WD_Keras-3

December 17, 2020

Create Keras Wide-and-Deep model

This notebook illustrates:

Creating a model using Keras. This requires TensorFlow 2.1

[ ]:
```
# Ensure the right version of Tensorflow is installed.
!pip freeze | grep tensorflow==2.1
```

[1]:
```
# change these to try this notebook out
BUCKET = 'qwiklabs-gcp-02-2449df839737'
PROJECT = 'qwiklabs-gcp-02-2449df839737'
REGION = 'us-central1'
```

[2]:
```
import os
os.environ['BUCKET'] = BUCKET
os.environ['PROJECT'] = PROJECT
os.environ['REGION'] = REGION
```

[3]:
```
%%bash
if ! gsutil ls | grep -q gs://${BUCKET}/; then
  gsutil mb -l ${REGION} gs://${BUCKET}
fi
```

[4]:
```
%%bash
ls *.csv
```

```
eval.csv
train.csv
```

0.1 Create Keras model

First, write an input_fn to read the data.

[5]:
```
import shutil
import numpy as np
import tensorflow as tf
print(tf.__version__)
```

```
2.3.1
```

```
[6]: # Determine CSV, label, and key columns
CSV_COLUMNS = 'weight_pounds,is_male,mother_age,plurality,gestation_weeks,key'.
 ↪split(',')
LABEL_COLUMN = 'weight_pounds'
KEY_COLUMN = 'key'

# Set default values for each CSV column. Treat is_male and plurality as␣
 ↪strings.
DEFAULTS = [[0.0], ['null'], [0.0], ['null'], [0.0], ['nokey']]
```

```
[7]: def features_and_labels(row_data):
    for unwanted_col in ['key']:
        row_data.pop(unwanted_col)
    label = row_data.pop(LABEL_COLUMN)
    return row_data, label  # features, label

# load the training data
def load_dataset(pattern, batch_size=1, mode=tf.estimator.ModeKeys.EVAL):
  dataset = (tf.data.experimental.make_csv_dataset(pattern, batch_size,␣
 ↪CSV_COLUMNS, DEFAULTS)
             .map(features_and_labels) # features, label
             )
  if mode == tf.estimator.ModeKeys.TRAIN:
        dataset = dataset.shuffle(1000).repeat()
  dataset = dataset.prefetch(1) # take advantage of multi-threading; 1=AUTOTUNE
  return dataset
```

Next, define the feature columns. mother_age and gestation_weeks should be numeric. The others (is_male, plurality) should be categorical.

```
[64]: ## Build a Keras wide-and-deep model using its Functional API
def rmse(y_true, y_pred):
    return tf.sqrt(tf.reduce_mean(tf.square(y_pred - y_true)))

# Helper function to handle categorical columns
def categorical_fc(name, values):
    orig = tf.feature_column.categorical_column_with_vocabulary_list(name,␣
 ↪values)
    wrapped = tf.feature_column.indicator_column(orig)
    return orig, wrapped

def build_wd_model(dnn_hidden_units = [64, 32], nembeds = 3):
    # input layer
    deep_inputs = {
        colname : tf.keras.layers.Input(name=colname, shape=(), dtype='float32')
           for colname in ['mother_age', 'gestation_weeks']
    }
```

```
    wide_inputs = {
        colname : tf.keras.layers.Input(name=colname, shape=(), dtype='string')
           for colname in ['is_male', 'plurality']
    }
    inputs = {**wide_inputs, **deep_inputs}

    # feature columns from inputs
    deep_fc = {
        colname : tf.feature_column.numeric_column(colname)
           for colname in ['mother_age', 'gestation_weeks']
    }
    wide_fc = {}
    is_male, wide_fc['is_male'] = categorical_fc('is_male', ['True', 'False',␣
↪'Unknown'])
    plurality, wide_fc['plurality'] = categorical_fc('plurality',
                      ['Single(1)', 'Twins(2)', 'Triplets(3)',
                       'Quadruplets(4)', 'Quintuplets(5)','Multiple(2+)'])

    # bucketize the float fields. This makes them wide
    age_buckets = tf.feature_column.bucketized_column(deep_fc['mother_age'],
                                                    boundaries=np.
↪arange(15,45,1).tolist())
    wide_fc['age_buckets'] = tf.feature_column.indicator_column(age_buckets)
    gestation_buckets = tf.feature_column.
↪bucketized_column(deep_fc['gestation_weeks'],
                                                    boundaries=np.
↪arange(17,47,1).tolist())
    wide_fc['gestation_buckets'] = tf.feature_column.
↪indicator_column(gestation_buckets)

    # cross all the wide columns. We have to do the crossing before we one-hot␣
↪encode
    crossed = tf.feature_column.crossed_column(
        [is_male, plurality, age_buckets, gestation_buckets],␣
↪hash_bucket_size=20000)
    deep_fc['crossed_embeds'] = tf.feature_column.embedding_column(crossed,␣
↪nembeds)

    # the constructor for DenseFeatures takes a list of numeric columns
    # The Functional API in Keras requires that you specify:␣
↪LayerConstructor()(inputs)
    wide_inputs = tf.keras.layers.DenseFeatures(wide_fc.values(),␣
↪name='wide_inputs')(inputs)
    deep_inputs = tf.keras.layers.DenseFeatures(deep_fc.values(),␣
↪name='deep_inputs')(inputs)
```

```
    # hidden layers for the deep side
    layers = [int(x) for x in dnn_hidden_units]
    deep = deep_inputs
    for layerno, numnodes in enumerate(layers):
        deep = tf.keras.layers.Dense(numnodes, activation='relu', name='dnn_{}'.
 ↪format(layerno+1))(deep)
    deep_out = deep

    # linear model for the wide side
    wide_out = tf.keras.layers.Dense(10, activation='relu',␣
 ↪name='linear')(wide_inputs)

    # concatenate the two sides
    both = tf.keras.layers.concatenate([deep_out, wide_out], name='both')

    # final output is a linear activation because this is regression
    output = tf.keras.layers.Dense(1, activation='linear', name='weight')(both)
    model = tf.keras.models.Model(inputs, output)
    model.compile(optimizer='adam', loss='mse', metrics=[rmse, 'mse'])
    return model

print("Here is our Wide-and-Deep architecture so far:\n")
model = build_wd_model()
print(model.summary())
```

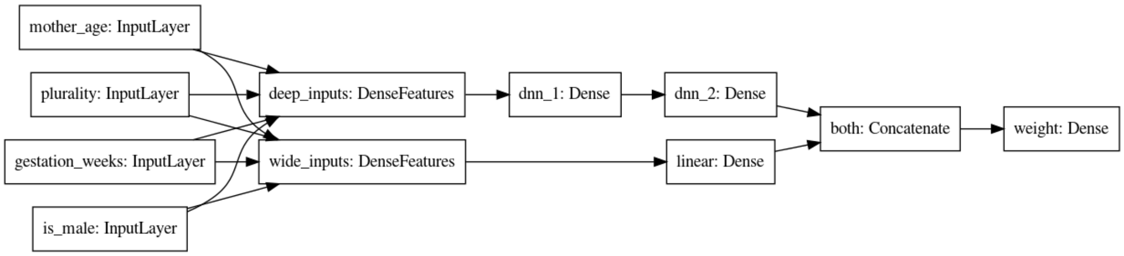
```
Here is our Wide-and-Deep architecture so far:

Model: "functional_21"
________________________________________________________________________________
__________________
Layer (type)                    Output Shape         Param #     Connected to
================================================================================
==================
gestation_weeks (InputLayer)    [(None,)]            0
________________________________________________________________________________
__________________
is_male (InputLayer)            [(None,)]            0
________________________________________________________________________________
__________________
mother_age (InputLayer)         [(None,)]            0
________________________________________________________________________________
__________________
plurality (InputLayer)          [(None,)]            0
________________________________________________________________________________
__________________
deep_inputs (DenseFeatures)     (None, 5)            60000
gestation_weeks[0][0]
```

```
                                                                is_male[0][0]
mother_age[0][0]
                                                                plurality[0][0]
________________________________________________________________________________
__________________
dnn_1 (Dense)                   (None, 64)           384
deep_inputs[0][0]
________________________________________________________________________________
__________________
wide_inputs (DenseFeatures)     (None, 71)           0
gestation_weeks[0][0]
                                                                is_male[0][0]
mother_age[0][0]
                                                                plurality[0][0]
________________________________________________________________________________
__________________
dnn_2 (Dense)                   (None, 32)           2080        dnn_1[0][0]
________________________________________________________________________________
__________________
linear (Dense)                  (None, 10)           720
wide_inputs[0][0]
________________________________________________________________________________
__________________
both (Concatenate)              (None, 42)           0           dnn_2[0][0]
                                                                linear[0][0]
________________________________________________________________________________
__________________
weight (Dense)                  (None, 1)            43          both[0][0]
================================================================================
==================
Total params: 63,227
Trainable params: 63,227
Non-trainable params: 0
________________________________________________________________________________
__________________
None
```

We can visualize the DNN using the Keras plot_model utility.

[65]:
```
tf.keras.utils.plot_model(model, 'wd_model.png', show_shapes=False,␣
↪rankdir='LR')
```

[65]:



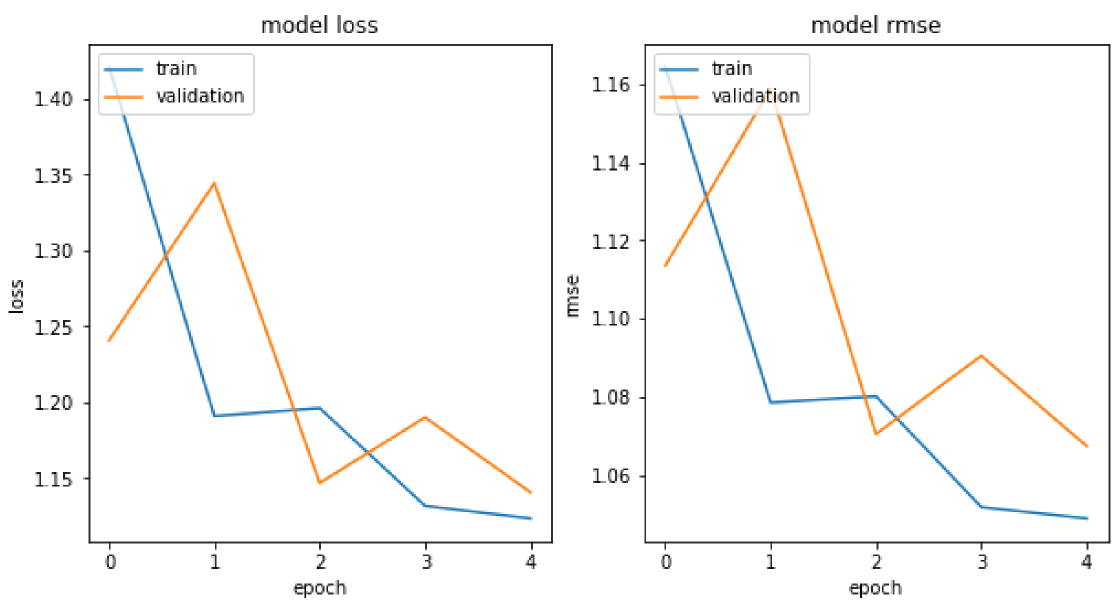
0.2 Train and evaluate

[66]:
```
TRAIN_BATCH_SIZE = 32
NUM_TRAIN_EXAMPLES = 10000 * 5 # training dataset repeats, so it will wrap␣
↪around
NUM_EVALS = 5  # how many times to evaluate
NUM_EVAL_EXAMPLES = 10000 # enough to get a reasonable sample, but not so much␣
↪that it slows down

trainds = load_dataset('train*', TRAIN_BATCH_SIZE, tf.estimator.ModeKeys.TRAIN)
evalds = load_dataset('eval*', 1000, tf.estimator.ModeKeys.EVAL).
↪take(NUM_EVAL_EXAMPLES//1000)

steps_per_epoch = NUM_TRAIN_EXAMPLES // (TRAIN_BATCH_SIZE * NUM_EVALS)

history = model.fit(trainds,
                    validation_data=evalds,
                    epochs=NUM_EVALS,
                    steps_per_epoch=steps_per_epoch)
```

```
Epoch 1/5
312/312 [==============================] - 3s 10ms/step - loss: 1.4212 - rmse:
1.1644 - mse: 1.4212 - val_loss: 1.2406 - val_rmse: 1.1135 - val_mse: 1.2406
Epoch 2/5
312/312 [==============================] - 3s 10ms/step - loss: 1.1908 - rmse:
1.0786 - mse: 1.1908 - val_loss: 1.3444 - val_rmse: 1.1588 - val_mse: 1.3444
Epoch 3/5
312/312 [==============================] - 3s 10ms/step - loss: 1.1961 - rmse:
1.0802 - mse: 1.1961 - val_loss: 1.1468 - val_rmse: 1.0706 - val_mse: 1.1468
Epoch 4/5
312/312 [==============================] - 2s 7ms/step - loss: 1.1317 - rmse:
1.0519 - mse: 1.1317 - val_loss: 1.1900 - val_rmse: 1.0906 - val_mse: 1.1900
Epoch 5/5
312/312 [==============================] - 3s 10ms/step - loss: 1.1233 - rmse:
1.0490 - mse: 1.1233 - val_loss: 1.1407 - val_rmse: 1.0675 - val_mse: 1.1407
```

0.3 Visualize loss curve

[67]:
```
# plot
import matplotlib.pyplot as plt
nrows = 1
ncols = 2
fig = plt.figure(figsize=(10, 5))

for idx, key in enumerate(['loss', 'rmse']):
    ax = fig.add_subplot(nrows, ncols, idx+1)
    plt.plot(history.history[key])
    plt.plot(history.history['val_{}'.format(key)])
    plt.title('model {}'.format(key))
    plt.ylabel(key)
    plt.xlabel('epoch')
    plt.legend(['train', 'validation'], loc='upper left');
```



0.4 Save the model

[68]:
```
import shutil, os, datetime
OUTPUT_DIR = 'babyweight_trained'
shutil.rmtree(OUTPUT_DIR, ignore_errors=True)
EXPORT_PATH = os.path.join(OUTPUT_DIR, datetime.datetime.now().
 ↪strftime('%Y%m%d%H%M%S'))
tf.saved_model.save(model, EXPORT_PATH) # with default serving function
print("Exported trained model to {}".format(EXPORT_PATH))
```

```
INFO:tensorflow:Assets written to: babyweight_trained/20201217213448/assets
```

```
Exported trained model to babyweight_trained/20201217213448
```

[69]:
```
!ls $EXPORT_PATH
```

```
assets  saved_model.pb  variables
```