[1]:
```
import h5py
import matplotlib.pyplot as plt
import numpy as np
import tensorflow.keras as K
from numpy.lib.recfunctions import structured_to_unstructured
from sklearn.model_selection import train_test_split
import pandas as pd
```

```
2024-04-16 16:46:04.583009: I tensorflow/core/platform/cpu_feature_guard.cc:182]
This TensorFlow binary is optimized to use available CPU instructions in
performance-critical operations.
To enable the following instructions: SSE4.1 SSE4.2, in other operations,
rebuild TensorFlow with the appropriate compiler flags.
```

1 Loading The Data

[2]:
```
with h5py.File("info/data/output_signal.h5", "r") as file:
    signal_data = file["events"][:]

with h5py.File("info/data/output_bg.h5", "r") as file:
    bg_data = file["events"][:]
```

2 'Unstructuring' Data

[4]:
```
signal_data = structured_to_unstructured(signal_data)
bg_data = structured_to_unstructured(bg_data)
```

3 Train - Validation - Test Splits

[5]:
```
X = np.concatenate([signal_data, bg_data])
y = np.concatenate([np.ones(signal_data.shape[0], dtype=int), np.zeros(bg_data.
 ↪shape[0], dtype=int)])

x_train, x_rem, y_train, y_rem = train_test_split(X, y, train_size=0.8)
x_val, x_test, y_val, y_test = train_test_split(x_rem, y_rem, train_size=0.5)
```

4 Data Preprocessing

[6]:
```
preprocessing_layer = K.layers.Normalization()
preprocessing_layer.adapt(x_train)
```

5 Model training

[7]:
```
model = K.Sequential(
    [
        preprocessing_layer,
        K.layers.Dense(50, activation="relu", name="hidden1"),
        K.layers.Dense(25, activation="relu", name="hidden2"),
        K.layers.Dense(10, activation="relu", name="hidden3"),
        K.layers.Dense(1, activation="sigmoid", name="output"),
    ]
)

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 normalization (Normalizatio  (None, 18)               37
 n)

 hidden1 (Dense)             (None, 50)                950

 hidden2 (Dense)             (None, 25)                1275

 hidden3 (Dense)             (None, 10)                260

 output (Dense)              (None, 1)                 11

=================================================================
Total params: 2,533
Trainable params: 2,496
Non-trainable params: 37
_________________________________________________________________
```

[8]:
```
model.compile(
    optimizer=K.optimizers.Adam(learning_rate=0.0002),
    loss=K.losses.BinaryCrossentropy(),
    metrics=[K.metrics.BinaryAccuracy()],
)
```

[9]:
```
early_stopping_callback = K.callbacks.EarlyStopping(
    monitor='val_loss',
    patience=10,
    min_delta=0.002,
    restore_best_weights=True,
    verbose=1,)
```

[10]:
```
fit_history = model.fit(
        x_train,
        y_train,
        batch_size=100,
        epochs=100,
        validation_data=(x_val, y_val),
        callbacks=[early_stopping_callback],
    )

print("Printing summary of the trained model:")
print(model.summary())
```

```
Epoch 1/100
1159/1159 [==============================] - 2s 1ms/step - loss: 0.4256 -
binary_accuracy: 0.8084 - val_loss: 0.3800 - val_binary_accuracy: 0.8312
        ⋮
Epoch 29/100
1159/1159 [==============================] - 1s 1ms/step - loss: 0.3594 -
binary_accuracy: 0.8435 - val_loss: 0.3579 - val_binary_accuracy: 0.8433
Epoch 30/100
1127/1159 [============================>.] - ETA: 0s - loss: 0.3591 -
binary_accuracy: 0.8439Restoring model weights from the end of the best epoch:
20.
1159/1159 [==============================] - 2s 1ms/step - loss: 0.3592 -
binary_accuracy: 0.8438 - val_loss: 0.3577 - val_binary_accuracy: 0.8437
Epoch 30: early stopping
Printing summary of the trained model:
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 normalization (Normalizatio  (None, 18)               37
 n)

 hidden1 (Dense)             (None, 50)                950

 hidden2 (Dense)             (None, 25)                1275

 hidden3 (Dense)             (None, 10)                260

 output (Dense)              (None, 1)                 11

=================================================================
Total params: 2,533
Trainable params: 2,496
Non-trainable params: 37
_________________________________________________________________
```

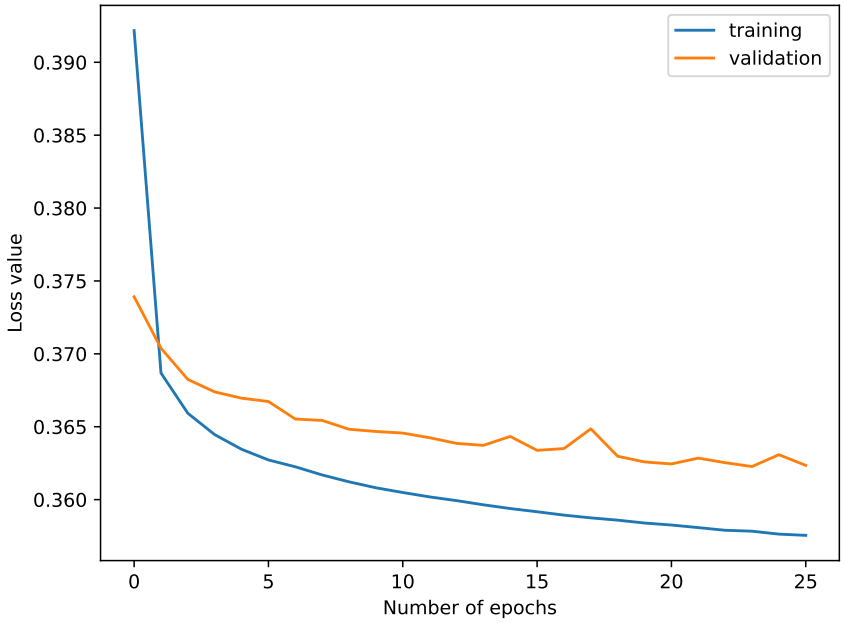
```
None
```

[11]:
```
save_name = "my_model"
print(f'Storing model with name "{save_name}" now. You can convert '
        'this to ONNX format with the "tf2onnx" command-line utility.')
model.save(save_name)
```

```
Storing model with name "my_model" now. You can convert this to ONNX format with
the "tf2onnx" command-line utility.

WARNING:absl:Found untraced functions such as _update_step_xla while saving
(showing 1 of 1). These functions will not be directly callable after loading.

INFO:tensorflow:Assets written to: my_model/assets

INFO:tensorflow:Assets written to: my_model/assets
```

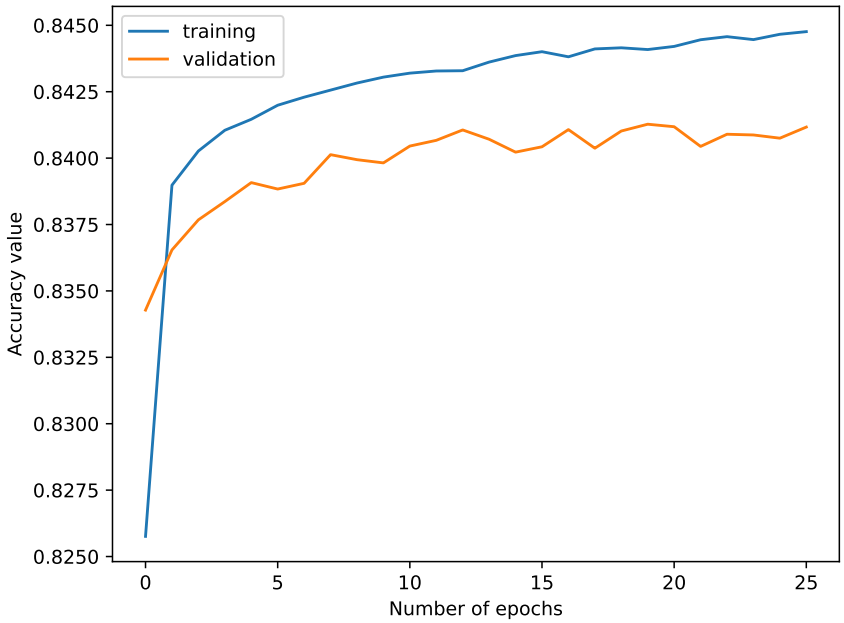
The following code produces a plot of the loss evolution for training and validation:

[12]:
```
plt.plot(fit_history.history["loss"], label="training")
plt.plot(fit_history.history["val_loss"], label="validation")
plt.xlabel("Number of epochs")
plt.ylabel("Loss value")
plt.legend()
plt.tight_layout()
plt.show()
```



The following code produces a plot of the accuracy evolution per epoch for training and validation:

[13]:
```
plt.figure()
plt.plot(fit_history.history["binary_accuracy"], label="training")
plt.plot(fit_history.history["val_binary_accuracy"], label="validation")
plt.xlabel("Number of epochs")
plt.ylabel("Accuracy value")
plt.legend()
plt.tight_layout()
#plt.savefig(output_file)
```

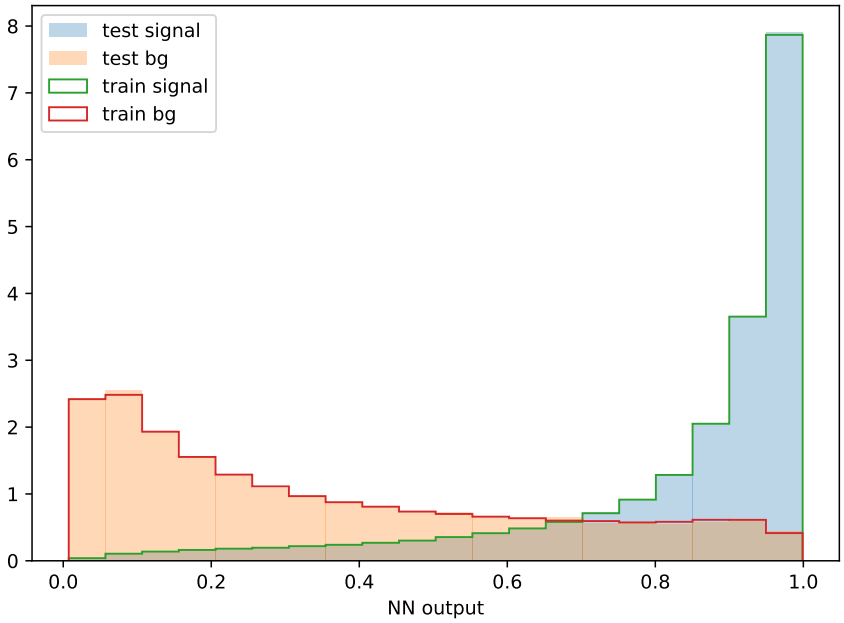


The following code plots the distribution of the neural-network output node for both training and test data to check for possible differences between the two. The datasets are sliced according to their truth labels (i.e. the two classes).

[14]:
```
"""Creates a plot of the NN output for training and test data.

    The function slices both training and test data according to the truth
    labels, so that the displayed spectra can be split into "background" and
    "signal" events (i.e. the two classes the model was trained on).

    """

_, bins, _ = plt.hist(model.predict(x_test[y_test.astype(bool)]), bins=20,␣
↪alpha=0.3, density=True, label="test signal")
plt.hist(model.predict(x_test[~y_test.astype(bool)]), bins=bins, alpha=0.3,␣
↪density=True, label="test bg")
```

```
plt.hist(model.predict(x_train[y_train.astype(bool)]), bins=bins, density=True,␣
 ↪histtype="step", label="train signal")
plt.hist(model.predict(x_train[~y_train.astype(bool)]), bins=bins, density=True,␣
 ↪histtype="step", label="train bg")
plt.xlabel("NN output")
plt.legend()
plt.tight_layout()
plt.show()
#plt.savefig(output_file)
print("Created plots of loss, accuracy, and NN output.")
```

```
1595/1595 [==============================] - 1s 422us/step
723/723 [==============================] - 0s 420us/step
12717/12717 [==============================] - 5s 429us/step
5823/5823 [==============================] - 3s 446us/step
```




```
Created plots of loss, accuracy, and NN output.
```