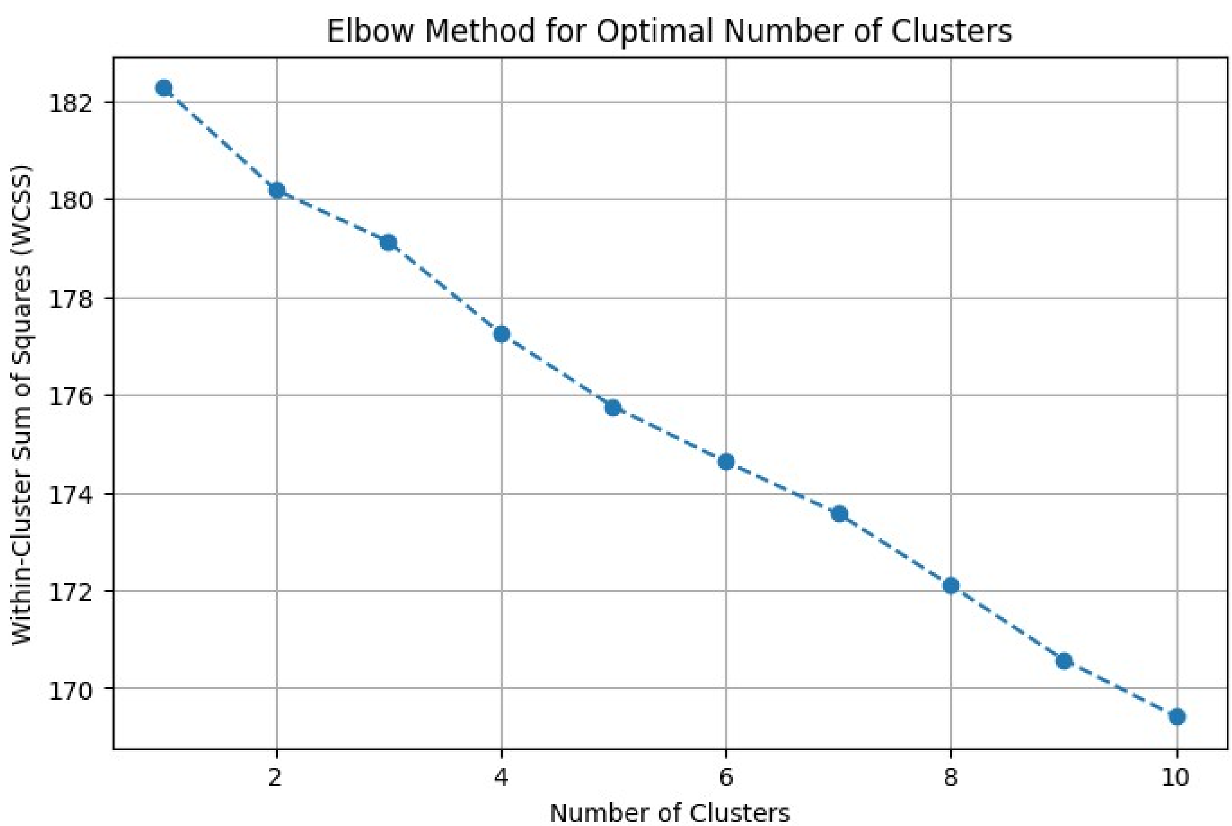
```python
import pandas as pd
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
from collections import Counter
from wordcloud import WordCloud
import nltk
nltk.download('stopwords')

from nltk.corpus import stopwords
# Get the default stop words from NLTK
stop_words = set(stopwords.words('english'))

# Add custom stop words that you specifically want to remove
custom_stop_words = {'to', 'the', 'and', 'our', 'with', 'be','and',
'is', 'of', 'in', 'a', 'will','may','on'}

# Combine the default and custom stop words
stop_words = stop_words.union(custom_stop_words)

def remove_stop_words(text):
    words = text.split()
    filtered_words = [word for word in words if word.lower() not in
stop_words]
    return ' '.join(filtered_words)


# 1. Load the Dataset
# Replace 'your_data.csv' with the path to your CSV file containing
national anthems and country information
df = pd.read_csv('/anthems.csv')
world_map =
pd.read_csv('/world_country_and_usa_states_latitude_and_longitude_valu
es.csv')
merged_data = pd.merge(df, world_map, on='Country', how='left')
# 2. Preprocess Text Data
# Example preprocessing: Remove punctuation, convert to lowercase, and
remove numbers
merged_data['Anthem'] = merged_data['Anthem'].str.replace('[^\w\s]',
'', regex=True).str.lower()
# Apply the function to the text column
merged_data['Anthem'] = merged_data['Anthem'].apply(remove_stop_words)

# 3. Vectorization using TF-IDF
vectorizer = TfidfVectorizer(max_features=5000)
tfidf_matrix = vectorizer.fit_transform(merged_data['Anthem'])

# 4. Determine Optimal Number of Clusters (optional: using the elbow
method)
```

```python
# Use elbow method to find optimal number of clusters
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300,
n_init=10, random_state=42)
    kmeans.fit(tfidf_matrix)
    wcss.append(kmeans.inertia_)

# Plotting the Elbow Graph
plt.figure(figsize=(8, 5))
plt.plot(range(1, 11), wcss, marker='o', linestyle='--')
plt.title('Elbow Method for Optimal Number of Clusters')
plt.xlabel('Number of Clusters')
plt.ylabel('Within-Cluster Sum of Squares (WCSS)')
plt.grid(True)
plt.show()

# 5. Fit K-Means Clustering
# Assuming optimal number of clusters found is 5 as per the report
optimal_clusters = 13
kmeans = KMeans(n_clusters=optimal_clusters, init='k-means++',
max_iter=300, n_init=10, random_state=42)
merged_data['Cluster'] = kmeans.fit_predict(tfidf_matrix)

# 6. Analyze Clusters and Print Nations in Each Cluster
cluster_groups = merged_data['Cluster'].unique()
for cluster in cluster_groups:
    cluster_data = merged_data[merged_data['Cluster'] == cluster]

    # Print the nations in each cluster
    countries_in_cluster = cluster_data['Country'].tolist()
    print(f"\nCluster {cluster}:")
    print(", ".join(countries_in_cluster))

    # Additional analysis like word frequency and word clouds
    all_words = ' '.join(cluster_data['Anthem']).split()
    word_freq = Counter(all_words)

    print("Most common words:")
    most_common_words = word_freq.most_common(10)
    for word, freq in most_common_words:
        print(f"{word}: {freq}")

    # Generate word cloud
    wordcloud = WordCloud(width=800, height=400,
background_color='white').generate_from_frequencies(word_freq)

    plt.figure(figsize=(8, 4))
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis('off')
```

```
    plt.title(f"Word Cloud for Cluster {cluster}")
    plt.show()

# 7. Optional: Visualize Clusters using PCA
pca = PCA(n_components=2)
pca_components = pca.fit_transform(tfidf_matrix.toarray())

plt.figure(figsize=(10, 7))
plt.scatter(pca_components[:, 0], pca_components[:, 1],
c=merged_data['Cluster'], cmap='viridis', alpha=0.7)
plt.title('PCA Visualization of National Anthem Clusters')
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.colorbar(label='Cluster')
plt.show()
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```




```
Cluster 12:
Albania, Belarus, Georgia, Moldova (the Republic of), Solomon Islands,
Tonga, Bahrain, Maldives, Pakistan, Palestine, Turkey, Djibouti
Most common words:
```

```
land: 17
flag: 13
shall: 12
warrior: 11
blessed: 9
god: 8
glory: 8
freedom: 8
nation: 8
sacred: 7
```

Word Cloud for Cluster 12


```
Cluster 3:
Armenia, Germany, Hungary, Italy, Luxembourg, Spain, Haiti, El
Salvador, Grenada, Bermuda, Greenland, Australia, Kiribati, Federated
States of Micronesia, Afghanistan, Israel, Mongolia, North Korea,
Qatar, Singapore, Syria, Thailand, Turkmenistan, Vietnam, Yemen,
Benin, Burkina Faso, Comoros, Democratic Republic of Congo, Ethiopia,
Gabon, Gambia, Malawi, Niger, Republic of the Congo, Rwanda, Saint
Helena, Togo, Tunisia, Western Sahara, Zambia
Most common words:
us: 104
let: 72
one: 42
people: 32
land: 27
every: 24
nation: 21
```

```
flag: 20
heart: 19
long: 19
```

Word Cloud for Cluster 3


```
Cluster 5:
Austria, Croatia, Czechia, Finland, Netherlands (the), Guyana,
Jamaica, Saint Lucia, Indonesia, Kyrgyzstan, Oman, Botswana, Lesotho,
Mauritania, Somalia, Zimbabwe
Most common words:
land: 57
us: 28
free: 15
indonesia: 14
love: 13
great: 12
people: 12
fathers: 10
dear: 10
oh: 9
```

Word Cloud for Cluster 5


```
Cluster 4:
Azerbaijan, Bosnia and Herzegovina, Iceland, Montenegro, Norway,
Romania, Serbia, Switzerland, Brazil, Colombia, Uruguay, United States
of America, Canada, Nicaragua, Puerto Rico, Belize, Antigua and
Barbuda, Dominica, New Zealand, Bangladesh, Brunei, India,
Philippines, Sri Lanka, Cameroon, Egypt, Ivory Coast, Mauritius,
Sierra Leone, Uganda
Most common words:
thy: 88
land: 52
thee: 50
god: 34
love: 30
thou: 28
us: 25
ever: 24
liberty: 22
stand: 21
```

Word Cloud for Cluster 4


```
Cluster 6:
Belgium, Estonia, United Kingdom of Great Britain and Northern Ireland
(the), Vanuatu, Bhutan, Japan, Jordan, Malaysia, Nepal, Morocco,
Seychelles, South Sudan, Swaziland
Most common words:
god: 19
king: 12
us: 11
land: 9
save: 9
queen: 9
live: 8
fatherland: 6
happiness: 6
reign: 6
```

Word Cloud for Cluster 6

Cluster 10:
Bulgaria, Slovakia, Venezuela, Papua New Guinea, Laos, South Korea, Uzbekistan, Angola, Cape Verde, Central African Republic, Equatorial Guinea, Guinea, Mali, Sao Tome and Principe, Senegal, South Africa
Most common words:
people: 30
us: 23
africa: 18
great: 15
let: 15
guinea: 12
sing: 10
new: 10
nation: 9
united: 9

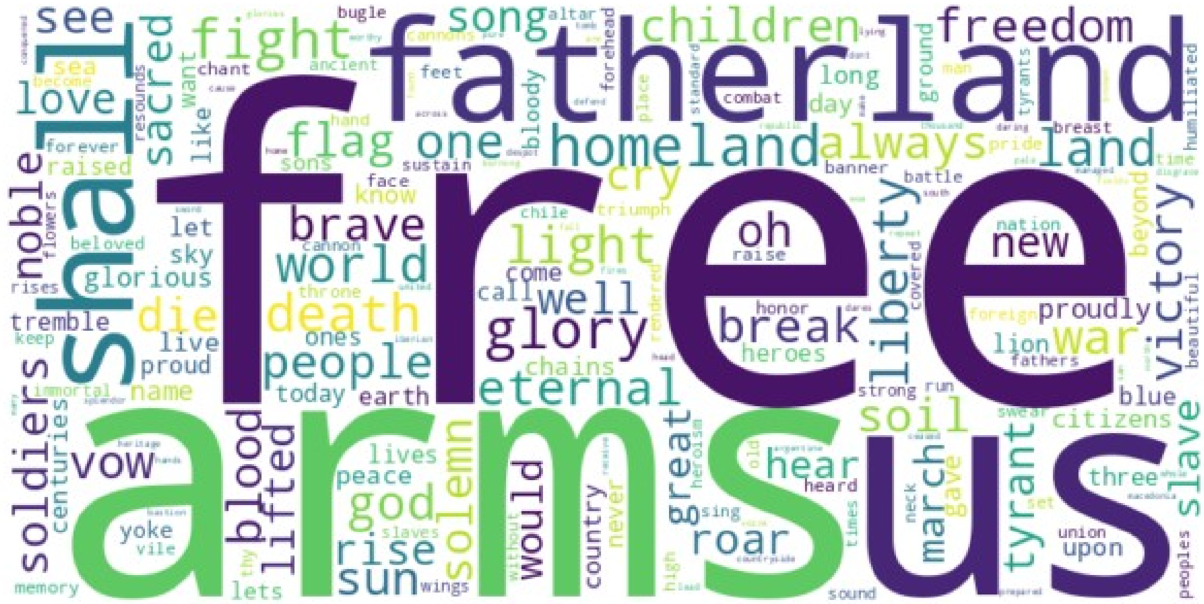
Word Cloud for Cluster 10


```
Cluster 1:
Cyprus, Denmark, Greece, Costa Rica, Iran, Liberia
Most common words:
hail: 21
liberty: 7
liberia: 6
glorious: 5
thee: 4
old: 4
thy: 4
shall: 4
prevail: 4
blue: 4
```

Word Cloud for Cluster 1


```
Cluster 2:
France, Ireland, Portugal, Republic of North Macedonia, Sweden,
Argentina, Chile, Ecuador, Paraguay, Peru, Suriname, Mexico,
Guatemala, Cuba, Dominican Republic, Honduras, Panama, Burundi,
Mozambique
Most common words:
free: 32
arms: 23
us: 22
fatherland: 21
shall: 18
homeland: 17
glory: 16
fight: 16
death: 14
liberty: 13
```

Word Cloud for Cluster 2




```
Cluster 9:
Latvia, Trinidad and Tobago, Fiji, Madagascar, Tanzania
Most common words:
bless: 20
god: 12
fiji: 10
ever: 5
africa: 5
tanzania: 5
beloved: 4
fatherland: 4
us: 4
latvia: 3
```


```
Cluster 11:
Liechtenstein, Lithuania, Bolivia, Barbados, Myanmar, Eritrea, Ghana,
Kenya, Nigeria
Most common words:
die: 14
freedom: 14
living: 13
homeland: 12
slaves: 12
nation: 12
name: 8
peace: 8
eritrea: 8
us: 7
```

Word Cloud for Cluster 11

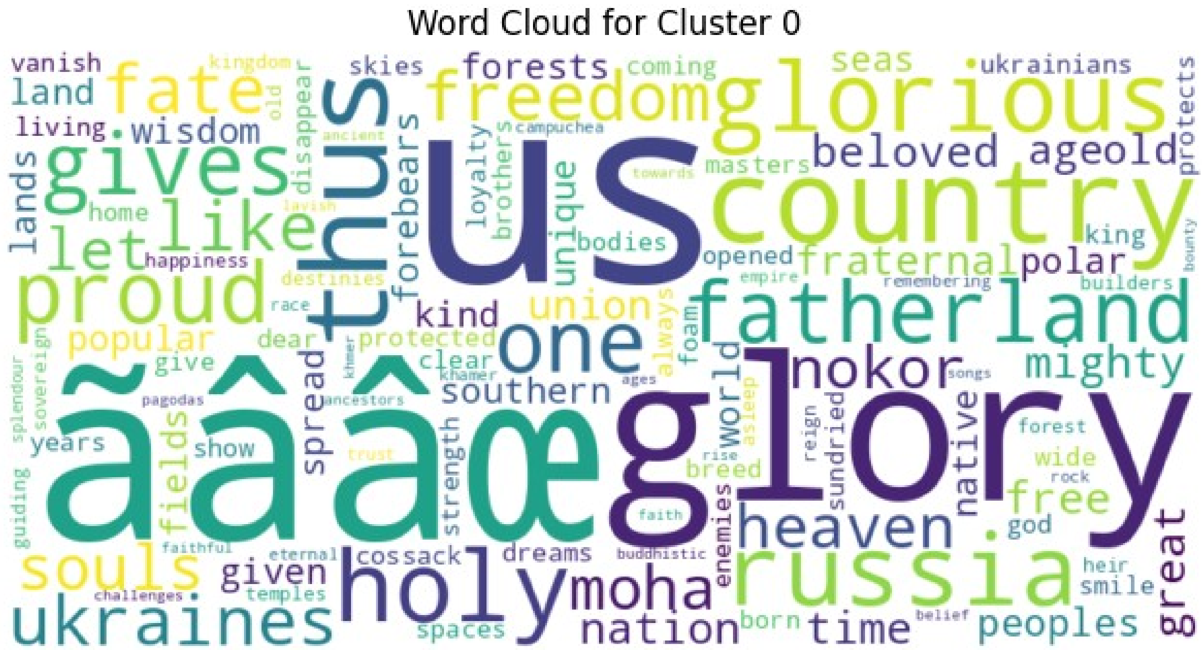

```
Cluster 8:
Malta, Slovenia, Iraq, Kazakhstan, Kuwait, Lebanon, Saudi Arabia,
Tajikistan, United Arab Emirates, Algeria, Chad, Guinea-Bissau, Libya,
Namibia, Sudan
Most common words:
country: 33
homeland: 24
glory: 17
god: 15
live: 14
us: 13
witness: 12
flag: 11
land: 10
long: 9
```

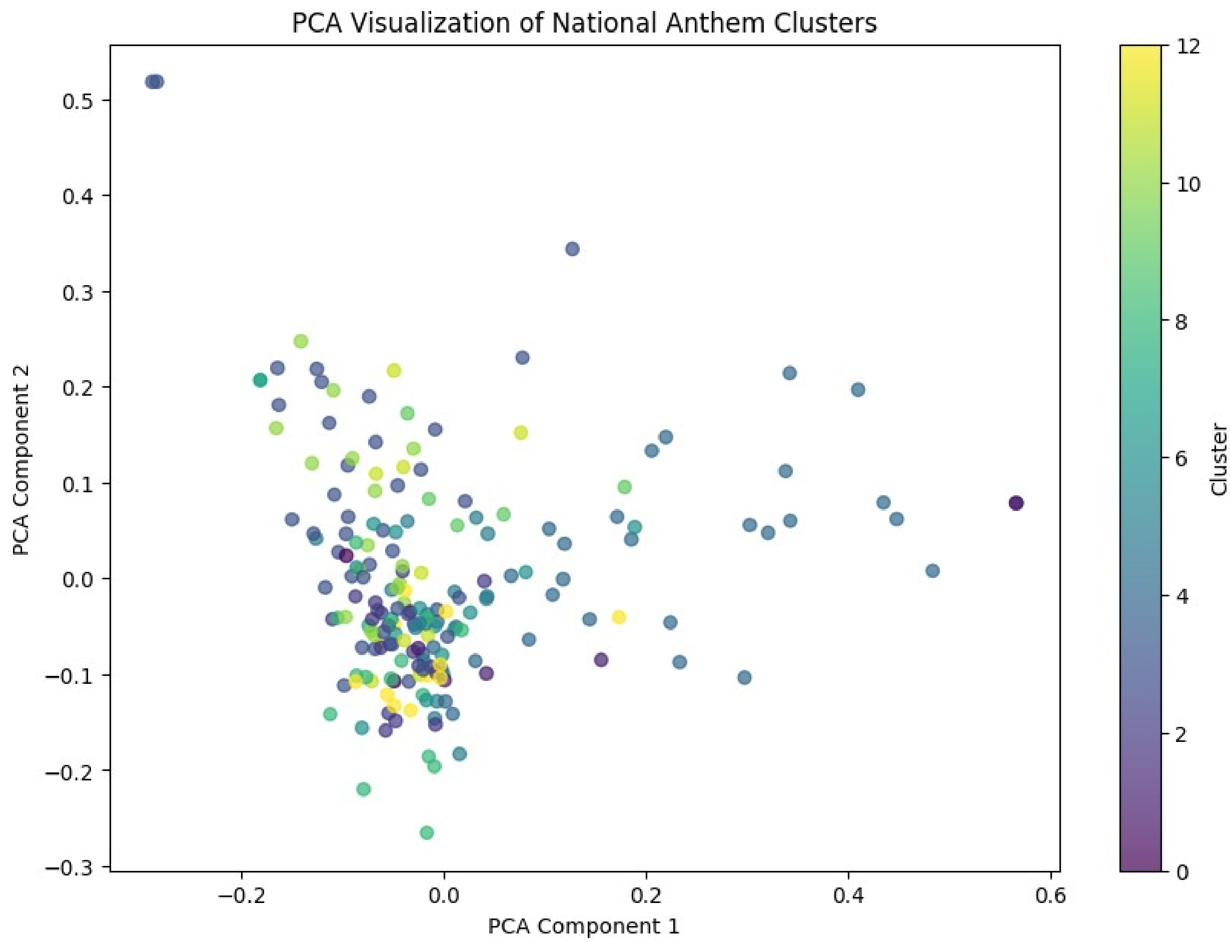
Word Cloud for Cluster 8


```
Cluster 7:
Poland, Bahamas, Samoa, China, Macau
Most common words:
march: 12
arise: 11
samoa: 5
us: 4
brave: 4
enemys: 4
gunfire: 4
shall: 3
god: 3
waving: 3
```

Word Cloud for Cluster 7


```
Cluster 0:
Russian Federation (the), Ukraine, Cambodia
Most common words:
us: 5
ãâãœ: 4
glory: 4
country: 3
thus: 3
russia: 2
holy: 2
glorious: 2
fatherland: 2
proud: 2
```


Word Cloud for Cluster 0
us
glory
ãâ âœ
glorious
country
fatherland
thus
proud
gives
freedom
fate
like
let
one
holy
russia
ukraines
heaven
nokor
moha
souls
mighty
nation
time
peoples
great
beloved
ageold
fraternal
polar
union
forests
wisdom
land
lands
kind
southern
world
native
free
unique
forebears
popular
protected
spread
fields
given
cossack
dreams
seas
ukrainians
skies
vanish
living
coming
kingdom
masters
opened
bodies
king
loyalty
brothers
disappear
home
happiness
dear
give
clear
years
show
strength
sundried
enemies
breed
wide
god
smile
heir
spaces
born
temples
forest
foam
always
protects
builders
destinies
reign
asleep


PCA Visualization of National Anthem Clusters
PCA Component 1
PCA Component 2
Cluster
−0.2
0.0
0.2
0.4
0.6
−0.3
−0.2
−0.1
0.0
0.1
0.2
0.3
0.4
0.5
0
2
4
6
8
10
12

```python
import plotly.express as px

fig = px.choropleth(
    merged_data,
    locations="Country",
    locationmode="country names",
    color="Cluster",
    hover_name="Country",
    title="National Anthems Clusters on World Map",
    # Use a discrete color scale instead of a continuous one
    color_discrete_sequence=px.colors.qualitative.Bold,
)
fig.update_layout(width=800, height=600)
fig.show(config={'scrollZoom': False})
fig.show()

# Define cluster labels based on the report's findings
cluster_labels = {
    0: "Unity and national glory",
    1: "Liberty and Triumph",
    2: "Freedom and Resistance",
    3: "Unity and collective strength",
    4: "Devotion and loyalty",
    5: "Love for land and heritage",
    6: "Monarchy and divine protection",
    7: "Call for action and Valor",
    8: "Homeland and Patriotism",
    9: "Fatherland, blessings and divinity",
    10: "Unity and Aspirational",
    11: "Struggle and sacrifice",
    12: "National Glory and Unity"
}

merged_data['Cluster_Label'] =
merged_data['Cluster'].map(cluster_labels)
merged_data.head()
```


```
{"summary":"{\n  \"name\": \"merged_data\",\n  \"rows\": 190,\n
\"fields\": [\n    {\n      \"column\": \"Country\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 190,\n        \"samples\": [\n
\"Senegal\",\n          \"South Sudan\",\n          \"Maldives\"\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"Alpha-2\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 188,\n        \"samples\": [\n
\"TN\",\n          \"ML\",\n          \"HU\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Alpha-3\",\n      \"properties\":
{\n        \"dtype\": \"string\",\n        \"num_unique_values\":
```

```
190,\n        \"samples\": [\n          \"SEN\",\n          \"SSD\",\n
\"MDV\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Continent\",\n      \"properties\": {\n        \"dtype\":
\"category\",\n        \"num_unique_values\": 6,\n        \"samples\":
[\n          \"Europe\",\n          \"South_America\",\n
\"Africa\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Anthem\",\n      \"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 188,\n        \"samples\": [\n
\"defenders homeland rally around glory time blood surges veins die
sake land let heavens roar thunder let thunderbolts rain fire men
youth tunisia rise might glory place traitors tunisia defend live die
loyal tunisia life dignity death glory nation inherited arms like
granite towers holding aloft proud flag flying boast boasts us arms
achieve ambitions glory sure realize hopes inflict defeat foes offer
peace friends people live destiny must surely respond oppression shall
vanish fetters certain break\",\n          \"country fatherhood
honorable gift fortress book bound ayia moritan spring harmony pillar
forgiveness hole peace protect fiancand pay hope hope meet answer
character blocked sun forehead go away nmac amjad expresses africa
freshest upstream gave birth dew father good pregnancy prey khasibah
find smona welcome enemy kept us young bitter got stable made covenant
promise promise give sense generosity protect fiancand pay hope hope
protect fiancand pay meet answer\",\n          \"countrys god countrys
god worship thy name wonder sublime suns heavens set thy crown thy
legions ages time thee day thousand years thousand years day eternitys
flowr homage tears reverently passes away icelands thousand years
icelands thousand years eternitys flowr homage tears reverently passes
away god god bow thee spirits fervent place thy care lord god fathers
age unto age breathing holiest prayer pray thank thee thousand years
safely protected stand pray bring thee homage tears destiny rest thy
hand iceland\\u00e3\\u00e2\\u00e2s thousand years icelands thousand
years hoarfrost morning tinted years thy sun rising high shall command
country\\u00e3\\u00e2\\u00e2s god country\\u00e3\\u00e2\\u00e2s god
life feeble quivering reed perish deprived thy spirit light redeem
uphold need inspire us morn thy courage love lead days strife evening
send peace thy heaven safeguard nation life iceland\\u00e3\\u00e2\\
u00e2s thousand years icelands thousand years prosper people diminish
tears guide thy wisdom life\"\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"country_code\",\n      \"properties\": {\n
\"dtype\": \"string\",\n        \"num_unique_values\": 174,\n
\"samples\": [\n          \"MZ\",\n          \"GW\",\n
\"MO\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"latitude\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 24.32746097355803,\n        \"min\": -
40.900557,\n        \"max\": 71.706936,\n
```

\"num_unique_values\": 175,\n   \"samples\": [\n   -
22.95764,\n   -0.023559,\n   22.198745\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"longitude\",\n
\"properties\": {\n   \"dtype\": \"number\",\n   \"std\":
65.06320615504403,\n   \"min\": -175.198242,\n   \"max\":
179.414413,\n   \"num_unique_values\": 175,\n   \"samples\":
[\n   18.49041,\n   37.906193,\n   113.543873\n
],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n
}\n   },\n   {\n   \"column\": \"usa_state_code\",\n
\"properties\": {\n   \"dtype\": \"category\",\n
\"num_unique_values\": 39,\n   \"samples\": [\n   \"NM\",\
n   \"TX\",\n   \"NV\"\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"usa_state_latitude\",\n
\"properties\": {\n   \"dtype\": \"number\",\n   \"std\":
4.641192611978554,\n   \"min\": 31.244823,\n   \"max\":
47.751074,\n   \"num_unique_values\": 39,\n   \"samples\":
[\n   34.97273,\n   31.968599,\n   38.80261\n
],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n
}\n   },\n   {\n   \"column\": \"usa_state_longitude\",\n
\"properties\": {\n   \"dtype\": \"number\",\n   \"std\":
14.548410111577963,\n   \"min\": -120.740139,\n   \"max\": -
69.445469,\n   \"num_unique_values\": 34,\n   \"samples\":
[\n   -120.740139,\n   -84.270018,\n   -
86.902298\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"usa_state\",\n   \"properties\": {\n   \"dtype\":
\"category\",\n   \"num_unique_values\": 39,\n
\"samples\": [\n   \"New Mexico\",\n   \"Texas\",\n
\"Nevada\"\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"Cluster\",\n   \"properties\": {\n   \"dtype\": \"int32\",\n
\"num_unique_values\": 13,\n   \"samples\": [\n   7,\n
11,\n   12\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"Cluster_Label\",\n   \"properties\": {\n   \"dtype\":
\"category\",\n   \"num_unique_values\": 13,\n
\"samples\": [\n   \"Call for action and Valor\",\n
\"Struggle and sacrifice\",\n   \"National Glory and Unity\"\n
],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n
}\n   }\n]\n}","type":"dataframe","variable_name":"merged_data"}


```
from transformers import BertTokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from imblearn.over_sampling import RandomOverSampler
import numpy as np
import torch
from sklearn.preprocessing import LabelEncoder
from torch.utils.data import DataLoader, TensorDataset, random_split
```

```python
from transformers import BertForSequenceClassification, AdamW,
get_cosine_schedule_with_warmup
from sklearn.utils.class_weight import compute_class_weight
from sklearn.metrics import classification_report, accuracy_score

# Load pre-trained BERT tokenizer
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')

# Tokenize the text
merged_data['Input_Ids'] = merged_data['Anthem'].apply(lambda x:
tokenizer.encode(x, add_special_tokens=True, truncation=True,
max_length=512))

X = merged_data['Input_Ids'].tolist()
y = merged_data['Cluster_Label'].tolist()

# Pad sequences to have the same length
X = pad_sequences(X, maxlen=512, padding='post', truncating='post')

# Convert to numpy arrays
X = np.array(X)
y = np.array(y)

# Oversampling the minority classes
ros = RandomOverSampler(random_state=42)
X_resampled, y_resampled = ros.fit_resample(X, y)

print(f"Original dataset shape: {X.shape}")
print(f"Resampled dataset shape: {X_resampled.shape}")

# Convert back to PyTorch tensors for model training
le = LabelEncoder()
y_resampled_encoded = le.fit_transform(y_resampled)  # Encode string
labels to integers
input_ids = torch.tensor(X_resampled)
labels = torch.tensor(y_resampled_encoded)

# Create attention masks
attention_masks = torch.tensor([[float(i != 0) for i in seq] for seq
in X_resampled])

# Compute class weights for the original labels (optional)
class_weights = compute_class_weight(class_weight='balanced',
classes=np.unique(labels), y=labels.numpy())
class_weights = torch.tensor(class_weights,
dtype=torch.float).to(device)

# Create TensorDataset
dataset = TensorDataset(input_ids, attention_masks, labels)
```

```
# Split into training and validation datasets
train_size = int(0.8 * len(dataset))
val_size = len(dataset) - train_size
train_dataset, val_dataset = random_split(dataset, [train_size,
val_size])

# Create DataLoader
batch_size = 4
train_dataloader = DataLoader(train_dataset, batch_size=batch_size,
shuffle=True)
val_dataloader = DataLoader(val_dataset, batch_size=batch_size,
shuffle=False)

# Load pre-trained BERT model with a classification head
model = BertForSequenceClassification.from_pretrained(
    'bert-base-uncased',
    num_labels=len(le.classes_),  # Number of unique cluster labels
    output_attentions=False,
    output_hidden_states=False
)

# Move model to GPU if available
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model.to(device)

# Set up the optimizer
optimizer = AdamW(model.parameters(), lr=2e-5, eps=1e-8,
weight_decay=0.01)

# Total number of training steps
total_steps = len(train_dataloader) * 10  # Adjust as needed

# Create the learning rate scheduler
scheduler = get_cosine_schedule_with_warmup(optimizer,
num_warmup_steps=0, num_training_steps=total_steps)

# Define loss function with class weights (optional)
loss_fn = torch.nn.CrossEntropyLoss(weight=class_weights)

# Function to train the model
def train_model(model, train_dataloader, val_dataloader, epochs):
    for epoch in range(epochs):
        model.train()
        total_loss = 0
        for batch in train_dataloader:
            batch_input_ids, batch_attention_mask, batch_labels =
tuple(t.to(device) for t in batch)
            model.zero_grad()
            outputs = model(batch_input_ids,
attention_mask=batch_attention_mask, labels=batch_labels)
```

```
            logits = outputs.logits

            # Calculate loss with class weights
            loss = loss_fn(logits, batch_labels)
            total_loss += loss.item()

            loss.backward()
            optimizer.step()
            scheduler.step()

        # Validation phase
        model.eval()
        val_loss = 0
        val_accuracy = 0
        for batch in val_dataloader:
            batch_input_ids, batch_attention_mask, batch_labels =
tuple(t.to(device) for t in batch)
            with torch.no_grad():
                outputs = model(batch_input_ids,
attention_mask=batch_attention_mask, labels=batch_labels)
                logits = outputs.logits

                loss = outputs.loss
                val_loss += loss.item()
                preds = torch.argmax(logits, dim=1)
                val_accuracy += (preds == batch_labels).float().mean()

        # Print loss and accuracy
        print(f"Epoch {epoch + 1}/{epochs}")
        print(f"Training loss: {total_loss / len(train_dataloader)}")
        print(f"Validation loss: {val_loss / len(val_dataloader)}")
        print(f"Validation accuracy: {val_accuracy /
len(val_dataloader)}")

# Function to evaluate the model
def evaluate_model(model, dataloader):
    model.eval()
    predictions, true_labels = [], []
    for batch in dataloader:
        batch_input_ids, batch_attention_mask, batch_labels =
tuple(t.to(device) for t in batch)
        with torch.no_grad():
            outputs = model(batch_input_ids,
attention_mask=batch_attention_mask)
        logits = outputs.logits
        preds = torch.argmax(logits, dim=1).cpu().numpy()
        labels = batch_labels.cpu().numpy()
        predictions.extend(preds)
        true_labels.extend(labels)
```

```
    return predictions, true_labels

# Train the model with oversampled data
train_model(model, train_dataloader, val_dataloader, epochs=10)

# Evaluate the model
predictions, true_labels = evaluate_model(model, val_dataloader)

# Generate a classification report
unique_classes = set(predictions + true_labels)
target_names = [label for label in le.classes_ if
le.transform([label])[0] in unique_classes]
print("Classification Report:")
print(classification_report(true_labels, predictions,
target_names=target_names, zero_division=1))
```

```
Original dataset shape: (190, 512)
Resampled dataset shape: (533, 512)

Some weights of BertForSequenceClassification were not initialized
from the model checkpoint at bert-base-uncased and are newly
initialized: ['classifier.bias', 'classifier.weight']
You should probably TRAIN this model on a down-stream task to be able
to use it for predictions and inference.
/usr/local/lib/python3.10/dist-packages/transformers/optimization.py:5
91: FutureWarning:

This implementation of AdamW is deprecated and will be removed in a
future version. Use the PyTorch implementation torch.optim.AdamW
instead, or set `no_deprecation_warning=True` to disable this warning


Epoch 1/10
Training loss: 2.5788676070275707
Validation loss: 2.4168148040771484
Validation accuracy: 0.22530865669250488
Epoch 2/10
Training loss: 2.216821682787387
Validation loss: 1.8776641775060583
Validation accuracy: 0.5030863881111145
Epoch 3/10
Training loss: 1.5211730772089735
Validation loss: 1.2232143029018685
Validation accuracy: 0.7345679402351379
Epoch 4/10
Training loss: 0.8572653320348151
Validation loss: 0.8538940317100949
Validation accuracy: 0.8117283582687378
Epoch 5/10
Training loss: 0.5148521750886864
```

```
Validation loss: 0.6443090482994362
Validation accuracy: 0.8518518805503845
Epoch 6/10
Training loss: 0.3183515698553246
Validation loss: 0.5761435815581569
Validation accuracy: 0.8703703880310059
Epoch 7/10
Training loss: 0.21943891215547223
Validation loss: 0.5423260888567677
Validation accuracy: 0.8703703880310059
Epoch 8/10
Training loss: 0.17703456932974754
Validation loss: 0.5367077365517616
Validation accuracy: 0.8703703880310059
Epoch 9/10
Training loss: 0.1652181737612341
Validation loss: 0.5295201316475868
Validation accuracy: 0.8703703880310059
Epoch 10/10
Training loss: 0.15906411660051792
Validation loss: 0.5289202768493582
Validation accuracy: 0.8703703880310059
Classification Report:
                                    precision    recall  f1-score
support

         Call for action and Valor       1.00      1.00      1.00
8
              Devotion and loyalty       0.86      0.86      0.86
7
Fatherland, blessings and divinity       0.92      1.00      0.96
12
            Freedom and Resistance       0.90      0.82      0.86
11
           Homeland and Patriotism       0.89      1.00      0.94
8
               Liberty and Triumph       0.83      1.00      0.91
5
        Love for land and heritage       0.70      0.88      0.78
8
    Monarchy and divine protection       0.88      0.70      0.78
10
          National Glory and Unity       1.00      1.00      1.00
8
            Struggle and sacrifice       0.67      1.00      0.80
6
            Unity and Aspirational       1.00      0.71      0.83
7
     Unity and collective strength       0.67      0.44      0.53
```

```
9
           Unity and national glory       1.00      1.00      1.00
8

                           accuracy                           0.87
107
                          macro avg       0.87      0.88      0.87
107
                       weighted avg       0.87      0.87      0.86
107
```