# Building Deep Learning Models with Keras

### LATEX, Puteaux, 2020, 2021

#### Table of Contents

- 1 Creating a Keras model
- 1.1 [note-1] Model building steps
- 1.2 [code-1] Model specification
- 1.3 [quiz-1] Understanding the data
- 1.4 [task-1] Specifying a model
- 2 Compiling and fitting a model
- 2.1 [note-1] Why need to compile the model
- 2.2 [code-1] Compiling a model
- 2.3 [note-2] What is fitting a model
- 2.4 [code-2] Fitting a model
- 2.5 [task-1] Compiling the model
- 2.6 [task-2] Fitting the model
- 3 Classification models
- 3.1 [note-1] Classification
- 3.2 [note-2] Transforming to categorical
- 3.3 [code-1] Classification
- 3.4 [quiz-1] Understanding the classification data
- 3.5 [task-1] Last steps in classification models
- 4 Using models
- 4.1 [note-1] Using models
- 4.2 [code-1] Saving, reloading, and using the model
- 4.3 [code-2] Verifying model structure
- 4.4 [task-1] Making predictions
- 5 Requirements

# 1 Creating a Keras model

## 1.1 [note-1] Model building steps

- Specify Architecture
- Compile
- Fit
- Predict

#### 1.2 [code-1] Model specification

## 1.3 [quiz-1] Understanding the data

- It will be started soon to building models in Keras to predict wages based on various professional and demographic factors by the next steps. Before starting building a model, it's good to understand the data by performing some exploratory analysis.
- It is recommended to use the .head() and .describe() methods in the IPython Shell to quickly overview the DataFrame.
- The target variable which will be predicting is wage\_per\_hour. Some of the predictor variables are binary indicators, where a value of 1 represents True, and 0 represents False.
- Of the nine predictor variables in the DataFrame, how many are binary indicators? The min and max values, as shown by .describe() will be informative here. How many binary indicator predictors are there?
  - $\square$  0.
  - $\square$  5.
  - $\boxtimes 6$ .

#### ► Package pre-loading

```
[2]: import pandas as pd
```

#### ▶ Data pre-loading

```
[3]: df = pd.read_csv('../Datasets/2. Hourly wages.csv')
    ▶ Quiz solution
[4]: df.head()
[4]:
        wage_per_hour
                        union
                                education_yrs
                                                experience_yrs
                                                                  age
                                                                       female
     0
                  5.10
                             0
                                             8
                                                              21
                                                                   35
                                                                             1
                                                                                   1
     1
                  4.95
                             0
                                             9
                                                              42
                                                                   57
                                                                             1
                                                                                   1
     2
                  6.67
                                                                   19
                                                                             0
                                                                                   0
                             0
                                            12
                                                              1
     3
                  4.00
                             0
                                            12
                                                              4
                                                                   22
                                                                             0
                                                                                   0
     4
                  7.50
                                            12
                                                              17
                                                                   35
                                                                             0
                             0
                                                                                   1
                manufacturing
                                construction
     0
             0
                                            0
                             1
     1
             0
                             1
                                            0
     2
             0
                                            0
                             1
     3
                                            0
             0
                             0
             0
                             0
    df.describe()
[5]:
             wage_per_hour
                                                          experience_yrs
                                  union
                                          education_yrs
                                                                                   age
                534.000000
                             534.000000
                                             534.000000
                                                              534.000000
                                                                            534.000000
     count
     mean
                  9.024064
                               0.179775
                                              13.018727
                                                                17.822097
                                                                             36.833333
                                               2.615373
     std
                  5.139097
                               0.384360
                                                                12.379710
                                                                             11.726573
                                                                             18.000000
     min
                  1.000000
                               0.000000
                                          2.00000
                                                                 0.000000
     25%
                  5.250000
                               0.000000
                                              12.000000
                                                                 8.000000
                                                                             28.000000
     50%
                  7.780000
                               0.000000
                                                                15.000000
                                                                             35.000000
                                              12.000000
     75%
                 11.250000
                               0.000000
                                              15.000000
                                                                26.000000
                                                                             44.000000
                 44.500000
                               1.000000
                                              18.000000
                                                                55.000000
                                                                             64.000000
     max
                 female
                                                   manufacturing
                                marr
                                            south
                                                                    construction
            534.000000
     count
                         534.000000
                                       534.000000
                                                       534.000000
                                                                      534.000000
     mean
               0.458801
                            0.655431
                                         0.292135
                                                         0.185393
                                                                        0.044944
     std
               0.498767
                            0.475673
                                         0.455170
                                                         0.388981
                                                                        0.207375
     min
               0.000000
                            0.000000
                                         0.000000
                                                         0.000000
                                                                        0.000000
     25%
               0.000000
                            0.000000
                                         0.000000
                                                         0.000000
                                                                        0.000000
               0.00000
     50%
                                         0.00000
                            1.000000
                                                         0.000000
                                                                        0.000000
     75%
               1.000000
                            1.000000
                                         1.000000
                                                         0.00000
                                                                        0.000000
               1.000000
                            1.000000
                                         1.000000
                                                         1.000000
                                                                        1.000000
     max
[6]: cols = df.columns
     count = 0
     for i in range(len(cols)):
         if ((len(df.iloc[:, i].unique()) == 2)
```

There are 6 binary indicator predictors here.

### 1.4 [task-1] Specifying a model

#### ▶ Package pre-loading

```
[7]: import pandas as pd
```

#### ▶ Data pre-loading

```
[8]: df = pd.read_csv('../Datasets/2. Hourly wages.csv')

target = df.iloc[:, 0].to_numpy()
predictors = df.iloc[:, 1:].to_numpy()
```

#### ► Task practice

```
[9]: # Import necessary modules
from tensorflow.keras.layers import Dense
from tensorflow.keras.models import Sequential

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

# Set up the model: model
model = Sequential()

# Add the first layer
model.add(Dense(50, activation='relu', input_shape=(n_cols, )))

# Add the second layer
model.add(Dense(32, activation='relu'))

# Add the output layer
model.add(Dense(1))
```

## 2 Compiling and fitting a model

#### 2.1 [note-1] Why need to compile the model

• Specify the optimizer:

- many options and mathematically complex
- 'adam' is usually a good choice
- Loss function:
  - 'mean\_squared\_error' common for regression

#### 2.2 [code-1] Compiling a model

## 2.3 [note-2] What is fitting a model

- Apply backpropagation and gradient descent with the data to update the weights.
- Scaling data before fitting can ease optimization.

#### 2.4 [code-2] Fitting a model

```
17/17 [============ ] - Os 2ms/step - loss: 74.1013
```

[11]: <tensorflow.python.keras.callbacks.History at 0x7f8c10086690>

## 2.5 [task-1] Compiling the model

▶ Package pre-loading

```
[12]: import pandas as pd
```

▶ Data pre-loading

```
[13]: df = pd.read_csv('../Datasets/2. Hourly wages.csv')
predictors = df.iloc[:, 1:].to_numpy()
```

## ▶ Task practice

```
[14]: # Import necessary modules
    from tensorflow.keras.layers import Dense
    from tensorflow.keras.models import Sequential

# Specify the model
    n_cols = predictors.shape[1]
    model = Sequential()
    model.add(Dense(50, activation='relu', input_shape=(n_cols, )))
    model.add(Dense(32, activation='relu'))
    model.add(Dense(1))

# Compile the model
    model.compile(optimizer='adam', loss='mean_squared_error')

# Verify that model contains information from compiling
    print("Loss function: " + model.loss)
```

Loss function: mean\_squared\_error

## 2.6 [task-2] Fitting the model

#### ▶ Data pre-loading

```
[15]: target = df.iloc[:, 0].to_numpy()
```

#### ► Task practice

```
[16]: # Import necessary modules
from tensorflow.keras.layers import Dense
from tensorflow.keras.models import Sequential

# Specify the model
n_cols = predictors.shape[1]
model = Sequential()
model.add(Dense(50, activation='relu', input_shape=(n_cols, )))
model.add(Dense(32, activation='relu'))
model.add(Dense(1))

# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error')

# Fit the model
```

```
model.fit(predictors, target)
```

```
17/17 [============ ] - Os 2ms/step - loss: 57.1017
```

[16]: <tensorflow.python.keras.callbacks.History at 0x7f8be06e8c50>

#### 3 Classification models

#### 3.1 [note-1] Classification

- 'categorical\_crossentropy' loss function.
- Similar to log loss:
  - lower is better
- Add metrics = ['accuracy'] to compile step for easy-to-understand diagnostics.
- The output layer has a separate node for each possible outcome and uses 'softmax' activation.

## 3.2 [note-2] Transforming to categorical

shot_clock	dribbles	touch_time	shot_dis	close_def_ dis	shot_result	shot_result		Outcome 0	Outcome 1
10.8	2	1.9	7.7	1.3	1	1		0	1
3.4	0	0.8	28.2	6.1	0	0	$\rightarrow$	1	0
0	3	2.7	10.1	0.9	0	0		1	0
10.3	2	1.9	17.2	3.4	0	0		1	0

#### 3.3 [code-1] Classification

```
return df
      data = pd.read_csv('../Datasets/4. Basketball shot log.csv')
      df = data_preparation(data)
      predictors = df.drop(['shot_result'], axis=1).to_numpy()
      n cols = predictors.shape[1]
      target = to_categorical(df.shot_result)
      model = Sequential()
      model.add(Dense(100, activation='relu', input_shape=(n_cols, )))
      model.add(Dense(100, activation='relu'))
      model.add(Dense(100, activation='relu'))
      model.add(Dense(2, activation='softmax'))
      model.compile(optimizer='adam',
                    loss='categorical_crossentropy',
                    metrics=['accuracy'])
      model.fit(predictors, target)
     accuracy: 0.6086
[17]: <tensorflow.python.keras.callbacks.History at 0x7f8bcc2d2790>
     3.4
          [quiz-1] Understanding the classification data
        • To start modeling with a new dataset for a classification problem. This data includes infor-
          mation about passengers on the Titanic. Use predictors such as age, fare, and where each
          passenger embarked from to predict who will survive. This data is from a tutorial on data
          science competitions. Look here for descriptions of the features.
        • It's smart to review the maximum and minimum values of each variable to ensure the data
          isn't misformatted or corrupted. What was the maximum age of passengers on the Titanic?
          Use the .describe() method in the IPython Shell to answer this question.
          \square 29.699.
          \boxtimes 80.
          \square 891.
```

#### ▶ Package pre-loading

 $\square$  It is not listed.

[18]: import pandas as pd

#### ▶ Data pre-loading

[19]: df = pd.read\_csv('../Datasets/5. Titanic.csv')

#### ▶ Quiz solution

```
[20]: df.head()
[20]:
         survived pclass
                                                           male
                                                                  age_was_missing
                              age
                                   sibsp parch
                                                     fare
                 0
                         3
                            22.0
                                                   7.2500
                                                                             False
      0
                                       1
                                                               1
                            38.0
                                                  71.2833
      1
                 1
                         1
                                       1
                                               0
                                                               0
                                                                             False
      2
                 1
                         3
                            26.0
                                       0
                                               0
                                                   7.9250
                                                               0
                                                                             False
      3
                 1
                         1
                            35.0
                                       1
                                               0
                                                  53.1000
                                                               0
                                                                             False
      4
                 0
                         3
                            35.0
                                       0
                                               0
                                                   8.0500
                                                                             False
                                                               1
         embarked_from_cherbourg
                                    embarked_from_queenstown
      0
                                                             0
      1
                                 1
                                 0
      2
                                                             0
      3
                                 0
                                                             0
      4
                                 0
                                                             0
         embarked_from_southampton
      0
                                   1
      1
                                   0
      2
                                   1
      3
                                   1
                                   1
[21]: df['age'].describe()
[21]: count
                891.000000
      mean
                 29.699118
      std
                 13.002015
      min
                  0.420000
      25%
                 22.000000
      50%
                 29.699118
      75%
                 35.000000
      max
                 80.000000
      Name: age, dtype: float64
[22]: max_age = int(df['age'].max())
      print('The maximum age of passengers on the Titanic is {}.'.format(max_age))
     The maximum age of passengers on the Titanic is 80.
```

#### 3.5 [task-1] Last steps in classification models

#### ▶ Package pre-loading

```
[23]: import pandas as pd
```

#### ▶ Data pre-loading

```
[24]: df = pd.read_csv('../Datasets/5. Titanic.csv')

df['age_was_missing'].replace(False, 0, inplace=True)

df['age_was_missing'].replace(True, 1, inplace=True)

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

#### ▶ Task practice

```
[25]: # Import necessary modules
      from tensorflow.keras.layers import Dense
      from tensorflow.keras.models import Sequential
      from tensorflow.keras.utils import to_categorical
      # Convert the target to categorical: target
      target = to_categorical(df.survived)
      # Set up the model
     model = Sequential()
      # Add the first layer
      model.add(Dense(32, activation='relu', input_shape=(n_cols, )))
      # Add the output layer
      model.add(Dense(2, activation='softmax'))
      # Compile the model
      model.compile(optimizer='sgd',
                    loss='categorical_crossentropy',
                    metrics=['accuracy'])
      # Fit the model
     model.fit(predictors, target)
```

[25]: <tensorflow.python.keras.callbacks.History at 0x7f8bcc1b3190>

## 4 Using models

#### 4.1 [note-1] Using models

- Save.
- Reload.
- Make predictions.

## 4.2 [code-1] Saving, reloading, and using the model

```
[26]: import pandas as pd
      from tensorflow.keras.layers import Dense
      from tensorflow.keras.models import Sequential
      from tensorflow.keras.utils import to_categorical
      from tensorflow.keras.models import load_model
      def data_preparation(data):
          df = data.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
      def classification_model(n_cols):
          model = Sequential()
          model.add(Dense(100, activation='relu', input_shape=(n_cols, )))
          model.add(Dense(100, activation='relu'))
          model.add(Dense(100, activation='relu'))
          model.add(Dense(2, activation='softmax'))
          model.compile(optimizer='adam',
                        loss='categorical_crossentropy',
                        metrics=['accuracy'])
          return (model)
      data = pd.read_csv('../Datasets/4. Basketball shot log.csv')
      df = data_preparation(data)
      predictors = df.drop(['shot_result'], axis=1).to_numpy()
      n_cols = predictors.shape[1]
      model = classification_model(n_cols)
      model.save('../Models/1. Model of basketball shot log.h5')
      my_model = load_model('.../Models/1. Model of basketball shot log.h5')
      predictions = my_model.predict(predictors)
      probability_true = predictions[:, 1]
```

## 4.3 [code-2] Verifying model structure

# [27]: my\_model.summary()

Model: "sequential\_7"

Layer (type)	Output Shape	Param #
dense_21 (Dense)	(None, 100)	600
dense_22 (Dense)	(None, 100)	10100
dense_23 (Dense)	(None, 100)	10100
dense_24 (Dense)	(None, 2)	202

Total params: 21,002 Trainable params: 21,002 Non-trainable params: 0

## [task-1] Making predictions

## ► Package pre-loading

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

#### ▶ Data pre-loading

```
[29]: df = pd.read_csv('../Datasets/5. 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)
      pred_data = pd.read_csv('../Datasets/6. Titanic predictors data.csv')
      pred_data.replace(False, 0, inplace=True)
      pred_data.replace(True, 1, inplace=True)
```

#### ► Task practice

```
[30]: # Specify, compile, and fit the model
    model = Sequential()
    model.add(Dense(32, activation='relu', input_shape=(n_cols, )))
    model.add(Dense(2, activation='softmax'))
    model.compile(optimizer='sgd',
               loss='categorical crossentropy',
               metrics=['accuracy'])
    model.fit(predictors, target)
    # Calculate predictions: predictions
    predictions = model.predict(pred_data)
    # Calculate predicted probability of survival: predicted_prob_true
    predicted_prob_true = predictions[:, 1]
    # print predicted_prob_true
    print(predicted_prob_true)
    accuracy: 0.5899
    [0.6272365 0.69750106 0.99999297 0.6836752 0.6775551 0.6711255
    0.72476214
    0.46056715 0.8549943 0.98583883 0.68532735 0.14717013 0.68848526
    0.9899076 \quad 0.5917994 \quad 0.94522053 \quad 0.9758321 \quad 0.6220191 \quad 0.9549868
    0.7000933 \quad 0.71821684 \ 0.93538254 \ 0.74775255 \ 0.69923514 \ 0.65353376
    0.7601951 \quad 0.56636417 \ 0.709714 \quad 0.51969117 \ 0.9882675 \quad 0.6146055
    0.75276166 0.9981142 0.959244 0.13130033 0.7325003 0.8988376
    0.60682535\ 0.8884945\ 0.72440106\ 0.6846784\ 0.68431187\ 0.8676819
    0.35615346 0.4988413 0.700127 0.69158924 0.7077357 0.70153165
    0.71755433 \ 0.9637747 \ 0.73155963 \ 0.666571 \ 0.6985411 \ 0.6310478
    0.5419165 ]
```

# 5 Requirements

```
[31]: from platform import python_version
  import tensorflow as tf

  python_version = ('python=={}'.format(python_version()))
  numpy_version = ('numpy=={}'.format(np.__version__))
  tensorflow_version = ('tensorflow=={}'.format(tf.__version__))
  pandas_version = ('pandas=={}'.format(pd.__version__))
```

```
writepath = '../../requirements.txt'
requirements = []
packages = [numpy_version, tensorflow_version, pandas_version]
try:
    with open(writepath, 'r+') as file:
        for line in file:
            requirements.append(line.strip('\n'))
except:
    with open(writepath, 'w+') as file:
        for line in file:
            requirements.append(line.strip('\n'))
with open(writepath, 'a+') as file:
    for package in packages:
        if package not in requirements:
            file.write(package + '\n')
max_characters = len(python_version)
for package in packages:
    if max(max_characters, len(package)) > max_characters:
        max_characters = max(max_characters, len(package))
print('#' * (max_characters + 8))
print('#' * 2 + ' ' * (max_characters + 4) + '#' * 2)
print('#' * 2 + ' ' * 2 + python_version + ' ' *
      (max_characters - len(python_version) + 2) + '#' * 2)
for package in packages:
    print('#' * 2 + ' ' * 2 + package + ' ' *
          (\max_{\text{characters}} - \text{len}(\text{package}) + 2) + '#' * 2)
print('#' * 2 + ' ' * (max_characters + 4) + '#' * 2)
print('#' * (max_characters + 8))
```

####