p9120_hw3_q3

November 6, 2022

1 P9120 HW3 Q3

The "spam" data" (https://web.stanford.edu/hastie/ElemStatLearn/data) has been divided into a training set and a test set. Fit a neural network to the training set, and calculate its classification error on the test set. Compare your results to the classification tree results presented in Section 9.2.5 of [ESL] on both the classification performance and interpretability of the final model.

```
In [132]: import pandas as pd
          import tensorflow as tf
          import numpy as np
          import matplotlib.pyplot as plt

          from numpy.random import seed
          seed(2022)
          tf.random.set_seed(2)
```

```
In [133]: plt.rcParams['figure.figsize'] = (14,10)
```

```
In [134]: ## Read in data
          X_train = pd.read_csv("X_train.csv", header = 0, index_col = 0)
          X_train = X_train.reset_index(drop=True)
          y_train = pd.read_csv("y_train.csv", header = 0, index_col = 0)
          y_train = y_train.reset_index(drop=True)

          X_test = pd.read_csv("X_test.csv", header = 0, index_col = 0)
          X_test = X_test.reset_index(drop=True)
          y_test = pd.read_csv("y_test.csv", header = 0, index_col = 0)
          y_test = y_test.reset_index(drop=True)
```

1.1 Use Keras to build a sequential model of 3 hidden layers, 2 dropout layers

```
In [135]: from tensorflow import keras
          from tensorflow.keras.models import Sequential
          from tensorflow.keras.layers import Dense, Dropout, BatchNormalization, Activation
          from sklearn.model_selection import train_test_split
          from sklearn.metrics import RocCurveDisplay
```

Taking 20% data out as our validation set

In [136]:
```
# validation set
X_train_, X_val = train_test_split(X_train, test_size=0.2, random_state = 42)
y_train_, y_val = train_test_split(y_train, test_size=0.2, random_state = 42)
```

In [137]:
```
# create model
METRICS = [
      keras.metrics.BinaryAccuracy(name='accuracy'),
      keras.metrics.AUC(name='auc')
]

model = Sequential([
    Dense(256, input_shape=(X_train.shape[1],), activation="relu"),
    BatchNormalization(),
    Dropout(0.4),
    Dense(128, activation='relu'),
    BatchNormalization(),
    Dropout(0.4),
    Dense(64, activation='relu'),
    BatchNormalization(),
    Dropout(0.4),
    Dense(1, activation='sigmoid')
]);

# Compile model
model.compile(optimizer = keras.optimizers.Adam(learning_rate=0.0001),
              loss = keras.losses.BinaryCrossentropy(),
              metrics=METRICS)
model.summary()
```

```
Model: "sequential_10"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_35 (Dense)             (None, 256)               14848
_________________________________________________________________
batch_normalization_25 (Batc (None, 256)               1024
_________________________________________________________________
dropout_14 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_36 (Dense)             (None, 128)               32896
_________________________________________________________________
batch_normalization_26 (Batc (None, 128)               512
_________________________________________________________________
dropout_15 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_37 (Dense)             (None, 64)                8256
_________________________________________________________________
batch_normalization_27 (Batc (None, 64)                256
```

```
_________________________________________________________________
dropout_16 (Dropout)         (None, 64)                0
_________________________________________________________________
dense_38 (Dense)             (None, 1)                 65
=================================================================
Total params: 57,857
Trainable params: 56,961
Non-trainable params: 896

_________________________________________________________________
```

In [138]:
```python
EPOCHS = 100
BATCH_SIZE = 40

early_stopping = tf.keras.callbacks.EarlyStopping(
    monitor='auc',
    verbose=2,
    patience=20,
    mode='max',
    restore_best_weights=True)

history = model.fit(
    X_train_,
    y_train_,
    epochs=200,
    validation_split=0.20,
    callbacks=[early_stopping],
    batch_size=40,
    verbose=0,
    validation_data=(X_val, y_val)
)
```

In [139]:
```python
results = model.evaluate(X_train, y_train, batch_size=BATCH_SIZE, verbose=0)
print("Loss: {:0.4f}".format(results[0]))
```

```
Loss: 0.1754
```

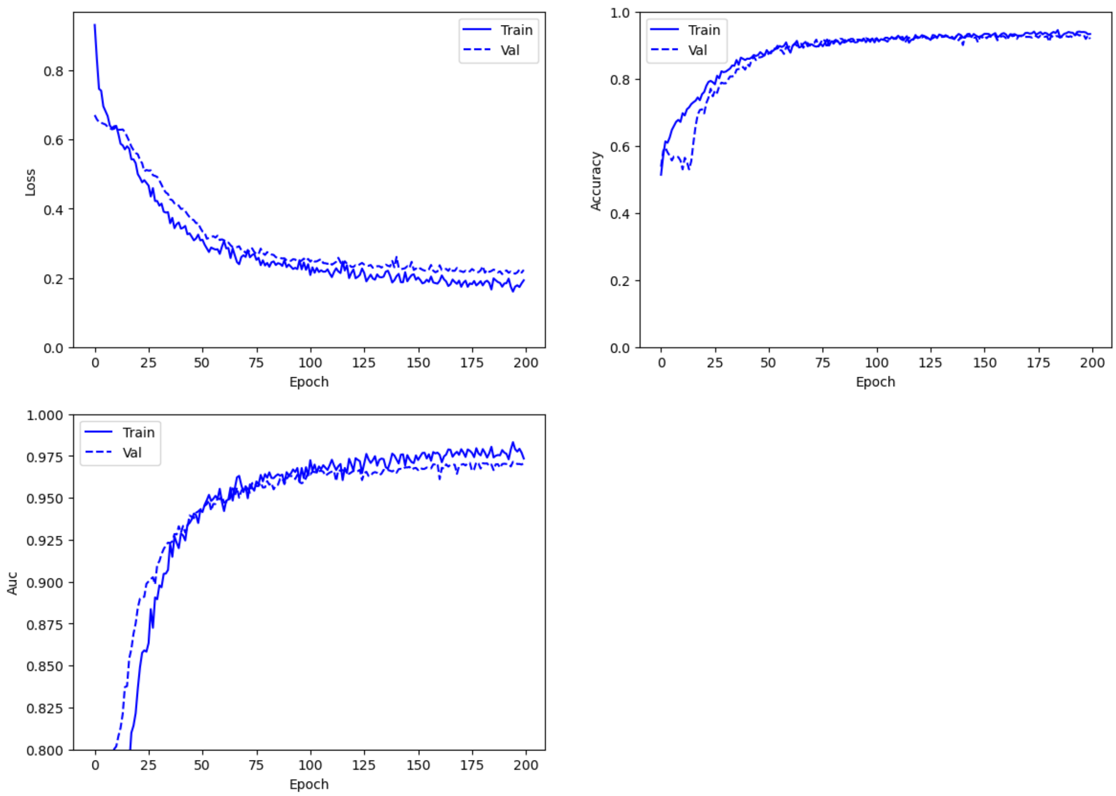
1.1.1 History Checking

In [140]:
```python
def plot_metrics(history):
    metrics = ['loss', 'accuracy', 'auc']
    for n, metric in enumerate(metrics):
        name = metric.replace("_"," ").capitalize()
        plt.subplot(2,2,n+1)
        plt.plot(history.epoch, history.history[metric],
                 color='b', label='Train')
        plt.plot(history.epoch, history.history['val_'+metric],
                 color='b', linestyle="--", label='Val')
```

```
        plt.xlabel('Epoch')
        plt.ylabel(name)
        if metric == 'loss':
            plt.ylim([0, plt.ylim()[1]])
        elif metric == 'auc':
            plt.ylim([0.8,1])
        else:
            plt.ylim([0,1])

        plt.legend()

plot_metrics(history)
```

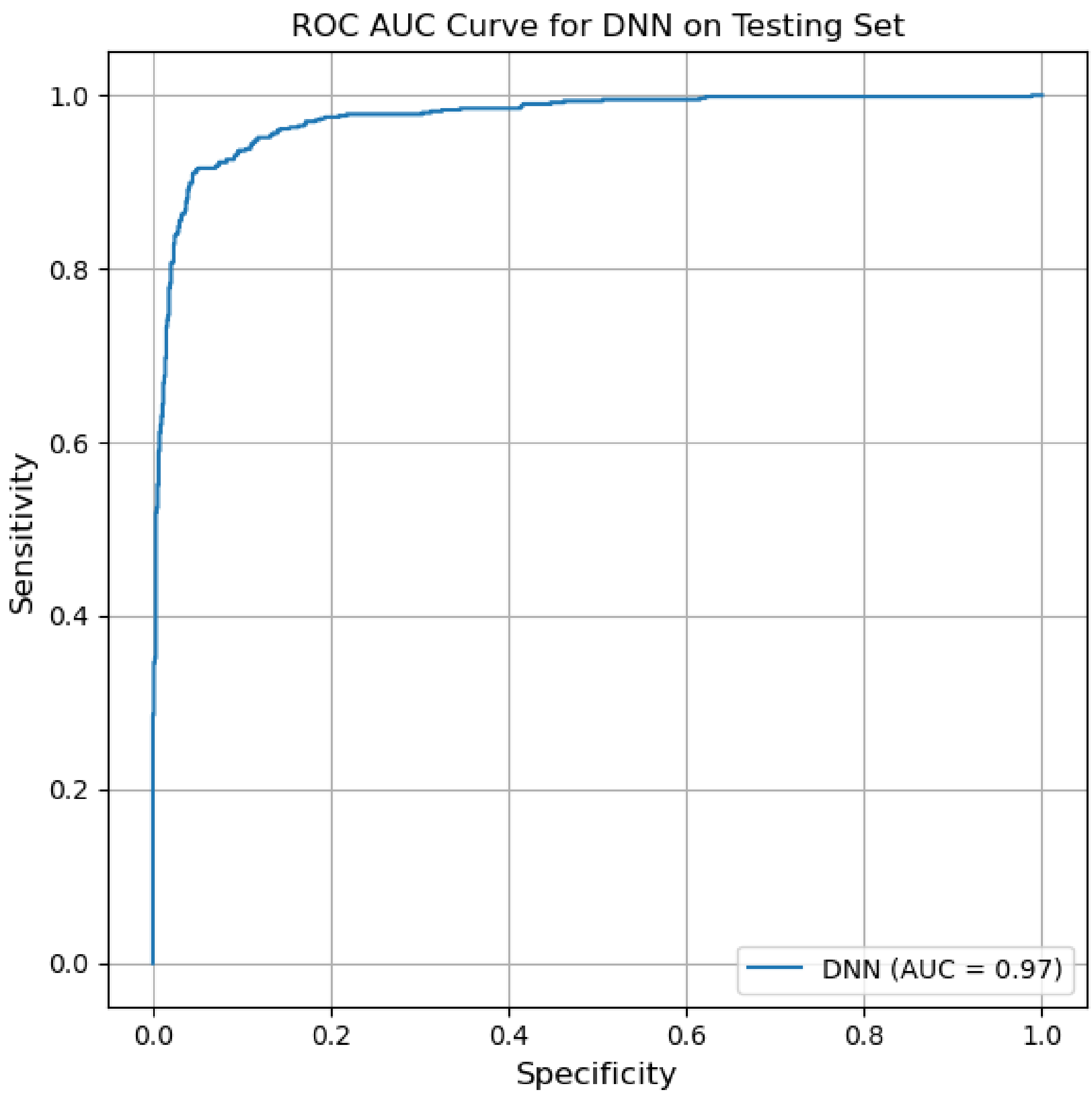


As the number of Epoch grows, the training and validation error decreases and the ROC AUC increases. Our training is indeed effective.

Then we can use the model to predict the test set:

```
In [141]: test_pred = model.predict(X_test, batch_size=BATCH_SIZE)
          plt.rcParams['figure.figsize'] = (6,6)
          RocCurveDisplay.from_predictions(y_test, test_pred, name = 'DNN')
          plt.title("ROC AUC Curve for DNN on Testing Set")
          plt.xlabel("Specificity", fontsize = 12)
          plt.ylabel("Sensitivity", fontsize = 12)
```

```
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.grid()
plt.tight_layout()
plt.show()
```



Calculate classification error:

In [143]:
```
# RSS
test_error = np.mean((np.array(y_test)-test_pred)**2)
## sqrt(RSS/(n-2))
test_error_sd = np.mean(
    np.sqrt((np.array(y_test)-test_pred)**2/(X_test.shape[0]-2)))
print("The classification error on the test set is %.3f and the standard deviation is
```

```
The classification error on the test set is 0.061 and the standard deviation is 0.003
```

- The classification error on the test set of the DNN model (0.061 ± 0.003) is better than that of the classification tree's, and it also gives a better classification rule for any loss with an area of 0.97 (0.97 > 0.95).
- However, the as shown on Fig. 9.5, the pruned tree from the classification tree result can be easily interpreted. The DNN model is black-boxed, therefore it is lack of interpretability compared to the classification tree.