7506R_TP2_GRUPO16_ENTREGA_REDES_NEURONALES

December 8, 2022

[3]:
```
!pip install numpy==1.21
!pip install dtreeviz
!pip install kneed
!pip install pyreadstat
!pip install visualkeras
!pip install keras_tuner
!pip install matplotlib==3.1.3
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: numpy==1.21 in /usr/local/lib/python3.8/dist-
packages (1.21.0)
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: dtreeviz in /usr/local/lib/python3.8/dist-
packages (1.4.1)
Requirement already satisfied: pytest in /usr/local/lib/python3.8/dist-packages
(from dtreeviz) (3.6.4)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.8/dist-
packages (from dtreeviz) (1.0.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.8/dist-packages
(from dtreeviz) (1.21.0)
Requirement already satisfied: pandas in /usr/local/lib/python3.8/dist-packages
(from dtreeviz) (1.3.5)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.8/dist-
packages (from dtreeviz) (3.1.3)
Requirement already satisfied: colour in /usr/local/lib/python3.8/dist-packages
(from dtreeviz) (0.1.5)
Requirement already satisfied: graphviz>=0.9 in /usr/local/lib/python3.8/dist-
packages (from dtreeviz) (0.10.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.8/dist-
packages (from matplotlib->dtreeviz) (0.11.0)
Requirement already satisfied: python-dateutil>=2.1 in
/usr/local/lib/python3.8/dist-packages (from matplotlib->dtreeviz) (2.8.2)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.8/dist-packages (from matplotlib->dtreeviz) (1.4.4)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in
/usr/local/lib/python3.8/dist-packages (from matplotlib->dtreeviz) (3.0.9)
```

```
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.8/dist-
packages (from python-dateutil>=2.1->matplotlib->dtreeviz) (1.15.0)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.8/dist-
packages (from pandas->dtreeviz) (2022.6)
Requirement already satisfied: more-itertools>=4.0.0 in
/usr/local/lib/python3.8/dist-packages (from pytest->dtreeviz) (9.0.0)
Requirement already satisfied: py>=1.5.0 in /usr/local/lib/python3.8/dist-
packages (from pytest->dtreeviz) (1.11.0)
Requirement already satisfied: attrs>=17.4.0 in /usr/local/lib/python3.8/dist-
packages (from pytest->dtreeviz) (22.1.0)
Requirement already satisfied: setuptools in /usr/local/lib/python3.8/dist-
packages (from pytest->dtreeviz) (57.4.0)
Requirement already satisfied: pluggy<0.8,>=0.5 in
/usr/local/lib/python3.8/dist-packages (from pytest->dtreeviz) (0.7.1)
Requirement already satisfied: atomicwrites>=1.0 in
/usr/local/lib/python3.8/dist-packages (from pytest->dtreeviz) (1.4.1)
Requirement already satisfied: scipy>=1.1.0 in /usr/local/lib/python3.8/dist-
packages (from scikit-learn->dtreeviz) (1.7.3)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.8/dist-packages (from scikit-learn->dtreeviz) (3.1.0)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.8/dist-
packages (from scikit-learn->dtreeviz) (1.2.0)
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: kneed in /usr/local/lib/python3.8/dist-packages
(0.8.1)
Requirement already satisfied: numpy>=1.14.2 in /usr/local/lib/python3.8/dist-
packages (from kneed) (1.21.0)
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.8/dist-
packages (from kneed) (1.7.3)
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: pyreadstat in /usr/local/lib/python3.8/dist-
packages (1.2.0)
Requirement already satisfied: pandas>=1.2.0 in /usr/local/lib/python3.8/dist-
packages (from pyreadstat) (1.3.5)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.8/dist-
packages (from pandas>=1.2.0->pyreadstat) (2022.6)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.8/dist-
packages (from pandas>=1.2.0->pyreadstat) (1.21.0)
Requirement already satisfied: python-dateutil>=2.7.3 in
/usr/local/lib/python3.8/dist-packages (from pandas>=1.2.0->pyreadstat) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.8/dist-
packages (from python-dateutil>=2.7.3->pandas>=1.2.0->pyreadstat) (1.15.0)
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: visualkeras in /usr/local/lib/python3.8/dist-
packages (0.0.2)
```

```
Requirement already satisfied: aggdraw>=1.3.11 in /usr/local/lib/python3.8/dist-
packages (from visualkeras) (1.3.15)
Requirement already satisfied: numpy>=1.18.1 in /usr/local/lib/python3.8/dist-
packages (from visualkeras) (1.21.0)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.8/dist-
packages (from visualkeras) (7.1.2)
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: keras_tuner in /usr/local/lib/python3.8/dist-
packages (1.1.3)
Requirement already satisfied: requests in /usr/local/lib/python3.8/dist-
packages (from keras_tuner) (2.23.0)
Requirement already satisfied: ipython in /usr/local/lib/python3.8/dist-packages
(from keras_tuner) (7.9.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.8/dist-
packages (from keras_tuner) (21.3)
Requirement already satisfied: numpy in /usr/local/lib/python3.8/dist-packages
(from keras_tuner) (1.21.0)
Requirement already satisfied: tensorboard in /usr/local/lib/python3.8/dist-
packages (from keras_tuner) (2.9.1)
Requirement already satisfied: kt-legacy in /usr/local/lib/python3.8/dist-
packages (from keras_tuner) (1.0.4)
Requirement already satisfied: pexpect in /usr/local/lib/python3.8/dist-packages
(from ipython->keras_tuner) (4.8.0)
Requirement already satisfied: jedi>=0.10 in /usr/local/lib/python3.8/dist-
packages (from ipython->keras_tuner) (0.18.2)
Requirement already satisfied: prompt-toolkit<2.1.0,>=2.0.0 in
/usr/local/lib/python3.8/dist-packages (from ipython->keras_tuner) (2.0.10)
Requirement already satisfied: decorator in /usr/local/lib/python3.8/dist-
packages (from ipython->keras_tuner) (4.4.2)
Requirement already satisfied: pickleshare in /usr/local/lib/python3.8/dist-
packages (from ipython->keras_tuner) (0.7.5)
Requirement already satisfied: pygments in /usr/local/lib/python3.8/dist-
packages (from ipython->keras_tuner) (2.6.1)
Requirement already satisfied: traitlets>=4.2 in /usr/local/lib/python3.8/dist-
packages (from ipython->keras_tuner) (5.6.0)
Requirement already satisfied: backcall in /usr/local/lib/python3.8/dist-
packages (from ipython->keras_tuner) (0.2.0)
Requirement already satisfied: setuptools>=18.5 in
/usr/local/lib/python3.8/dist-packages (from ipython->keras_tuner) (57.4.0)
Requirement already satisfied: parso<0.9.0,>=0.8.0 in
/usr/local/lib/python3.8/dist-packages (from jedi>=0.10->ipython->keras_tuner)
(0.8.3)
Requirement already satisfied: six>=1.9.0 in /usr/local/lib/python3.8/dist-
packages (from prompt-toolkit<2.1.0,>=2.0.0->ipython->keras_tuner) (1.15.0)
Requirement already satisfied: wcwidth in /usr/local/lib/python3.8/dist-packages
(from prompt-toolkit<2.1.0,>=2.0.0->ipython->keras_tuner) (0.2.5)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in
```

```
/usr/local/lib/python3.8/dist-packages (from packaging->keras_tuner) (3.0.9)
Requirement already satisfied: ptyprocess>=0.5 in /usr/local/lib/python3.8/dist-
packages (from pexpect->ipython->keras_tuner) (0.7.0)
Requirement already satisfied: chardet<4,>=3.0.2 in
/usr/local/lib/python3.8/dist-packages (from requests->keras_tuner) (3.0.4)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.8/dist-packages (from requests->keras_tuner) (2022.9.24)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.8/dist-
packages (from requests->keras_tuner) (2.10)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in
/usr/local/lib/python3.8/dist-packages (from requests->keras_tuner) (1.24.3)
Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in
/usr/local/lib/python3.8/dist-packages (from tensorboard->keras_tuner) (1.8.1)
Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.8/dist-
packages (from tensorboard->keras_tuner) (1.0.1)
Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in
/usr/local/lib/python3.8/dist-packages (from tensorboard->keras_tuner) (0.4.6)
Requirement already satisfied: protobuf<3.20,>=3.9.2 in
/usr/local/lib/python3.8/dist-packages (from tensorboard->keras_tuner) (3.19.6)
Requirement already satisfied: wheel>=0.26 in /usr/local/lib/python3.8/dist-
packages (from tensorboard->keras_tuner) (0.38.4)
Requirement already satisfied: google-auth<3,>=1.6.3 in
/usr/local/lib/python3.8/dist-packages (from tensorboard->keras_tuner) (2.15.0)
Requirement already satisfied: absl-py>=0.4 in /usr/local/lib/python3.8/dist-
packages (from tensorboard->keras_tuner) (1.3.0)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.8/dist-
packages (from tensorboard->keras_tuner) (3.4.1)
Requirement already satisfied: grpcio>=1.24.3 in /usr/local/lib/python3.8/dist-
packages (from tensorboard->keras_tuner) (1.51.1)
Requirement already satisfied: tensorboard-data-server<0.7.0,>=0.6.0 in
/usr/local/lib/python3.8/dist-packages (from tensorboard->keras_tuner) (0.6.1)
Requirement already satisfied: pyasn1-modules>=0.2.1 in
/usr/local/lib/python3.8/dist-packages (from google-
auth<3,>=1.6.3->tensorboard->keras_tuner) (0.2.8)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in
/usr/local/lib/python3.8/dist-packages (from google-
auth<3,>=1.6.3->tensorboard->keras_tuner) (5.2.0)
Requirement already satisfied: rsa<5,>=3.1.4 in /usr/local/lib/python3.8/dist-
packages (from google-auth<3,>=1.6.3->tensorboard->keras_tuner) (4.9)
Requirement already satisfied: requests-oauthlib>=0.7.0 in
/usr/local/lib/python3.8/dist-packages (from google-auth-
oauthlib<0.5,>=0.4.1->tensorboard->keras_tuner) (1.3.1)
Requirement already satisfied: importlib-metadata>=4.4 in
/usr/local/lib/python3.8/dist-packages (from
markdown>=2.6.8->tensorboard->keras_tuner) (4.13.0)
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.8/dist-
packages (from importlib-
metadata>=4.4->markdown>=2.6.8->tensorboard->keras_tuner) (3.11.0)
```

```
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in
/usr/local/lib/python3.8/dist-packages (from pyasn1-modules>=0.2.1->google-
auth<3,>=1.6.3->tensorboard->keras_tuner) (0.4.8)
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.8/dist-
packages (from requests-oauthlib>=0.7.0->google-auth-
oauthlib<0.5,>=0.4.1->tensorboard->keras_tuner) (3.2.2)
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: matplotlib==3.1.3 in
/usr/local/lib/python3.8/dist-packages (3.1.3)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.8/dist-packages (from matplotlib==3.1.3) (1.4.4)
Requirement already satisfied: python-dateutil>=2.1 in
/usr/local/lib/python3.8/dist-packages (from matplotlib==3.1.3) (2.8.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.8/dist-
packages (from matplotlib==3.1.3) (0.11.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in
/usr/local/lib/python3.8/dist-packages (from matplotlib==3.1.3) (3.0.9)
Requirement already satisfied: numpy>=1.11 in /usr/local/lib/python3.8/dist-
packages (from matplotlib==3.1.3) (1.21.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.8/dist-
packages (from python-dateutil>=2.1->matplotlib==3.1.3) (1.15.0)
```

[4]:
```
import pandas as pd
import numpy as np
import csv
import statistics
from math import inf
import random


#Visualización
import matplotlib.pyplot as plt
from seaborn import color_palette
import seaborn as sns

#modelos y métricas
from sklearn import metrics
from sklearn.model_selection import train_test_split,RandomizedSearchCV,␣
 ↪GridSearchCV, cross_val_score
from sklearn.metrics import confusion_matrix, precision_recall_curve,␣
 ↪roc_curve, recall_score, accuracy_score,f1_score, precision_score, auc,␣
 ↪roc_auc_score, mean_squared_error, silhouette_score,␣
 ↪classification_report,mean_absolute_error, max_error, median_absolute_error,␣
 ↪r2_score, explained_variance_score
```

```
#preprocesamiento
from sklearn.preprocessing import MinMaxScaler, StandardScaler

# Pickle
import pickle
import pyreadstat

# Redes Neuronales
import tensorflow as tf
from tensorflow import keras
from keras.utils.vis_utils import plot_model
import visualkeras
import keras_tuner as kt

#configuración warnings
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
warnings.simplefilter(action='ignore', category=UserWarning)
```

1 Redes Neuronales

Creamos los datasets.

[5]:
```
url = 'https://drive.google.com/file/d/1ziV8Kmuw_Vtv7aX1zGnfMdoLMdOnfoOr/view?
 ↪usp=share_link'
path = 'https://drive.google.com/uc?export=download&id='+url.split('/')[-2]

ds_train = pd.read_csv(path)

url = 'https://drive.google.com/file/d/1j34_hlvFOJV_8TN2jdnV2GXSArfWlUUK/view?
 ↪usp=share_link'
path = 'https://drive.google.com/uc?export=download&id='+url.split('/')[-2]

ds_test = pd.read_csv(path)
```

[6]:
```
de_temp_train = ds_train.copy()

de_temp_train.loc[ds_train["tipo_precio"]=="bajo", "target"]= 0
de_temp_train.loc[ds_train["tipo_precio"]=="medio", "target"]= 1
de_temp_train.loc[ds_train["tipo_precio"]=="alto", "target"]= 2
```

Asignamos valores numéricos a los tipos de precio para trabajar con ellos.

[7]:
```
de_temp_test = ds_test.copy()

de_temp_test.loc[ds_test["tipo_precio"]=="bajo", "target"]= 0
de_temp_test.loc[ds_test["tipo_precio"]=="medio", "target"]= 1
```

```
de_temp_test.loc[ds_test["tipo_precio"]=="alto", "target"]= 2
```

[8]:
```
ds_train_x = de_temp_train.drop(['id', 'tipo_precio', 'property_price',␣
 ↪'target'], axis='columns', inplace=False)
ds_test_x = de_temp_test.drop(['id', 'tipo_precio', 'property_price',␣
 ↪'target'], axis='columns', inplace=False)
```

[9]:
```
ds_train_rn_x = pd.get_dummies(ds_train_x, columns=["barrio","property_type"],␣
 ↪drop_first=True)
ds_test_rn_x = pd.get_dummies(ds_test_x, columns=["barrio","property_type"],␣
 ↪drop_first=True)
```

1.1 Regresion

[10]:
```
ds_train_rn_y = de_temp_train['property_price'].copy()
ds_test_rn_y = de_temp_test['property_price'].copy()
```

[11]:
```
columnas_predictoras=ds_train_rn_x.columns.to_list()

d_in=len(columnas_predictoras)
```

Estandarizamos y escalamos los datos.

[12]:
```
sscaler=StandardScaler()
sscaler.fit(pd.DataFrame(ds_train_rn_x))
```

[12]:
```
StandardScaler()
```

[13]:
```
x_train_transform=sscaler.transform(pd.DataFrame(ds_train_rn_x))
x_test_transform=sscaler.transform(pd.DataFrame(ds_test_rn_x))
```

Modelo de una capa Entrenamos un modelo usando keras de una capa para regresión.

[14]:
```
rn = keras.Sequential([keras.layers.Dense(1,input_shape=(d_in,))])
```

[15]:
```
rn.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 1)                 79

=================================================================
Total params: 79
Trainable params: 79
```

```
Non-trainable params: 0
_________________________________________________________________
```

[16]:
```
rn.compile(
  optimizer=keras.optimizers.Adam(lr=0.001, beta_1=0.9, beta_2=0.999),
  loss='mse',
  metrics=['mae'],
)
```

[17]:
```
rn.fit(x_train_transform,ds_train_rn_y,epochs=10,batch_size=16,verbose=False)
```

[17]:
```
<keras.callbacks.History at 0x7ffae4946ee0>
```

[18]:
```
pred = rn.predict(x_test_transform)
```

```
500/500 [==============================] - 1s 1ms/step
```

[19]:
```
mae=mean_absolute_error(ds_test_rn_y,pred)
mse=mean_squared_error(ds_test_rn_y,pred)

print(f"Error absoluto medio {mae}")
print(f"Error cuadrático medio {mse}")
```

```
Error absoluto medio 216483.477021418
Error cuadrático medio 127312474563.47418
```

[22]:
```
# Guardamos el modelo
import pickle

filename = 'rn_reg.sav'
pickle.dump(rn, open(filename, 'wb'))
```

Modelo multicapa Entrenamos keras secuencial de varias capas para regresión.

[23]:
```
d_out=1

rn = keras.Sequential([
    keras.layers.Dense(3,input_shape=(d_in,), activation="relu"),
    keras.layers.Dense(6, activation="tanh" ),
    keras.layers.Dense(d_out, "sigmoid")])
```

[24]:
```
rn.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_1 (Dense)             (None, 3)                 237
```

```
 dense_2 (Dense)             (None, 6)                 24

 dense_3 (Dense)             (None, 1)                 7

=================================================================
Total params: 268
Trainable params: 268
Non-trainable params: 0
_________________________________________________________________
```

[25]:
```
rn.compile(
  optimizer=keras.optimizers.Adam(lr=0.001, beta_1=0.9, beta_2=0.999),
  loss='mse',
  metrics=['mae'],
)
```

[26]:
```
rn.fit(x_train_transform,ds_train_rn_y,epochs=10,batch_size=16,verbose=False)
```

[26]:
```
<keras.callbacks.History at 0x7ffae475f670>
```

[27]:
```
y_pred=rn.predict(x_test_transform)

mae=mean_absolute_error(ds_test_rn_y,y_pred)
mse=mean_squared_error(ds_test_rn_y,y_pred)

print(f"Error absoluto medio {mae}")
print(f"Error cuadrático medio {mse}")
```

```
500/500 [==============================] - 1s 1ms/step
Error absoluto medio 216511.92879024698
Error cuadrático medio 127358774601.02214
```

Se puede observar que aumentando la cantidad de capas de la red no se obtiene una mejora, por el contrario, el error aumenta. Por lo tanto, en este caso nos podemos quedar con un modelo de una única capa

[30]:
```
# Guardamos el modelo
filename = 'rn_multi_reg.sav'
pickle.dump(rn, open(filename, 'wb'))
```

1.2 Clasificacion

[31]:
```
ds_train_rn_y = de_temp_train['target'].copy()
ds_test_rn_y = de_temp_test['target'].copy()
```

Hacemos una busqueda de hiperparametros

[32]:
```
random.seed(1)
activations = ['relu', 'tanh', 'sigmoid', 'softmax']

mejores_hyperparametros = {
    'func_activacion_1': '',
    'func_activacion_2': '',
    'func_activacion_3': '',
    'epochs': 0,
    'batch_size': 0,
}

mejores_metricas = inf

for i in range(0,5):

  cant_salidas = random.randint(0,3)
  func_activacion_1 = activations[random.randint(0,3)]
  func_activacion_2 = activations[random.randint(0,3)]
  func_activacion_3 = activations[random.randint(0,3)]
  modelo = keras.Sequential([
      # input_shape solo en la primer capa
      keras.layers.Dense(1, input_shape=(d_in,), activation=activations[random.
 ↪randint(0,3)]),

      keras.layers.Dense(cant_salidas, activation=func_activacion_1),
      keras.layers.Dense(cant_salidas, activation=func_activacion_2),

      keras.layers.Dense(1, activation=func_activacion_3),
     ])

  # Compilamos el modelo
  modelo.compile(
  optimizer=keras.optimizers.Adam(lr=0.001, beta_1=0.9, beta_2=0.999),
  loss='mse',
  metrics=['mae'],
  )

  # Entrenamiento del modelo
  epochs = random.randint(50,150)
  batch_size = random.randint(50,200)

  print(f"Probando con: {cant_salidas} salidas, {func_activacion_1},␣
 ↪{func_activacion_2}, {func_activacion_3}, {epochs} epochs, {batch_size}␣
 ↪batch_size")
  history = modelo.fit(x_train_transform,␣
 ↪ds_train_rn_y,epochs=epochs,batch_size=batch_size,verbose=False)
```

```
  y_pred = modelo.predict(x_test_transform)

  y_pred = y_pred.flatten()
  mse = metrics.mean_squared_error(
        y_true  = ds_test_rn_y,
        y_pred  = y_pred,
        squared = True
        )

  print("Metricas obtenidas:")
  print(f"mse:{mse}")
  print()

  if mse < mejores_metricas:
    mejores_metricas = mse

    mejores_hyperparametros['cant_salidas'] = cant_salidas
    mejores_hyperparametros['func_activacion_1'] = func_activacion_1
    mejores_hyperparametros['func_activacion_2'] = func_activacion_2
    mejores_hyperparametros['func_activacion_3'] = func_activacion_3
    mejores_hyperparametros['epochs'] = epochs
    mejores_hyperparametros['batch_size'] = batch_size


print(mejores_metricas)
print(mejores_hyperparametros)
```

```
Probando con: 1 salidas, relu, sigmoid, relu, 147 epochs, 165 batch_size
500/500 [==============================] - 1s 1ms/step
Metricas obtenidas:
mse:0.6670012104920617

Probando con: 3 salidas, softmax, tanh, relu, 53 epochs, 149 batch_size
500/500 [==============================] - 1s 1ms/step
Metricas obtenidas:
mse:0.6669583781684852

Probando con: 3 salidas, relu, softmax, sigmoid, 125 epochs, 76 batch_size
500/500 [==============================] - 1s 2ms/step
Metricas obtenidas:
mse:0.5284800284175839

Probando con: 2 salidas, relu, relu, relu, 98 epochs, 105 batch_size
500/500 [==============================] - 1s 1ms/step
Metricas obtenidas:
mse:0.42645220278499735
```

```
Probando con: 3 salidas, relu, tanh, softmax, 120 epochs, 109 batch_size
500/500 [==============================] - 1s 1ms/step
Metricas obtenidas:
mse:0.6669584244778505

0.42645220278499735
{'func_activacion_1': 'relu', 'func_activacion_2': 'relu', 'func_activacion_3':
'relu', 'epochs': 98, 'batch_size': 105, 'cant_salidas': 2}
```

[33]:
```
columnas_predictoras=ds_train_rn_x.columns.to_list()

d_in=len(columnas_predictoras)
```

[34]:
```
sscaler=StandardScaler()
sscaler.fit(pd.DataFrame(ds_train_rn_x))
```

[34]:
```
StandardScaler()
```

[35]:
```
x_train_transform=sscaler.transform(pd.DataFrame(ds_train_rn_x))
x_test_transform=sscaler.transform(pd.DataFrame(ds_test_rn_x))
```

[36]:
```
# calcula la cantidad de clases
classes=int(de_temp_train.loc[:,'target'].max()+1)

modelo = keras.Sequential([
    keras.layers.Dense(3,input_shape=(d_in,), activation='relu'),
    keras.layers.Dense(7, activation='softmax'),
    keras.layers.Dense(classes, activation='sigmoid')])

modelo.summary()
```

```
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_24 (Dense)            (None, 3)                 237

 dense_25 (Dense)            (None, 7)                 28

 dense_26 (Dense)            (None, 3)                 24

=================================================================
Total params: 289
Trainable params: 289
Non-trainable params: 0
_________________________________________________________________
```

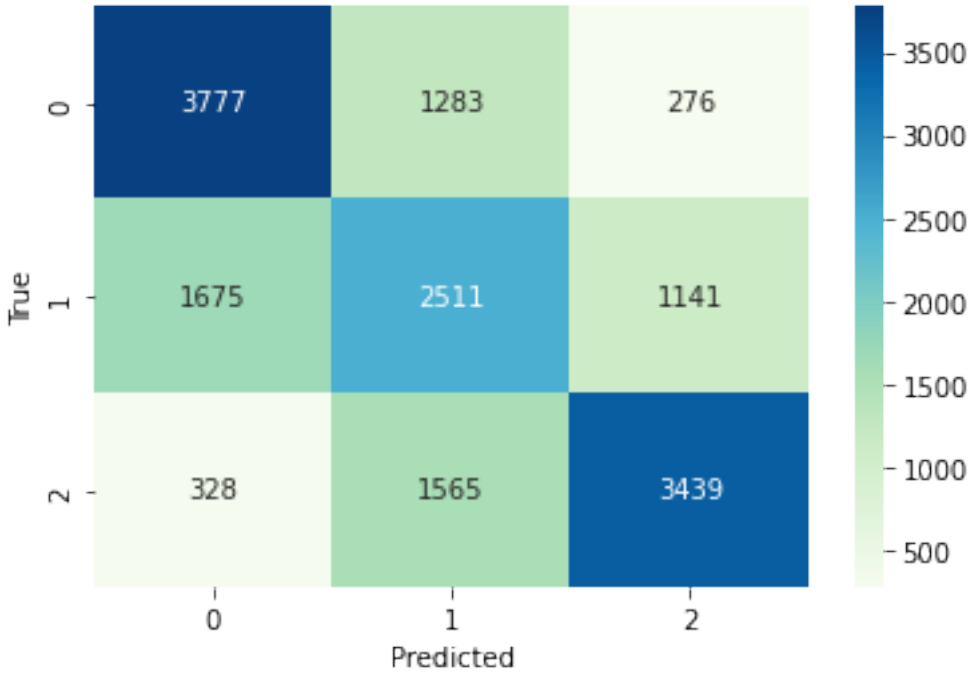
[37]:
```
modelo.compile(
  optimizer=keras.optimizers.Adam(lr=0.001, beta_1=0.9, beta_2=0.999),
  loss='sparse_categorical_crossentropy',
  metrics=['accuracy'],
)

cant_epochs=125

historia = modelo.
 ↪fit(x_train_transform,ds_train_rn_y,epochs=cant_epochs,batch_size=76,verbose=False)
```

[38]:
```
y_pred = modelo.predict(x_test_transform)

y_pred = np.argmax(y_pred,axis = 1)
```

```
500/500 [==============================] - 1s 1ms/step
```

[39]:
```
#Calculo las métricas en el conjunto de evaluación
accuracy=accuracy_score(ds_test_rn_y,y_pred)

print(classification_report(ds_test_rn_y,y_pred))
print("Accuracy: "+str(accuracy))
print(" ")

#Creo la matriz de confusión
tabla=confusion_matrix(ds_test_rn_y, y_pred)

#Grafico la matriz de confusión
sns.heatmap(tabla,cmap='GnBu',annot=True,fmt='g')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```

```
              precision    recall  f1-score   support

         0.0       0.65      0.71      0.68      5336
         1.0       0.47      0.47      0.47      5327
         2.0       0.71      0.64      0.68      5332

    accuracy                           0.61     15995
   macro avg       0.61      0.61      0.61     15995
weighted avg       0.61      0.61      0.61     15995

Accuracy: 0.608127539856205
```



[41]:
```
# Guardamos el modelo
filename = 'rn_multi_clf.sav'
pickle.dump(modelo, open(filename, 'wb'))
```

Por los resultados de la matriz de confusión podemos inferir que nuestro modelo roza el underfitting ya que no se ajusta a los datos de entrenamiento y por eso apenas puede predecir bien la mitad de los datos de testing.

1.3 Conclusiones

Sabemos que las redes neuronales pueden ser una herramienta muy valiosa al momento de entrenar un modelo y predecir datos, aunque en nuestro caso los resultados no fueron muy buenos. Al igual que con el primer trabajo practico nos inclinamos a pensar que la causa del mal desempeño es debido a nuestro set de datos que no es del todo bueno. Aun haciendo una busqueda de hiperparametros los resultados de la combinacion optima no son muy buenos.