# s09_roc_2

March 23, 2024

## 1 Mitsiu Alejandro Carreño Sarabia - E23S-18014

## 2 Introducción

El objetivo de este notebook es entrenar una red neuronal que pueda determinar una imágen de número manuscrito entre 0 y 9. Las caracteristicas de las imágenes es que deben de ser de 8x8 pixeles (64 en total). Dónde cada pixel tiene un valor entre 0 y 16 (escala de grises).

Finalmente una vez obtenido el modelo de predicción se evaluará el rendimiento del clasificador mediante un analisis del área bajo la curva y las curvas ROC multiclase.

### 2.1 Carga de datos

[1]:
```
from sklearn.datasets import load_digits

import numpy as np
import pandas as pd
```

[2]:
```
data = load_digits()

print(data.DESCR)
print(data.feature_names)
```

```
.. _digits_dataset:

Optical recognition of handwritten digits dataset
--------------------------------------------------

**Data Set Characteristics:**

:Number of Instances: 1797
:Number of Attributes: 64
:Attribute Information: 8x8 image of integer pixels in the range 0..16.
:Missing Attribute Values: None
:Creator: E. Alpaydin (alpaydin '@' boun.edu.tr)
:Date: July; 1998

This is a copy of the test set of the UCI ML hand-written digits datasets
```

https://archive.ics.uci.edu/ml/datasets/Optical+Recognition+of+Handwritten+Digits

The data set contains images of hand-written digits: 10 classes where each class refers to a digit.

Preprocessing programs made available by NIST were used to extract normalized bitmaps of handwritten digits from a preprinted form. From a total of 43 people, 30 contributed to the training set and different 13 to the test set. 32x32 bitmaps are divided into nonoverlapping blocks of 4x4 and the number of on pixels are counted in each block. This generates an input matrix of 8x8 where each element is an integer in the range 0..16. This reduces dimensionality and gives invariance to small distortions.

For info on NIST preprocessing routines, see M. D. Garris, J. L. Blue, G. T. Candela, D. L. Dimmick, J. Geist, P. J. Grother, S. A. Janet, and C. L. Wilson, NIST Form-Based Handprint Recognition System, NISTIR 5469, 1994.

|details-start|
**References**
|details-split|

- C. Kaynak (1995) Methods of Combining Multiple Classifiers and Their Applications to Handwritten Digit Recognition, MSc Thesis, Institute of Graduate Studies in Science and Engineering, Bogazici University.
- E. Alpaydin, C. Kaynak (1998) Cascading Classifiers, Kybernetika.
- Ken Tang and Ponnuthurai N. Suganthan and Xi Yao and A. Kai Qin. Linear dimensionalityreduction using relevance weighted LDA. School of Electrical and Electronic Engineering Nanyang Technological University. 2005.
- Claudio Gentile. A New Approximate Maximal Margin Classification Algorithm. NIPS. 2000.

|details-end|

['pixel_0_0', 'pixel_0_1', 'pixel_0_2', 'pixel_0_3', 'pixel_0_4', 'pixel_0_5', 'pixel_0_6', 'pixel_0_7', 'pixel_1_0', 'pixel_1_1', 'pixel_1_2', 'pixel_1_3', 'pixel_1_4', 'pixel_1_5', 'pixel_1_6', 'pixel_1_7', 'pixel_2_0', 'pixel_2_1', 'pixel_2_2', 'pixel_2_3', 'pixel_2_4', 'pixel_2_5', 'pixel_2_6', 'pixel_2_7', 'pixel_3_0', 'pixel_3_1', 'pixel_3_2', 'pixel_3_3', 'pixel_3_4', 'pixel_3_5', 'pixel_3_6', 'pixel_3_7', 'pixel_4_0', 'pixel_4_1', 'pixel_4_2', 'pixel_4_3', 'pixel_4_4', 'pixel_4_5', 'pixel_4_6', 'pixel_4_7', 'pixel_5_0', 'pixel_5_1', 'pixel_5_2', 'pixel_5_3', 'pixel_5_4', 'pixel_5_5', 'pixel_5_6', 'pixel_5_7', 'pixel_6_0', 'pixel_6_1', 'pixel_6_2', 'pixel_6_3', 'pixel_6_4', 'pixel_6_5', 'pixel_6_6', 'pixel_6_7', 'pixel_7_0', 'pixel_7_1', 'pixel_7_2', 'pixel_7_3', 'pixel_7_4', 'pixel_7_5', 'pixel_7_6', 'pixel_7_7']

[3]:
```
X = pd.DataFrame(data.data, columns=data.feature_names)
y = pd.DataFrame(data.target, columns=["Type"])
```

[4]:
```
X.tail()
```

[4]:

| | pixel_0_0 | pixel_0_1 | pixel_0_2 | pixel_0_3 | pixel_0_4 | pixel_0_5 | \ |
|---|---|---|---|---|---|---|---|
| 1792 | 0.0 | 0.0 | 4.0 | 10.0 | 13.0 | 6.0 | |
| 1793 | 0.0 | 0.0 | 6.0 | 16.0 | 13.0 | 11.0 | |
| 1794 | 0.0 | 0.0 | 1.0 | 11.0 | 15.0 | 1.0 | |
| 1795 | 0.0 | 0.0 | 2.0 | 10.0 | 7.0 | 0.0 | |
| 1796 | 0.0 | 0.0 | 10.0 | 14.0 | 8.0 | 1.0 | |

| | pixel_0_6 | pixel_0_7 | pixel_1_0 | pixel_1_1 | … | pixel_6_6 | pixel_6_7 | \ |
|---|---|---|---|---|---|---|---|---|
| 1792 | 0.0 | 0.0 | 0.0 | 1.0 | … | 4.0 | 0.0 | |
| 1793 | 1.0 | 0.0 | 0.0 | 0.0 | … | 1.0 | 0.0 | |
| 1794 | 0.0 | 0.0 | 0.0 | 0.0 | … | 0.0 | 0.0 | |
| 1795 | 0.0 | 0.0 | 0.0 | 0.0 | … | 2.0 | 0.0 | |
| 1796 | 0.0 | 0.0 | 0.0 | 2.0 | … | 8.0 | 0.0 | |

| | pixel_7_0 | pixel_7_1 | pixel_7_2 | pixel_7_3 | pixel_7_4 | pixel_7_5 | \ |
|---|---|---|---|---|---|---|---|
| 1792 | 0.0 | 0.0 | 2.0 | 14.0 | 15.0 | 9.0 | |
| 1793 | 0.0 | 0.0 | 6.0 | 16.0 | 14.0 | 6.0 | |
| 1794 | 0.0 | 0.0 | 2.0 | 9.0 | 13.0 | 6.0 | |
| 1795 | 0.0 | 0.0 | 5.0 | 12.0 | 16.0 | 12.0 | |
| 1796 | 0.0 | 1.0 | 8.0 | 12.0 | 14.0 | 12.0 | |

| | pixel_7_6 | pixel_7_7 |
|---|---|---|
| 1792 | 0.0 | 0.0 |
| 1793 | 0.0 | 0.0 |
| 1794 | 0.0 | 0.0 |
| 1795 | 0.0 | 0.0 |
| 1796 | 1.0 | 0.0 |

[5 rows x 64 columns]

[5]:
```
y.tail()
```

[5]:

| | Type |
|---|---|
| 1792 | 9 |
| 1793 | 0 |
| 1794 | 8 |
| 1795 | 9 |
| 1796 | 8 |

### 2.2 Estandarización

[6]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

[7]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=117)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

### 2.3 Implementar modelo

[8]:
```
from tensorflow import keras
```

```
2024-03-23 05:05:48.452105: I tensorflow/core/util/port.cc:113] oneDNN custom
operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn them
off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2024-03-23 05:05:48.519168: I tensorflow/core/platform/cpu_feature_guard.cc:210]
This TensorFlow binary is optimized to use available CPU instructions in
performance-critical operations.
To enable the following instructions: AVX2 AVX_VNNI FMA, in other operations,
rebuild TensorFlow with the appropriate compiler flags.
```

[9]:
```
model = keras.Sequential([
    keras.layers.Input(shape=(64,)),
    #keras.layers.Dense(128, activation="relu"),
    keras.layers.Dense(12, activation="relu"),
    keras.layers.Dense(10, activation="softmax")
])

model.compile(optimizer="adam", loss="sparse_categorical_crossentropy",␣
↪metrics=["accuracy"])
```

```
2024-03-23 05:05:50.723309: E
external/local_xla/xla/stream_executor/cuda/cuda_driver.cc:282] failed call to
cuInit: UNKNOWN ERROR (34)
```

[10]:
```
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.
↪2, random_state=117)
```

### 2.4 Entrenamiento

Se aplicaron pocas epocas para disminuir la precisión del modelo

[11]:
```
model.fit(X_train, y_train, epochs=2, validation_data=(X_val, y_val))
```

```
Epoch 1/2
36/36             1s 8ms/step -
accuracy: 0.1725 - loss: 2.3756 - val_accuracy: 0.2257 - val_loss: 2.1288
Epoch 2/2
36/36             0s 4ms/step -
accuracy: 0.2819 - loss: 2.0386 - val_accuracy: 0.3403 - val_loss: 1.8444
```

[11]:
```
<keras.src.callbacks.history.History at 0x7f4f3240d090>
```

### 2.5 Evaluación de modelo

[12]:
```
test_loss, test_accuracy = model.evaluate(X_test, y_test)
print(f"Perdida test: {test_loss:.4f}")
print(f"Precision test: {test_accuracy * 100 :.2f}%")
```

```
12/12             0s 2ms/step -
accuracy: 0.4072 - loss: 1.7681
Perdida test: 1.8184
Precision test: 39.72%
```

[13]:
```
y_pred = model.predict(X_test)
```

```
12/12             0s 5ms/step
```

### 2.6 ROC

Las curvas ROC usualmente se componen de evaluar los verdaderos positivos (eje Y) contra 1 - los falsos positivos (eje X) siendo la esquina superior izq el punto ideal. Tamién es posible calcular el área bajo la curva la cuál entre más se acerque a 1 es mejor.

### 2.7 One vs rest

Las curvas ROC usualmente se aplican a clasificaciones binarias, en los que los verdaderos positivos y falsos positivos son obvios. Cuando se trata de una categorización multiclase la noción de veraderos positivos y falsos positivos se logra a traves de **binarizar los resultados**, esto se puede llevar a cabo de dos maneras.

- One vs Rest en el que se compara cada clase contra todas las demás (que se asumen como una sola)
- One vs One en el que se compara cada una de las combinaciones posibles de clases.

Durante este analisis únicamente se evaluó mediante el esquema One vs Rest en el que la clase en cuestion se interpreta como la clase positiva y el resto como la clase negativa

### 2.8 One-hot-encode OvR fashion

[14]:
```
from sklearn.preprocessing import LabelBinarizer
```

[15]:
```
label_binarizer = LabelBinarizer().fit(y_train)
y_onehot_test = label_binarizer.transform(y_test)
```

[16]:
```
print(y_onehot_test.shape)
print(y_onehot_test[:10])
```

```
(360, 10)
[[0 0 0 0 0 0 1 0 0 0]
 [0 0 0 0 0 0 1 0 0 0]
 [1 0 0 0 0 0 0 0 0 0]
 [1 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 1 0 0 0 0 0]
 [0 0 0 0 0 0 0 1 0 0]
 [0 0 0 0 0 0 0 0 0 1]
 [0 0 0 1 0 0 0 0 0 0]
 [0 0 0 0 0 0 1 0 0 0]
 [1 0 0 0 0 0 0 0 0 0]]
```

[17]:
```
for i in range(10):
    print(f"{i} == {label_binarizer.transform([i])}")
```

```
0 == [[1 0 0 0 0 0 0 0 0 0]]
1 == [[0 1 0 0 0 0 0 0 0 0]]
2 == [[0 0 1 0 0 0 0 0 0 0]]
3 == [[0 0 0 1 0 0 0 0 0 0]]
4 == [[0 0 0 0 1 0 0 0 0 0]]
5 == [[0 0 0 0 0 1 0 0 0 0]]
6 == [[0 0 0 0 0 0 1 0 0 0]]
7 == [[0 0 0 0 0 0 0 1 0 0]]
8 == [[0 0 0 0 0 0 0 0 1 0]]
9 == [[0 0 0 0 0 0 0 0 0 1]]
```

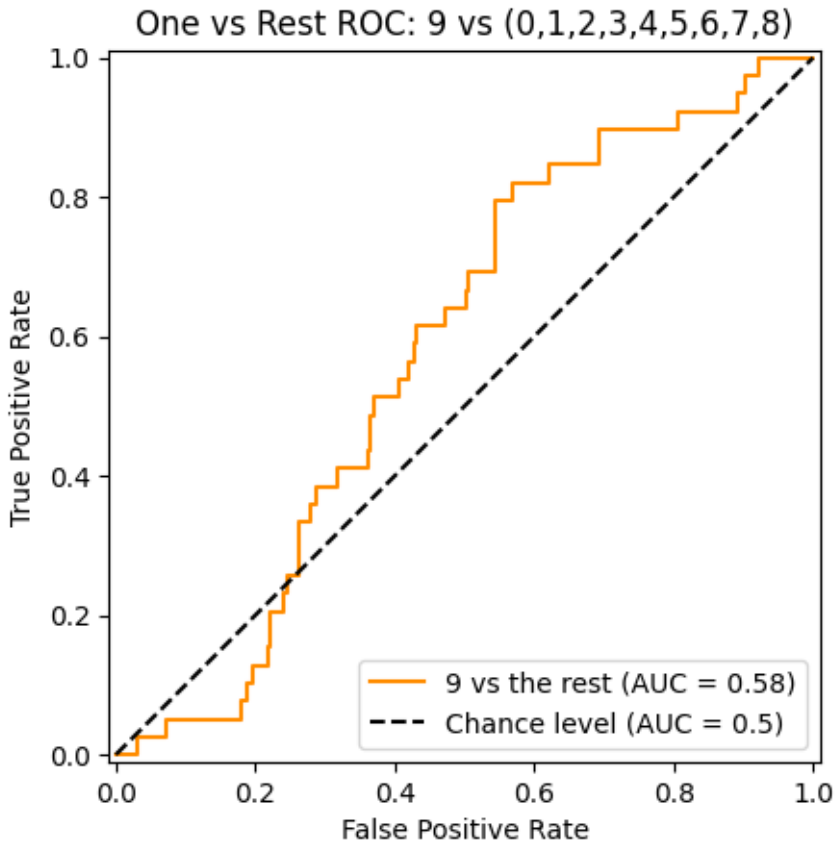
[18]:
```
for i in range(10):
    class_id = np.flatnonzero(label_binarizer.classes_ == i)[0]
    print(f"{i} == {class_id}")
```

```
0 == 0
1 == 1
2 == 2
3 == 3
4 == 4
5 == 5
6 == 6
7 == 7
```

```
8 == 8
9 == 9
```

Nos damos cuenta que dada la naturaleza númerica de las clases **el onehot encoding genera exactamente los mismos resultados** que tomar la clase de manera directa, pero el procedimiento anterior es útil cuando tenemos categorías nominales.

[19]:
```python
import matplotlib.pyplot as plt

from sklearn.metrics import RocCurveDisplay

display = RocCurveDisplay.from_predictions(
    y_onehot_test[:, class_id],
    y_pred[:, i],
    name=f"{i} vs the rest",
    color="darkorange",
    plot_chance_level=True
)
_ = display.ax_.set(
    xlabel="False Positive Rate",
    ylabel="True Positive Rate",
    title="One vs Rest ROC: 9 vs (0,1,2,3,4,5,6,7,8)"
)
```



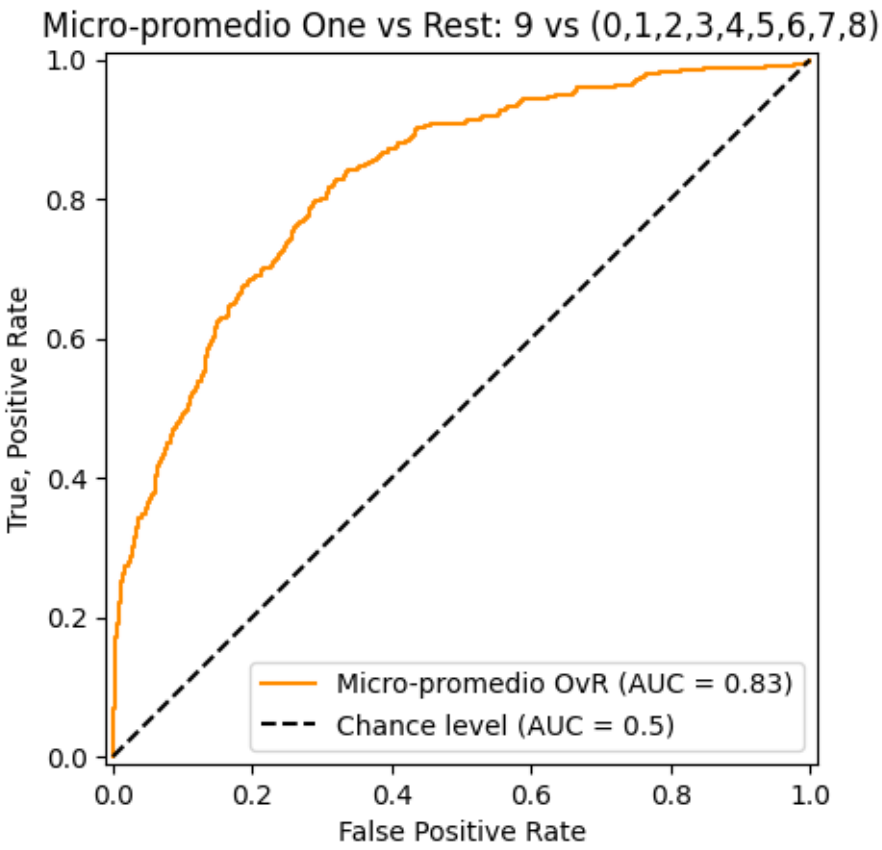
### 2.9 ROC con micro-promedio OvR

El micropromedio toma en cuenta las contribuciones de todas las clases. Es recomendable con clasificaciones muy imbalanceadas.

Para el micro-promedio se aplica el método ravel de numpy mediante el cuál se suman los true positive, false positive, true negative y true positive de cada una de las clases.

Ejemplo y_pred = [ [1,2,3,4], [3,4,6,7]] y_pred.ravel() == [1,2,3,4, 3,4,6,7]

[20]:
```
display = RocCurveDisplay.from_predictions(
    y_onehot_test.ravel(),
    y_pred.ravel(),
    name="Micro-promedio OvR",
    color="darkorange",
    plot_chance_level=True
)
_ = display.ax_.set(
    xlabel="False Positive Rate",
    ylabel="True, Positive Rate",
    title="Micro-promedio One vs Rest: 9 vs (0,1,2,3,4,5,6,7,8)"
)
```




Podemos notar que por tomar los promedios de cada categoría la curva se suaviza.

### 2.10 Calculando el micro-promedio de todas las categorías

Podemos observar que para obtener el micro-promedio es muy **similar a obtener el roc_curve simple (una clasificación binaria) con la función roc_curve(y_real, y_pred)**

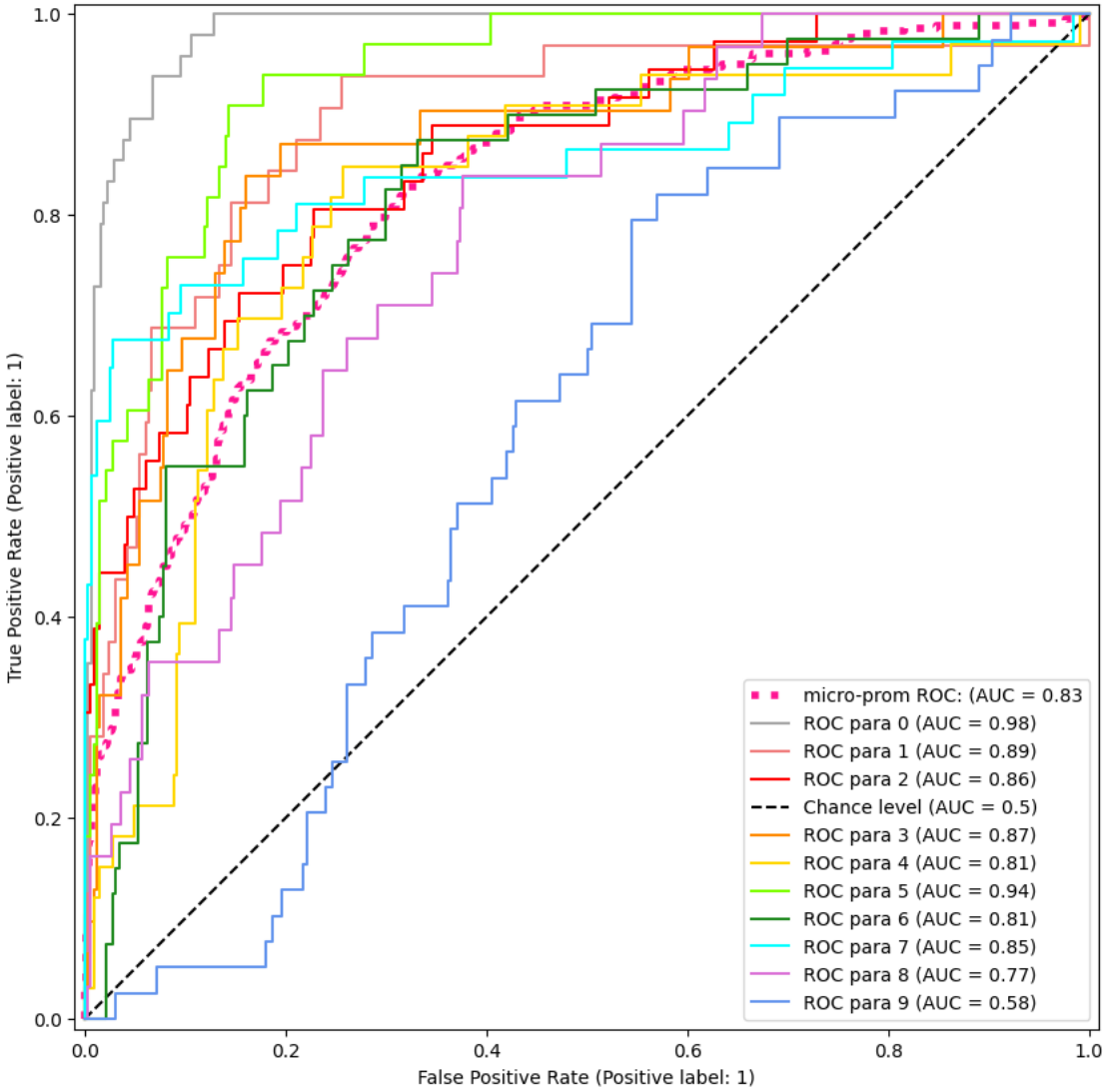
También es posible obtener el valor del área con la función roc_auc_score en donde **se especifica el average micro y multi_class ovr**

[21]:
```
from sklearn.metrics import auc, roc_curve

fpr, tpr, roc_auc = dict(), dict(), dict()

# Micro-promedio
fpr["micro"], tpr["micro"], _ = roc_curve(y_onehot_test.ravel(), y_pred.ravel())
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])

print(f"Micro-promedio One vs Rest ROC AUC: {roc_auc['micro']}")

#====================
```

```
from sklearn.metrics import roc_auc_score

micro_roc_auc_ovr = roc_auc_score(
    y_test,
    y_pred,
    multi_class="ovr",
    average="micro"
)
print(f"Micro-promedio función: {micro_roc_auc_ovr}")
```

```
Micro-promedio One vs Rest ROC AUC: 0.8259276406035666
Micro-promedio función: 0.8259276406035666
```

[24]:
```
fig, ax = plt.subplots(figsize=(10,10))

# Dibujar el roc micro
plt.plot(
    fpr["micro"],
    tpr["micro"],
    label=f"micro-prom ROC: (AUC = {roc_auc['micro']:.2f}",
    color="deeppink",
    linestyle=":",
    linewidth=4
)

colors = ["darkgray",
          "lightcoral",
          "red",
          "darkorange",
          "gold",
          "chartreuse",
          "forestgreen",
          "aqua",
          "orchid",
          "cornflowerblue"]

# Dibujar cada una de las categorías
for i in range(10):
    RocCurveDisplay.from_predictions(
        y_onehot_test[:, i],
        y_pred[:, i],
        name=f"ROC para {i}",
        color=colors[i],
        ax = ax,
        plot_chance_level=(i == 2)
    )
```




### 2.11 ROC con macro-promedio OvR

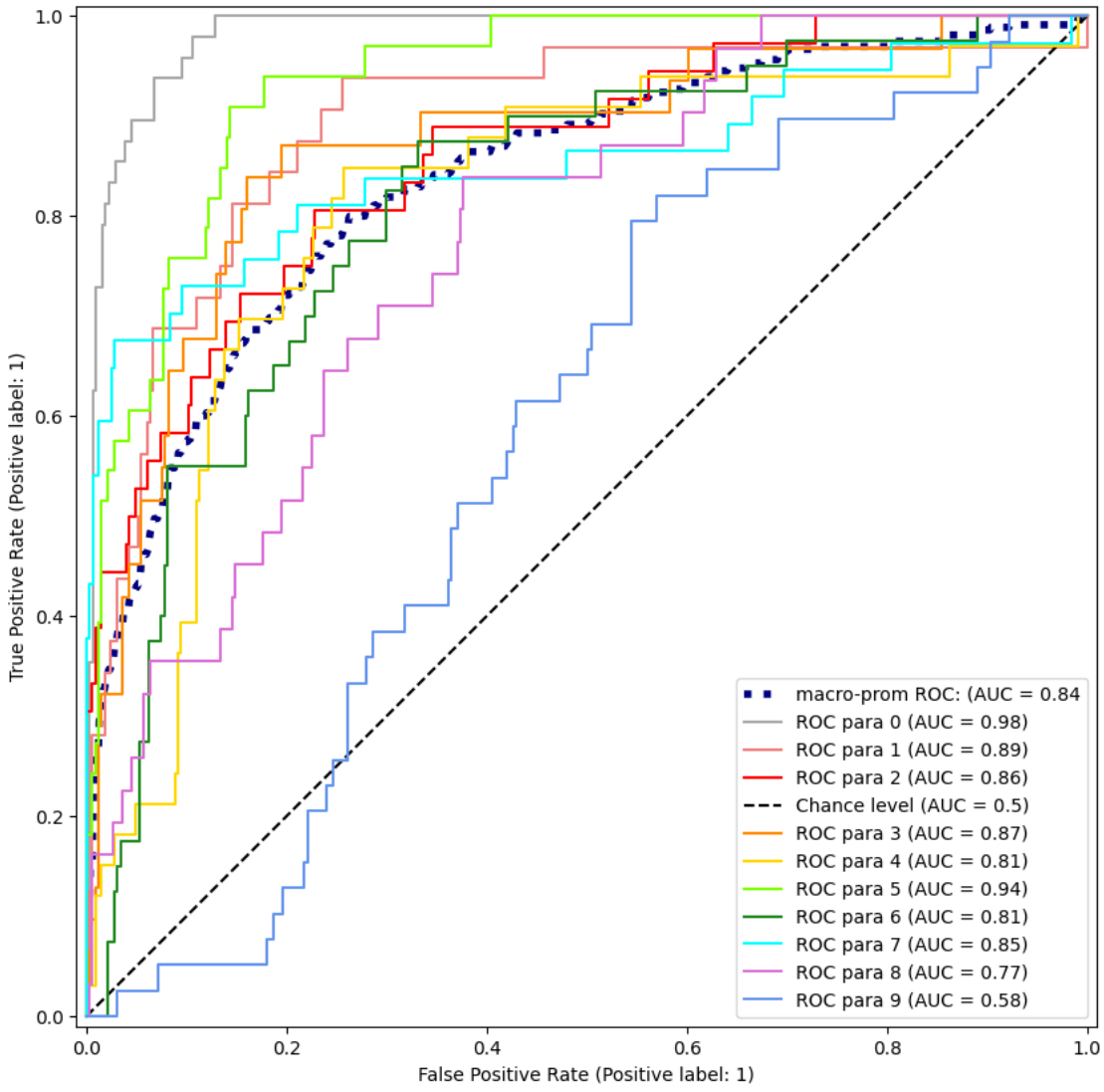
[22]:
```
for i in range(10):
    fpr[i], tpr[i], _ = roc_curve(y_onehot_test[:, i], y_pred[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Start, end, num of elements
fpr_grid = np.linspace(0.0, 1.0, 1000)
#print(fpr_grid)

# Interpolar todas las curvas ROC en nuestro espacio
mean_tpr = np.zeros_like(fpr_grid)
```

```
for i in range(10):
    mean_tpr += np.interp(fpr_grid, fpr[i], tpr[i]) # interpolación lineal
    # Curve fitting using linear polynomials to construct new data points
    # within the range of a discrete set of known data points

mean_tpr /= 10

fpr["macro"] = fpr_grid
tpr["macro"] = mean_tpr
roc_auc["macro"] = auc(fpr["macro"], tpr["macro"])

print(f"Macro-promedio OvR ROC AUC: {roc_auc['macro']}")

#========================================
macro_roc_auc_ovr = roc_auc_score(
    y_test,
    y_pred,
    multi_class="ovr",
    average="macro"
)
print(f"Macro-promedio función: {macro_roc_auc_ovr}")
```

```
Macro-promedio OvR ROC AUC: 0.8366590730165393
Macro-promedio función: 0.8367323386952424
```

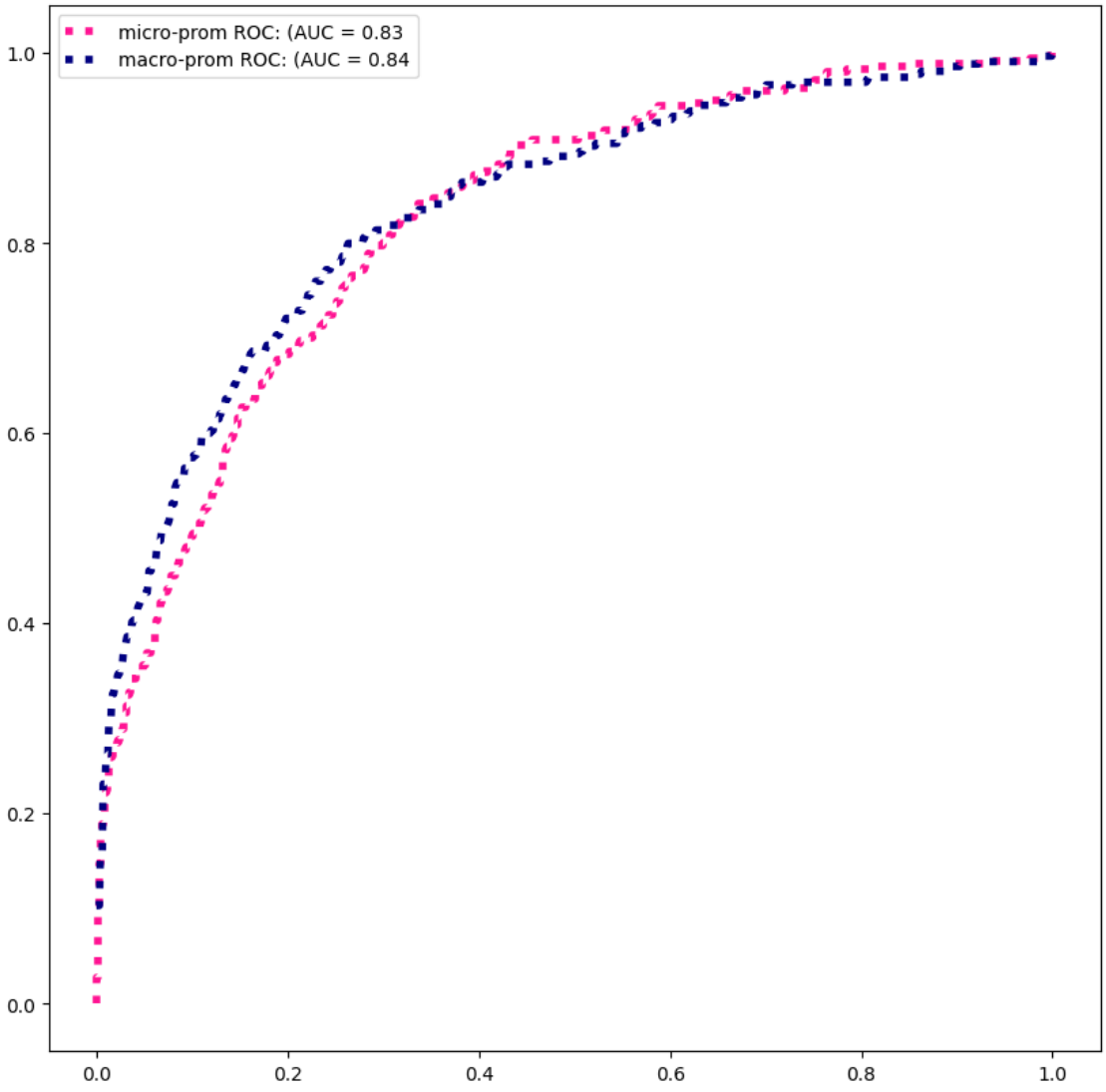
[23]:
```
fig, ax = plt.subplots(figsize=(10,10))

plt.plot(
    fpr["macro"],
    tpr["macro"],
    label=f"macro-prom ROC: (AUC = {roc_auc['macro']:.2f}",
    color="navy",
    linestyle=":",
    linewidth=4
)

colors = ["darkgray",
          "lightcoral",
          "red",
          "darkorange",
          "gold",
          "chartreuse",
          "forestgreen",
          "aqua",
          "orchid",
          "cornflowerblue"]
```

```
for i in range(10):
    RocCurveDisplay.from_predictions(
        y_onehot_test[:, i],
        y_pred[:, i],
        name=f"ROC para {i}",
        color=colors[i],
        ax = ax,
        plot_chance_level=(i == 2)
    )
```



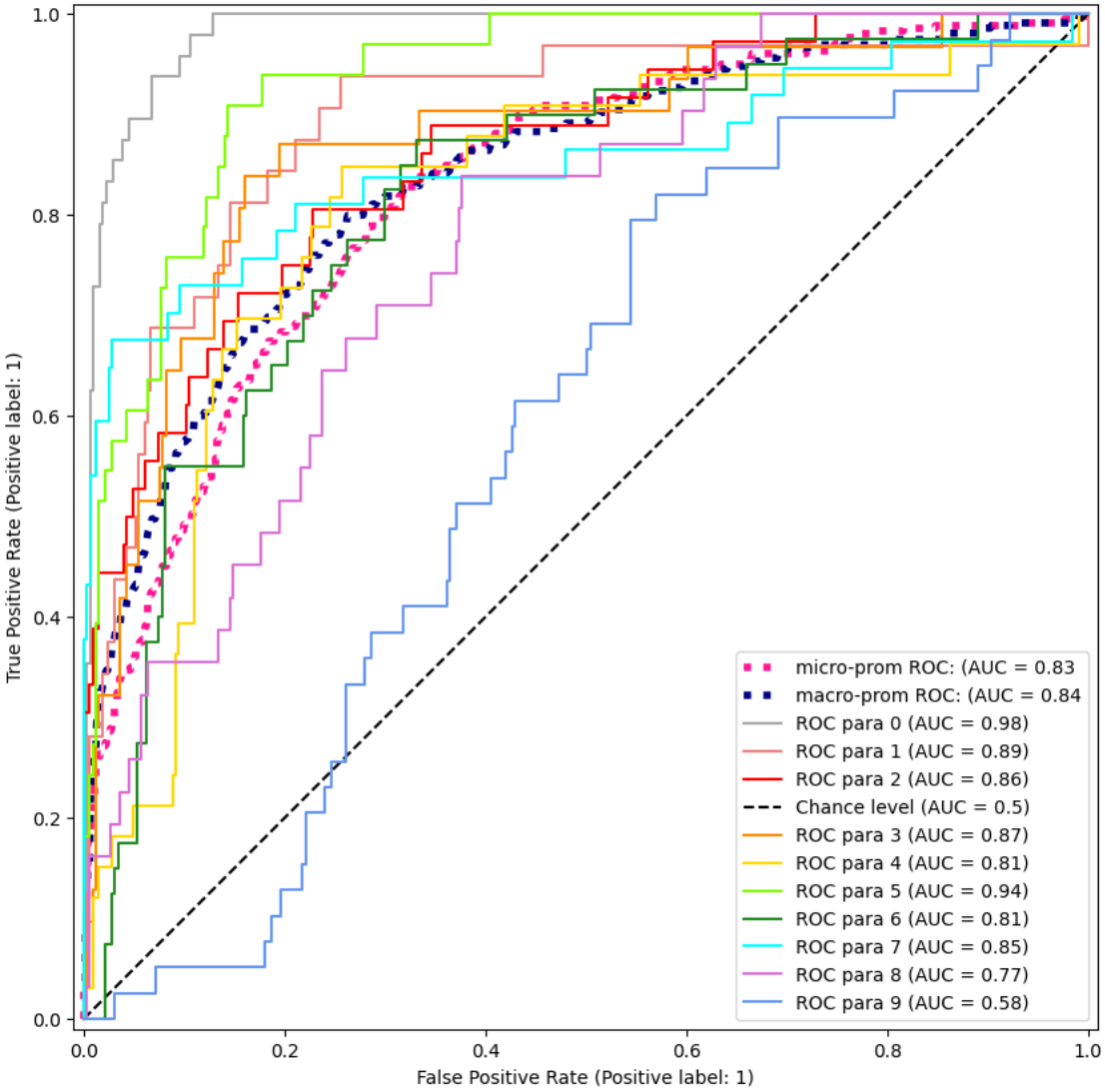

[28]:
```
fig, ax = plt.subplots(figsize=(10,10))

# Dibujar el roc micro
```

```
plt.plot(
    fpr["micro"],
    tpr["micro"],
    label=f"micro-prom ROC: (AUC = {roc_auc['micro']:.2f}",
    color="deeppink",
    linestyle=":",
    linewidth=4
)

plt.plot(
    fpr["macro"],
    tpr["macro"],
    label=f"macro-prom ROC: (AUC = {roc_auc['macro']:.2f}",
    color="navy",
    linestyle=":",
    linewidth=4
)

plt.legend(loc="best")
plt.show()
```




[26]:
```
fig, ax = plt.subplots(figsize=(10,10))

# Dibujar el roc micro
plt.plot(
    fpr["micro"],
    tpr["micro"],
    label=f"micro-prom ROC: (AUC = {roc_auc['micro']:.2f}",
    color="deeppink",
    linestyle=":",
    linewidth=4
)

plt.plot(
```

```
    fpr["macro"],
    tpr["macro"],
    label=f"macro-prom ROC: (AUC = {roc_auc['macro']:.2f}",
    color="navy",
    linestyle=":",
    linewidth=4
)


colors = ["darkgray",
          "lightcoral",
          "red",
          "darkorange",
          "gold",
          "chartreuse",
          "forestgreen",
          "aqua",
          "orchid",
          "cornflowerblue"]

# Dibujar cada una de las categorías
for i in range(10):
    RocCurveDisplay.from_predictions(
        y_onehot_test[:, i],
        y_pred[:, i],
        name=f"ROC para {i}",
        color=colors[i],
        ax = ax,
        plot_chance_level=(i == 2)
    )
```




Conclusiones: Después de haber "empeorado" la red es mucho más sencillo notar cuales es la categoría que peor evalua, y también se puede comparar con las otras cateogorías. Como interpretación personal puedo asumir que el dígito 9, así como el 8 y 6 son los peores clasificados dada su cercanía geometríca con el 0 (el mejor evaluado).

Creo que las funciones ROC multiclase es una herramienta poderosa que nos permite evaluar de manera aisalada el desempeño de nuestros modelos de clasificación.

[ ]: