face recognize

April 22, 2025

1

1.1

```
[144]: #
    train_dir = "split_data/train"
    test_dir = "split_data/test"
    test_out_dir = "split_data/test_out"
```

```
[145]: #
def preprocess_image(image_path, target_size=(64, 64), is_train=False):
    img = Image.open(image_path).convert("L")  #
    width, height = img.size

if is_train:
    # 1.
    scale = np.random.uniform(0.8, 1.2)  #
    new_size = (int(target_size[0] * scale), int(target_size[1] * scale))
    img = img.resize(new_size)

# 2.
    x = np.random.randint(0, new_size[0] - target_size[0] + 1)
    y = np.random.randint(0, new_size[1] - target_size[1] + 1)
```

```
img = img.crop((x, y, x + target_size[0], y + target_size[1]))
      # 3.
      if np.random.random() > 0.5:
           img = img.rotate(np.random.randint(-15, 15)) #
      if np.random.random() > 0.5:
          img = img.transpose(Image.FLIP LEFT RIGHT)
      enhancer = ImageEnhance.Brightness(img)
      img = enhancer.enhance(np.random.uniform(0.7, 1.3)) #
      enhancer = ImageEnhance.Contrast(img)
      img = enhancer.enhance(np.random.uniform(0.8, 1.2)) #
      if np.random.random() > 0.3: #
           img = img.filter(ImageFilter.GaussianBlur(radius=np.random.
\hookrightarrowuniform(0, 1)))
  else:
      x = (width - target_size[0]) // 2
      y = (height - target size[1]) // 2
      img = img.crop((x, y, x + target_size[0], y + target_size[1]))
  #
  img = ImageOps.equalize(img)
  img = np.array(img) / 255.0
  return img.flatten() #
```

```
[146]: #
       def load_dataset(data_dir, target_size=(64, 64), max_images_per_person=None):
           # print(f" {data_dir} ...")
           data = []
           labels = []
           filenames = []
           for subject_id in os.listdir(data_dir):
               subject_path = os.path.join(data_dir, subject_id)
               if os.path.isdir(subject_path):
                   images = os.listdir(subject_path)
                   if max_images_per_person:
                       images = images[:max_images_per_person]
                   for img_name in images:
                       img_path = os.path.join(subject_path, img_name)
                       img = preprocess_image(img_path, target_size)
                       data.append(img)
                       labels.append(subject_id)
                       filenames.append(f"{subject_id}/{img_name}") #
```

```
print(f"{data_dir} ")
return np.array(data), np.array(labels), filenames
```

1.4 PCA

```
[147]: # PCA
       def pca reduction(train_data, test_data, test_out_data, n_components):
                             {n_components} ...")
           print(f"
                     PCA
           train_data_flat = train_data.reshape(train_data.shape[0], -1)
           test_data_flat = test_data.reshape(test_data.shape[0], -1)
           test_out_data_flat = test_out_data.reshape(test_out_data.shape[0], -1)
           mean face = np.mean(train data flat, axis=0)
           train data centered = train data flat - mean face
           test_data_centered = test_data_flat - mean_face
           test_out_data_centered = test_out_data_flat - mean_face
                n_components
           max_components = min(train_data_centered.shape[0], train_data_centered.
        \hookrightarrowshape [1])
           if n_components > max_components:
               print(f" : n_components={n_components} {max_components}")
               n_components = max_components
           pca = PCA(n_components=n_components)
           train_data_pca = pca.fit_transform(train_data_centered)
           test_data_pca = pca.transform(test_data_centered)
           test_out_data_pca = pca.transform(test_out_data_centered)
           print("PCA
           return train_data_pca, test_data_pca, test_out_data_pca
```

1.5 SVM

```
# grid_search.fit(train_data, binary_labels)
# best_sum = grid_search.best_estimator_
# classifiers[label] = best_sum

for label in unique_labels:
    binary_labels = (train_labels == label).astype(int)

# svm = SVC(probability=True, C=0.01, gamma=0.001, kernel='rbf')
    svm.fit(train_data, binary_labels)
    classifiers[label] = svm

print("SVM ")
return classifiers
```

```
Γ149]: #
       def vote_predict(classifiers, data, threshold):
           # print("
                       ...")
           predictions = []
           all_scores = []
           for sample in data:
               scores = []
               for label, classifier in classifiers.items():
                   score = classifier.predict_proba([sample])[0][1]
                   scores.append(score)
               max_score = np.max(scores)
               all_scores.append(max_score)
               if max_score < threshold:</pre>
                   predictions.append("OUT")
               else:
                   predictions.append("IN")
           # print("
                        ")
           return np.array(predictions), np.array(all_scores)
```

```
def predict_person(classifiers, data):
    predictions = []
    for sample in data:
        scores = []
        labels = []
        for label, classifier in classifiers.items():
            score = classifier.predict_proba([sample])[0][1]
            scores.append(score)
            labels.append(label)
            predicted_label = labels[np.argmax(scores)]
            predictions.append(predicted_label)
```

```
Γ151]: #
            10
       def plot_mean_and_top_eigenfaces(train_data, n_components=50, top_n=10):
          print("
                   10 ...")
          train_data_flat = train_data.reshape(train_data.shape[0], -1)
          mean_face = np.mean(train_data_flat, axis=0)
           # PCA
          pca = PCA(n_components=n_components)
          pca.fit(train_data_flat - mean_face)
           eigenfaces = pca.components_.reshape((n_components, 64, 64))
           explained_variance_ratio = pca.explained_variance_ratio_
          plt.figure(figsize=(12, 6))
          plt.subplot(1, top_n + 1, 1)
          plt.imshow(mean face.reshape(64, 64), cmap='gray')
          plt.title("Mean Face")
          plt.axis("off")
           # 10
          for i in range(top_n):
              plt.subplot(1, top_n + 1, i + 2)
              plt.imshow(eigenfaces[i], cmap='gray')
              plt.title(f"Eigenface {i + 1}\n({explained_variance_ratio[i]:.2%})")
              plt.axis("off")
          plt.tight_layout()
          plt.show()
          print(" ")
                    Excel = 50
       import pandas as pd
       def save_pca_to_excel_with_filenames(train_data, filenames, n_components=50,_u
        ⇔output_file="pca_results.xlsx"):
          print(" PCA
                          Excel ...")
          train_data_flat = train_data.reshape(train_data.shape[0], -1)
          mean_face = np.mean(train_data_flat, axis=0)
           # PCA
          pca = PCA(n_components=n_components)
          train_data_pca = pca.fit_transform(train_data_flat - mean_face)
           explained_variance_ratio = pca.explained_variance_ratio_
```

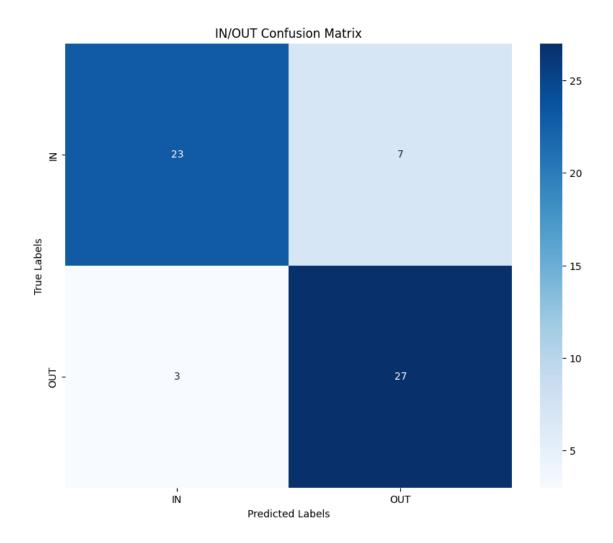
```
#
     df_pca = pd.DataFrame(train_data_pca, columns=[f"PC{i + 1}" for i in_
  →range(n_components)])
     df_pca.insert(0, "Filename", filenames) #
     df pca.to excel(output file, index=False, sheet name="PCA Results")
     #
     df_variance = pd.DataFrame({
          "Principal Component": [f"PC(i + 1)" for i in range(n components)],
          "Explained Variance (%)": explained_variance_ratio * 100
     })
     with pd.ExcelWriter(output_file, mode="a", engine="openpyxl") as writer:
          df_variance.to_excel(writer, index=False, sheet_name="Explained_"

¬Variance")
     print(f"PCA
                       {output_file} ")
n = 6 \#
train_data, train_labels, filenames = load_dataset(train_dir,_
  →max_images_per_person=n)
       10
plot_mean_and_top_eigenfaces(train_data, n_components=40, top_n=10)
   PCA
save_pca_to_excel_with_filenames(train_data, filenames, n_components=40,_u
  →output_file="pca_results.xlsx")
split_data/train
    10 ...
            Eigenface 1 Eigenface 2 Eigenface 3 Eigenface 4 Eigenface 5 Eigenface 6 Eigenface 7 Eigenface 8 Eigenface 9 Eigenface 10 (22.04%) (20.03%) (8.42%) (5.08%) (4.78%) (4.78%) (3.55%) (3.55%) (3.45%) (2.94%) (2.41%)
     Mean Face
```

PCA Excel ...
PCA pca_results.xlsx

```
[155]: #
                 n = 6 \#
                 train_data, train_labels, filenames = load_dataset(train_dir,_
                   →max_images_per_person=n)
                 test_data, test_labels, filenames = load_dataset(test_dir,_u
                    →max_images_per_person=n)
                 test_out_data, test_out_labels, filenames = load_dataset(test_out_dir,_u
                   →max_images_per_person=n)
                 print("
                                           ")
                 print(f" : \{train\_data.shape\}, : \{test\_data.shape\}, : \{test\_out\_data.shape\}, : \{test\_out\_data.shape], : \{test\_out\_data.
                    ⇒shape}")
                 # PCA
                 n components = 50
                 train_data_pca, test_data_pca, test_out_data_pca = pca_reduction(train_data,__
                   st_data, test_out_data, n_components)
                 classifiers = train_svm_classifiers(train_data_pca, train_labels)
                 # print(" ...")
                 all_predictions, all_scores = vote_predict(classifiers, np.
                  Goncatenate([test_data_pca, test_out_data_pca]), 0.5)
                 true_labels = np.concatenate([np.ones(len(test_labels)), np.
                   ⇒zeros(len(test_out_labels))])
                 fpr, tpr, thresholds = roc_curve(true_labels, all_scores)
                 roc_auc = auc(fpr, tpr)
                 optimal_threshold = thresholds[np.argmax(tpr - fpr)]
                 print(f" : {optimal threshold:.3f}")
                 test_predictions, _ = vote_predict(classifiers, test_data_pca,_
                   →optimal_threshold)
                 test_out_predictions, _ = vote_predict(classifiers, test_out_data_pca,_
                   ⇔optimal threshold)
                 all_predictions = np.concatenate([test_predictions, test_out_predictions])
                 all_true_labels = np.concatenate([["IN"] * len(test_labels), ["OUT"] *__
                   →len(test_out_labels)])
                 # ==========
                                                                                            _____
                 cm = confusion_matrix(all_true_labels, all_predictions, labels=["IN", "OUT"])
                 tp, fp, fn, tn = cm[0,0], cm[1,0], cm[0,1], cm[1,1]
```

```
#
in_out_accuracy = accuracy_score(all_true_labels, all_predictions)
in_out_precision = precision_score(all_true_labels, all_predictions,_
 →pos_label="IN")
in out recall = recall score(all true labels, all predictions, pos label="IN")
in_out_f1 = f1_score(all_true_labels, all_predictions, pos_label="IN")
in_out_specificity = tn / (tn + fp) if (tn + fp) != 0 else 0.0
in_out_kappa = cohen_kappa_score(all_true labels, all_predictions)
#
print("\n====
                   ====")
print(f" : {in_out_accuracy:.2f}")
print(f" : {in_out_precision:.2f}")
print(f" : {in_out_recall:.2f}")
print(f" : {in_out_specificity:.2f}")
print(f"F1 : {in_out_f1:.2f}")
print(f"Kappa : {in_out_kappa:.2f}")
print(f"AUC: {roc_auc:.2f}")
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=["IN", "OUT"], yticklabels=["IN", "OUT"])
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('IN/OUT Confusion Matrix')
plt.show()
split_data/train
split data/test
split_data/test_out
  : (60, 4096), : (30, 4096), : (30, 4096)
  PCA
          50
PCA
   SVM
SVM
  : 0.737
 : 0.83
 : 0.88
 : 0.77
 : 0.90
F1: 0.82
Kappa : 0.67
AUC: 0.86
```

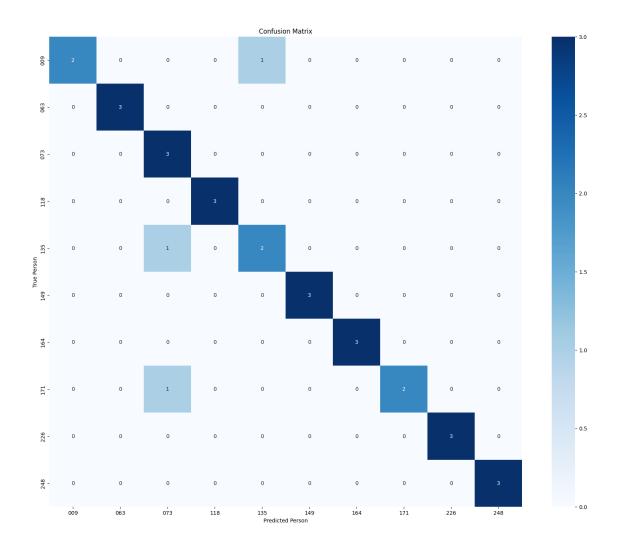


```
person_recall_macro = recall_score(test_labels, person_predictions,_u
 ⇔average='macro')
person_kappa = cohen_kappa_score(test_labels, person_predictions)
print("\n====
                  ====")
print(f" : {person_accuracy:.2f}")
print(f" F1 : {person_f1_weighted:.2f}")
print(f" F1 : {person_f1_macro:.2f}")
print(f" : {person_precision_macro:.2f}")
print(f" : {person_recall_macro:.2f}")
print(f"Kappa : {person_kappa:.2f}")
plt.figure(figsize=(20, 16))
sns.heatmap(person_cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=person_labels, yticklabels=person_labels)
plt.xlabel('Predicted Person')
plt.ylabel('True Person')
plt.title('Confusion Matrix')
plt.show()
```

: 0.90 F1 : 0.90 F1 : 0.90 : 0.93 : 0.90 Kappa : 0.89

====

====



```
train_data_pca, test_data_pca, test_out_data_pca =_
pca_reduction(train_data, test_data, test_out_data, n_components)
          classifiers = train_svm_classifiers(train_data_pca, train_labels)
          all_predictions, all_scores = vote_predict(classifiers, np.
→concatenate([test_data_pca, test_out_data_pca]), 0.5)
          true_labels = np.concatenate([np.ones(len(test_labels)), np.
⇔zeros(len(test_out_labels))])
          fpr, tpr, thresholds = roc_curve(true_labels, all_scores)
          optimal_threshold = thresholds[np.argmax(tpr - fpr)]
          test_predictions, _ = vote_predict(classifiers, test_data_pca,__
→optimal_threshold)
          test_out_predictions, _ = vote_predict(classifiers,_

    dest_out_data_pca, optimal_threshold)

          all_predictions = np.concatenate([test_predictions,_
→test_out_predictions])
          all_true_labels = np.concatenate([["IN"] * len(test_labels),_
in_out_accuracy = accuracy_score(all_true labels, all_predictions)
          accuracies.append(in_out_accuracy)
      mean_accuracy = np.mean(accuracies)
      std_accuracy = np.std(accuracies)
      print(f"n = {n}, : {mean_accuracy:.2f}, : {std_accuracy:.2f}")
      results.append((n, mean_accuracy, std_accuracy))
  n values, mean accuracies, std accuracies = zip(*results)
  plt.figure(figsize=(8, 6))
  plt.errorbar(n_values, mean_accuracies, yerr=std_accuracies, fmt='o-',_

color='b', ecolor='r', capsize=5)
  plt.xlabel("Number of Images per Person (n)")
  plt.ylabel("Accuracy")
  plt.title("Accuracy vs Number of Images per Person")
  plt.grid()
  plt.show()
  print(" n ")
```

```
n_components
def evaluate_different_components(train_data, train_labels, test_data,__
 otest_labels, test_out_data, test_out_labels, n_components_values, ∪

¬num_repeats=10):
   print("
                n components ...")
   results = []
   for n components in n components values:
        \# print(f'' n n\_components = \{n\_components\}'')
        accuracies = []
       for repeat in range(num_repeats):
            # print(f" {repeat + 1}/{num_repeats} ...")
            train_data_pca, test_data_pca, test_out_data_pca =_
 pca_reduction(train_data, test_data, test_out_data, n_components)
            classifiers = train_svm_classifiers(train_data_pca, train_labels)
            all_predictions, all_scores = vote_predict(classifiers, np.
 →concatenate([test_data_pca, test_out_data_pca]), 0.5)
            true_labels = np.concatenate([np.ones(len(test_labels)), np.
 ⇒zeros(len(test out labels))])
            fpr, tpr, thresholds = roc_curve(true_labels, all_scores)
            optimal_threshold = thresholds[np.argmax(tpr - fpr)]
            test_predictions, _ = vote_predict(classifiers, test_data_pca,__
 →optimal_threshold)
            test_out_predictions, _ = vote_predict(classifiers,_

    dest_out_data_pca, optimal_threshold)

            all_predictions = np.concatenate([test_predictions,_
 →test_out_predictions])
            all_true_labels = np.concatenate([["IN"] * len(test_labels),_
 →["OUT"] * len(test_out_labels)])
            in_out_accuracy = accuracy_score(all_true_labels, all_predictions)
            accuracies.append(in_out_accuracy)
       mean_accuracy = np.mean(accuracies)
       std_accuracy = np.std(accuracies)
       print(f"n_components = {n_components}, : {mean_accuracy:.2f}, :_
 results.append((n_components, mean_accuracy, std_accuracy))
```

```
#
    n_components_values, mean_accuracies, std_accuracies = zip(*results)
    plt.figure(figsize=(8, 6))
    plt.errorbar(n_components_values, mean_accuracies, yerr=std_accuracies, ⊔
 plt.xlabel("Number of Principal Components (n_components)")
    plt.ylabel("Accuracy")
    plt.title("Accuracy vs Number of Principal Components")
    plt.grid()
    plt.show()
    print(" n_components
                               ")
      n n_components
if __name__ == "__main__":
    test_data, test_labels, _ = load_dataset(test_dir, max_images_per_person=n)
    test_out_data, test_out_labels , _ = load_dataset(test_out_dir,_
 →max_images_per_person=n)
    n_{values} = [1,2,3,4,5,6] #
    evaluate different n(train dir, test_data, test_labels, test_out_data, u
 →test_out_labels, n_components=50, n_values=n_values)
    train_data, train_labels, _ = load_dataset(train_dir,_
 →max_images_per_person=6)
          n_components
    n_components_values = [10, 20, 30, 40, 50]
    evaluate_different_components(train_data, train_labels, test_data,_u
  stest_labels, test_out_data, test_out_labels, n_components_values)
split_data/test
split_data/test_out
      n
split_data/train
          50
  PCA
 : n_components=50
                       10
PCA
   SVM
SVM
split_data/train
          50
 : n_components=50
                       10
PCA
```

```
SVM ...
SVM
split_data/train
  PCA
       50
 : n_components=50
                       10
  SVM ...
SVM
split_data/train
  PCA 50
 : n_components=50
                       10
PCA
  SVM ...
SVM
split_data/train
 PCA
       50
 : n_components=50
                       10
PCA
  SVM ...
SVM
split_data/train
  PCA
          50
 : n_components=50
                       10
PCA
   SVM ...
SVM
split_data/train
  PCA
          50
 : n_components=50
                       10
PCA
  SVM ...
SVM
split_data/train
  PCA
          50
 : n_components=50
                        10
PCA
  SVM ...
SVM
split_data/train
  PCA
          50
: n_components=50
                        10
PCA
  SVM ...
SVM
split_data/train
  PCA
          50
 : n_components=50
                       10
```

PCA

```
SVM ...
SVM
n = 1, : 0.66, : 0.04
split_data/train
  PCA
          50
 : n_components=50
                        20
   SVM ...
SVM
split_data/train
  PCA
          50
 : n_components=50
                        20
   SVM ...
SVM
split_data/train
  PCA
          50
 : n_components=50
                        20
PCA
   SVM ...
SVM
split_data/train
  PCA
          50
 : n_components=50
                        20
PCA
   SVM ...
SVM
split_data/train
   PCA
          50
 : n_components=50
                        20
PCA
   SVM ...
SVM
split_data/train
  PCA
          50
 : n_components=50
                        20
PCA
   SVM ...
SVM
split_data/train
  PCA
          50
 : n_components=50
                        20
PCA
   SVM ...
SVM
split_data/train
   PCA
          50
 : n_components=50
                        20
```

```
PCA
  SVM ...
SVM
split_data/train
       50
 PCA
: n_components=50
                      20
  SVM ...
SVM
split_data/train
  PCA
       50
: n_components=50
                      20
  SVM ...
SVM
n = 2, : 0.63, : 0.05
split_data/train
  PCA
       50
: n_components=50
                      30
PCA
  SVM ...
SVM
split_data/train
 PCA 50
: n_components=50
                      30
PCA
  SVM ...
SVM
split_data/train
 PCA
       50
 : n_components=50
                      30
PCA
  SVM ...
SVM
split_data/train
  PCA
          50
: n_components=50
                      30
  SVM ...
SVM
split_data/train
          50
 PCA
 : n_components=50
                      30
PCA
  SVM ...
SVM
split_data/train
  PCA
       50
```

```
: n_components=50
                       30
PCA
   SVM ...
SVM
split_data/train
  PCA
          50
: n_components=50
                        30
PCA
  SVM ...
SVM
split_data/train
  PCA
          50
: n_components=50
                       30
  SVM ...
SVM
split_data/train
  PCA
       50
 : n_components=50
                       30
PCA
  SVM ...
SVM
split_data/train
  PCA 50
 : n_components=50
                       30
PCA
  SVM ...
SVM
n = 3, : 0.70, : 0.03
split_data/train
  PCA
          50
 : n_components=50
                       40
PCA
  SVM ...
SVM
split_data/train
  PCA
          50
 : n_components=50
                        40
PCA
  SVM ...
SVM
split_data/train
  PCA
          50
: n_components=50
                       40
PCA
   SVM ...
SVM
split_data/train
```

```
PCA
          50
 : n_components=50
                        40
PCA
   SVM ...
SVM
split_data/train
  PCA
       50
 : n_components=50
                        40
PCA
  SVM ...
SVM
split_data/train
 PCA
         50
: n_components=50
                        40
PCA
  SVM ...
SVM
split_data/train
  PCA
          50
 : n_components=50
                        40
  SVM ...
SVM
split_data/train
  PCA
          50
 : n_components=50
                        40
PCA
   SVM ...
SVM
split_data/train
  PCA
          50
 : n_components=50
                        40
PCA
  SVM ...
SVM
split_data/train
  PCA
          50
 : n_components=50
                        40
PCA
  SVM ...
SVM
n = 4, : 0.74, : 0.03
split_data/train
  PCA
          50
PCA
   SVM
SVM
split_data/train
```

```
PCA 50 ...
PCA
  SVM ...
SVM
split_data/train
 PCA 50 ...
PCA
  SVM ...
SVM
split_data/train
 PCA 50 ...
PCA
  SVM ...
SVM
split_data/train
PCA 50 ...
  SVM ...
SVM
split_data/train
 PCA 50 ...
PCA
 SVM ...
SVM
split_data/train
 PCA 50 ...
PCA
 SVM ...
SVM
split_data/train
 PCA 50 ...
PCA
  SVM ...
SVM
split_data/train
PCA 50 ...
PCA
  SVM ...
SVM
split_data/train
PCA 50 ...
PCA
  SVM ...
SVM
n = 5, : 0.78, : 0.02
split_data/train
PCA 50 ...
PCA
```

```
SVM ...
SVM
split_data/train
 PCA 50 ...
PCA
  SVM ...
SVM
split_data/train
 PCA 50 ...
PCA
  SVM ...
SVM
split_data/train
 PCA 50 ...
PCA
  SVM ...
SVM
split_data/train
PCA 50 ...
PCA
  SVM ...
SVM
split_data/train
PCA 50 ...
PCA
  SVM ...
SVM
split_data/train
 PCA 50 ...
PCA
 SVM ...
split_data/train
PCA 50 ...
PCA
  SVM ...
SVM
split_data/train
 PCA 50 ...
PCA
  SVM ...
SVM
split_data/train
PCA 50 ...
PCA
 SVM ...
SVM
n = 6, : 0.83, : 0.02
```



```
n
split_data/train
      n_components
   PCA
           10 ...
PCA
   SVM
{\tt SVM}
   PCA
           10
PCA
   SVM
SVM
   PCA
           10
PCA
   SVM
SVM
   PCA
           10
PCA
   SVM
SVM
   PCA
           10
```

```
PCA
 SVM ...
SVM
  PCA
      10 ...
PCA
  SVM ...
SVM
  PCA
      10
PCA
  SVM ...
SVM
      10
  PCA
PCA
 SVM ...
SVM
  PCA
      10 ...
PCA
  SVM ...
SVM
PCA
      10
PCA
  SVM ...
SVM
n_{\text{components}} = 10, : 0.78, : 0.02
 PCA
         20
            •••
PCA
  SVM ...
SVM
  PCA
      20
PCA
  SVM ...
SVM
  PCA
         20
PCA
  SVM ...
SVM
  PCA
         20
PCA
  SVM ...
SVM
  PCA
         20
PCA
  SVM ...
SVM
 PCA
         20
PCA
  SVM ...
```

SVM

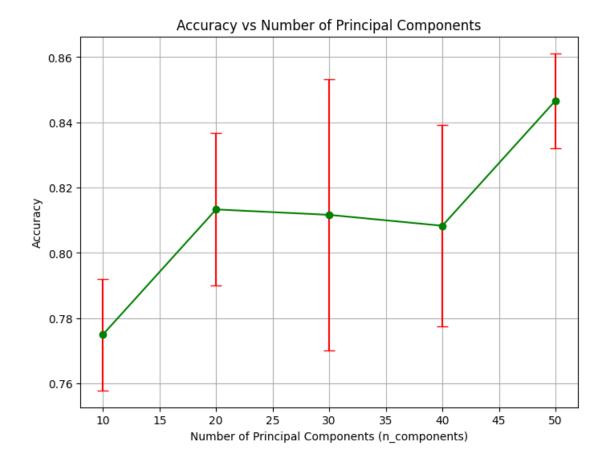
```
PCA 20 ...
PCA
  SVM ...
SVM
  PCA
          20
PCA
  SVM
SVM
  PCA
          20
PCA
  SVM
SVM
  PCA
          20
PCA
  SVM ...
SVM
n_{\text{components}} = 20, : 0.81, : 0.02
  PCA
        30
PCA
  SVM ...
SVM
  PCA
          30
PCA
  SVM ...
SVM
  PCA
          30
PCA
  SVM
SVM
  PCA
          30
PCA
   SVM ...
SVM
  PCA
          30
PCA
   SVM
SVM
  PCA
          30
PCA
  SVM
SVM
  PCA
          30
PCA
  SVM
SVM
  PCA
          30
PCA
```

SVM

```
SVM
 PCA 30 ...
PCA
  SVM ...
SVM
  PCA
         30
PCA
  SVM ...
SVM
n_{\text{components}} = 30, : 0.81, : 0.04
  PCA
       40
PCA
  SVM ...
SVM
  PCA
        40
PCA
  SVM ...
SVM
  PCA
         40
PCA
  SVM ...
SVM
  PCA
          40
PCA
  SVM
SVM
  PCA
        40
PCA
  SVM
SVM
  PCA
          40
PCA
  SVM
SVM
  PCA
         40
PCA
  SVM
SVM
 PCA
          40
PCA
  SVM
SVM
  PCA
         40
PCA
  SVM ...
SVM
  PCA
          40
```

PCA

```
SVM ...
SVM
n_{components} = 40, : 0.81, : 0.03
  PCA
       50
PCA
  SVM ...
SVM
  PCA
      50
PCA
  SVM ...
SVM
  PCA
      50
PCA
  SVM ...
SVM
  PCA
      50
PCA
  SVM ...
SVM
  PCA
       50
PCA
  SVM ...
SVM
  PCA 50 ...
PCA
  SVM ...
SVM
  PCA
         50
PCA
  SVM ...
SVM
  PCA
      50
PCA
  SVM ...
SVM
  PCA
      50
PCA
  SVM ...
SVM
      50 ...
  PCA
PCA
  SVM ...
SVM
n_{components} = 50, : 0.85, : 0.01
```



n_components