Building deep learning models with keras

Puteaux, Fall/Winter 2020-2021

- §1 Introduction to Deep Learning in Python
- §1.3 Building deep learning models with keras

1 Creating a keras model

- 1.1 What are the model-building steps?
 - The Keras workflow has four steps:
 - specify Architecture
 - compile
 - fit
 - predict

1.2 Code of model specification:

[5]:

count

wage_per_hour

534.000000

1.3 Practice question for 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('ref2. Hourly wages.csv')
     ▶ Question-solving method:
[4]: df.head()
[4]:
         wage_per_hour
                          union
                                   education_yrs
                                                     experience_yrs
                                                                        age
                                                                             female
                                                                                       marr
                    5.10
                                                                                   1
                               0
                                                 8
                                                                   21
                                                                         35
                                                                                          1
                   4.95
                               0
                                                 9
                                                                         57
                                                                                   1
     1
                                                                   42
                                                                                          1
     2
                   6.67
                                                12
                                                                         19
                                                                                   0
                                                                                          0
                               0
                                                                    1
     3
                    4.00
                                                                                   0
                                                                                          0
                               0
                                                12
                                                                    4
                                                                         22
     4
                   7.50
                               0
                                                12
                                                                   17
                                                                         35
                                                                                   0
                                                                                          1
         south
                 manufacturing
                                   construction
     0
              0
     1
              0
                               1
                                                0
     2
              0
                                                0
                               1
     3
                                                0
              0
                               0
              0
                               0
                                                0
     df.describe()
[5]:
```

education_yrs

534.000000

union

534.000000

experience_yrs

534.000000

age

534.000000

```
9.024064
                              0.179775
                                             13.018727
                                                             17.822097
                                                                          36.833333
    mean
     std
                 5.139097
                              0.384360
                                                             12.379710
                                                                          11.726573
                                             2.615373
                 1.000000
                              0.000000
                                             2.000000
                                                              0.000000
                                                                          18.000000
    min
     25%
                 5.250000
                              0.000000
                                             12.000000
                                                              8.000000
                                                                          28.000000
     50%
                                                             15.000000
                                                                          35.000000
                 7.780000
                              0.000000
                                             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
                                          south manufacturing
                                                                 construction
                               marr
            534.000000 534.000000
                                     534.000000
                                                     534.000000
                                                                    534.000000
     count
              0.458801
                           0.655431
                                       0.292135
                                                       0.185393
     mean
                                                                      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
     50%
              0.000000
                           1.000000
                                       0.000000
                                                       0.000000
                                                                      0.000000
     75%
                           1.000000
              1.000000
                                       1.000000
                                                       0.000000
                                                                      0.000000
     max
              1.000000
                           1.000000
                                       1.000000
                                                       1.000000
                                                                      1.000000
[6]: cols = df.columns
     count = 0
```

There are 6 binary indicator predictors here.

1.4 Practice exercises for creating a Keras model:

▶ Package pre-loading:

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

▶ Data pre-loading:

```
[8]: df = pd.read_csv('ref2. Hourly wages.csv')

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

▶ Model specifying practice:

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

```
from 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 Why is it necessary to compile the model?
 - Specify the optimizer:
 - many options and mathematically complex
 - adam is usually a good choice
 - Loss function:
 - mean_squared_error is common for regression

2.2 Code of compiling a model:

2.3 What is fitting a model?

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

2.4 Code of fitting a model:

2.5 Practice exercises for compiling and fitting a model:

▶ Package pre-loading:

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

▶ Data pre-loading:

```
[13]: df = pd.read_csv('ref2. Hourly wages.csv')
predictors = df.iloc[:, 1:].to_numpy()
```

▶ Model compiling practice:

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

▶ Data re-pre-loading:

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

► Model fitting practice:

```
[16]: # Import necessary modules
    import keras
    from keras.layers import Dense
    from 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)
```

[16]: <tensorflow.python.keras.callbacks.History at 0x7fd96e48f550>

3 Classification models

3.1 How to compile the classification model with Keras?

- Use 'categorical_crossentropy' loss function, which is similar to log loss, but 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 How to transform the target value into 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 of classification:

```
[17]: import pandas as pd
      from keras.layers import Dense
      from keras.models import Sequential
      def data_preparation(df):
          df = df.reindex(columns=[
              'SHOT_CLOCK', 'DRIBBLES', 'TOUCH_TIME', 'SHOT_DIST', 'CLOSE_DEF_DIST',
              'SHOT_RESULT'
          1)
          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
[18]: from keras.utils.np_utils import to_categorical
      data = pd.read_csv('ref5. 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)
      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: 0.6068
[18]: <tensorflow.python.keras.callbacks.History at 0x7fd954a66590>
     3.4 Practice question for 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. The predictors such as age, fare, and where each
          passenger embarked to could be used to predict who will survive. This data is from a tutorial
          on data science competitions. There are 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.
          ⊠ 80.
          □ 891.
          \square It is not listed.
     ▶ Package pre-loading:
[19]: import pandas as pd
     ▶ Data pre-loading:
[20]: df = pd.read_csv('ref6. Titanic.csv')
     ► Question-solving method:
[21]: df.head()
[21]:
         survived pclass
                                         parch
                                                                 age_was_missing
                             age
                                  sibsp
                                                    fare
                                                          male
                0
                            22.0
                                                  7.2500
                                                                           False
      0
                                       1
      1
                1
                         1
                            38.0
                                              0
                                                 71.2833
                                                                           False
                                                              0
      2
                1
                            26.0
                                              0
                                                  7.9250
                                                                           False
      3
                                                                           False
                1
                         1
                            35.0
                                       1
                                              0
                                                 53.1000
                                                              0
                0
                         3
                            35.0
                                                  8.0500
                                                              1
                                                                           False
         embarked_from_cherbourg
                                   embarked_from_queenstown
      0
                                                            0
      1
                                1
      2
                                0
                                                            0
      3
                                0
```

```
4
                               0
                                                          0
         embarked_from_southampton
      0
      1
                                 0
      2
                                  1
      3
                                  1
      4
                                  1
[22]: df['age'].describe()
[22]: count
               891.000000
                29.699118
     mean
      std
                13.002015
     min
                0.420000
      25%
                22.000000
      50%
                29.699118
      75%
                35.000000
                80.000000
     max
     Name: age, dtype: float64
[23]: 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 Practice exercises for classification models:
     ▶ Package pre-loading:
[24]: import pandas as pd
     ▶ Data pre-loading:
[25]: df = pd.read_csv('ref6. 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]
     ▶ Classification models practice:
[26]: # Import necessary modules
      import keras
      from keras.layers import Dense
      from keras.models import Sequential
```

```
from 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)
    0.5994
[26]: <tensorflow.python.keras.callbacks.History at 0x7fd9533e1950>
```

4 Using models

4.1 How to use models?

- Save.
- Reload.
- Make predictions.

4.2 Code of saving, reloading, and using the model reloaded:

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

data = pd.read_csv('ref5. Basketball shot log.csv')

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
      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)
     4003/4003 [============= ] - 5s 1ms/step - loss: 0.6636 -
     accuracy: 0.6062
[27]: <tensorflow.python.keras.callbacks.History at 0x7fd953553450>
[28]: from keras.models import load_model
      model.save('ref7. Model file.h5')
      my_model = load_model('ref7. Model file.h5')
      predictions = my_model.predict(predictors)
      probability_true = predictions[:, 1]
      probability_true
[28]: array([0.40594074, 0.32399714, 0.29844287, ..., 0.39887083, 0.32704052,
             0.3955048 ], dtype=float32)
[29]: 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

4.3 Practice exercises for using models:

▶ Package pre-loading:

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

▶ Data pre-loading:

```
[31]: df = pd.read_csv('ref6. 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('ref8. Titanic predictors data.csv')
      pred_data.replace(False, 0, inplace=True)
      pred_data.replace(True, 1, inplace=True)
```

► Making predictions practice:

```
[32]: # 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)
0.5785
[0.46402523 \ 0.5921409 \ 0.9999273 \ 0.7663655 \ 0.52398753 \ 0.51178104
0.28148016\ 0.5681087\ 0.4458243\ 0.9282887\ 0.5351253\ 0.53740656
0.45552713 0.8895884 0.5160431 0.3519259 0.5469126 0.81220806
0.43032184\ 0.8470085\ 0.9935336\ 0.5362614\ 0.28667322\ 0.58596545
0.9431871 0.59334135 0.9650976 0.9699065 0.5989654 0.9669046
0.56204987 0.5336981 0.9594674 0.67796016 0.56222713 0.5251262
0.71574086 \ 0.5083044 \ 0.576449 \ 0.4511685 \ 0.9595517 \ 0.52266526
0.8049595 \quad 0.9963193 \quad 0.89705867 \quad 0.26874813 \quad 0.7202186 \quad 0.92825663
0.41592917 0.61183465 0.99998534 0.37461117 0.69608366 0.55560493
0.4620269 0.92955095 0.5375804 0.6937474 0.5351856 0.8505897
0.37344947 0.43886235 0.56586283 0.60457915 0.5679306 0.5664585
0.53257746 0.9858825 0.7241232 0.5036335 0.57002354 0.48111126
0.53353465\ 0.77744293\ 0.48965743\ 0.81994593\ 0.62445176\ 0.7421769
0.575239 ]
```