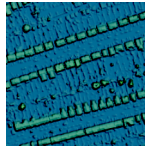


ResNet

December 31, 2021

```
[1]: from IPython.display import Image
Image(filename='LIDAR/LIDAR_24974.png')
```

[1]:



```
[1]: # imports
import numpy as np
import pandas as pd
import h5py as h5py
import PIL

# Others
import numpy as np
from sklearn.model_selection import train_test_split

# For AUC estimation and ROC plots
from sklearn.metrics import roc_curve, auc

# Plots
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# Image and directories
#import cv2
import os

# Tensorflow
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras import optimizers
from tensorflow.keras.models import Sequential
```

```
from tensorflow.keras.layers import *
from tensorflow import keras
```

```
[2]: # read csv file
df = pd.read_csv("EmbeddingData_C3_9528.csv")

# add a path column to augment the absolute path of the image
df["path"] = [os.path.join("LIDAR/", "LIDAR_" + str(i) + '.png') for i in df.id.
               ↪values]
df["path"][0]
```

```
[2]: 'LIDAR/LIDAR_48552.png'
```

```
[3]: # create train and test split
train, test = train_test_split(df,
                                test_size = 0.225,
                                random_state = 250918939)
```

0.1 preparing the model

```
[4]: # check running time
from tensorflow.python.client import device_lib
print(device_lib.list_local_devices())
```

```
[name: "/device:CPU:0"
device_type: "CPU"
memory_limit: 268435456
locality {
}
incarnation: 16367262059075039945
, name: "/device:GPU:0"
device_type: "GPU"
memory_limit: 4155965440
locality {
  bus_id: 1
  links {
  }
}
incarnation: 13730991801835170683
physical_device_desc: "device: 0, name: NVIDIA GeForce RTX 2060, pci bus id:
0000:01:00.0, compute capability: 7.5"
]
```

```
[4]: # download ResNet from Google
import tensorflow.keras.layers
from tensorflow.keras.applications.resnet_v2 import ResNet50V2, preprocess_input
initial_model = ResNet50V2(weights = "imagenet",
                             include_top = False,
```

```
input_shape=(224,224,3))
```

```
[5]: # define the pre-trained parameters to be untrainable
initial_model.trainable = False
#initial_model.summary()
```

0.2 add head layers

```
[6]: # input layer
input = keras.Input(shape=(224,224)+(3,),name = "image_only_input")

# define a temporary model to construct the whole ResNet model
tempModel = initial_model(input,training=False)
```

```
[7]: # now start to add head layers
tempModel = Flatten()(tempModel)

# add dense layers and drop out
tempModel = Dense(64, activation="relu")(tempModel)
tempModel = Dropout(0.5)(tempModel)
tempModel = Dense(32, activation="relu")(tempModel)
tempModel = Dropout(0.5)(tempModel)

# final output layer
output = Dense(1, activation="relu")(tempModel)

# put all together
ResnetModel = keras.Model(input, output)
```

```
[8]: ResnetModel.summary()
```

Model: "model"

Layer (type)	Output Shape	Param #
image_only_input (InputLayer [(None, 224, 224, 3)])		0
resnet50v2 (Functional)	(None, 7, 7, 2048)	23564800
flatten (Flatten)	(None, 100352)	0
dense (Dense)	(None, 64)	6422592
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 32)	2080

```

-----
dropout_1 (Dropout)                (None, 32)                0
-----
dense_2 (Dense)                    (None, 1)                  33
=====
Total params: 29,989,505
Trainable params: 6,424,705
Non-trainable params: 23,564,800
-----

```

0.3 define image generators

```

[7]: # define the parameters
from tensorflow.keras.applications.resnet_v2 import preprocess_input
input_size = (224,224)
batch = 32
DataDirectory = 'LIDAR'

# define image generators
from tensorflow.keras.preprocessing.image import ImageDataGenerator

train_datagen = ImageDataGenerator(
    rescale=None,
    shear_range=0,
    zoom_range=0.2,
    horizontal_flip=True,
    vertical_flip=True,
    preprocessing_function=preprocess_input,
    validation_split=0.2
)

test_datagen = ImageDataGenerator(
    rescale=None,
    shear_range=0,
    zoom_range=0,
    horizontal_flip=False,
    vertical_flip=False,
    preprocessing_function=preprocess_input
)

# point to data
train_generator = train_datagen.flow_from_dataframe(
    train,
    directory='.',
    x_col='path',
    y_col='education',
    target_size=input_size,

```

```

        batch_size=batch,
        shuffle=True,
        class_mode='raw',
        subset='training',
        interpolation='bilinear'
    )

    validation_generator = train_datagen.flow_from_dataframe(
        train,
        directory='.',
        x_col='path',
        y_col='education',
        target_size=input_size,
        batch_size=batch,
        shuffle=True,
        class_mode='raw',
        subset='validation',
        interpolation='bilinear'
    )

    test_generator = test_datagen.flow_from_dataframe(
        test,
        directory='.',
        x_col='path',
        y_col='education',
        target_size=input_size,
        batch_size=batch,
        shuffle=False,
        class_mode='raw',
        interpolation='bilinear'
    )

```

Found 22768 validated image filenames.

Found 5692 validated image filenames.

Found 8263 validated image filenames.

0.4 Warming up the model

```

[9]: # compile the model with warm-up learning rate,
    initial_model.trainable = False
    opt = optimizers.Adam(learning_rate = 0.000001, decay = 0.001/100)
    ResnetModel.compile(loss='mean_squared_error', optimizer=opt, metrics=[keras.
        ↪metrics.mean_squared_error])
    #ResnetModel.summary()

```

```

[13]: # warming up the model with 2 epochs and half the regular step size
    ResnetModel.fit(

```

```

    train_generator,
    epochs = 2,
    validation_data = validation_generator,
    steps_per_epoch = 711,
    validation_steps = 177
)

```

Epoch 1/2

711/711 [=====] - 311s 438ms/step - loss: 153.3801 - mean_squared_error: 153.3801 - val_loss: 110.1336 - val_mean_squared_error: 110.1336

Epoch 2/2

711/711 [=====] - 311s 437ms/step - loss: 150.8490 - mean_squared_error: 150.8490 - val_loss: 107.6208 - val_mean_squared_error: 107.6208

[13]: <tensorflow.python.keras.callbacks.History at 0x28e29cf31f0>

0.5 training the whole model

```

[10]: # now training the whole model
initial_model.trainable=True

# recompile the model
opt = optimizers.Adam(learning_rate = 9e-7, decay = 0.001/200)
ResnetModel.compile(loss='mean_squared_error', optimizer=opt, metrics=[keras.
    ↳ metrics.mean_squared_error])

#ResnetModel.summary()

```

```

[19]: # add callback
checkpoint_path = 'checkpoint3-4/ResnetModel.{val_loss:.3f}.h5'
checkpoint_dir = os.path.dirname(checkpoint_path)

def scheduler(epoch,lr):
    if epoch < 2:
        return lr
    else:
        return lr * tf.math.exp(-0.15)

my_callback = [
    # save the weights of the best performing model to the checkpoint folder
    tf.keras.callbacks.ModelCheckpoint(filepath=checkpoint_path,
        save_best_only=True,
        save_weights_only=True),
    # stop training when validation error stays within 0.001 for 5 rounds

```

```

tf.keras.callbacks.EarlyStopping(monitor='val_loss',
                                min_delta = 0.001,
                                patience=15),
# training with a declining learning rate
tf.keras.callbacks.LearningRateScheduler(scheduler, verbose=1)
]

```

```

[21]: # train the whole model
epochs = 10

ResnetModel.fit(
    train_generator,
    epochs=epochs,
    validation_data=validation_generator,
    steps_per_epoch=711,
    validation_steps=177,
    callbacks=my_callback
)

```

Epoch 1/10

Epoch 00001: LearningRateScheduler reducing learning rate to 1.9999999949504854e-06.
711/711 [=====] - 317s 441ms/step - loss: 88.9125 - mean_squared_error: 88.9125 - val_loss: 73.3715 - val_mean_squared_error: 73.3715

Epoch 2/10

Epoch 00002: LearningRateScheduler reducing learning rate to 1.9999999949504854e-06.
711/711 [=====] - 311s 437ms/step - loss: 88.5203 - mean_squared_error: 88.5203 - val_loss: 80.6348 - val_mean_squared_error: 80.6348

Epoch 3/10

Epoch 00003: LearningRateScheduler reducing learning rate to tf.Tensor(1.7214159e-06, shape=(), dtype=float32).
711/711 [=====] - 312s 439ms/step - loss: 87.4389 - mean_squared_error: 87.4389 - val_loss: 80.1978 - val_mean_squared_error: 80.1978

Epoch 4/10

Epoch 00004: LearningRateScheduler reducing learning rate to tf.Tensor(1.4816363e-06, shape=(), dtype=float32).
711/711 [=====] - 312s 438ms/step - loss: 86.6994 - mean_squared_error: 86.6994 - val_loss: 75.0118 - val_mean_squared_error: 75.0118

Epoch 5/10

```
Epoch 00005: LearningRateScheduler reducing learning rate to  
tf.Tensor(1.2752562e-06, shape=(), dtype=float32).  
711/711 [=====] - 314s 442ms/step - loss: 85.9460 -  
mean_squared_error: 85.9460 - val_loss: 79.8085 - val_mean_squared_error:  
79.8085
```

Epoch 6/10

```
Epoch 00006: LearningRateScheduler reducing learning rate to  
tf.Tensor(1.0976231e-06, shape=(), dtype=float32).  
711/711 [=====] - 318s 447ms/step - loss: 85.0023 -  
mean_squared_error: 85.0023 - val_loss: 76.8640 - val_mean_squared_error:  
76.8640
```

Epoch 7/10

```
Epoch 00007: LearningRateScheduler reducing learning rate to  
tf.Tensor(9.447329e-07, shape=(), dtype=float32).  
711/711 [=====] - 313s 440ms/step - loss: 84.3783 -  
mean_squared_error: 84.3783 - val_loss: 77.0948 - val_mean_squared_error:  
77.0948
```

Epoch 8/10

```
Epoch 00008: LearningRateScheduler reducing learning rate to  
tf.Tensor(8.1313914e-07, shape=(), dtype=float32).  
711/711 [=====] - 312s 439ms/step - loss: 85.4346 -  
mean_squared_error: 85.4346 - val_loss: 78.9316 - val_mean_squared_error:  
78.9316
```

Epoch 9/10

```
Epoch 00009: LearningRateScheduler reducing learning rate to  
tf.Tensor(6.9987533e-07, shape=(), dtype=float32).  
711/711 [=====] - 314s 442ms/step - loss: 84.8661 -  
mean_squared_error: 84.8661 - val_loss: 78.7238 - val_mean_squared_error:  
78.7238
```

Epoch 10/10

```
Epoch 00010: LearningRateScheduler reducing learning rate to  
tf.Tensor(6.0238824e-07, shape=(), dtype=float32).  
711/711 [=====] - 311s 438ms/step - loss: 84.1133 -  
mean_squared_error: 84.1133 - val_loss: 73.8476 - val_mean_squared_error:  
73.8476
```

[21]: <tensorflow.python.keras.callbacks.History at 0x14a368bfe50>

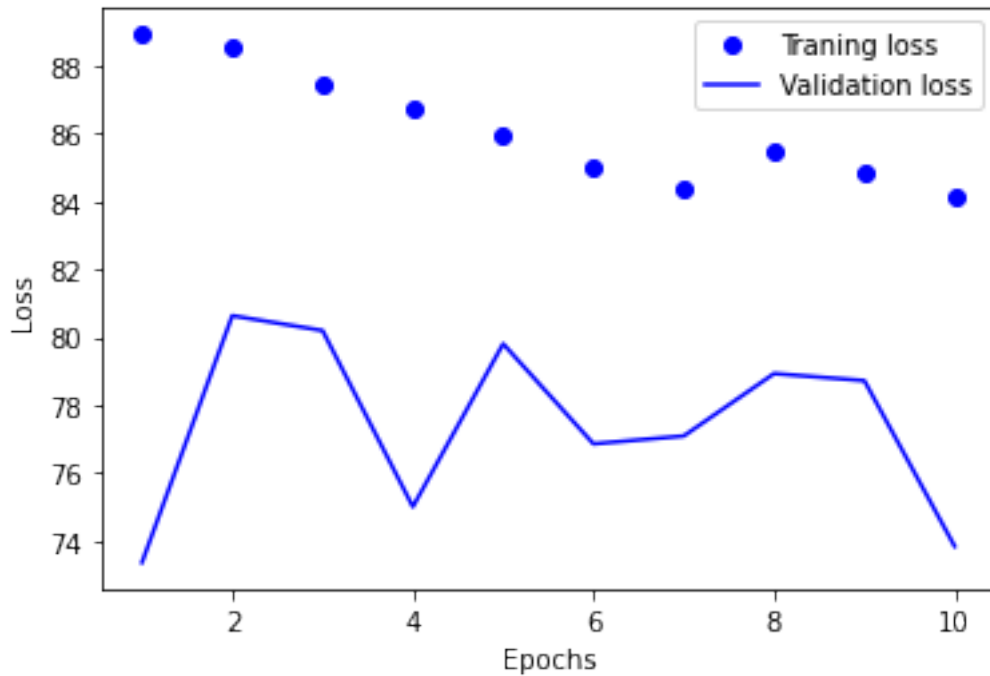
```
[22]: # check graph  
loss = ResnetModel.history.history["loss"]  
val_loss = ResnetModel.history.history["val_loss"]
```



```

epochs = range(1, len(loss)+1)
plt.plot(epochs, loss, "bo", label="Traning loss")
plt.plot(epochs, val_loss, "b", label="Validation loss")
#plt.ylim([65,85])
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()

```



[]:

0.6 test performance

```

[24]: # define the loss function (mse)
def mean_squared_loss(ytrue,ypred):
    ytrue, ypred = np.array(ytrue), np.array(ypred)
    return np.mean((ytrue-ypred)**2)

```

```

[25]: # assess the performance

#ResnetModel = keras.models.load_model("my_Resnet")
#ResnetModel.load_weights("checkpoint3-3/ResnetModel.72.110.h5")
test_generator.reset()
prediction = ResnetModel.predict(test_generator)

```

```
prediction = prediction.reshape(-1)
mse = mean_squared_loss(test_generator.labels, prediction)
print("The mean squared error of prediction is %.3f" % (mse))
```

The mean squared error of prediction is 79.146

[]: