

```
1 !pip install unidecode
```

→ Collecting unidecode

  Downloading Unidecode-1.3.8-py3-none-any.whl.metadata (13 kB)

  Downloading Unidecode-1.3.8-py3-none-any.whl (235 kB)

  235.5/235.5 kB 5.1 MB/s eta 0:00:00

Installing collected packages: unidecode

Successfully installed unidecode-1.3.8

```
1 !pip install datasets
```

→ Collecting datasets

  Downloading datasets-3.0.1-py3-none-any.whl.metadata (20 kB)

Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.10/dist-packages (from datasets)

Collecting pyarrow>=15.0.0 (from datasets)

  Downloading pyarrow-17.0.0-cp310-cp310-manylinux\_2\_28\_x86\_64.whl.metadata (3.3 kB)

Collecting dill<0.3.9,>=0.3.0 (from datasets)

  Downloading dill-0.3.8-py3-none-any.whl.metadata (10 kB)

Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: requests>=2.32.2 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: tqdm>=4.66.3 in /usr/local/lib/python3.10/dist-packages (from datasets)

Collecting xxhash (from datasets)

  Downloading xxhash-3.5.0-cp310-cp310-manylinux\_2\_17\_x86\_64.manylinux2014\_x86\_64.whl.metadata (3.3 kB)

Collecting multiprocessing (from datasets)

  Downloading multiprocessing-0.70.16-py310-none-any.whl.metadata (7.2 kB)

Requirement already satisfied: fsspec<=2024.6.1,>=2023.1.0 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: aiohttp in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: huggingface-hub>=0.22.0 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: aiohappyeyeballs>=2.3.0 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: aiosignal>=1.1.2 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: attrs>=17.3.0 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: frozenlist>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: multidict<7.0,>=4.5 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: yarl<2.0,>=1.0 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: async-timeout<5.0,>=4.0 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packages (from datasets)

Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from datasets)

Downloaded datasets-3.0.1-py3-none-any.whl (471 kB)

  471.6/471.6 kB 12.7 MB/s eta 0:00:00

Downloaded dill-0.3.8-py3-none-any.whl (116 kB)

  116.3/116.3 kB 7.2 MB/s eta 0:00:00

Downloaded pyarrow-17.0.0-cp310-cp310-manylinux\_2\_28\_x86\_64.whl (39.9 MB)

  39.9/39.9 MB 16.2 MB/s eta 0:00:00

```
Downloading multiprocessing-0.70.16-py310-none-any.whl (134 kB)
    ━━━━━━━━━━━━━━━━ 134.8/134.8 kB 8.9 MB/s eta 0:00:00
Downloading xxhash-3.5.0-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (194 kB)
    ━━━━━━━━━━━━━━ 194.1/194.1 kB 8.9 MB/s eta 0:00:00
Installing collected packages: xxhash, pyarrow, dill, multiprocessing, datasets
Attempting uninstall: pyarrow
  Found existing installation: pyarrow 14.0.2
Uninstalling pyarrow-14.0.2:
  Successfully uninstalled pyarrow-14.0.2
ERROR: pip's dependency resolver does not currently take into account all the packages that
cudf-cu12 24.4.1 requires pyarrow<15.0.0a0,>=14.0.1, but you have pyarrow 17.0.0 which is
Successfullly installed datasets-3.0.1 dill-0.3.8 multiprocessing-0.70.16 pyarrow-17.0.0 xxh-3.5.0
```

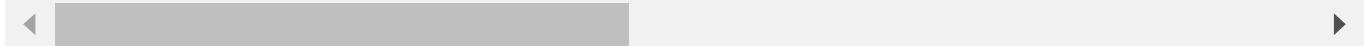
```
1 import json
2 import os
3 from unidecode import unidecode
```

## ▼ TASK 1

Sentences were extracted for 27 languages that use Roman-script characters. Each language is identified by a locale (e.g., 'en-US' for English spoken in the US). Sentences were filtered out for the required locales and each locale's sentences were saved in a separate text file. Deaccenting: Some languages contain accented characters, which were normalized using Python's unidecode library, depending on the desired preprocessing.

```
1 from datasets import load_dataset
2 dataset = load_dataset("qanastek/MASSIVE")
```

```
→ /usr/local/lib/python3.10/dist-packages/huggingface_hub/utils/_token.py:89: UserWarning:  
  The secret `HF_TOKEN` does not exist in your Colab secrets.  
  To authenticate with the Hugging Face Hub, create a token in your settings tab (https://)  
  You will be able to reuse this secret in all of your notebooks.  
  Please note that authentication is recommended but still optional to access public model  
  warnings.warn(  
MASSIVE.py: 100% 32.3k/32.3k [00:00<00:00, 660kB/s]  
README.md: 100% 34.1k/34.1k [00:00<00:00, 1.26MB/s]  
The repository for qanastek/MASSIVE contains custom code which must be executed to corre  
You can avoid this prompt in future by passing the argument `trust_remote_code=True`.  
Do you wish to run the custom code? [y/N] y  
Downloading data: 100% 39.5M/39.5M [00:01<00:00, 42.6MB/s]  
Generating train split: 587214/0 [03:57<00:00, 1615.58 examples/s]  
Generating validation split: 103683/0 [00:49<00:00, 2657.42 examples/s]  
Generating test split: 151674/0 [01:14<00:00, 3026.94 examples/s]
```



```
1 roman_script_locales = [  
2     'af-ZA', 'da-DK', 'de-DE', 'en-US', 'es-ES', 'fr-FR', 'fi-FI', 'hu-HU', 'is-IS', 'it-  
3     'jv-ID', 'lv-LV', 'ms-MY', 'nb-NO', 'nl-NL', 'pl-PL', 'pt-PT', 'ro-RO', 'ru-RU', 'sl-  
4     'sv-SE', 'sq-AL', 'sw-KE', 'tl-PH', 'tr-TR', 'vi-VN', 'cy-GB'  
5 ]  
6  
7 output_dir = 'language_files'  
8 os.makedirs(output_dir, exist_ok=True)  
9  
10 def extract_and_save(dataset, locales, partition='train'):  
11     for locale in locales:  
12         subset = dataset[partition].filter(lambda x: x['locale'] == locale)  
13  
14         with open(f'{output_dir}/{locale}.txt', 'w', encoding='utf-8') as f:  
15             for item in subset:  
16                 utt = unidecode(item['utt'])  
17                 f.write(utt + '\n')  
18  
19 extract_and_save(dataset, roman_script_locales, partition='train')
```

Filter: 100%	587214/587214 [01:23<00:00, 10172.56 examples/s]
Filter: 100%	587214/587214 [01:06<00:00, 9435.64 examples/s]
Filter: 100%	587214/587214 [01:16<00:00, 9649.33 examples/s]
Filter: 100%	587214/587214 [01:10<00:00, 8160.74 examples/s]
Filter: 100%	587214/587214 [01:05<00:00, 10435.23 examples/s]
Filter: 100%	587214/587214 [01:14<00:00, 4796.60 examples/s]
Filter: 100%	587214/587214 [01:23<00:00, 9930.76 examples/s]
Filter: 100%	587214/587214 [01:08<00:00, 9413.24 examples/s]
Filter: 100%	587214/587214 [01:07<00:00, 6799.97 examples/s]
Filter: 100%	587214/587214 [01:06<00:00, 8552.44 examples/s]
Filter: 100%	587214/587214 [01:05<00:00, 11078.16 examples/s]
Filter: 100%	587214/587214 [01:05<00:00, 10589.23 examples/s]
Filter: 100%	587214/587214 [01:06<00:00, 9791.36 examples/s]
Filter: 100%	587214/587214 [01:05<00:00, 8991.34 examples/s]
Filter: 100%	587214/587214 [01:07<00:00, 10493.33 examples/s]
Filter: 100%	587214/587214 [01:05<00:00, 9234.42 examples/s]
Filter: 100%	587214/587214 [01:07<00:00, 10821.15 examples/s]
Filter: 100%	587214/587214 [01:06<00:00, 8788.26 examples/s]
Filter: 100%	587214/587214 [01:05<00:00, 6617.10 examples/s]
Filter: 100%	587214/587214 [01:06<00:00, 7861.75 examples/s]
Filter: 100%	587214/587214 [01:07<00:00, 10607.44 examples/s]
Filter: 100%	587214/587214 [01:05<00:00, 10006.79 examples/s]
Filter: 100%	587214/587214 [01:05<00:00, 9581.58 examples/s]
Filter: 100%	587214/587214 [01:04<00:00, 11499.37 examples/s]
Filter: 100%	587214/587214 [01:04<00:00, 11852.81 examples/s]
Filter: 39%	229000/587214 [00:25<01:08, 5232.49 examples/s]
Filter: 0%	0/587214 [00:00<?, ? examples/s]

## ▼ TASK 2

The text data is vectorized using CountVectorizer, which transforms the sentences into numerical feature vectors based on word frequency (bag-of-words model). **Model Training:** The Multinomial Naive Bayes classifier is then trained on the vectorized text data. This method is well-suited for text classification tasks, as it works with categorical data and can handle the high-dimensional feature space generated from text.

```

1 from sklearn.feature_extraction.text import CountVectorizer
2 from sklearn.naive_bayes import MultinomialNB
3 from sklearn.model_selection import train_test_split
4 from sklearn import metrics
5 import glob

1 def load_sentences_from_files(folder):
2     sentences = []
3     labels = []
4
5     for filepath in glob.glob(f"{folder}/*.txt"):
6         locale = os.path.basename(filepath).replace('.txt', '')
7         with open(filepath, 'r', encoding='utf-8') as file:
8             for line in file:
9                 sentences.append(line.strip())
10            labels.append(locale)
11
12 return sentences, labels

1 X, y = load_sentences_from_files(output_dir)
2
3 X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)
4
5 vectorizer = CountVectorizer()
6 X_train_vec = vectorizer.fit_transform(X_train)
7 X_val_vec = vectorizer.transform(X_val)
8
9 model = MultinomialNB()
10 model.fit(X_train_vec, y_train)
11
12 y_pred_train = model.predict(X_train_vec)
13 y_pred_val = model.predict(X_val_vec)
14
15 print("Training Accuracy:", metrics.accuracy_score(y_train, y_pred_train))
16 print("Validation Accuracy:", metrics.accuracy_score(y_val, y_pred_val))
17 print(metrics.classification_report(y_val, y_pred_val))

→ Training Accuracy: 0.989782953092456
Validation Accuracy: 0.980217447246526
      precision    recall   f1-score   support

```

af-ZA	0.98	0.97	0.98	2313
cy-GB	1.00	0.99	0.99	2295
da-DK	0.92	0.94	0.93	2281
de-DE	0.99	0.98	0.99	2265
en-US	0.86	0.99	0.92	2219
es-ES	0.98	0.98	0.98	2349
fi-FI	1.00	0.98	0.99	2254
fr-FR	0.99	0.99	0.99	2345
hu-HU	0.99	0.98	0.99	2304
is-IS	1.00	0.98	0.99	2337
it-IT	0.99	0.99	0.99	2284
jv-ID	0.99	0.98	0.99	2254
lv-LV	0.99	0.99	0.99	2360
ms-MY	0.98	0.99	0.99	2269
nb-NO	0.95	0.92	0.93	2287
nl-NL	0.98	0.96	0.97	2320
pl-PL	0.99	0.99	0.99	2312
pt-PT	0.98	0.98	0.98	2296
ro-RO	0.99	0.98	0.99	2287
ru-RU	0.99	0.99	0.99	2238
sl-SL	1.00	0.98	0.99	2380
sq-AL	0.99	0.99	0.99	2344
sv-SE	0.98	0.97	0.98	2219
sw-KE	1.00	0.99	0.99	2306
tl-PH	0.99	1.00	0.99	2335
tr-TR	0.99	0.98	0.99	2333
vi-VN	0.99	1.00	0.99	2390
accuracy			0.98	62176
macro avg	0.98	0.98	0.98	62176
weighted avg	0.98	0.98	0.98	62176

## ▼ TASK-3

To simplify the classification task further, the 27 languages are grouped into 4 continent-based categories: Asia, Africa, Europe, and North America. The sentences for each language group are collapsed into four files corresponding to these continents.

This step reduces the complexity of the classification task by focusing on continent-level classification rather than language-level classification. The dataset is now treated as a four-class classification problem.

```

1 continent_groups = {
2     'Africa': ['af-ZA', 'sw-KE'],
3     'Asia': ['ms-MY', 'tl-PH', 'jv-ID', 'vi-VN', 'tr-TR'],
4     'Europe': ['da-DK', 'de-DE', 'en-US', 'es-ES', 'fr-FR', 'fi-FI', 'hu-HU', 'is-IS',
5                'nl-NL', 'pl-PL', 'pt-PT', 'ro-RO', 'ru-RU', 'sl-SL', 'sv-SE', 'sq-AL'],

```

```

6     'North America': ['en-US']
7

```

The goal here is to build a Regularized Discriminant Analysis (RDA) model. RDA is a hybrid of Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA), with a hyperparameter lambda that controls the trade-off between the two models.

**Feature Representation:** Sentences are converted into numerical features using TfidfVectorizer (Term Frequency-Inverse Document Frequency), which provides a more refined feature representation than simple word counts by considering how important a word is across all documents. **LDA vs. QDA:** LDA assumes the same covariance matrix across all classes (simpler, less variance). QDA allows different covariance matrices for each class (more flexible, but potentially overfits). **Blending the Models:** RDA is simulated by blending the predictions of LDA and QDA based on lambda. For lambda = 0, LDA is used; for lambda = 1, QDA is used ; for values in between, the predictions are blended.

```

1 def group_by_continent(language_folder, continent_groups, output_dir):
2     continent_sentences = {continent: [] for continent in continent_groups.keys()}
3     for filepath in glob.glob(f"{language_folder}/*.txt"):
4         locale = os.path.basename(filepath).replace('.txt', '')
5         for continent, locales in continent_groups.items():
6             if locale in locales:
7                 with open(filepath, 'r', encoding='utf-8') as file:
8                     sentences = file.readlines()
9                     continent_sentences[continent].extend(sentences)
10    for continent, sentences in continent_sentences.items():
11        with open(f"{output_dir}/{continent}.txt", 'w', encoding='utf-8') as f:
12            for sentence in sentences:
13                f.write(sentence)
14 continent_output_dir = 'continent_files'
15 os.makedirs(continent_output_dir, exist_ok=True)
16 group_by_continent('language_files', continent_groups, continent_output_dir)

```

```

1 from sklearn.feature_extraction.text import TfidfVectorizer
2 from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
3 from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis as QDA
4 import numpy as np

```

```

1 def load_continent_data(continent_folder):
2     X = []
3     y = []
4
5     for filepath in glob.glob(f"{continent_folder}/*.txt"):
6         continent = os.path.basename(filepath).replace('.txt', '')
7         with open(filepath, 'r', encoding='utf-8') as file:
8             sentences = file.readlines()

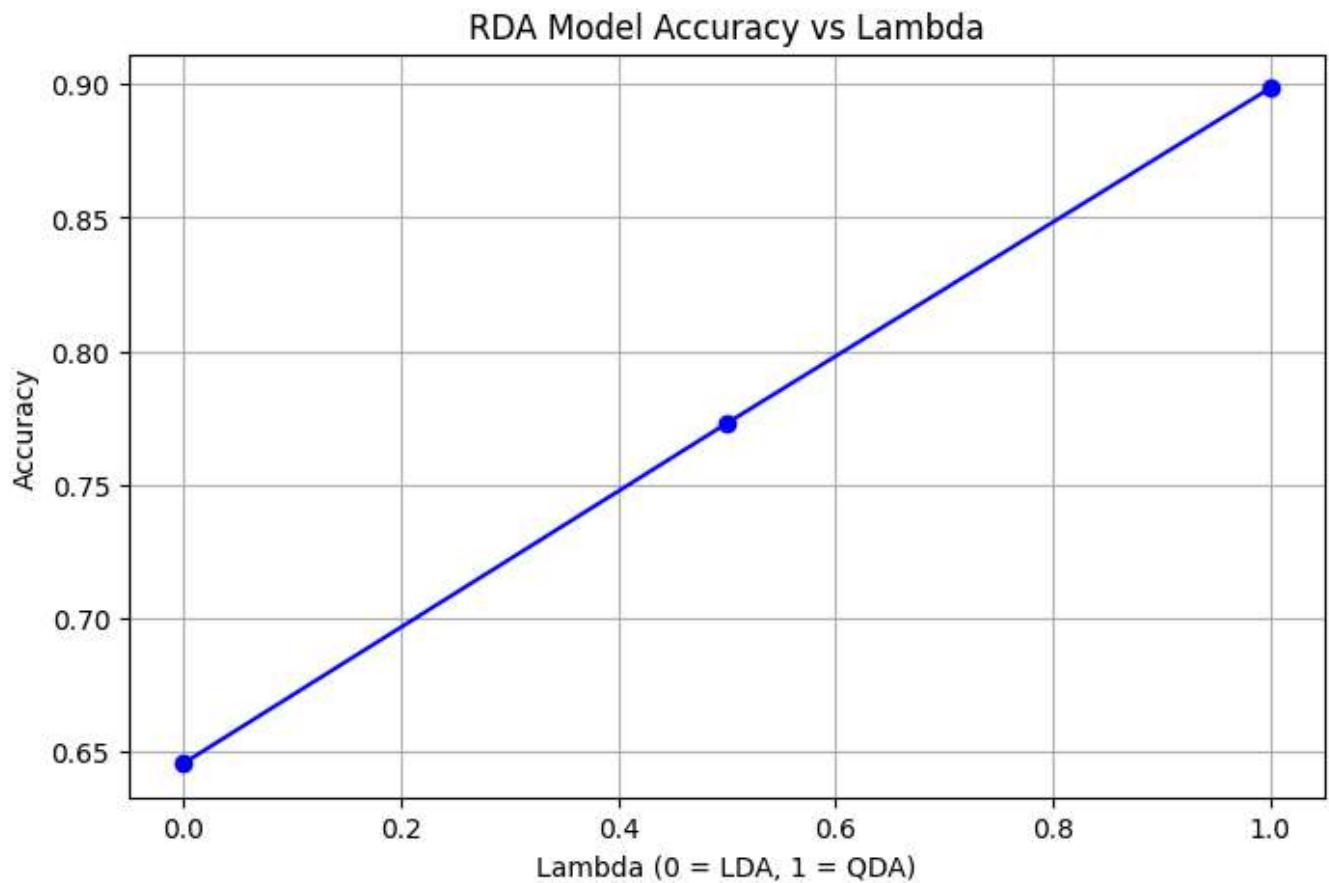
```

```
9         X.extend(sentences)
10        y.extend([continent] * len(sentences))
11
12    return X, y
13 X, y = load_continent_data(continent_output_dir)
14 vectorizer = TfidfVectorizer(max_features=500, stop_words='english')
15 X_vec = vectorizer.fit_transform(X)

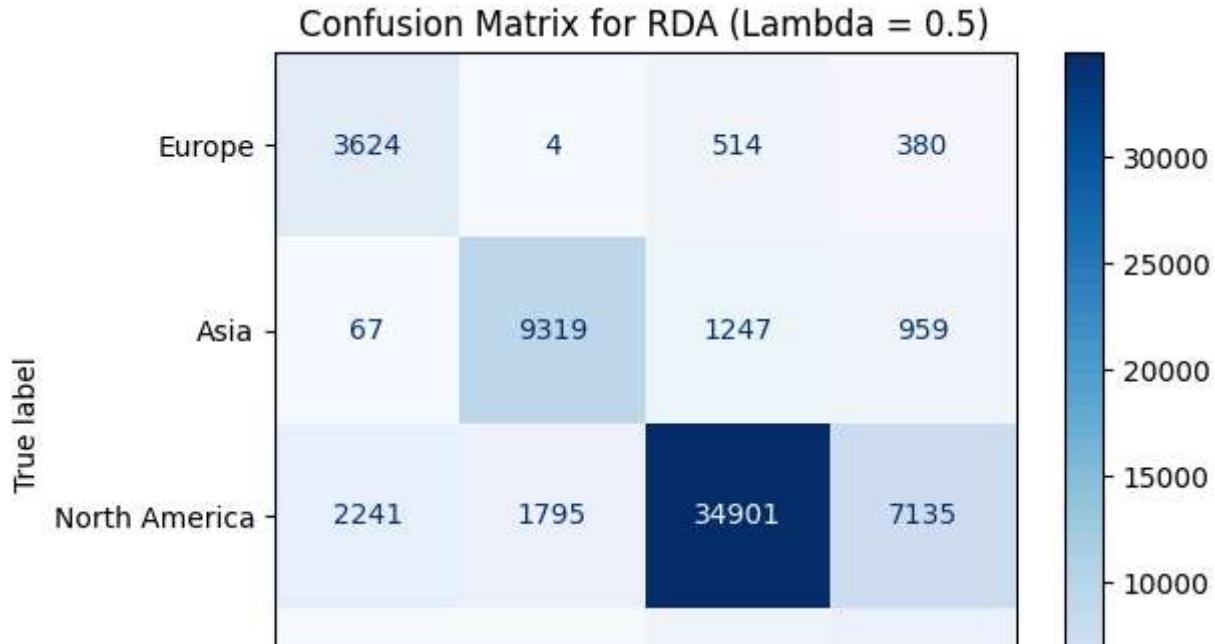
1 import matplotlib.pyplot as plt
2 from sklearn.model_selection import train_test_split
3 from sklearn import metrics
4 from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
5 from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis as QDA
6 import numpy as np
7 from sklearn.metrics import ConfusionMatrixDisplay, confusion_matrix
8
9 # Train-test split
10 X_train, X_val, y_train, y_val = train_test_split(X_vec, y, test_size=0.2, random_state=
11
12 # Function to implement RDA with lambda and return accuracy
13 def RDA_optimized(X_train, y_train, X_val, y_val, lambda_param):
14     lda_model = LDA()
15     qda_model = QDA()
16
17     # Train LDA and QDA models
18     lda_model.fit(X_train.toarray(), y_train)
19     qda_model.fit(X_train.toarray(), y_train)
20
21     # Get predictions from both LDA and QDA
22     lda_pred = lda_model.predict(X_val.toarray())
23     qda_pred = qda_model.predict(X_val.toarray())
24
25     # Blend predictions using lambda
26     blended_pred = np.where(np.random.rand(len(lda_pred)) < lambda_param, lda_pred, qda_
27
28     # Calculate accuracy
29     accuracy = metrics.accuracy_score(y_val, blended_pred)
30
31     return accuracy, blended_pred
32
33 # Lambda values to test
34 lambda_values = [0.0, 0.5, 1.0]
35 accuracies = []
36
37 # Run the RDA model for each lambda and store accuracies
38 for lambda_param in lambda_values:
39     accuracy, preds = RDA_optimized(X_train, y_train, X_val, y_val, lambda_param)
40     accuracies.append(accuracy)
41     print(f"Lambda: {lambda_param}, Accuracy: {accuracy}")
42
43 # Visualizing Accuracy vs Lambda
```

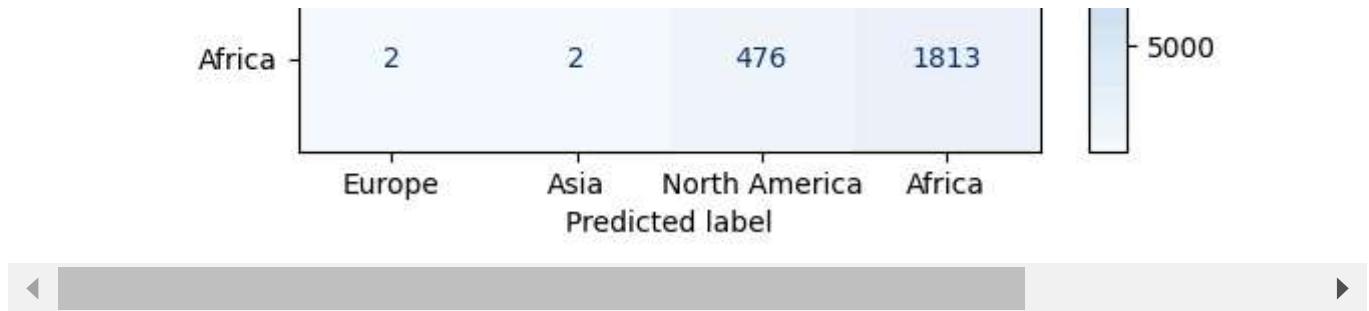
```
44 plt.figure(figsize=(8, 5))
45 plt.plot(lambda_values, accuracies, marker='o', linestyle='-', color='b')
46 plt.title('RDA Model Accuracy vs Lambda')
47 plt.xlabel('Lambda (0 = LDA, 1 = QDA)')
48 plt.ylabel('Accuracy')
49 plt.grid(True)
50 plt.show()
51
52 # Pick a lambda value for confusion matrix visualization
53 lambda_param = 0.5
54 accuracy, preds = RDA_optimized(X_train, y_train, X_val, y_val, lambda_param)
55
56 # Generate the confusion matrix
57 cm = confusion_matrix(y_val, preds)
58
59 # Plot confusion matrix
60 disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=set(y_val))
61 disp.plot(cmap=plt.cm.Blues)
62 plt.title(f'Confusion Matrix for RDA (Lambda = {lambda_param})')
63 plt.show()
64
```

```
→ /usr/local/lib/python3.10/dist-packages/sklearn/discriminant_analysis.py:947: UserWarning  
  warnings.warn("Variables are collinear")  
Lambda: 0.0, Accuracy: 0.6453108764093736  
/usr/local/lib/python3.10/dist-packages/sklearn/discriminant_analysis.py:947: UserWarning  
  warnings.warn("Variables are collinear")  
Lambda: 0.5, Accuracy: 0.7729028055646024  
/usr/local/lib/python3.10/dist-packages/sklearn/discriminant_analysis.py:947: UserWarning  
  warnings.warn("Variables are collinear")  
Lambda: 1.0, Accuracy: 0.8986646815242172
```



```
/usr/local/lib/python3.10/dist-packages/sklearn/discriminant_analysis.py:947: UserWarning  
  warnings.warn("Variables are collinear")
```





Double-click (or enter) to edit