Model validation

Puteaux, Fall/Winter 2020-2021

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##                            ##
##  Deep Learning in Python   ##
##                            ##
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```

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§1 Introduction to Deep Learning in Python
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§1.4 Fine-tuning keras models
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```
§1.4.2 Model validation
```

1. Why is it important to choose validation in deep learning?

- Repeated training from cross-validation would take a long time, so it is common to use validation split rather than cross-validation.
- Deep learning is widely used in large datasets because the single validation score is based on a large amount of data and is reliable.

2. Code of model validation:

[1]:
```python
import pandas as pd
from keras.layers import Dense
from keras.models import Sequential
from keras.utils.np_utils import to_categorical


def data_preparation(df):
    df = df.reindex(columns=[
        'SHOT_CLOCK', 'DRIBBLES', 'TOUCH_TIME', 'SHOT_DIST', 'CLOSE_DEF_DIST',
        'SHOT_RESULT'
    ])
    df['SHOT_CLOCK'] = df['SHOT_CLOCK'].fillna(0)
    df['SHOT_RESULT'].replace('missed', 0, inplace=True)
    df['SHOT_RESULT'].replace('made', 1, inplace=True)
    df.columns = df.columns.str.lower()
    return df


data = pd.read_csv('ref1. Basketball shot log.csv')
```

```
data = data_preparation(data)

predictors = data.drop(['shot_result'], axis=1).to_numpy()
n_cols = predictors.shape[1]
target = to_categorical(data.shot_result)
input_shape = (n_cols, )


def get_new_model(input_shape=input_shape):
    model = Sequential()
    model.add(Dense(100, activation='relu', input_shape=input_shape))
    model.add(Dense(100, activation='relu'))
    model.add(Dense(2, activation='softmax'))
    return (model)


model = get_new_model()
```

[2]:
```
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
model.fit(predictors, target, validation_split=0.3)
```

```
2802/2802 [==============================] - 11s 4ms/step - loss: 0.6687 -
accuracy: 0.6029 - val_loss: 0.6518 - val_accuracy: 0.6157
```

[2]:
```
<tensorflow.python.keras.callbacks.History at 0x7fdfac48cc50>
```

3. Code of early stopping:

[3]:
```
from keras.callbacks import EarlyStopping

early_stopping_monitor = EarlyStopping(patience=2)

model.fit(predictors,
          target,
          validation_split=0.3,
          epochs=20,
          callbacks=[early_stopping_monitor])
```

```
Epoch 1/20
2802/2802 [==============================] - 9s 3ms/step - loss: 0.6534 -
accuracy: 0.6178 - val_loss: 0.6506 - val_accuracy: 0.6189
Epoch 2/20
2802/2802 [==============================] - 8s 3ms/step - loss: 0.6516 -
accuracy: 0.6193 - val_loss: 0.6505 - val_accuracy: 0.6168
Epoch 3/20
2802/2802 [==============================] - 8s 3ms/step - loss: 0.6508 -
```

```
accuracy: 0.6195 - val_loss: 0.6525 - val_accuracy: 0.6137
Epoch 4/20
2802/2802 [==============================] - 8s 3ms/step - loss: 0.6503 -
accuracy: 0.6204 - val_loss: 0.6498 - val_accuracy: 0.6187
Epoch 5/20
2802/2802 [==============================] - 8s 3ms/step - loss: 0.6497 -
accuracy: 0.6207 - val_loss: 0.6501 - val_accuracy: 0.6191
Epoch 6/20
2802/2802 [==============================] - 10s 4ms/step - loss: 0.6495 -
accuracy: 0.6205 - val_loss: 0.6496 - val_accuracy: 0.6186
Epoch 7/20
2802/2802 [==============================] - 7s 3ms/step - loss: 0.6493 -
accuracy: 0.6211 - val_loss: 0.6496 - val_accuracy: 0.6188
Epoch 8/20
2802/2802 [==============================] - 8s 3ms/step - loss: 0.6491 -
accuracy: 0.6207 - val_loss: 0.6491 - val_accuracy: 0.6195
Epoch 9/20
2802/2802 [==============================] - 8s 3ms/step - loss: 0.6487 -
accuracy: 0.6208 - val_loss: 0.6498 - val_accuracy: 0.6205
Epoch 10/20
2802/2802 [==============================] - 8s 3ms/step - loss: 0.6487 -
accuracy: 0.6217 - val_loss: 0.6498 - val_accuracy: 0.6196
```

[3]:
```
<tensorflow.python.keras.callbacks.History at 0x7fdfaeeb5610>
```

4. What kind of experimentations could be included in deep learning?

- Experiment with different architectures.
- More layers.
- Fewer layers.
- Layers with more nodes.
- Layers with fewer nodes.
- Creating a great model requires experimentation.

5. Practice exercises for model validation:

▶ Package pre-loading:

[4]:
```python
import pandas as pd
from keras.layers import Dense
from keras.models import Sequential
from keras.utils import to_categorical
```

▶ Data pre-loading:

[5]:
```python
df = pd.read_csv('ref4. Titanic.csv')
```

```
df.replace(False, 0, inplace=True)
df.replace(True, 1, inplace=True)

predictors = df.drop(['survived'], axis=1).to_numpy()
n_cols = predictors.shape[1]
target = to_categorical(df.survived)
input_shape = (n_cols, )
```

▶ **Evaluating model accuracy on validation dataset practice:**

[6]:
```
# Save the number of columns in predictors: n_cols
n_cols = predictors.shape[1]
input_shape = (n_cols, )

# Specify the model
model = Sequential()
model.add(Dense(100, activation='relu', input_shape=input_shape))
model.add(Dense(100, activation='relu'))
model.add(Dense(2, activation='softmax'))

# Compile the model
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Fit the model
hist = model.fit(predictors, target, validation_split=0.3)
```

```
20/20 [==============================] - 1s 59ms/step - loss: 1.3215 - accuracy:
0.5981 - val_loss: 0.5621 - val_accuracy: 0.7201
```

▶ **Early stopping optimization optimizing practice:**

[7]:
```
# Import EarlyStopping
from keras.callbacks import EarlyStopping

# Save the number of columns in predictors: n_cols
n_cols = predictors.shape[1]
input_shape = (n_cols, )

# Specify the model
model = Sequential()
model.add(Dense(100, activation='relu', input_shape=input_shape))
model.add(Dense(100, activation='relu'))
model.add(Dense(2, activation='softmax'))

# Compile the model
model.compile(optimizer='adam',
```

```
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Define early_stopping_monitor
early_stopping_monitor = EarlyStopping(patience=2)

# Fit the model
model.fit(predictors,
          target,
          validation_split=0.3,
          epochs=30,
          callbacks=[early_stopping_monitor])
```

```
Epoch 1/30
20/20 [==============================] - 1s 60ms/step - loss: 1.0821 - accuracy:
0.5435 - val_loss: 0.5677 - val_accuracy: 0.7090
Epoch 2/30
20/20 [==============================] - 0s 5ms/step - loss: 0.6576 - accuracy:
0.6523 - val_loss: 0.5399 - val_accuracy: 0.7313
Epoch 3/30
20/20 [==============================] - 0s 5ms/step - loss: 0.6287 - accuracy:
0.6817 - val_loss: 0.5657 - val_accuracy: 0.7351
Epoch 4/30
20/20 [==============================] - 0s 7ms/step - loss: 0.6250 - accuracy:
0.6815 - val_loss: 0.6273 - val_accuracy: 0.6530
```

[7]:

```
<tensorflow.python.keras.callbacks.History at 0x7fdfb028d650>
```

▶ **Package re-pre-loading:**

[8]:

```
import matplotlib.pyplot as plt
```

▶ **Code pre-loading:**

[9]:

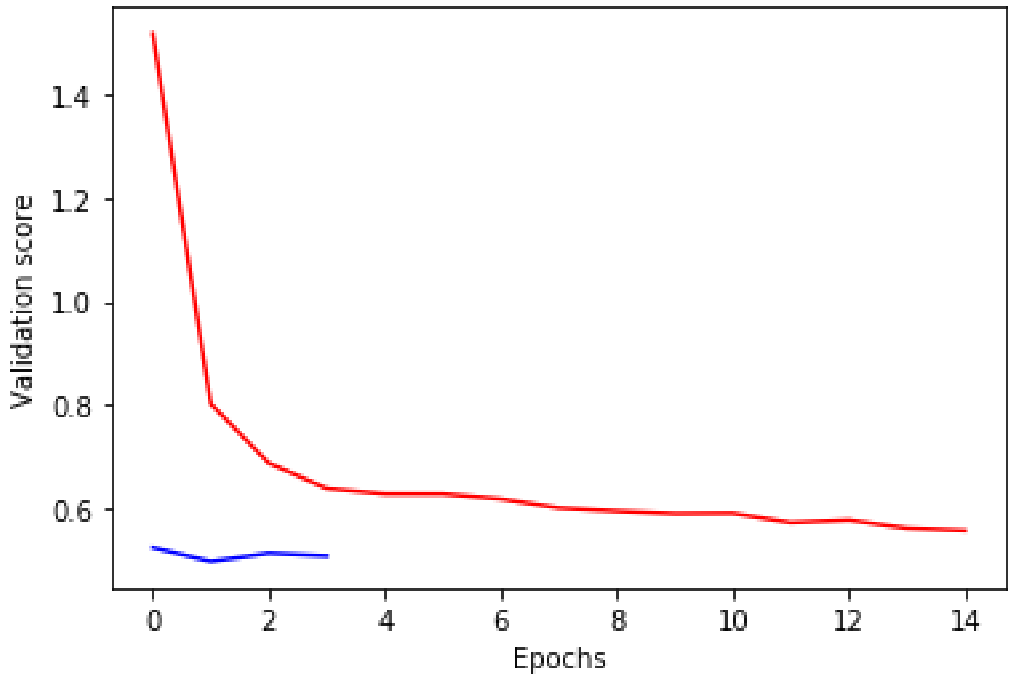
```
model_1 = Sequential()
model_1.add(Dense(10, activation='relu', input_shape=input_shape))
model_1.add(Dense(10, activation='relu'))
model_1.add(Dense(2, activation='softmax'))
model_1.compile(optimizer='adam',
                loss='categorical_crossentropy',
                metrics=['accuracy'])
```

▶ **Experimenting with wider networks practice:**

[10]:

```
# Define early_stopping_monitor
early_stopping_monitor = EarlyStopping(patience=2)

# Create the new model: model_2
```

```python
model_2 = Sequential()

# Add the first and second layers
model_2.add(Dense(100, activation='relu', input_shape=input_shape))
model_2.add(Dense(100, activation='relu'))

# Add the output layer
model_2.add(Dense(2, activation='softmax'))

# Compile model_2
model_2.compile(optimizer='adam',
                loss='categorical_crossentropy',
                metrics=['accuracy'])

# Fit model_1
model_1_training = model_1.fit(predictors,
                               target,
                               epochs=15,
                               validation_split=0.2,
                               callbacks=[early_stopping_monitor],
                               verbose=False)

# Fit model_2
model_2_training = model_2.fit(predictors,
                               target,
                               epochs=15,
                               validation_split=0.2,
                               callbacks=[early_stopping_monitor],
                               verbose=False)

# Create the plot
plt.plot(model_1_training.history['val_loss'], 'r',
         model_2_training.history['val_loss'], 'b')
plt.xlabel('Epochs')
plt.ylabel('Validation score')
plt.show()
```



► **Code re-pre-loading:**

[11]:
```
model_1 = Sequential()
model_1.add(Dense(50, activation='relu', input_shape=input_shape))
model_1.add(Dense(2, activation='softmax'))
model_1.compile(optimizer='adam',
                loss='categorical_crossentropy',
                metrics=['accuracy'])
```

► **Network layers adding practice:**

[12]:
```
# The input shape to use in the first hidden layer
input_shape = (n_cols, )

# Create the new model: model_2
model_2 = Sequential()

# Add the first, second, and third hidden layers
model_2.add(Dense(50, activation='relu', input_shape=input_shape))
model_2.add(Dense(50, activation='relu'))
model_2.add(Dense(50, activation='relu'))

# Add the output layer
model_2.add(Dense(2, activation='softmax'))
```

```
# Compile model_2
model_2.compile(optimizer='adam',
                loss='categorical_crossentropy',
                metrics=['accuracy'])

# Fit model 1
model_1_training = model_1.fit(predictors,
                               target,
                               epochs=20,
                               validation_split=0.4,
                               callbacks=[early_stopping_monitor],
                               verbose=False)

# Fit model 2
model_2_training = model_2.fit(predictors,
                               target,
                               epochs=20,
                               validation_split=0.4,
                               callbacks=[early_stopping_monitor],
                               verbose=False)

# Create the plot
plt.plot(model_1_training.history['val_loss'], 'r',
         model_2_training.history['val_loss'], 'b')
plt.xlabel('Epochs')
plt.ylabel('Validation score')
plt.show()
```