File overview

This notebook implements **Support Vector Machines (SVM)** classification for the subreddit prediction dataset. Hyperparameter tuning is performed, and the model's accuracy is evaluated using **10-fold cross-validation**.

Load modules

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import warnings
warnings.filterwarnings("ignore", category=UserWarning) # This will
suppress UserWarnings
import time
from sklearn.feature extraction.text import TfidfVectorizer
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.model selection import KFold
from sklearn.metrics import accuracy score, classification report
from sklearn.feature_selection import mutual info classif
from sklearn.feature selection import SelectKBest
from sklearn.model selection import GridSearchCV
from sklearn.pipeline import Pipeline
import nltk
from nltk.tokenize import word tokenize
from nltk.stem import WordNetLemmatizer
from nltk.corpus import stopwords, words
# Ensure required NLTK resources are downloaded
try:
    nltk.download('punkt')
    nltk.download('stopwords')
    nltk.download('words')
except Exception as e:
    print(f"Error downloading NLTK resources: {e}")
# Define stopwords list
specific_stopwords = ["https", "subreddit", "www", "com"] ## some
specific words for the given dataset
stopwords list = stopwords.words('english') +specific stopwords +
stopwords.words('french') # dataset is both in english and in french
```

```
[nltk_data] Downloading package punkt to /home/clatimie/nltk_data...
[nltk_data] Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data] /home/clatimie/nltk_data...
[nltk_data] Package stopwords is already up-to-date!
[nltk_data] Downloading package words to /home/clatimie/nltk_data...
[nltk_data] Package words is already up-to-date!
```

Load training dataset

```
# Define the path to the training data file
path_training = "../datasets/Train.csv"
# Read the CSV file into a pandas DataFrame
training data = pd.read csv(path training, delimiter=',')
# Set column names explicitly for better readability
training data.columns = ['text', 'subreddit']
# Shuffle dataset
training data = training data.sample(frac=1,
random state=42).reset index(drop=True)
# Separate the training data into two series: texts and subreddit
labels
x_train = training_data['text'] # Contains the Reddit posts
or comments
y_train = training_data['subreddit'] # Contains the subreddit each
post originates from
# Get unique subreddit labels
unique labels = np.unique(y train) # List of unique subreddits in
the dataset
n samples training = x train.shape[0]
n classes = unique labels.shape[0]
print(f"Training dataset has {n_samples_training} examples and there
are {n classes} classes")
Training dataset has 1399 examples and there are 4 classes
```

Load test dataset

```
# Define the path to the training data file
path_test = "../datasets/Test.csv"

# Read the CSV file into a pandas DataFrame
x_test = pd.read_csv(path_test, delimiter=',')["body"]
```

```
n_samples_test = x_test.shape[0]
print(f"Test dataset has {n_samples_test} examples")
Test dataset has 600 examples
```

Lemma Tokenizer from NLTK

```
class LemmaTokenizer:
    def __init__(self, stopwords=None):
        self.wnl = WordNetLemmatizer()
        self.stop_words = stopwords

def __call__(self, doc):
    # Tokenize the document and apply lemmatization and filtering
    return [
        self.wnl.lemmatize(t, pos="v") for t in word_tokenize(doc)
        if t.isalpha() and t.lower() not in self.stop_words]
```

Hyperparameters search

```
""" # Define the parameter grid for hyperparameter search
param grid = {
    'svc__kernel': ['linear', 'rbf', 'poly'], # Different kernel
    'select k': [1000, 2000, 3000, 4000], # Different values for top
k features
    'svc C': [0.1, 0.2], # Different values for C (controls slack in
SVM)
    'svc gamma': ['scale', 0.001, 0.01, 0.1] # Gamma values for RBF
and poly kernels
# Define the pipeline
pipeline = Pipeline([
    ('vectorizer', TfidfVectorizer(
        lowercase=True,
        tokenizer=LemmaTokenizer(stopwords=stopwords list)
    ('select', SelectKBest(mutual_info_classif)), # Placeholder for k
parameter
    ('scaler', StandardScaler(with mean=False)), # Use
with mean=False for sparse data
    ('svc', SVC()) # SVM classifier
1)
# Use GridSearchCV to find the best combination of hyperparameters
grid search = GridSearchCV(
   estimator=pipeline,
   param grid=param grid,
   cv=5, # 10-fold cross-validation
```

```
scoring='accuracy',
    verbose=3, # To display progress
    n jobs=-1 # Use all available cores
# Fit the model to the training data and search for best parameters
grid search.fit(x_train, y_train)
# Get the best parameters and corresponding score
best params = grid search.best params
best score = grid search.best score
print("Best Parameters:", best params)
print(f"Best Cross-Validated Accuracy: {best_score:.4f}") """
' # Define the parameter grid for hyperparameter search\nparam grid =
      \'svc_kernel\': [\'linear\', \'rbf\', \'poly\'], # Different
                   \'select__k\': [1000, 2000, 3000, 4000], #
kernel options\n
Different values for top k features\n
                                       \'svc C\': [0.1, 0.2],
Different values for C (controls slack in SVM)\n \'svc gamma\':
[\'scale\', 0.001, 0.01, 0.1] # Gamma values for RBF and poly
kernels\n\n# Define the pipeline\npipeline = Pipeline([\n
(\'vectorizer\', TfidfVectorizer(\n
                                          lowercase=True,\n
tokenizer=LemmaTokenizer(stopwords=stopwords list)\n
(\'select\', SelectKBest(mutual info classif)), # Placeholder for k
               (\'scaler\', StandardScaler(with mean=False)), # Use
parameter\n
with mean=False for sparse data\n (\'svc\', SVC()) # SVM
classifier\n])\n\n# Use GridSearchCV to find the best combination of
hyperparameters\ngrid search = GridSearchCV(\n
                                                 estimator=pipeline.\
                                cv=5, # 10-fold cross-validation\n
     param grid=param grid,\n
scoring=\'accuracy\',\n
                          verbose=3, # To display progress\n
n jobs=-1 # Use all available cores\n)\n\n# Fit the model to the
training data and search for best parameters\ngrid search.fit(x train,
y_train)\n\n# Get the best parameters and corresponding score\
nbest params = grid search.best params \nbest score =
grid search.best score \n\nprint("Best Parameters:", best params)\
nprint(f"Best Cross-Validated Accuracy: {best score:.4f}")
```

10-fold cross validation

```
vectorizer = TfidfVectorizer(
    lowercase=True,
    tokenizer=LemmaTokenizer(stopwords=stopwords_list)
)

x_train_tfidf = vectorizer.fit_transform(x_train)

selector = SelectKBest(mutual_info_classif, k=3000)
x_train_mi = selector.fit_transform(x_train_tfidf, y_train)
```

```
scaler = StandardScaler()
x train svc = scaler.fit transform(np.asarray(x train mi.todense()))
classifier = SVC(kernel="rbf",gamma='scale', C=1)
accuracies = []
class_accuracies = {class_name: [] for class_name in set(y_train)} #
To store accuracy for each class
kf = KFold(n splits=10, shuffle=True, random state=42)
fold = 0
# Start measuring time
start time = time.time()
accuracies = []
training accuracies = []
class accuracies = {class name: [] for class name in set(y train)} #
To store accuracy for each class
kf = KFold(n splits=10, shuffle=True, random state=42)
fold = 0
for train index, val index in kf.split(x train svc):
    fold += 1
    X train fold, X val fold = x train svc[train index],
x train svc[val index]
    y fold train, y fold val = y train[train index],
y train[val index]
    # Train the classifier
    classifier.fit(X train fold, y fold train)
    # Predict and evaluate on the validation set
    y pred = classifier.predict(X val fold)
    y_pred_training = classifier.predict(X train fold)
    # Display results for each fold
    print(f"\nFold n°{fold}:")
    # Get accuracy per class
    class accuracy = classification report(y fold val, y pred,
output dict=True)
    print("Classification Report:\n",
classification report(y fold val, y pred))
    accuracy = accuracy score(y fold val, y pred)
    accuracies.append(accuracy)
    accuracy training = accuracy score(y pred training, y fold train)
    training accuracies.append(accuracy training)
```

```
for label, metrics in class accuracy.items():
        if label != 'accuracy' and label!="macro avg" and label!=
"weighted avg":
            class accuracies[label].append(metrics['precision'])
# Compute total time
end time = time.time()
total time = end_time - start_time
print(f"\nTotal computing time for 10 folds: {total time:.2f}
seconds")
# Mean accuracy across 10 folds
mean_accuracy = np.mean(accuracies)
print(f"Mean Accuracy across 10 folds for SVM classifier:
{mean accuracy:.4f}")
# Average accuracy for each class
print("\nAverage Accuracy per Class:")
for label, accuracies in class accuracies.items():
    avg class accuracy = np.mean(accuracies)
    print(f"Class {label}: {avg class accuracy:.4f}")
# Mean training accuracy across 10 folds
mean training accuracy = np.mean(accuracy training)
print(f"Mean training accuracy across 10 folds for SVM classifier:
{mean training accuracy:.4f}")
Fold n°1:
Classification Report:
               precision recall f1-score support
    Brussels
                   0.69
                             0.87
                                       0.77
                                                   38
                   0.71
                             0.84
                                       0.77
                                                   32
      London
    Montreal
                   0.90
                             0.59
                                       0.72
                                                   32
    Toronto
                   0.85
                             0.74
                                       0.79
                                                   38
                                       0.76
                                                   140
    accuracy
                   0.79
                             0.76
                                       0.76
                                                   140
   macro avg
weighted avg
                   0.79
                             0.76
                                       0.76
                                                   140
```