

FCN-FFA-30E-14L-01

March 24, 2021

1 Are Relations Relevant in CNNs? *A Study Based on a Facial Dataset*

1.1 FCN with Features Further Apart (*30 Epochs - 14 Layers*)

1.1.1 Imports, Seed, GPU integration

```
[1]: import numpy as np
import random
import tensorflow as tf
```

```
[2]: # Seeds for better reproducibility
seed = 42
np.random.seed(seed)
random.seed(seed)
tf.random.set_seed(seed)
```

```
[3]: from tensorflow.keras.layers import Dropout, Conv2D, GlobalMaxPooling2D, \
↳BatchNormalization, Activation, MaxPool2D
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.python.keras.models import Sequential
from sklearn.metrics import confusion_matrix
import itertools
import matplotlib.pyplot as plt
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
%matplotlib inline
```

```
[4]: physical_devices = tf.config.experimental.list_physical_devices('GPU')
print("Num GPUs Available: ", len(physical_devices))
tf.config.experimental.set_memory_growth(physical_devices[0], True)
```

Num GPUs Available: 1

1.1.2 Data preparation

```
[5]: train_path = '../..//picasso_dataset/FFA-data/middle/train'
valid_path = '../..//picasso_dataset/FFA-data/middle/valid'
test_path = '../..//picasso_dataset/FFA-data/middle/test'

[6]: train_batches = ImageDataGenerator(preprocessing_function=tf.keras.applications.
    ↳vgg16.preprocess_input) \
    .flow_from_directory(directory=train_path, target_size=(224,224),
    ↳classes=['no_face', 'face'], batch_size=20)

valid_batches = ImageDataGenerator(preprocessing_function=tf.keras.applications.
    ↳vgg16.preprocess_input) \
    .flow_from_directory(directory=valid_path, target_size=(224,224),
    ↳classes=['no_face', 'face'], batch_size=10)

test_batches = ImageDataGenerator(preprocessing_function=tf.keras.applications.
    ↳vgg16.preprocess_input) \
    .flow_from_directory(directory=test_path, target_size=(224,224),
    ↳classes=['no_face', 'face'], batch_size=10, shuffle=False)
```

Found 16002 images belonging to 2 classes.

Found 998 images belonging to 2 classes.

Found 3000 images belonging to 2 classes.

```
[7]: assert train_batches.n == 16002
assert valid_batches.n == 998
assert test_batches.n == 3000
assert train_batches.num_classes == valid_batches.num_classes == test_batches.
    ↳num_classes == 2
```

1.1.3 Building and training the FCN

```
[8]: dropout_rate=0.2
```

```
[9]: model = Sequential(name = "FCN-FFA")

model.add(Conv2D(filters=32, kernel_size=(3, 3), activation='relu', padding =
    ↳'same', input_shape=(224,224,3), name = "Conv_1"))
model.add(MaxPool2D(pool_size=(2, 2), name = "Max_1"))
model.add(Dropout(rate=dropout_rate, name = "DO_1"))
model.add(BatchNormalization(name = "BN_1"))

model.add(Conv2D(filters=64, kernel_size=(3, 3), activation='relu', padding =
    ↳'same', name = "Conv_2"))
model.add(MaxPool2D(pool_size=(2, 2), name = "Max_2"))
```

```

model.add(Conv2D(filters=128, kernel_size=(3, 3), activation='relu', padding =
↳ 'same', name = "Conv_3"))
model.add(MaxPool2D(pool_size=(2, 2), name = "Max_3"))
model.add(Dropout(rate=dropout_rate, name = "DO_3"))

model.add(Conv2D(filters=256, kernel_size=(3, 3), activation='relu', padding =
↳ 'same', name = "Conv_4"))
model.add(MaxPool2D(pool_size=(2, 2), name = "Max_4"))

# Fully connected layer
model.add(Conv2D(filters=2, kernel_size=(1,1), name = "Conv_con"))
model.add(GlobalMaxPooling2D(name = "GMax_con"))
model.add(Activation('softmax', name = "Act_con"))

model.summary()
untrained_weights = list(model.get_weights()[0][0][0][0])

```

Model: "FCN-FFA"

Layer (type)	Output Shape	Param #
Conv_1 (Conv2D)	(None, 224, 224, 32)	896
Max_1 (MaxPooling2D)	(None, 112, 112, 32)	0
DO_1 (Dropout)	(None, 112, 112, 32)	0
BN_1 (BatchNormalization)	(None, 112, 112, 32)	128
Conv_2 (Conv2D)	(None, 112, 112, 64)	18496
Max_2 (MaxPooling2D)	(None, 56, 56, 64)	0
Conv_3 (Conv2D)	(None, 56, 56, 128)	73856
Max_3 (MaxPooling2D)	(None, 28, 28, 128)	0
DO_3 (Dropout)	(None, 28, 28, 128)	0
Conv_4 (Conv2D)	(None, 28, 28, 256)	295168
Max_4 (MaxPooling2D)	(None, 14, 14, 256)	0
Conv_con (Conv2D)	(None, 14, 14, 2)	514
GMax_con (GlobalMaxPooling2D)	(None, 2)	0

```

Act_con (Activation)                (None, 2)                0
=====
Total params: 389,058
Trainable params: 388,994
Non-trainable params: 64
-----

```

```

[10]: model.compile(optimizer=Adam(learning_rate=0.0001),
                loss='categorical_crossentropy',
                metrics=['accuracy'] )

```

```

[11]: history = model.fit(x=train_batches,
                steps_per_epoch=len(train_batches),
                validation_data=valid_batches,
                validation_steps=len(valid_batches),
                epochs=30,
                verbose=2 )

```

Epoch 1/30

WARNING:tensorflow:Callbacks method `on_train_batch_end` is slow compared to the batch time (batch time: 0.0137s vs `on_train_batch_end` time: 0.0214s). Check your callbacks.

801/801 - 41s - loss: 0.6572 - accuracy: 0.5897 - val_loss: 0.5036 - val_accuracy: 0.7655

Epoch 2/30

801/801 - 41s - loss: 0.3322 - accuracy: 0.8609 - val_loss: 0.2869 - val_accuracy: 0.8778

Epoch 3/30

801/801 - 41s - loss: 0.2041 - accuracy: 0.9199 - val_loss: 0.1887 - val_accuracy: 0.9269

Epoch 4/30

801/801 - 41s - loss: 0.1400 - accuracy: 0.9470 - val_loss: 0.1193 - val_accuracy: 0.9609

Epoch 5/30

801/801 - 41s - loss: 0.1098 - accuracy: 0.9608 - val_loss: 0.1297 - val_accuracy: 0.9549

Epoch 6/30

801/801 - 41s - loss: 0.0844 - accuracy: 0.9698 - val_loss: 0.0835 - val_accuracy: 0.9719

Epoch 7/30

801/801 - 41s - loss: 0.0738 - accuracy: 0.9734 - val_loss: 0.0907 - val_accuracy: 0.9629

Epoch 8/30

801/801 - 43s - loss: 0.0610 - accuracy: 0.9796 - val_loss: 0.0606 - val_accuracy: 0.9810

Epoch 9/30

801/801 - 42s - loss: 0.0545 - accuracy: 0.9814 - val_loss: 0.0442 - val_accuracy: 0.9850

Epoch 10/30
801/801 - 42s - loss: 0.0467 - accuracy: 0.9834 - val_loss: 0.0545 -
val_accuracy: 0.9780
Epoch 11/30
801/801 - 42s - loss: 0.0351 - accuracy: 0.9883 - val_loss: 0.0384 -
val_accuracy: 0.9850
Epoch 12/30
801/801 - 42s - loss: 0.0345 - accuracy: 0.9878 - val_loss: 0.0390 -
val_accuracy: 0.9810
Epoch 13/30
801/801 - 43s - loss: 0.0327 - accuracy: 0.9894 - val_loss: 0.0305 -
val_accuracy: 0.9910
Epoch 14/30
801/801 - 43s - loss: 0.0249 - accuracy: 0.9911 - val_loss: 0.0283 -
val_accuracy: 0.9920
Epoch 15/30
801/801 - 43s - loss: 0.0225 - accuracy: 0.9931 - val_loss: 0.0405 -
val_accuracy: 0.9880
Epoch 16/30
801/801 - 43s - loss: 0.0245 - accuracy: 0.9915 - val_loss: 0.0240 -
val_accuracy: 0.9940
Epoch 17/30
801/801 - 43s - loss: 0.0228 - accuracy: 0.9922 - val_loss: 0.0259 -
val_accuracy: 0.9920
Epoch 18/30
801/801 - 43s - loss: 0.0176 - accuracy: 0.9941 - val_loss: 0.0207 -
val_accuracy: 0.9940
Epoch 19/30
801/801 - 43s - loss: 0.0175 - accuracy: 0.9946 - val_loss: 0.0248 -
val_accuracy: 0.9920
Epoch 20/30
801/801 - 43s - loss: 0.0186 - accuracy: 0.9938 - val_loss: 0.0228 -
val_accuracy: 0.9920
Epoch 21/30
801/801 - 43s - loss: 0.0174 - accuracy: 0.9941 - val_loss: 0.0342 -
val_accuracy: 0.9890
Epoch 22/30
801/801 - 43s - loss: 0.0168 - accuracy: 0.9943 - val_loss: 0.0285 -
val_accuracy: 0.9930
Epoch 23/30
801/801 - 43s - loss: 0.0151 - accuracy: 0.9953 - val_loss: 0.0239 -
val_accuracy: 0.9900
Epoch 24/30
801/801 - 43s - loss: 0.0147 - accuracy: 0.9947 - val_loss: 0.0139 -
val_accuracy: 0.9950
Epoch 25/30
801/801 - 42s - loss: 0.0128 - accuracy: 0.9963 - val_loss: 0.0180 -
val_accuracy: 0.9940

```

Epoch 26/30
801/801 - 42s - loss: 0.0131 - accuracy: 0.9959 - val_loss: 0.0144 -
val_accuracy: 0.9950
Epoch 27/30
801/801 - 41s - loss: 0.0145 - accuracy: 0.9957 - val_loss: 0.0215 -
val_accuracy: 0.9940
Epoch 28/30
801/801 - 42s - loss: 0.0121 - accuracy: 0.9958 - val_loss: 0.0205 -
val_accuracy: 0.9930
Epoch 29/30
801/801 - 42s - loss: 0.0128 - accuracy: 0.9961 - val_loss: 0.0183 -
val_accuracy: 0.9940
Epoch 30/30
801/801 - 42s - loss: 0.0085 - accuracy: 0.9973 - val_loss: 0.0175 -
val_accuracy: 0.9950

```

1.1.4 Saving the model

```

[12]: filename='models/FCN-FFA-30E-14L-01.h5'

[13]: model.save(filename)
      saved_weights = list(model.get_weights()[0][0][0][0])

```

1.1.5 Loading the saved model

```

[14]: loaded_model = load_model(filename)
      loaded_weights = list(loaded_model.get_weights()[0][0][0][0])

[15]: # Assertion that the model was saved and loaded successfully
      assert untrained_weights != saved_weights
      assert saved_weights == loaded_weights

```

1.1.6 Accuracy and loss of the trained model

```

[16]: scores = loaded_model.evaluate(test_batches, verbose=2)
      print("Accuracy: %.2f%%" % (scores[1]*100))
      print("Loss: %.2f%%" % (scores[0]*100))

```

```

300/300 - 7s - loss: 0.0130 - accuracy: 0.9960
Accuracy: 99.60%
Loss: 1.30%

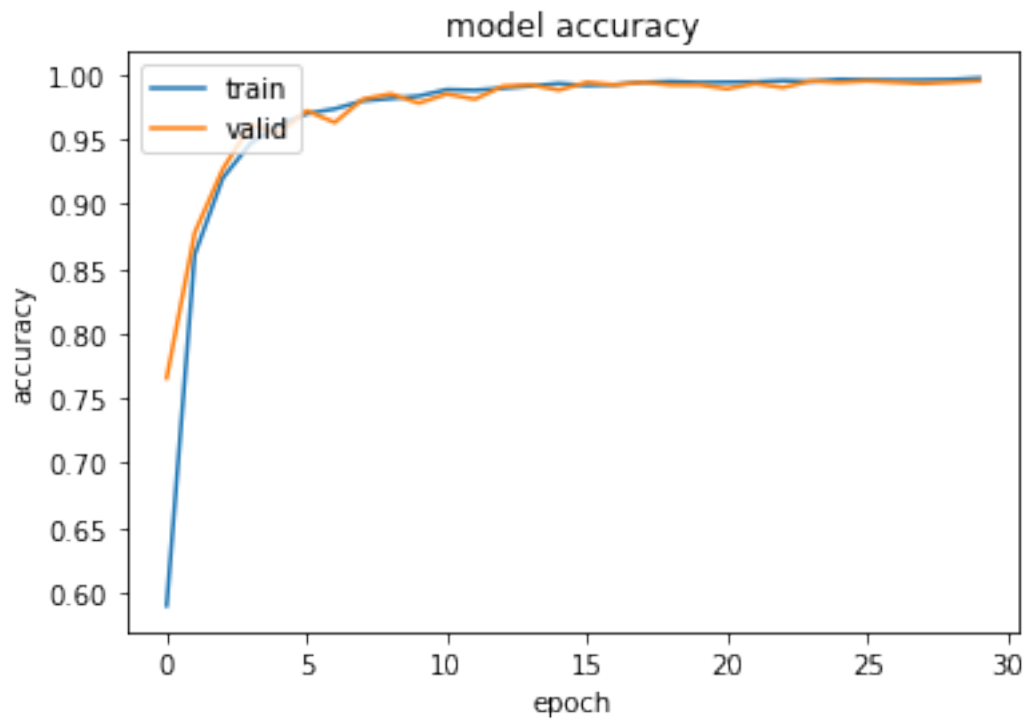
```

```

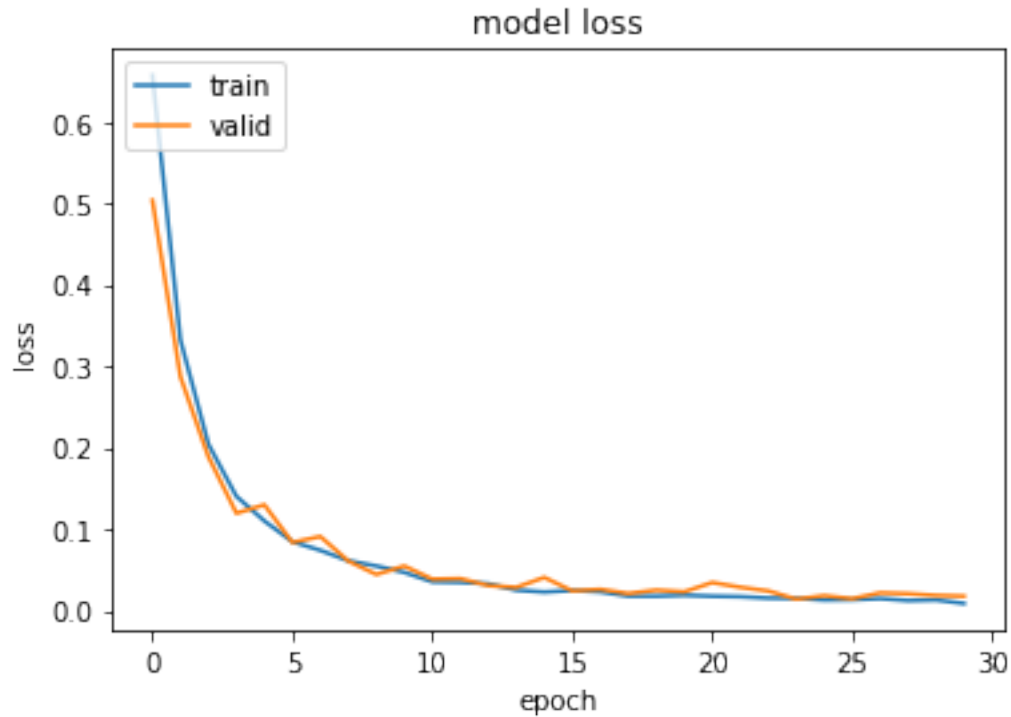
[17]: #Course of accuracy
      plt.plot(history.history['accuracy'])
      plt.plot(history.history['val_accuracy'])
      plt.title('model accuracy')
      plt.ylabel('accuracy')

```

```
plt.xlabel('epoch')
plt.legend(['train', 'valid'], loc='upper left')
plt.show()
```



```
[18]: #Course of loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'valid'], loc='upper left')
plt.show()
```



1.1.7 Testing the CNN

```
[19]: predictions = loaded_model.predict(x=test_batches, steps=len(test_batches),
    ↪ verbose=0)
```

1.1.8 Index of wrongly predicted pictures

```
[20]: y_true=test_batches.classes
y_pred=np.argmax(predictions, axis=-1)
cm = confusion_matrix(y_true = y_true, y_pred = y_pred)
```

```
[21]: face_but_predicted_no_face=[]
no_face_but_predicted_face=[]

for i in range(len(predictions)):
    if y_true[i] != y_pred[i]:
        if y_true[i] == 1:
            face_but_predicted_no_face.append(i+8001-1500) #Index of file
    ↪ on disk
        else:
            no_face_but_predicted_face.append(i+8001) #Index of file on disk
```



```

print("Data from class 'face', that was wrongly predicted as 'no-face' [",
      len(face_but_predicted_no_face), "] :")
print(face_but_predicted_no_face)
print("-----")
print("Data from class 'no-face', that was wrongly predicted as 'face' [",
      len(no_face_but_predicted_face), "] :")
print(no_face_but_predicted_face)

```

Data from class 'face', that was wrongly predicted as 'no-face' [0] :
 []

 Data from class 'no-face', that was wrongly predicted as 'face' [12] :
 [8193, 8241, 8244, 8436, 8524, 8602, 8604, 8723, 8754, 8894, 9090, 9210]

1.1.9 Confusion matrix

```

[22]: def plot_confusion_matrix(cm, classes,
                                normalize=False,
                                title='Confusion matrix',
                                cmap=plt.cm.Blues):

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, cm[i, j],
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')

```

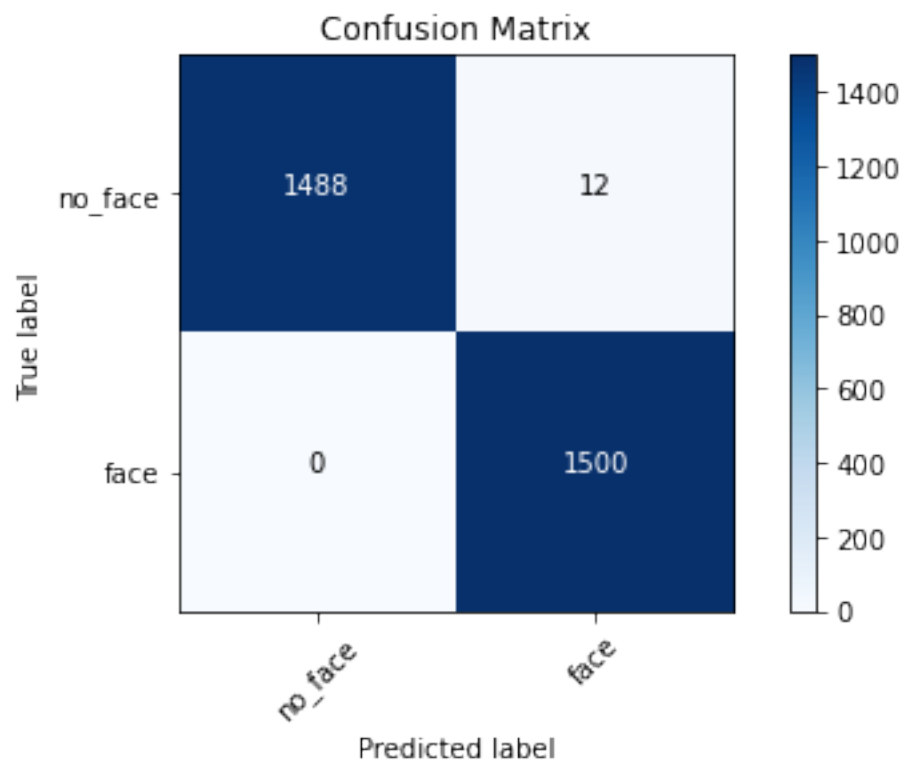
```
[23]: test_batches.class_indices
```

```
[23]: {'no_face': 0, 'face': 1}
```

```
[24]: cm_plot_labels = ['no_face', 'face']  
plot_confusion_matrix(cm=cm, classes=cm_plot_labels, title='Confusion Matrix')
```

Confusion matrix, without normalization

```
[[1488  12]  
 [  0 1500]]
```



```
[ ]:
```