313	0	0	0	-9	A	
2	1	4054	0	0	0	-9	G	
3	1	4165	0	0	0	-9	G	
4	1	4373	0	0	0	-9	G	

	SNP_2	SNP_3	SNP_4	...	SNP_26507	SNP_26508	SNP_26509	SNP_26510	SNP_26511	\
0	A	G	A	...	A	A	G	A	A	
1	A	G	A	...	A	A	A	A	A	
2	A	A	A	...	A	A	A	A	A	
3	A	G	A	...	A	A	G	G	A	
4	A	G	A	...	A	A	A	A	A	

	SNP_26512	SNP_26513	SNP_26514	SNP_26515	SNP_26516
0	A	G	G	G	G
1	A	G	G	G	G
2	A	G	G	G	G
3	A	G	G	G	G
4	A	G	G	G	G

[5 rows x 26522 columns]

```
In [4]: print(df_full.info()) # Check column types
print(df_full.describe()) # Get summary statistics
print(df_full.isnull().sum()) # Check for missing values
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 986 entries, 0 to 985
Columns: 26522 entries, Family_ID to SNP_26516
dtypes: int64(6), object(26516)
memory usage: 199.5+ MB
None

```

	Family_ID	Individual_ID	Paternal_ID	Maternal_ID	Sex	Phenotype
count	986.000000	986.000000	986.0	986.0	986.0	986.0
mean	47.805274	4497.562880	0.0	0.0	0.0	-9.0
std	27.105333	288.401283	0.0	0.0	0.0	0.0
min	1.000000	4000.000000	0.0	0.0	0.0	-9.0
25%	24.000000	4247.250000	0.0	0.0	0.0	-9.0
50%	48.000000	4501.500000	0.0	0.0	0.0	-9.0
75%	70.000000	4747.750000	0.0	0.0	0.0	-9.0
max	96.000000	4994.000000	0.0	0.0	0.0	-9.0
Family_ID	0					
Individual_ID	0					
Paternal_ID	0					
Maternal_ID	0					
Sex	0					
	..					
SNP_26512	0					
SNP_26513	0					
SNP_26514	0					
SNP_26515	0					
SNP_26516	0					

```

Length: 26522, dtype: int64

```

```

In [8]: # Select only SNP columns
snp_data = df_full.iloc[:, 6:] # Excluding metadata columns

# Count unique values (alleles) for each SNP
allele_counts = snp_data.apply(lambda col: col.value_counts())

# Display allele frequencies for first 5 SNPs
print(allele_counts.head())

```

	SNP_1	SNP_2	SNP_3	SNP_4	SNP_5	SNP_6	SNP_7	SNP_8	SNP_9	SNP_10	...	\
0	2.0	2.0	NaN	NaN	1.0	1.0	8.0	8.0	1.0	1.0	...	
A	345.0	816.0	340.0	832.0	428.0	858.0	551.0	120.0	76.0	2.0	...	
C	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	
G	639.0	168.0	646.0	154.0	557.0	127.0	427.0	858.0	909.0	983.0	...	
T	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	

	SNP_26507	SNP_26508	SNP_26509	SNP_26510	SNP_26511	SNP_26512	\
0	NaN	NaN	1.0	1.0	6.0	6.0	
A	757.0	967.0	253.0	724.0	895.0	977.0	
C	NaN	NaN	NaN	NaN	NaN	NaN	
G	229.0	19.0	732.0	261.0	85.0	3.0	
T	NaN	NaN	NaN	NaN	NaN	NaN	

	SNP_26513	SNP_26514	SNP_26515	SNP_26516
0	NaN	NaN	3.0	3.0
A	228.0	20.0	59.0	1.0
C	NaN	NaN	NaN	NaN
G	758.0	966.0	924.0	982.0
T	NaN	NaN	NaN	NaN

[5 rows x 26516 columns]

```
In [9]: # Count missing values in the dataset
missing_values = df_full.isnull().sum()

# Print columns with missing values
print(missing_values[missing_values > 0])

Series([], dtype: int64)
```

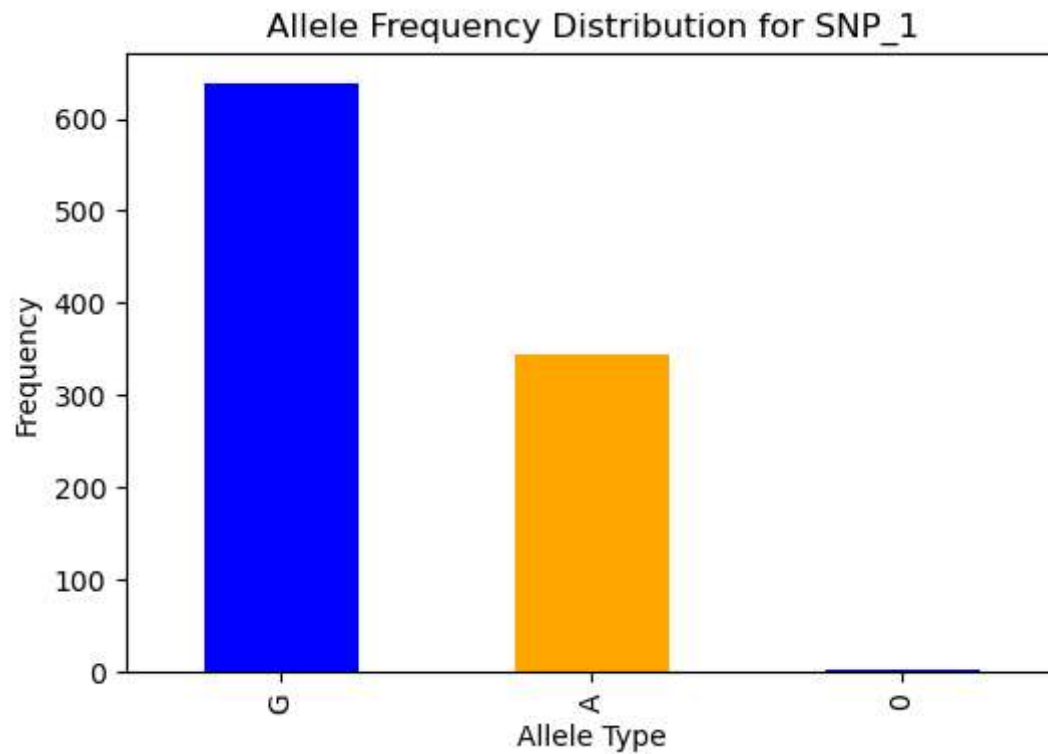
```
In [10]: import matplotlib.pyplot as plt

# Get the first SNP column (example)
snp_column = snp_data.columns[0]

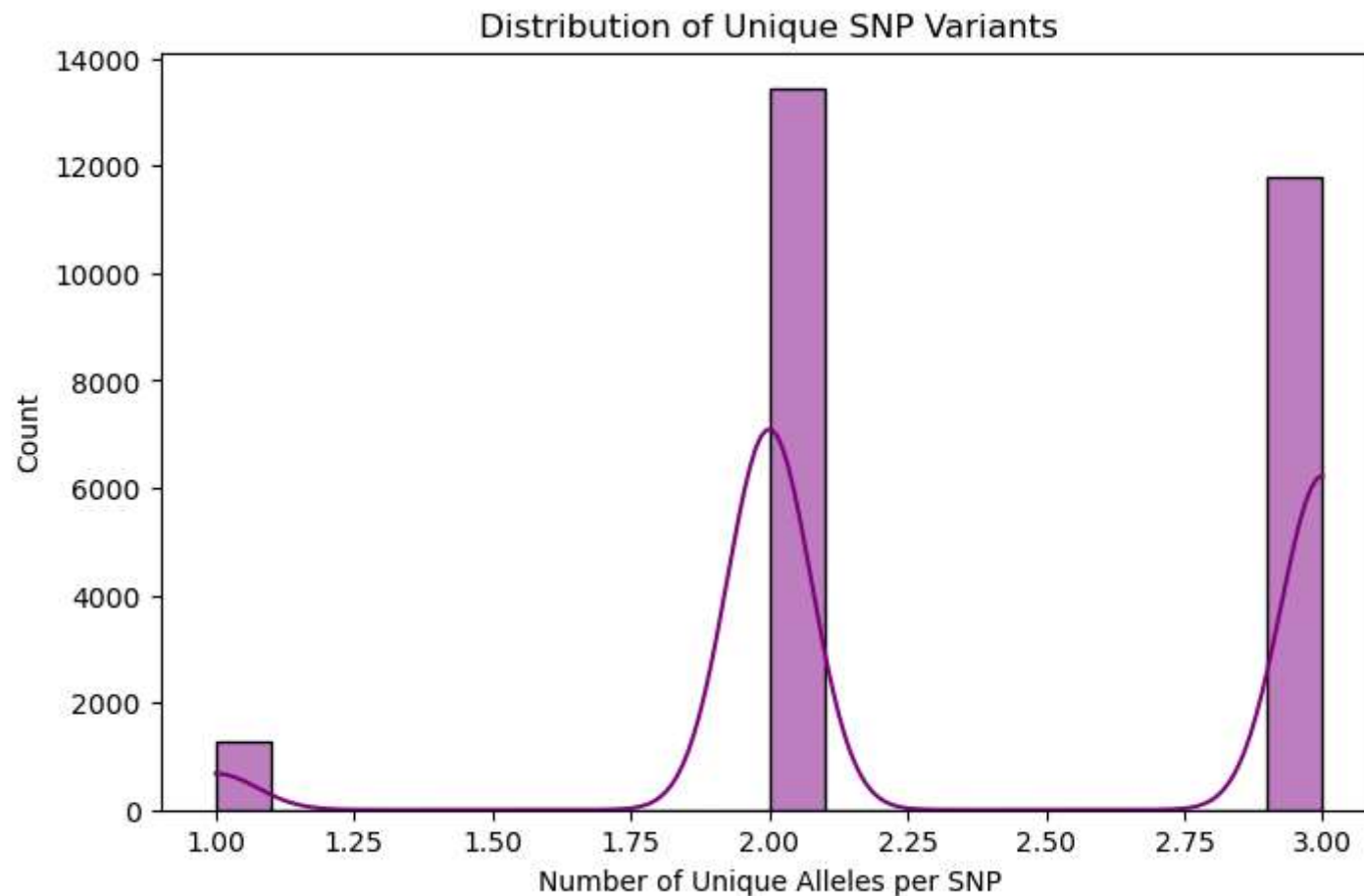
# Count allele occurrences
allele_counts = snp_data[snp_column].value_counts()

# Plot
plt.figure(figsize=(6, 4))
allele_counts.plot(kind='bar', color=['blue', 'orange'])
plt.xlabel("Allele Type")
plt.ylabel("Frequency")
```

```
plt.title(f"Allele Frequency Distribution for {snp_column}")  
plt.show()
```



```
In [11]: import seaborn as sns  
  
# Count the number of unique alleles per SNP  
num_unique_alleles = snp_data.nunique()  
  
# Plot distribution  
plt.figure(figsize=(8, 5))  
sns.histplot(num_unique_alleles, bins=20, kde=True, color="purple")  
plt.xlabel("Number of Unique Alleles per SNP")  
plt.ylabel("Count")  
plt.title("Distribution of Unique SNP Variants")  
plt.show()
```



```
In [12]: df_full.to_csv("processed_genetic_data.csv", index=False)
print("Processed genetic data saved as 'processed_genetic_data.csv'.")
```

Processed genetic data saved as 'processed\_genetic\_data.csv'.

```
In [13]: from sklearn.decomposition import PCA
from sklearn.preprocessing import LabelEncoder, StandardScaler
import numpy as np

# Select only SNP columns (excluding metadata)
snp_data = df_full.iloc[:, 6:].copy()

# Convert allele pairs into numeric values (A/G → 0, G/G → 1, A/A → 2)
def encode_snp(col):
    unique_vals = col.unique()
```

```

mapping = {val: i for i, val in enumerate(unique_vals)}
return col.map(mapping)

# Apply encoding to all SNP columns
snp_encoded = snp_data.apply(encode_snp)

# Standardize data before PCA
scaler = StandardScaler()
snp_scaled = scaler.fit_transform(snp_encoded)

print("SNP data successfully encoded and standardized!")

```

SNP data successfully encoded and standardized!

```

In [14]: # Apply PCA
pca = PCA(n_components=2)
pca_result = pca.fit_transform(snp_scaled)

# Convert to DataFrame
df_pca = pd.DataFrame(pca_result, columns=["PC1", "PC2"])

# Add metadata for visualization
df_pca["Phenotype"] = df_full["Phenotype"]

print(df_pca.head()) # Show first few PCA-transformed rows

```

	PC1	PC2	Phenotype
0	37.905687	-2.344110	-9
1	-17.132511	20.429012	-9
2	40.269471	-2.201245	-9
3	55.590880	-5.874212	-9
4	-21.472823	40.152571	-9

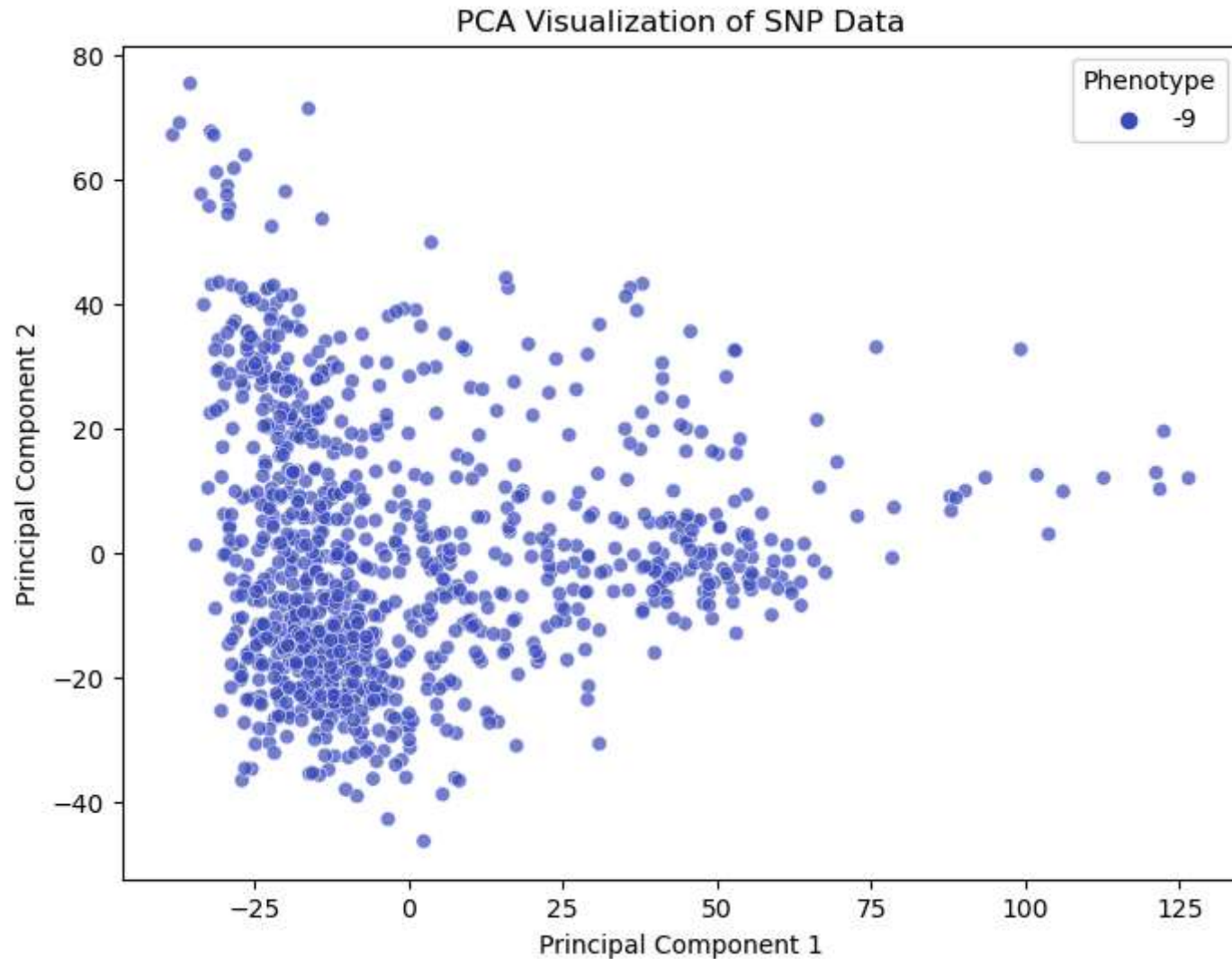
```

In [15]: import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8, 6))
sns.scatterplot(x="PC1", y="PC2", hue=df_pca["Phenotype"], palette="coolwarm", alpha=0.7, data=df_pca)

plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.title("PCA Visualization of SNP Data")
plt.legend(title="Phenotype")
plt.show()

```



```
In [16]: explained_variance = pca.explained_variance_ratio_  
print(f"PC1 explains {explained_variance[0]*100:.2f}% of the variance")  
print(f"PC2 explains {explained_variance[1]*100:.2f}% of the variance")
```

```
PC1 explains 3.07% of the variance  
PC2 explains 1.69% of the variance
```

```
In [17]: from sklearn.decomposition import PCA  
  
# Apply PCA with 3 components  
pca_3d = PCA(n_components=3)
```



```
pca_result_3d = pca_3d.fit_transform(snp_scaled)

# Convert to DataFrame
df_pca_3d = pd.DataFrame(pca_result_3d, columns=["PC1", "PC2", "PC3"])

# Add metadata for visualization
df_pca_3d["Phenotype"] = df_full["Phenotype"]

print(df_pca_3d.head()) # Show first few PCA-transformed rows
```

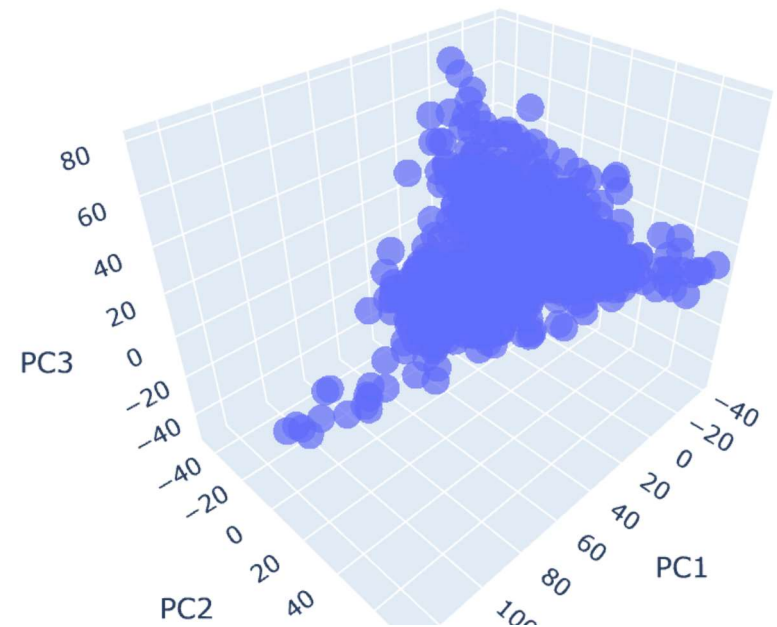
	PC1	PC2	PC3	Phenotype
0	37.905747	-2.336705	-19.484211	-9
1	-17.132508	20.434945	35.855234	-9
2	40.269437	-2.206716	-2.525267	-9
3	55.590880	-5.867082	-8.748254	-9
4	-21.472791	40.142954	-4.625787	-9

In [18]: `import plotly.express as px`

```
# Create a 3D scatter plot
fig = px.scatter_3d(df_pca_3d, x="PC1", y="PC2", z="PC3",
                    color=df_pca_3d["Phenotype"].astype(str), # Convert phenotype to string for color coding
                    title="3D PCA Visualization of SNP Data",
                    labels={"Phenotype": "Phenotype"},
                    opacity=0.7)

fig.show()
```

## 3D PCA Visualization of SNP Data



```
In [19]: explained_variance = pca_3d.explained_variance_ratio_  
print(f"PC1 explains {explained_variance[0]*100:.2f}% of the variance")  
print(f"PC2 explains {explained_variance[1]*100:.2f}% of the variance")  
print(f"PC3 explains {explained_variance[2]*100:.2f}% of the variance")
```

PC1 explains 3.07% of the variance

PC2 explains 1.69% of the variance

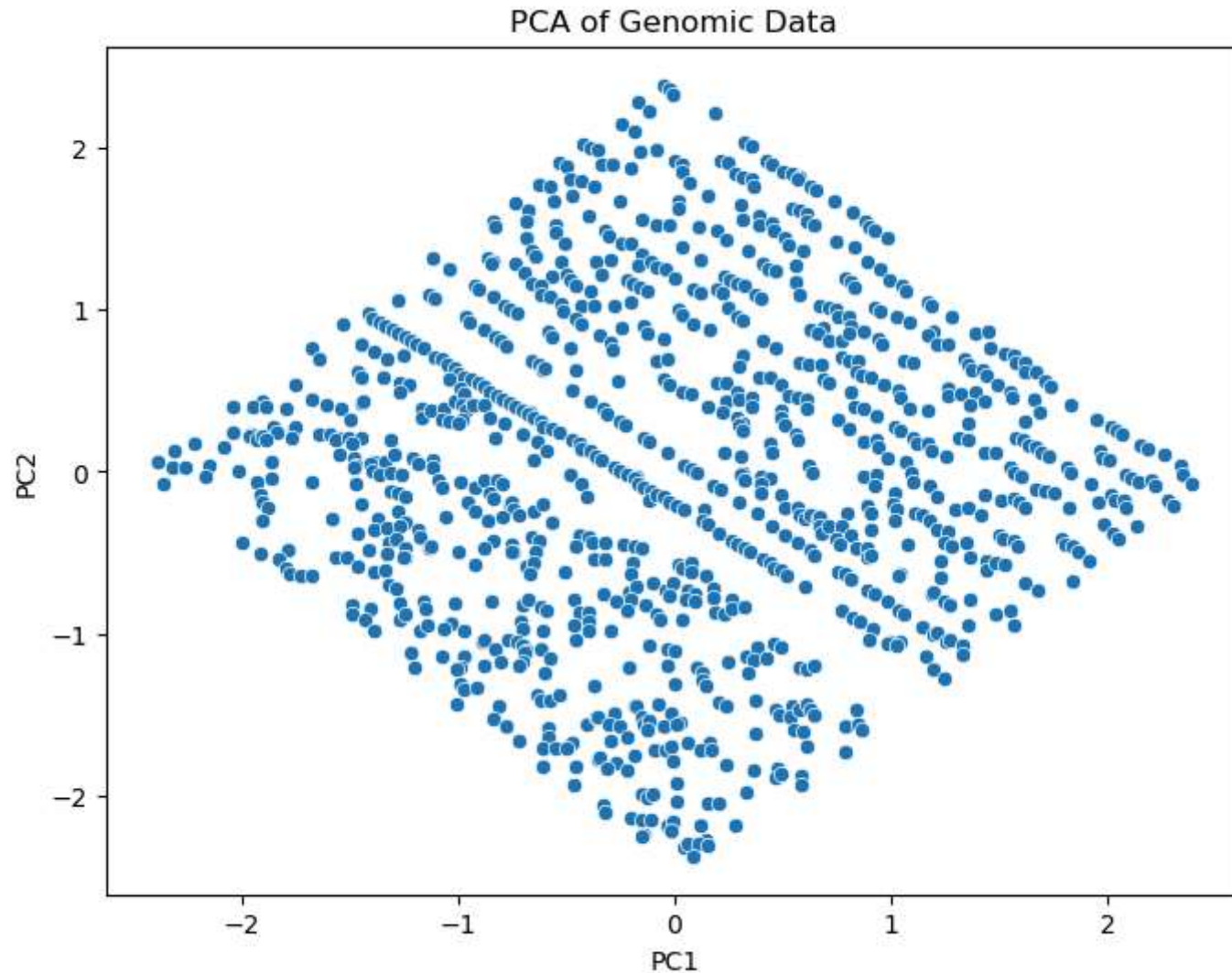
PC3 explains 1.34% of the variance

```
In [20]: # Standardize the data before PCA
scaler = StandardScaler()
scaled_data = scaler.fit_transform(df_full.select_dtypes(include=[np.number]))

# Apply PCA
pca = PCA(n_components=2)
pca_result = pca.fit_transform(scaled_data)

# Convert to DataFrame for visualization
pca_df = pd.DataFrame(data=pca_result, columns=['PC1', 'PC2'])

# Scatter plot of PCA results
plt.figure(figsize=(8, 6))
sns.scatterplot(x=pca_df['PC1'], y=pca_df['PC2'])
plt.title("PCA of Genomic Data")
plt.show()
```



```
In [ ]: import seaborn as sns
import matplotlib.pyplot as plt

# Compute SNP correlation matrix
snp_corr = snp_encoded.corr()

# Plot heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(snp_corr, cmap="coolwarm", linewidths=0.5, vmin=-1, vmax=1)
```

```
plt.title("SNP Correlation Heatmap")
plt.show()
```

```
In [ ]: import numpy as np

# Compute pairwise LD ( $r^2$ ) manually
ld_matrix = np.corrcoef(snp_encoded.T) ** 2 # Squared correlation for LD

# Plot heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(ld_matrix, cmap="viridis", linewidths=0.5)
plt.title("Linkage Disequilibrium (LD) Matrix")
plt.xlabel("SNPs")
plt.ylabel("SNPs")
plt.show()
```

```
In [ ]: import numpy as np
from sklearn.decomposition import PCA

# Run PCA on SNP data
pca = PCA(n_components=2)
pca_result = pca.fit_transform(snp_scaled)

# Get PCA Loadings (SNP influence)
loadings = pca.components_.T

# Scatter plot for PCA
plt.figure(figsize=(8, 6))
plt.scatter(loadings[:, 0], loadings[:, 1], alpha=0.7, color="red")
plt.xlabel("PC1 Loadings")
plt.ylabel("PC2 Loadings")
plt.title("PCA Biplot: SNP Influence")
plt.show()
```

```
In [ ]: from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

# Test different K values (number of clusters)
inertia = []
K_range = range(1, 11)

for k in K_range:
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    kmeans.fit(snp_scaled)
```

```
inertia.append(kmeans.inertia_)

# Plot Elbow Curve
plt.figure(figsize=(8, 5))
plt.plot(K_range, inertia, marker="o", linestyle="--")
plt.xlabel("Number of Clusters (K)")
plt.ylabel("Inertia")
plt.title("Elbow Method for Optimal K")
plt.show()
```

```
In [ ]: # Choose the optimal K (e.g., from elbow method)
        optimal_k = 3

        # Run K-Means
        kmeans = KMeans(n_clusters=optimal_k, random_state=42, n_init=10)
        snp_clusters = kmeans.fit_predict(snp_scaled)

        # Add cluster labels to dataframe
        df_full["Cluster"] = snp_clusters

        print(df_full[["Phenotype", "Cluster"]].head()) # Check assigned clusters
```

```
In [ ]: import seaborn as sns

        plt.figure(figsize=(8, 6))
        sns.scatterplot(x=pca_result[:, 0], y=pca_result[:, 1], hue=df_full["Cluster"], palette="viridis", alpha=0.7)
        plt.xlabel("PC1")
        plt.ylabel("PC2")
        plt.title("K-Means Clustering of SNPs in PCA Space")
        plt.legend(title="Cluster")
        plt.show()
```

```
In [ ]: from sklearn.cluster import DBSCAN

        # Run DBSCAN
        dbscan = DBSCAN(eps=2, min_samples=5) # Adjust eps for better separation
        db_clusters = dbscan.fit_predict(snp_scaled)

        # Add DBSCAN clusters to dataframe
        df_full["DBSCAN_Cluster"] = db_clusters

        # Visualize in PCA space
        plt.figure(figsize=(8, 6))
        sns.scatterplot(x=pca_result[:, 0], y=pca_result[:, 1], hue=df_full["DBSCAN_Cluster"], palette="coolwarm", alpha=0.7)
```

```
plt.xlabel("PC1")  
plt.ylabel("PC2")  
plt.title("DBSCAN Clustering of SNPs in PCA Space")  
plt.legend(title="Cluster")  
plt.show()
```

In [ ]: