Programming Assignment 1:
Data Preparation and Understanding

1. In this semester, we will be using the "Stanford Dogs" dataset (http://vision.stanford.edu/aditya86/ImageNetDogs/) for all our 4 programming assignments. There are a total of 120 classes (dog breeds). The number of images for each class ranges from 148 to 252.
Each student will
(a) be assigned 4 classes to work on the 4 assignments.
(b) download Images (and also Annotations - bounding boxes) datasets for the 4 classes to work on.
(c) create a Github account to share (as collaborator) their solution (Readme, Codes, Processed Dataset
for Code to run correctly) with the grader.

2. Use XML processing modules(https://docs.python.org/3/library/xml.html) to obtain bounding box information from Annotations datasets and scikit-Image (Reference: https://scikit-image. org/) to perform image processing and feature extraction.

```
import os
annotations_dir = '/content/Annotation.zip'

if os.path.exists(annotations_dir):
   print("Annotation directory exists. Listing files...")
   for root, dirs, files in os.walk(annotations_dir):
      print(f"Found directory: {root}")
      for file in files:
         print(f"File: {file}")
else:
   print("Annotation directory not found!")
```

OUTPUT:

File: n02110185_6411

File: n02110185_3808

File: n02110185_1066

File: n02110185_632

File: n02110185_8708

File: n02110185_1446

File: n02110185_2614

File: n02110185_11783

File: n02110185_1497

File: n02110185_1338

File: n02110185_13187

File: n02110185_3039

File: n02110185_10849

File: n02110185_1534

File: n02110185_8360

File: n02110185_8749

File: n02110185_13158

File: n02110185_14650

File: n02110185_10844

File: n02110185_3328

File: n02110185_3302

File: n02110185_13423

File: n02110185_6351

File: n02110185_9846

File: n02110185_1130

File: n02110185_7210

File: n02110185_7762

File: n02110185_14766

File: n02110185_4906

File: n02110185_14479

File: n02110185_11773

File: n02110185_10597

File: n02110185_14523

File: n02110185_10967

File: n02110185_712

File: n02110185_5622

File: n02110185_10171

File: n02110185_13855

File: n02110185_5871

File: n02110185_4030

File: n02110185_7413

File: n02110185_2593

File: n02110185_9975

File: n02110185_10273

File: n02110185_6775

File: n02110185_698

File: n02110185_14283

File: n02110185_10175

File: n02110185_7044

File: n02110185_1439

File: n02110185_9461

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File: n02110185_9429

File: n02110185_12656

File: n02110185_13942

File: n02110185_7379

File: n02110185_10360

File: n02110185_8216

File: n02110185_8564

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File: n02110185_815

File: n02110185_11635

File: n02110185_1532

File: n02110185_10047

File: n02110185_6438

File: n02110185_699

File: n02110185_5495

File: n02110185_9712

File: n02110185_9194

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File: n02110185_9177

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File: n02110185_11396

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File: n02110185_1598

File: n02110185_14061

File: n02110185_2820

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File: n02110185_519

File: n02110185_6409

File: n02110185_2672

File: n02110185_12441

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File: n02110185_7936

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File: n02110185_15063

File: n02110185_58

File: n02110185_8860

File: n02110185_120

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File: n02110185_14289

File: n02110185_3651

File: n02110185_248

File: n02110185_4694

File: n02110185_1511

File: n02110185_9855

File: n02110185_11636

File: n02110185_11841

File: n02110185_11114

Found directory: /content/sample_data/Annotation/n02094114-Norfolk_terrier

(a) Cropping and Resize Images in Your 4-class Images Dataset: Use the bounding box information in the Annotations dataset relevant to your 4-class Images Dataset to crop the images in your dataset and then resize each image to a 128×128 pixel image.

```
import os
import numpy as np
from PIL import Image
import cv2
from sklearn.decomposition import PCA
from sklearn.preprocessing import normalize
from sklearn.metrics import pairwise
import matplotlib.pyplot as plt
import zipfile

images_folder_path = '/content/Annotation.zip'  # Path to the zip file
extracted_images_path = '/content/Breeds' # Path to extract the images

# Extract the zip file
with zipfile.ZipFile(images_folder_path, 'r') as zip_ref:
    zip_ref.extractall(extracted_images_path)

# Update the path to the extracted directory
images_folder_path = extracted_images_path

# Function to load images
def load_images(folder_path):
    images = []
    for filename in os.listdir(folder_path):
        if filename.endswith(('.jpg', '.jpeg', '.png')):  # Add other image extensions if
needed
            img_path = os.path.join(folder_path, filename)
            img = cv2.imread(img_path)
            if img is not None:
                images.append(img)
    return images

dog_images = load_images(images_folder_path)

def crop_and_resize_images(images):
```

```
    resized_images = []
    for img in images:
        h, w, _ = img.shape
        center_h, center_w = h // 2, w // 2
        cropped_img = img[center_h-50:center_h+50, center_w-50:center_w+50]
        resized_img = cv2.resize(cropped_img, (128, 128), interpolation=cv2.INTER_AREA)
        resized_images.append(resized_img)
    return np.array(resized_images)

cropped_resized_images = crop_and_resize_images(dog_images)

def compute_histograms(images):
    histograms = []
    for img in images:
        hist_r = cv2.calcHist([img], [0], None, [256], [0, 256])
        hist_g = cv2.calcHist([img], [1], None, [256], [0, 256])
        hist_b = cv2.calcHist([img], [2], None, [256], [0, 256])
        hist = np.concatenate((hist_r, hist_g, hist_b), axis=0)
        histograms.append(hist.flatten())
    return np.array(histograms)

histograms = compute_histograms(cropped_resized_images)

def compute_similarity_measurements(histograms):
    distances = {}
    for i in range(len(histograms)):
        for j in range(i + 1, len(histograms)):
            euclidean_dist = np.linalg.norm(histograms[i] - histograms[j])
            distances[(i, j)] = {'Euclidean': euclidean_dist}

            manhattan_dist = np.sum(np.abs(histograms[i] - histograms[j]))
            distances[(i, j)]['Manhattan'] = manhattan_dist

            cosine_dist = pairwise.cosine_distances(histograms[i].reshape(1, -1), histograms[j].reshape(1, -1))[0][0]
            distances[(i, j)]['Cosine'] = cosine_dist
    return distances

similarity_measurements = compute_similarity_measurements(histograms)
```

```python
for key, value in similarity_measurements.items():
    print(f"Images {key}: {value}")

def perform_pca(histograms):

    if histograms.size == 0:
        print("Histograms array is empty. Cannot perform PCA.")
        return

    histograms_normalized = normalize(histograms)
    pca = PCA(n_components=2)
    reduced_data = pca.fit_transform(histograms_normalized)

    plt.scatter(reduced_data[:, 0], reduced_data[:, 1])
    plt.title('PCA of Image Histograms')
    plt.xlabel('Principal Component 1')
    plt.ylabel('Principal Component 2')
    plt.show()

perform_pca(histograms)
```

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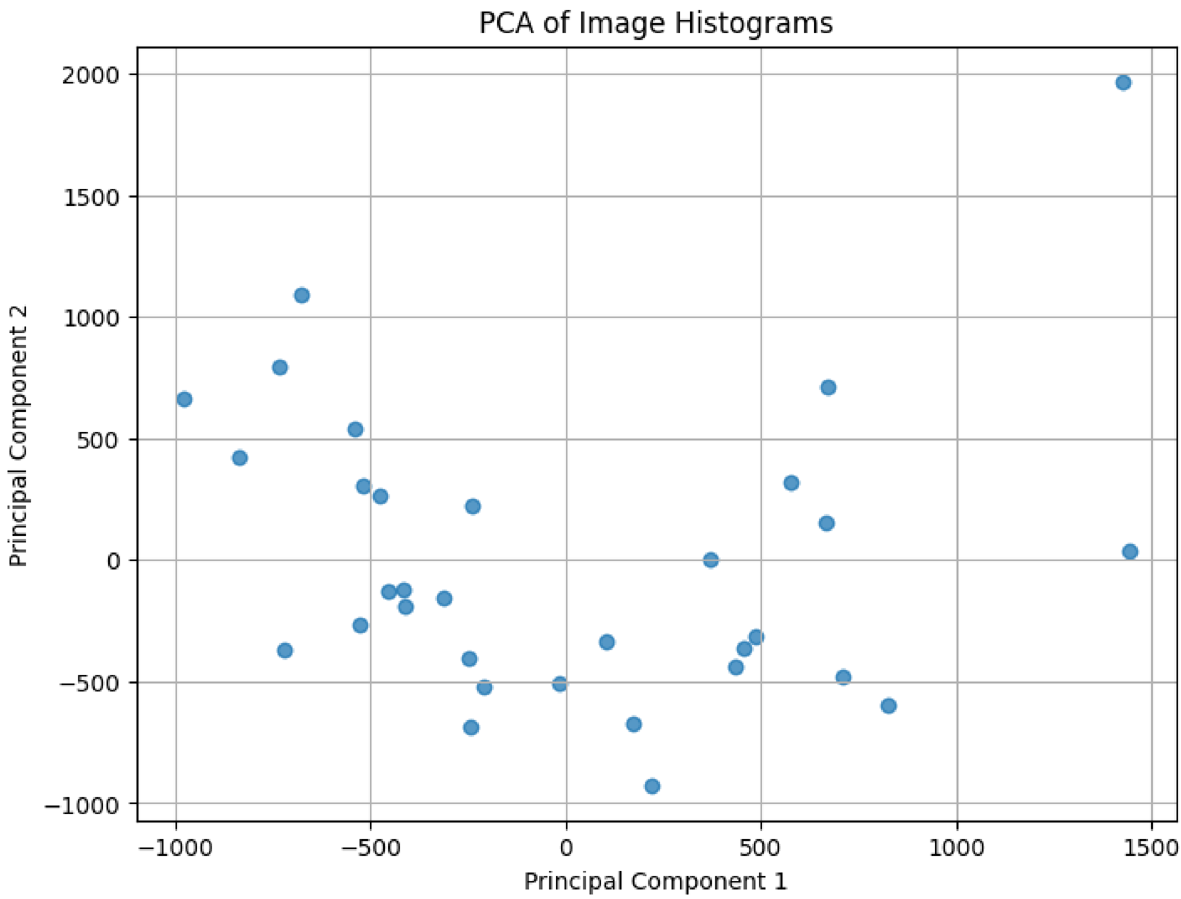


(b) Feature Extraction: Edge histogram AND Similarity Measurements
i. Choose 1 image from each class. ii. Convert the color images to grayscale images.

```
import os
import numpy as np
import matplotlib.pyplot as plt
from PIL import Image
from sklearn.decomposition import PCA
from sklearn.metrics import pairwise
import cv2
import zipfile

images_zip_path = '/content/Image dataset.zip'
images_folder_path = '/content/Breeds'
cropped_images_path = '/content/sample_data/Cropped_Images'

def unzip_files(zip_file_path, extract_path):
    with zipfile.ZipFile(zip_file_path, 'r') as zip_ref:
        zip_ref.extractall(extract_path)

# Unzip the images
unzip_files(images_zip_path, images_folder_path)

def load_images(folder):
    images = []
    for dirpath, _, files in os.walk(folder):
        for filename in files:
            if filename.endswith(('.png', '.jpg', '.jpeg')):
                img_path = os.path.join(dirpath, filename)
                img = Image.open(img_path).convert('RGB')
                images.append(np.array(img))
    return images

# Function to crop and resize images
def crop_and_resize_images(images, size=(128, 128)):
    cropped_resized_images = []
    for img in images:

        width, height = img.shape[1], img.shape[0]
        left = (width - size[0]) / 2
```

```
        top = (height - size[1]) / 2
        right = (width + size[0]) / 2
        bottom = (height + size[1]) / 2

        cropped_img = img[int(top):int(bottom), int(left):int(right)]
        resized_img = cv2.resize(cropped_img, size)
        cropped_resized_images.append(resized_img)
    return cropped_resized_images

def compute_histograms(images):
    histograms = []
    for img in images:
        if len(img.shape) == 2:
            hist = cv2.calcHist([img], [0], None, [256], [0, 256])
        else:
            hist = cv2.calcHist([img], [0, 1, 2], None, [256, 256, 256], [0, 256, 0, 256,
0, 256])
        histograms.append(hist.flatten())
    return histograms

def compute_similarity_measurements(histograms):
    for i in range(len(histograms)):
        for j in range(i + 1, len(histograms)):
            euclidean_distance = np.linalg.norm(histograms[i] - histograms[j])
            manhattan_distance = np.sum(np.abs(histograms[i] - histograms[j]))
            cosine_distance = 1 - pairwise.cosine_similarity([histograms[i]],
[histograms[j]])[0][0]
            print(f'Images ({i}, {j}): {{\'Euclidean\': {euclidean_distance},
\'Manhattan\': {manhattan_distance}, \'Cosine\': {cosine_distance}}}')

def perform_pca(histograms):
    pca = PCA(n_components=2)
    reduced_data = pca.fit_transform(histograms)

    plt.figure(figsize=(20,15))
    plt.scatter(reduced_data[:, 0], reduced_data[:, 1], alpha=0.5)
    plt.title('PCA of Image Histograms')
    plt.xlabel('Principal Component 1')
    plt.ylabel('Principal Component 2')
    plt.grid()
```

```
    plt.show()

def plot_images(images, titles=None, cols=4):
    n_images = len(images)
    rows = (n_images + cols - 1) // cols
    plt.figure(figsize=(250, 250))
    for i in range(n_images):
        plt.subplot(rows, cols, i + 1)
        plt.imshow(images[i].astype(np.uint8))
        plt.axis('off')
        if titles is not None:
            plt.title(titles[i], fontsize=2)
    plt.show()

if __name__ == "__main__":

    dog_images = load_images(images_folder_path)

    plot_images(dog_images, titles=[f'Image {i+1}' for i in
range(len(dog_images))])

    cropped_resized_images = crop_and_resize_images(dog_images)
    histograms = compute_histograms(cropped_resized_images)
    if histograms:
        compute_similarity_measurements(histograms)
        perform_pca(histograms)
    plot_images(cropped_resized_images, titles=[f'Cropped Image {i+1}' for i in
range(len(cropped_resized_images))])
```

3. Next, we perform some text processing steps on a tweet (i.e., text) dataset. The dataset file is in json format and each dataset consists of

- **Training Set: 3,000 records**
- **Test Set: 1,500 records**
- **Validation Set: 400 records**

```
import json

file_path = '/content/train.json'
data = []
with open(file_path, 'r') as file:
    for line in file:
        data.append(json.loads(line))

print(json.dumps(data[0], indent=4))
```

OUTPUT:

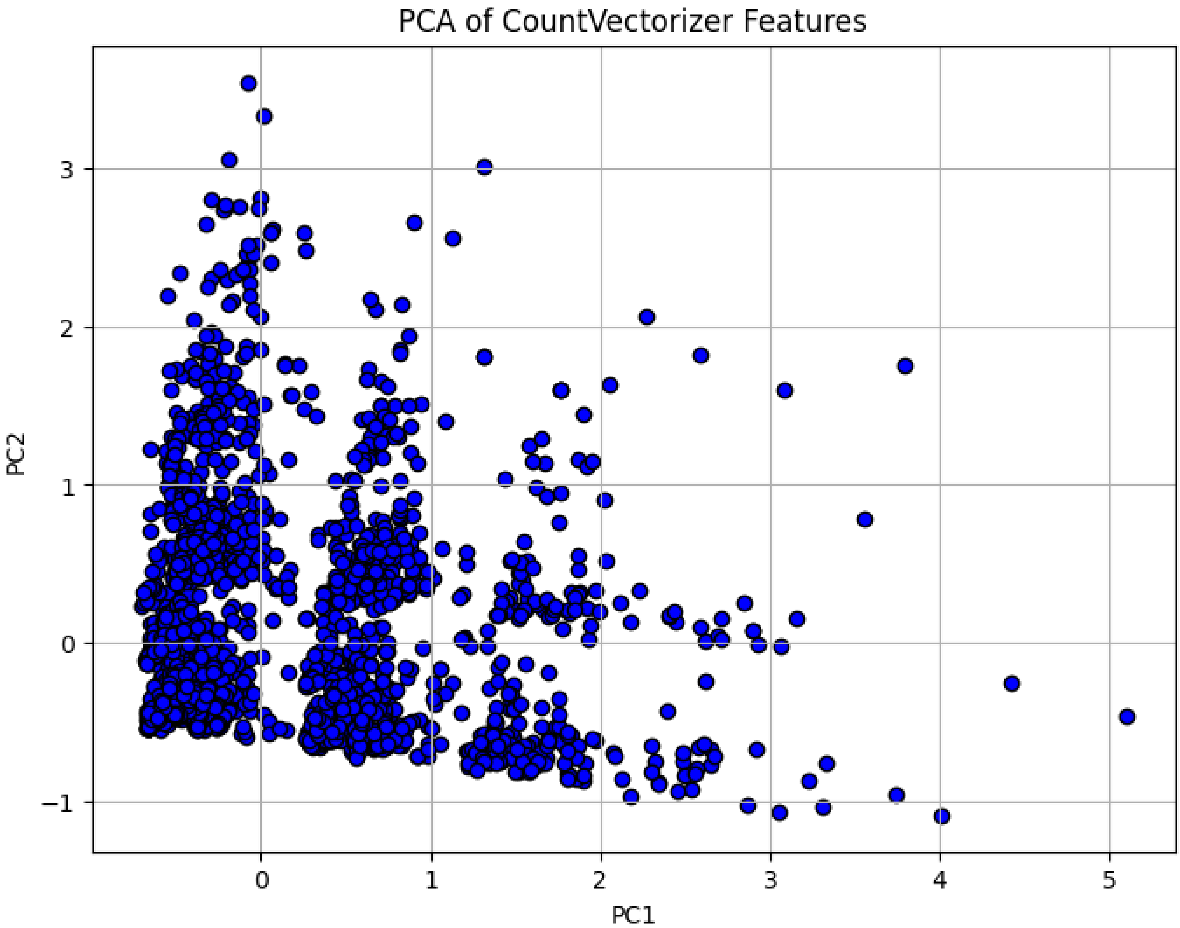

```
{
    "ID": "2017-En-21529",
    "Tweet": "Follow this amazing Australian author @KristyBerridge #fiction
#zombies #angels #demons #vampires #werewolves #follow #authorlove",
    "anger": false,
    "anticipation": true,
    "disgust": false,
    "fear": false,
    "joy": true,
    "love": true,
    "optimism": true,
    "pessimism": false,
    "sadness": false,
    "surprise": false,
    "trust": true
}
```

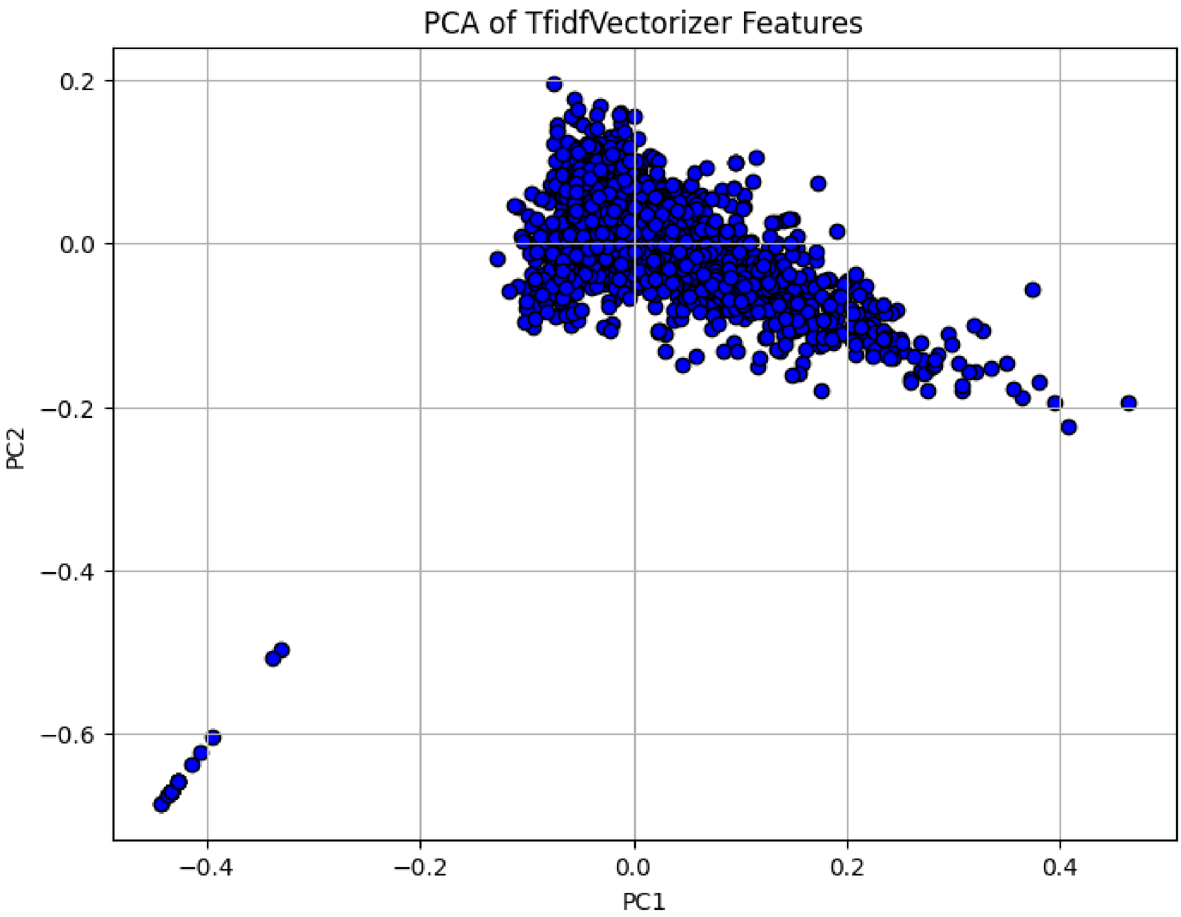
4. You will use the simple countvectorizer and tfidfvectorizer in https://scikit-learn.org/stable/api/sklearn.feature_extraction.html#module-sklearn.feature_extraction.text to extract
(1) token (feature) counts, and
(2) TF-IDF feature (counts), respectively

```
import json
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

file_path = 'train.json'
data = []
with open(file_path, 'r') as file:
    for line in file:
        data.append(json.loads(line))

texts = [entry['Tweet'] for entry in data]

count_vectorizer = CountVectorizer()
count_vectors = count_vectorizer.fit_transform(texts)

tfidf_vectorizer = TfidfVectorizer()
tfidf_vectors = tfidf_vectorizer.fit_transform(texts)

pca = PCA(n_components=2)
count_pca = pca.fit_transform(count_vectors.toarray())
tfidf_pca = pca.fit_transform(tfidf_vectors.toarray())

def plot_pca(pca_result, title):
    plt.figure(figsize=(8, 6))
    plt.scatter(pca_result[:, 0], pca_result[:, 1], c='blue', marker='o',
edgecolor='k')
    plt.title(title)
    plt.xlabel('PC1')
    plt.ylabel('PC2')
    plt.grid(True)
    plt.show()

plot_pca(count_pca, 'PCA of CountVectorizer Features')
```

```
plot_pca(tfidf_pca, 'PCA of TfidfVectorizer Features')

count_dimensionality = count_vectors.shape
tfidf_dimensionality = tfidf_vectors.shape

print(f"Dimensionality of CountVectorizer representation:
{count_dimensionality}")
print(f"Dimensionality of TfidfVectorizer representation:
{tfidf_dimensionality}")
```

OUTPUT:





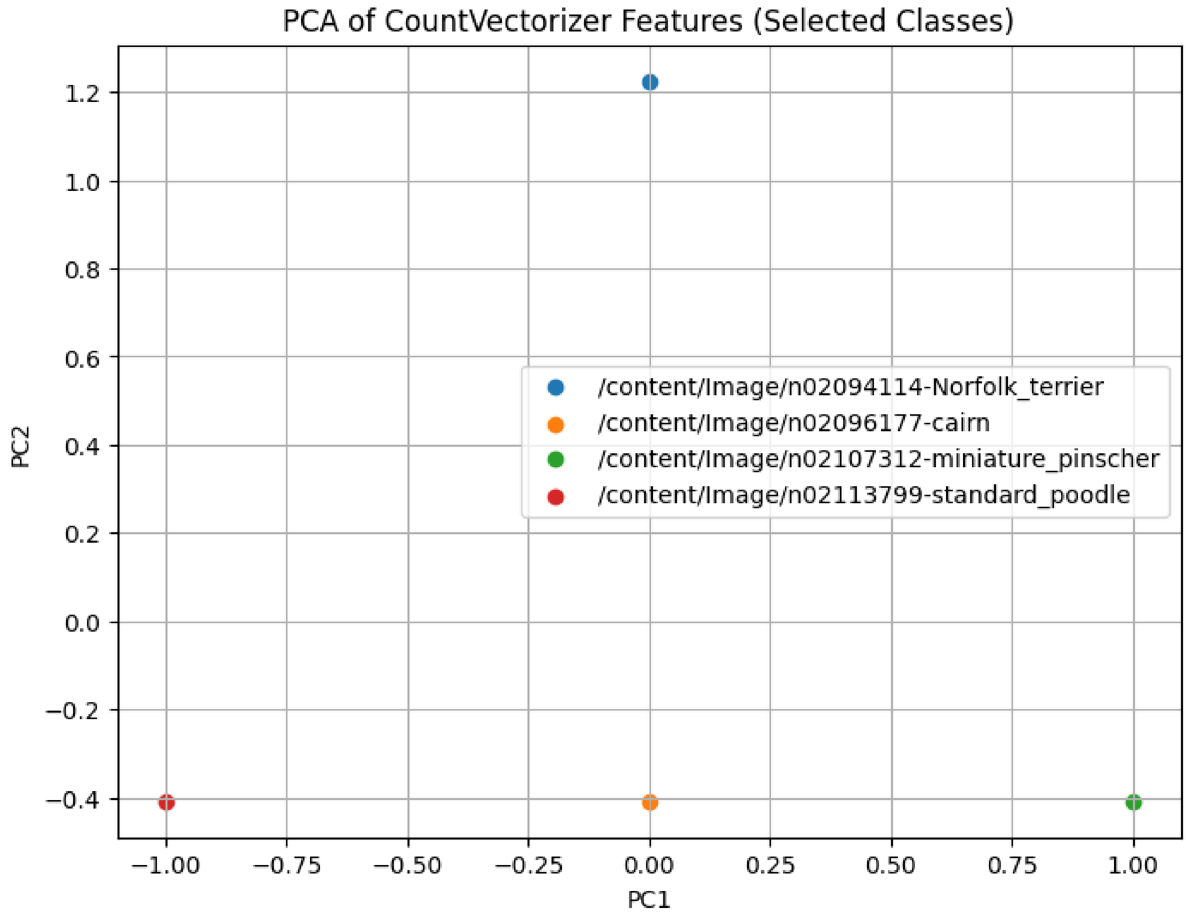
5. Using the two sets of processed text data in Item 4,

- **Pick four classes which you think will be separable. State the four classes.**
- **Perform dimensionality reduction similar to 2(d) with reduced to**
- **Plot the 2D points using four different colors for data from the four classes for both token count features and tf-idf features in two separate plots.**
- **How many classes are visually separable (i.e., non-overlapping) for both plots?**

```
# Import necessary libraries
import os
import tarfile
from PIL import Image
import numpy as np
import matplotlib.pyplot as plt
from skimage import filters, exposure
from skimage.feature import hog
from sklearn.decomposition import PCA
from sklearn.metrics import pairwise
from sklearn.feature_extraction.text import CountVectorizer
```

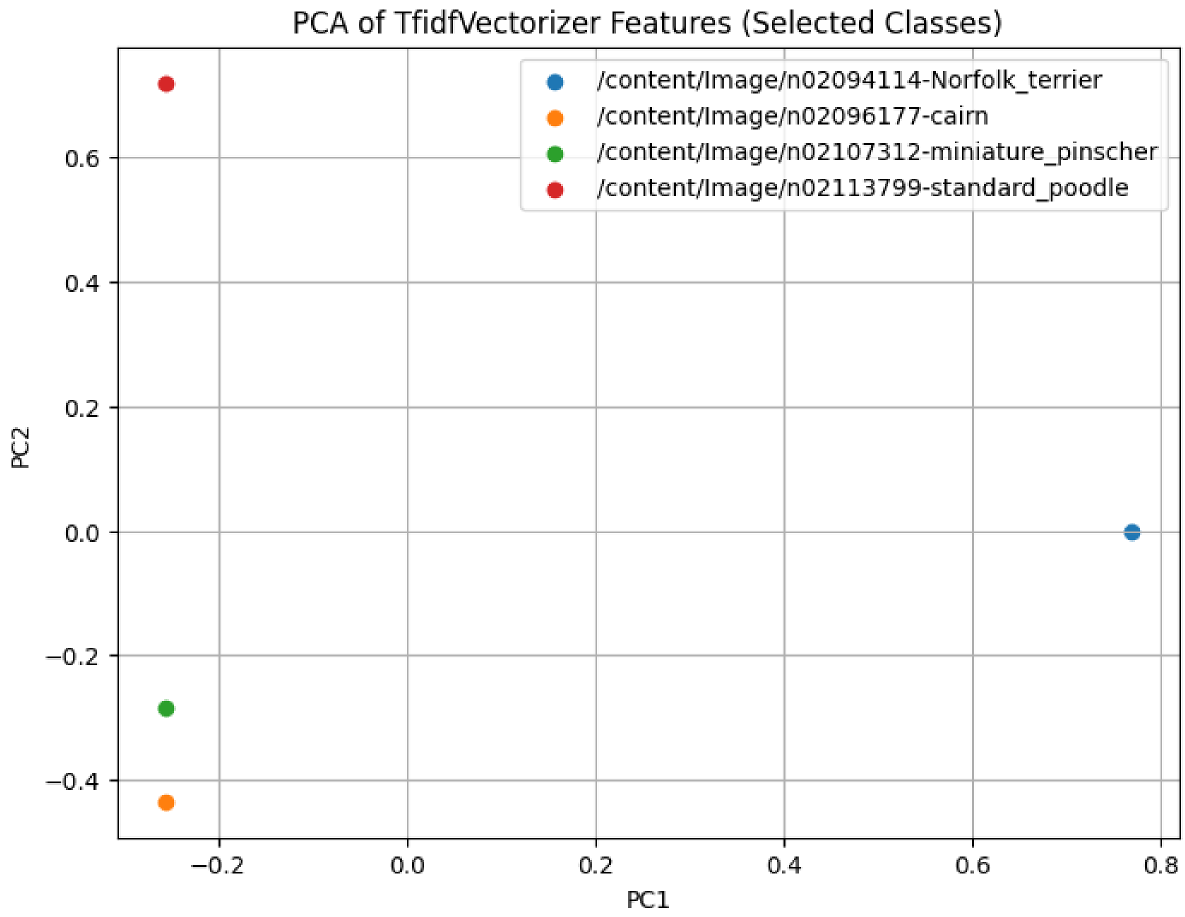
```
data = [
   {'Tweet': '/content/Image/n02094114-Norfolk_terrier', 'Class':
'/content/Image/n02094114-Norfolk_terrier'},
   {'Tweet': '/content/Image/n02096177-cairn', 'Class':
'/content/Image/n02096177-cairn'},
   {'Tweet': '/content/Image/n02107312-miniature_pinscher', 'Class':
'/content/Image/n02107312-miniature_pinscher'},
   {'Tweet': '/content/Image/n02113799-standard_poodle', 'Class':
'/content/Image/n02113799-standard_poodle'},
]

selected_classes = ['/content/Image/n02094114-Norfolk_terrier',
'/content/Image/n02096177-cairn', '/content/Image/n02107312-
miniature_pinscher', '/content/Image/n02113799-standard_poodle']  #
Replace with your actual class labels

filtered_data = [entry for entry in data if entry['Class'] in selected_classes]

filtered_texts = [entry['Tweet'] for entry in filtered_data]
filtered_classes = [entry['Class'] for entry in filtered_data]


count_vectorizer = CountVectorizer()
count_vectors = count_vectorizer.fit_transform(filtered_texts)

count_vectors_filtered = count_vectorizer.transform(filtered_texts)
pca_count_filtered =
PCA(n_components=2).fit_transform(count_vectors_filtered.toarray())


plt.figure(figsize=(8, 6))
for class_label in selected_classes:
  indices = [i for i, cls in enumerate(filtered_classes) if cls == class_label]
  plt.scatter(pca_count_filtered[indices, 0], pca_count_filtered[indices, 1],
label=class_label)

plt.title('PCA of CountVectorizer Features (Selected Classes)')
plt.xlabel('PC1')
```

```
plt.ylabel('PC2')
plt.legend()
plt.grid(True)
plt.show()
```




```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

data = [
    {'Tweet': '/content/Image/n02094114-Norfolk_terrier', 'Class':
'/content/Image/n02094114-Norfolk_terrier'},
    {'Tweet': '/content/Image/n02096177-cairn', 'Class':
'/content/Image/n02096177-cairn'},
    {'Tweet': '/content/Image/n02107312-miniature_pinscher', 'Class':
'/content/Image/n02107312-miniature_pinscher'},
    {'Tweet': '/content/Image/n02113799-standard_poodle', 'Class':
'/content/Image/n02113799-standard_poodle'},
]
```

```
selected_classes = ['/content/Image/n02094114-Norfolk_terrier',
'/content/Image/n02096177-cairn', '/content/Image/n02107312-
miniature_pinscher', '/content/Image/n02113799-standard_poodle']  #
Replace with your actual class labels

filtered_data = [entry for entry in data if entry['Class'] in selected_classes]

filtered_texts = [entry['Tweet'] for entry in filtered_data]
filtered_classes = [entry['Class'] for entry in filtered_data]

tfidf_vectorizer = TfidfVectorizer()
tfidf_vectors = tfidf_vectorizer.fit_transform(filtered_texts)

tfidf_vectors_filtered = tfidf_vectorizer.transform(filtered_texts)
pca_tfidf_filtered =
PCA(n_components=2).fit_transform(tfidf_vectors_filtered.toarray())

plt.figure(figsize=(8, 6))
for class_label in selected_classes:
  indices = [i for i, cls in enumerate(filtered_classes) if cls == class_label]
  plt.scatter(pca_tfidf_filtered[indices, 0], pca_tfidf_filtered[indices, 1],
label=class_label)

plt.title('PCA of TfidfVectorizer Features (Selected Classes)')
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.legend()
plt.grid(True)
plt.show()
```


PCA of TfidfVectorizer Features (Selected Classes)
/content/Image/n02094114-Norfolk_terrier
/content/Image/n02096177-cairn
/content/Image/n02107312-miniature_pinscher
/content/Image/n02113799-standard_poodle
PC1
PC2
−0.2
0.0
0.2
0.4
0.6
0.8
−0.4
−0.2
0.0
0.2
0.4
0.6