

HW5_Task3

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1 Applied Machine Learning Homework 5

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2 Task 3

```
In [1]: # base packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from keras import utils
```

Using TensorFlow backend.

Import Data

```
In [0]: # import packages for import zip files
import zipfile
import imageio
from skimage import io

In [3]: # package for load data from google drive
from google.colab import drive
drive.mount('/gdrive')
```

Drive already mounted at /gdrive; to attempt to forcibly remount, call drive.mount("/gdrive", force_remount=True).

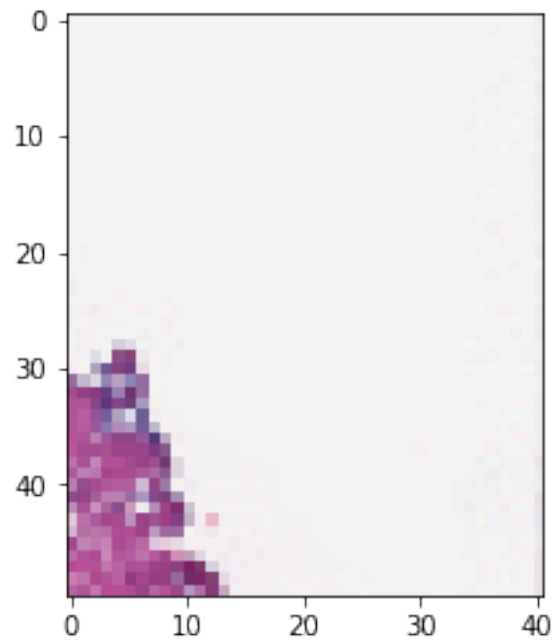
```
In [0]: # get images
file_dir = '/gdrive/My Drive/Colab Notebooks/Data/IDC_regular_ps50_idx5.zip'

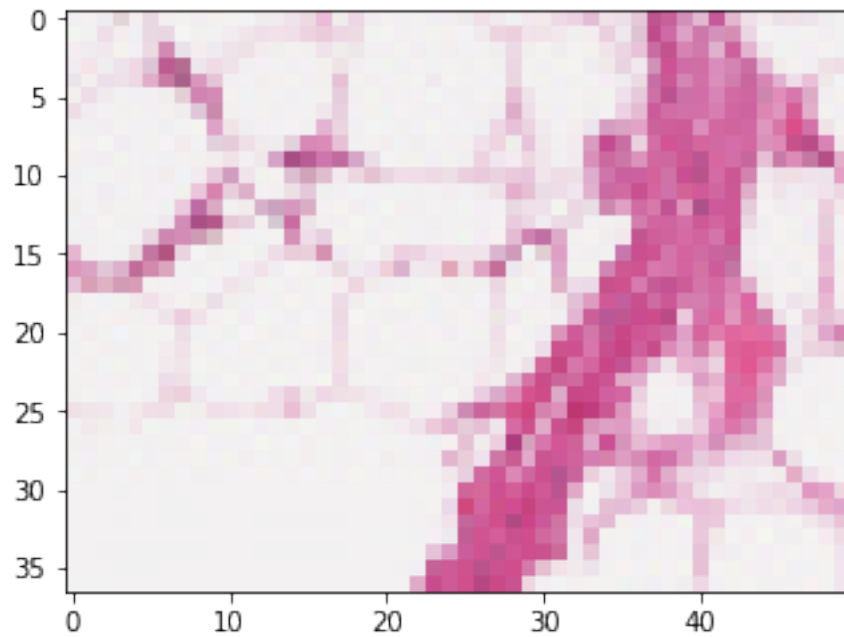
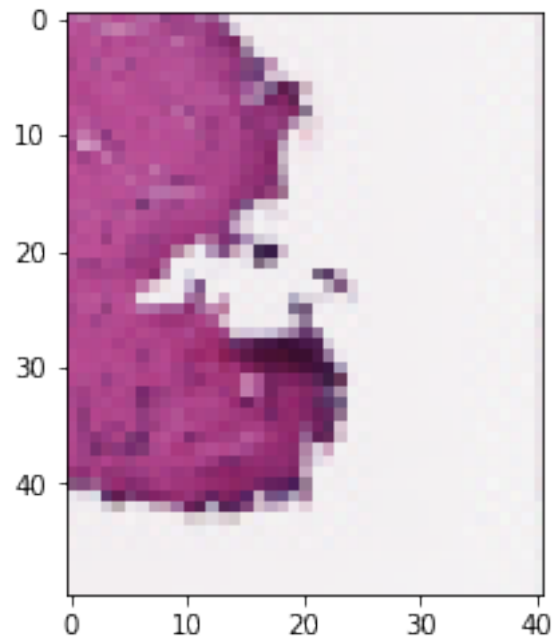
# zipfile
archive = zipfile.ZipFile(file_dir)

# due to memory limit, only extract first 75,000 pictures for this task
images = [f.filename for f in archive.filelist if f.is_dir() == False][:75000]
ic = io.ImageCollection(images, load_func = (lambda x: imageio.imread(archive.read(x))))
```

Drop irregular shape images

```
In [5]: # There are some irregular shape images
# just show the first 3 images
count = 0
for idx, image in enumerate(ic):
    if image.shape != (50, 50, 3):
        count += 1
        plt.figure()
        plt.imshow(image)
    if count == 3:
        break
```





These irregular shapes are incompatible with our neural networks, so we will simply exclude them from our sample.

```
In [0]: # get all images with proper shape  
X, y = [], []
```

```

for idx, image in enumerate(ic):
    if image.shape == (50, 50, 3):
        X.append(image)
        y.append(images[idx][-5])

# scale features to be between 0 and 1
X = np.array(X) / 255.0
y = utils.to_categorical(np.array(y))

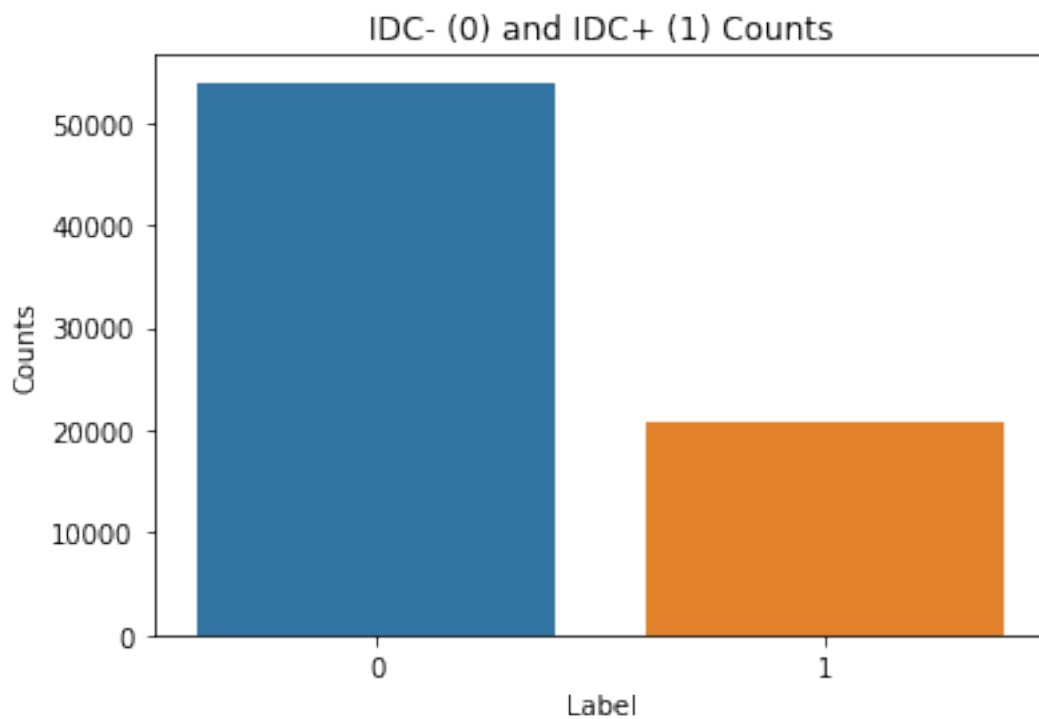
# free memory
del ic, images, archive

```

```

In [7]: # visualize imbalance
_ = sns.countplot(y[:, 1].astype(int))
_ = plt.xlabel('Label')
_ = plt.ylabel('Counts')
_ = plt.title('IDC- (0) and IDC+ (1) Counts')

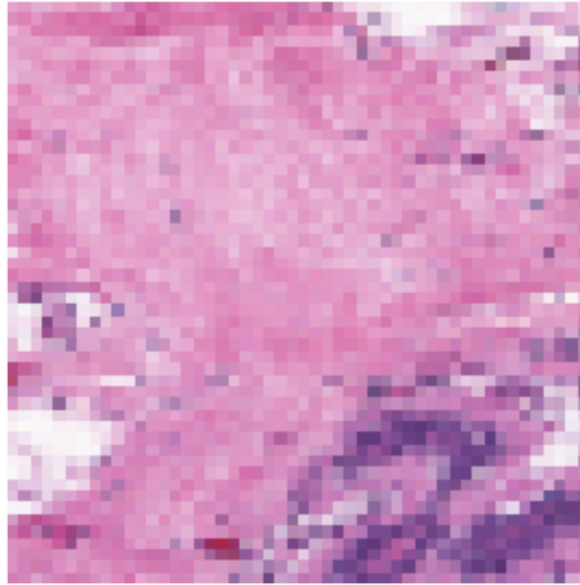
```



```

In [8]: # sample
_ = plt.imshow((X[0] * 255).astype(int))
_ = plt.axis('off')

```



2.1 Task 3.1

Start with a model without residual connections (using batch normalization is likely to be helpful and you should try it, whether you use dropout is your choice).

```
In [0]: # 80%-20% split data for training and testing
        from sklearn.model_selection import train_test_split
        X_train, X_test, y_train, y_test = train_test_split(
            X, y, stratify = y, test_size = 0.2)

        del X, y

        # 80% 20% training data split for training and validating
        X_train, X_val, y_train, y_val = train_test_split(
            X_train, y_train, stratify = y_train, test_size = 0.2)

In [10]: from sklearn.utils import class_weight
         class_weights = class_weight.compute_class_weight('balanced',
                                                         [0, 1],
                                                         y_train[:,1])

         class_weights

Out[10]: array([0.69380777, 1.78993795])

In [0]: # model parameter
        batch_size = 50
```

```

num_classes = 2
epochs = 10

# input image dimensions
img_rows, img_cols = 50, 50
input_shape = (img_rows, img_cols, 3)

In [0]: # user defined f1 metric
import tensorflow as tf
import keras.backend as K

def f1(y_true, y_pred):
    y_pred = K.round(y_pred)
    tp = K.sum(K.cast(y_true*y_pred, 'float'), axis=0)
    tn = K.sum(K.cast((1-y_true)*(1-y_pred), 'float'), axis=0)
    fp = K.sum(K.cast((1-y_true)*y_pred, 'float'), axis=0)
    fn = K.sum(K.cast(y_true*(1-y_pred), 'float'), axis=0)

    p = tp / (tp + fp + K.epsilon())
    r = tp / (tp + fn + K.epsilon())

    f1 = 2*p*r / (p+r+K.epsilon())
    f1 = tf.where(tf.is_nan(f1), tf.zeros_like(f1), f1)
    return K.mean(f1)

In [13]: from keras import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, BatchNormalization

cnn = Sequential()

##### cluster1
cnn.add(Conv2D(32, kernel_size=(3, 3), activation='relu',
               input_shape=input_shape))
cnn.add(BatchNormalization())
cnn.add(MaxPooling2D(pool_size=(2, 2)))

##### cluster2
cnn.add(Conv2D(64, (3, 3), activation='relu'))
cnn.add(BatchNormalization())
cnn.add(MaxPooling2D(pool_size=(2, 2)))

##### cluster 3
cnn.add(Conv2D(128, (3, 3), activation='relu'))
cnn.add(BatchNormalization())
cnn.add(MaxPooling2D(pool_size=(2, 2)))

##### flat for dense
cnn.add(Flatten())

```

```

cnn.add(Dense(128, activation='relu'))
cnn.add(Dense(64, activation='relu'))
cnn.add(Dense(32, activation='relu'))
cnn.add(Dense(2, activation='softmax'))

cnn.compile(optimizer='adam', loss="binary_crossentropy", metrics=['acc', f1])

cnn.summary()

```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/framework/op_def_registry.py:101: Instructions for updating:
Colocations handled automatically by placer.

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 48, 48, 32)	896
batch_normalization_1 (Batch Normalization)	(None, 48, 48, 32)	128
max_pooling2d_1 (MaxPooling2D)	(None, 24, 24, 32)	0
conv2d_2 (Conv2D)	(None, 22, 22, 64)	18496
batch_normalization_2 (Batch Normalization)	(None, 22, 22, 64)	256
max_pooling2d_2 (MaxPooling2D)	(None, 11, 11, 64)	0
conv2d_3 (Conv2D)	(None, 9, 9, 128)	73856
batch_normalization_3 (Batch Normalization)	(None, 9, 9, 128)	512
max_pooling2d_3 (MaxPooling2D)	(None, 4, 4, 128)	0
flatten_1 (Flatten)	(None, 2048)	0
dense_1 (Dense)	(None, 128)	262272
dense_2 (Dense)	(None, 64)	8256
dense_3 (Dense)	(None, 32)	2080
dense_4 (Dense)	(None, 2)	66
Total params: 366,818		
Trainable params: 366,370		
Non-trainable params: 448		

```
In [14]: hist_cnn = cnn.fit(X_train,
                             y_train,
                             batch_size=batch_size,
                             epochs=epochs,
                             verbose=1,
                             validation_data=(X_val,y_val),
                             class_weight = class_weights)
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/ops/math_ops.py:

Instructions for updating:

Use tf.cast instead.

Train on 47888 samples, validate on 11973 samples

Epoch 1/10

47888/47888 [=====] - 17s 346us/step - loss: 0.3855 - acc: 0.8297 - f

Epoch 2/10

47888/47888 [=====] - 12s 247us/step - loss: 0.3507 - acc: 0.8463 - f

Epoch 3/10

47888/47888 [=====] - 12s 240us/step - loss: 0.3333 - acc: 0.8545 - f

Epoch 4/10

47888/47888 [=====] - 12s 241us/step - loss: 0.3211 - acc: 0.8594 - f

Epoch 5/10

47888/47888 [=====] - 11s 240us/step - loss: 0.3083 - acc: 0.8673 - f

Epoch 6/10

47888/47888 [=====] - 11s 240us/step - loss: 0.2958 - acc: 0.8734 - f

Epoch 7/10

47888/47888 [=====] - 11s 240us/step - loss: 0.2817 - acc: 0.8804 - f

Epoch 8/10

47888/47888 [=====] - 12s 251us/step - loss: 0.2634 - acc: 0.8905 - f

Epoch 9/10

47888/47888 [=====] - 12s 244us/step - loss: 0.2413 - acc: 0.9004 - f

Epoch 10/10

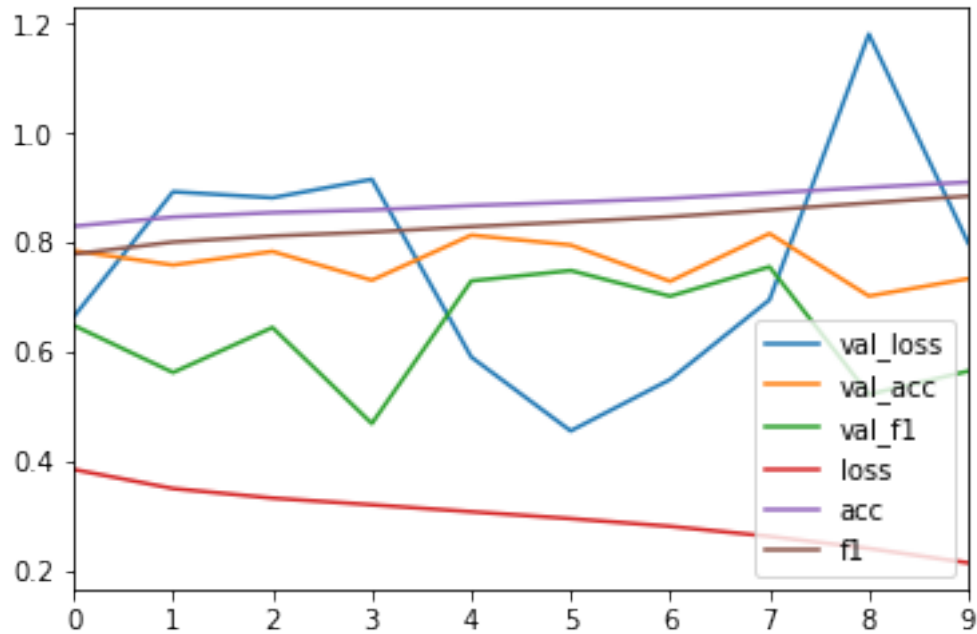
47888/47888 [=====] - 12s 240us/step - loss: 0.2151 - acc: 0.9101 - f

```
In [15]: # check test set score
         cnn.evaluate(X_test, y_test)
```

14966/14966 [=====] - 2s 123us/step

```
Out[15]: [0.7865344994243064, 0.7386075103408781, 0.5704361179901543]
```

```
In [16]: # visualize
         _ = pd.DataFrame(hist_cnn.history).plot()
```

3 Summary

In this section, we constructed a relatively simple network comprised of some max pooling, convolutional, and batch normalization layers. We trained the model for 10 epochs, and achieved a test set accuracy score of 0.74. Since the classes are somewhat imbalanced, we also developed an F1 scoring metric, which was 0.57 for the test set. These metrics will act as our baseline from here on out.

3.1 3.2 Augment the data using rotations, mirroring and possibly other transformations. How much can you improve your original model by data augmentation?

```
In [0]: # apply ImageDataGenerator to augment data
from keras.preprocessing.image import ImageDataGenerator

# apply rotation, shift, zoom and flip
train_datagen = ImageDataGenerator(
    rotation_range=90,
    width_shift_range=0.2,
    height_shift_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    vertical_flip=True,
    fill_mode='nearest')

train_datagen.fit(X_train)
```

```

In [18]: cnn2 = Sequential()

##### cluster1
cnn2.add(Conv2D(32, kernel_size=(3, 3), activation='relu',
               input_shape=input_shape))
cnn2.add(BatchNormalization())
cnn2.add(MaxPooling2D(pool_size=(2, 2)))

##### cluster2
cnn2.add(Conv2D(64, (3, 3), activation='relu'))
cnn2.add(BatchNormalization())
cnn2.add(MaxPooling2D(pool_size=(2, 2)))

##### cluster 3
cnn2.add(Conv2D(128, (3, 3), activation='relu'))
cnn2.add(BatchNormalization())
cnn2.add(MaxPooling2D(pool_size=(2, 2)))

##### flat for dense
cnn2.add(Flatten())
cnn2.add(Dense(128, activation='relu'))
cnn2.add(Dense(64, activation='relu'))
cnn2.add(Dense(32, activation='relu'))
cnn2.add(Dense(2, activation='softmax'))

cnn2.compile(optimizer='adam', loss="binary_crossentropy", metrics=['acc', f1])

cnn2.summary()

```

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 48, 48, 32)	896
batch_normalization_4 (Batch Normalization)	(None, 48, 48, 32)	128
max_pooling2d_4 (MaxPooling2D)	(None, 24, 24, 32)	0
conv2d_5 (Conv2D)	(None, 22, 22, 64)	18496
batch_normalization_5 (Batch Normalization)	(None, 22, 22, 64)	256
max_pooling2d_5 (MaxPooling2D)	(None, 11, 11, 64)	0
conv2d_6 (Conv2D)	(None, 9, 9, 128)	73856
batch_normalization_6 (Batch Normalization)	(None, 9, 9, 128)	512

```

max_pooling2d_6 (MaxPooling2 (None, 4, 4, 128)          0
-----
flatten_2 (Flatten)          (None, 2048)          0
-----
dense_5 (Dense)              (None, 128)         262272
-----
dense_6 (Dense)              (None, 64)          8256
-----
dense_7 (Dense)              (None, 32)          2080
-----
dense_8 (Dense)              (None, 2)           66
=====
Total params: 366,818
Trainable params: 366,370
Non-trainable params: 448
-----

```

```

In [19]: hist_cnn2 = cnn2.fit_generator(
        train_datagen.flow(X_train,y_train, batch_size=batch_size),
        steps_per_epoch = len(X_train) / batch_size,
        epochs = epochs,
        validation_data = (X_val,y_val),
        verbose=1,
        class_weight = class_weights)

```

```

Epoch 1/10
958/957 [=====] - 40s 42ms/step - loss: 0.3924 - acc: 0.8282 - f1: 0.7
Epoch 2/10
958/957 [=====] - 40s 41ms/step - loss: 0.3619 - acc: 0.8415 - f1: 0.7
Epoch 3/10
958/957 [=====] - 38s 40ms/step - loss: 0.3523 - acc: 0.8456 - f1: 0.8
Epoch 4/10
958/957 [=====] - 39s 41ms/step - loss: 0.3447 - acc: 0.8491 - f1: 0.8
Epoch 5/10
958/957 [=====] - 38s 39ms/step - loss: 0.3362 - acc: 0.8541 - f1: 0.8
Epoch 6/10
958/957 [=====] - 39s 41ms/step - loss: 0.3296 - acc: 0.8581 - f1: 0.8
Epoch 7/10
958/957 [=====] - 38s 39ms/step - loss: 0.3230 - acc: 0.8602 - f1: 0.8
Epoch 8/10
958/957 [=====] - 39s 41ms/step - loss: 0.3198 - acc: 0.8614 - f1: 0.8
Epoch 9/10
958/957 [=====] - 38s 40ms/step - loss: 0.3152 - acc: 0.8652 - f1: 0.8
Epoch 10/10
958/957 [=====] - 40s 42ms/step - loss: 0.3110 - acc: 0.8656 - f1: 0.8

```

```

In [20]: # check test set score

```

```

cnn2.evaluate(X_test, y_test)

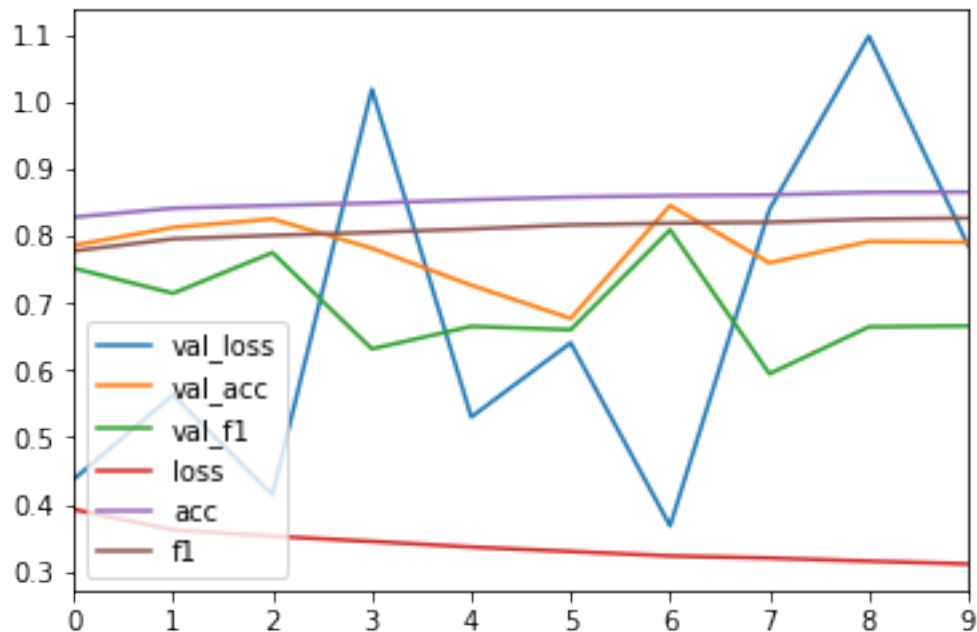
14966/14966 [=====] - 2s 126us/step

Out[20]: [0.7662685723144167, 0.7940665508167287, 0.6709475991847951]

In [21]: # visualize?
pd.DataFrame(hist_cnn2.history).plot()

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x7f0b401d7fd0>

```



4 Summary

In this section, we introduced several transformations to our data, in order to hopefully construct a more robust model. Specifically, we used the ImageGenerator class in Keras to perform rotations of up to 90 degrees, as well as several types of flips, zooms, and shifts.

By training on this transformed data used the same network as in task 3.1, we were able to noticeably improve both our test set accuracy and F1 score 0.79 and 0.67, respectively. It should also be noted that the difference between the training and validation set scores were not nearly as large as they were for task 3.1.

5 Taks 3.3

Build a deeper model using residual connections. Show that you can build a deep model that would not be able to learn if you remove the residual connections (i.e. compare a deep model with and without residual connections while the rest of the architecture is constant).

Deep net

```
In [22]: cnn3 = Sequential()

##### cluster1
cnn3.add(Conv2D(4, kernel_size=(3, 3), activation='relu',
               input_shape=input_shape, padding = 'same'))
cnn3.add(BatchNormalization())

# create additional 51 layers
for i in range(51):
    cnn3.add(Conv2D(4, (3, 3), activation='relu', padding = 'same'))
    cnn3.add(BatchNormalization())

##### flat for dense
cnn3.add(Flatten())
cnn3.add(Dense(32, activation='relu'))
cnn3.add(Dense(16, activation='relu'))
cnn3.add(Dense(2, activation='softmax'))

cnn3.compile(optimizer='adam', loss="binary_crossentropy", metrics=['acc', f1])

cnn3.summary()
```

Layer (type)	Output Shape	Param #
conv2d_7 (Conv2D)	(None, 50, 50, 4)	112
batch_normalization_7 (Batch Normalization)	(None, 50, 50, 4)	16
conv2d_8 (Conv2D)	(None, 50, 50, 4)	148
batch_normalization_8 (Batch Normalization)	(None, 50, 50, 4)	16
conv2d_9 (Conv2D)	(None, 50, 50, 4)	148
batch_normalization_9 (Batch Normalization)	(None, 50, 50, 4)	16
conv2d_10 (Conv2D)	(None, 50, 50, 4)	148
batch_normalization_10 (Batch Normalization)	(None, 50, 50, 4)	16
conv2d_11 (Conv2D)	(None, 50, 50, 4)	148
batch_normalization_11 (Batch Normalization)	(None, 50, 50, 4)	16
conv2d_12 (Conv2D)	(None, 50, 50, 4)	148

batch_normalization_12	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_13	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_13	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_14	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_14	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_15	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_15	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_16	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_16	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_17	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_17	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_18	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_18	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_19	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_19	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_20	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_20	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_21	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_21	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_22	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_22	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_23	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_23	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_24	(Conv2D)	(None, 50, 50, 4)	148

batch_normalization_24	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_25	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_25	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_26	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_26	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_27	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_27	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_28	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_28	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_29	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_29	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_30	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_30	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_31	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_31	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_32	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_32	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_33	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_33	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_34	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_34	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_35	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_35	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_36	(Conv2D)	(None, 50, 50, 4)	148

batch_normalization_36	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_37	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_37	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_38	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_38	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_39	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_39	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_40	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_40	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_41	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_41	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_42	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_42	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_43	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_43	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_44	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_44	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_45	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_45	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_46	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_46	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_47	(Conv2D)	(None, 50, 50, 4)	148
batch_normalization_47	(Batch Normalization)	(None, 50, 50, 4)	16
conv2d_48	(Conv2D)	(None, 50, 50, 4)	148

batch_normalization_48 (Batch Normalization)	(None, 50, 50, 4)	16
conv2d_49 (Conv2D)	(None, 50, 50, 4)	148
batch_normalization_49 (Batch Normalization)	(None, 50, 50, 4)	16
conv2d_50 (Conv2D)	(None, 50, 50, 4)	148
batch_normalization_50 (Batch Normalization)	(None, 50, 50, 4)	16
conv2d_51 (Conv2D)	(None, 50, 50, 4)	148
batch_normalization_51 (Batch Normalization)	(None, 50, 50, 4)	16
conv2d_52 (Conv2D)	(None, 50, 50, 4)	148
batch_normalization_52 (Batch Normalization)	(None, 50, 50, 4)	16
conv2d_53 (Conv2D)	(None, 50, 50, 4)	148
batch_normalization_53 (Batch Normalization)	(None, 50, 50, 4)	16
conv2d_54 (Conv2D)	(None, 50, 50, 4)	148
batch_normalization_54 (Batch Normalization)	(None, 50, 50, 4)	16
conv2d_55 (Conv2D)	(None, 50, 50, 4)	148
batch_normalization_55 (Batch Normalization)	(None, 50, 50, 4)	16
conv2d_56 (Conv2D)	(None, 50, 50, 4)	148
batch_normalization_56 (Batch Normalization)	(None, 50, 50, 4)	16
conv2d_57 (Conv2D)	(None, 50, 50, 4)	148
batch_normalization_57 (Batch Normalization)	(None, 50, 50, 4)	16
conv2d_58 (Conv2D)	(None, 50, 50, 4)	148
batch_normalization_58 (Batch Normalization)	(None, 50, 50, 4)	16
flatten_3 (Flatten)	(None, 10000)	0
dense_9 (Dense)	(None, 32)	320032
dense_10 (Dense)	(None, 16)	528

```
dense_11 (Dense)                (None, 2)                34
=====
Total params: 329,086
Trainable params: 328,670
Non-trainable params: 416
-----
```

```
In [23]: hist_cnn3 = cnn3.fit(X_train,
                               y_train,
                               batch_size=batch_size,
                               epochs=epochs,
                               verbose=1,
                               validation_data=(X_val,y_val),
                               class_weight = class_weights)
```

Train on 47888 samples, validate on 11973 samples

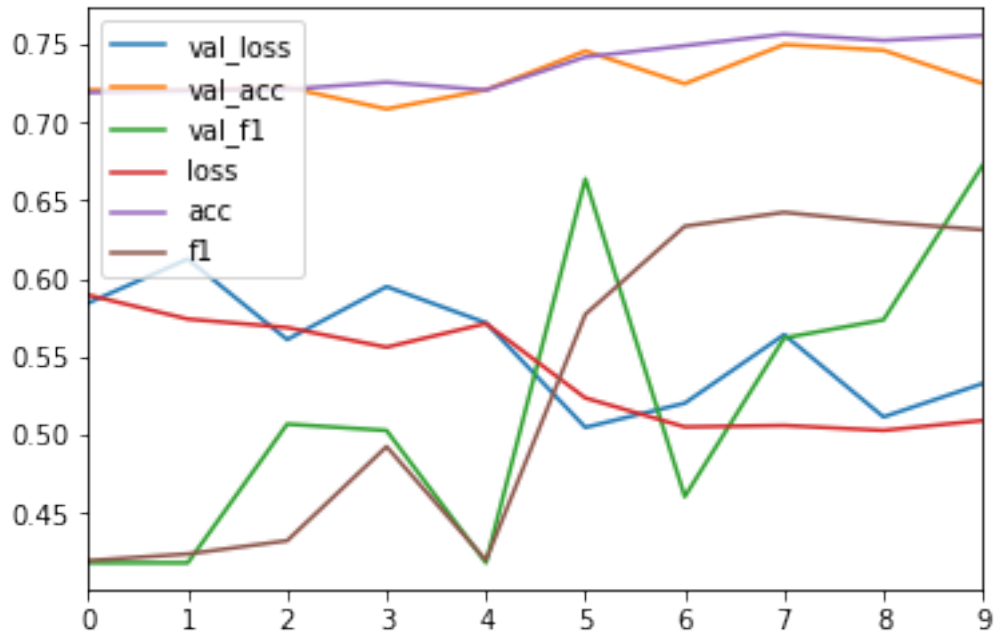
```
Epoch 1/10
47888/47888 [=====] - 81s 2ms/step - loss: 0.5894 - acc: 0.7191 - f1:
Epoch 2/10
47888/47888 [=====] - 71s 1ms/step - loss: 0.5740 - acc: 0.7202 - f1:
Epoch 3/10
47888/47888 [=====] - 71s 1ms/step - loss: 0.5686 - acc: 0.7211 - f1:
Epoch 4/10
47888/47888 [=====] - 72s 1ms/step - loss: 0.5560 - acc: 0.7256 - f1:
Epoch 5/10
47888/47888 [=====] - 71s 1ms/step - loss: 0.5712 - acc: 0.7206 - f1:
Epoch 6/10
47888/47888 [=====] - 71s 1ms/step - loss: 0.5235 - acc: 0.7418 - f1:
Epoch 7/10
47888/47888 [=====] - 71s 1ms/step - loss: 0.5050 - acc: 0.7490 - f1:
Epoch 8/10
47888/47888 [=====] - 72s 1ms/step - loss: 0.5059 - acc: 0.7564 - f1:
Epoch 9/10
47888/47888 [=====] - 71s 1ms/step - loss: 0.5028 - acc: 0.7524 - f1:
Epoch 10/10
47888/47888 [=====] - 71s 1ms/step - loss: 0.5091 - acc: 0.7556 - f1:
```

```
In [24]: # check test set score
         cnn3.evaluate(X_test, y_test)
```

```
14966/14966 [=====] - 4s 290us/step
```

```
Out[24]: [0.5279028024103781, 0.7272484297661894, 0.6746583132442427]
```

```
In [25]: # visualization
         _ = pd.DataFrame(hist_cnn3.history).plot()
```



Deep ResNet

```
In [26]: from keras.layers import (Dense, Flatten, Conv2D,
                                     BatchNormalization, Input,
                                     add, MaxPooling2D)

from keras import Model

num_classes = 2

inputs = Input(shape=(50,50,3))

lst = [None] * int(5*13)
# total 13 * 4 = 52 conv layers
for i in range(13):
    # 1
    if i == 0:
        lst[0+i*5] = Conv2D(4, (3, 3), activation = 'relu',
                             padding = 'same')(inputs)
    else:
        lst[0+i*5] = Conv2D(4, (3, 3), activation = 'relu',
                             padding = 'same')(lst[4+(i-1)*5])
    # 2
    lst[1+i*5] = Conv2D(4, (3, 3), activation = 'relu',
                         padding = 'same')(lst[0+i*5])
```

```

# 3
lst[2+i*5] = Conv2D(4, (3, 3), activation = 'relu',
                    padding = 'same')(lst[1+i*5])

# 4
lst[3+i*5] = Conv2D(4, (3, 3), activation = 'relu',
                    padding = 'same')(lst[2+i*5])

# skip
lst[4+i*5] = add([lst[0+i*5], lst[3+i*5]])

flat = Flatten()(lst[-1])
dense1 = Dense(32, activation='relu')(flat)
dense2 = Dense(16, activation='relu')(dense1)
prediction = Dense(2, activation='softmax')(dense2)

model = Model(inputs = inputs, outputs = prediction)

model.compile(optimizer='adam', loss="binary_crossentropy", metrics=['acc', f1])

model.summary()

```

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, 50, 50, 3)	0	
conv2d_59 (Conv2D)	(None, 50, 50, 4)	112	input_1[0][0]
conv2d_60 (Conv2D)	(None, 50, 50, 4)	148	conv2d_59[0][0]
conv2d_61 (Conv2D)	(None, 50, 50, 4)	148	conv2d_60[0][0]
conv2d_62 (Conv2D)	(None, 50, 50, 4)	148	conv2d_61[0][0]
add_1 (Add)	(None, 50, 50, 4)	0	conv2d_59[0][0] conv2d_62[0][0]
conv2d_63 (Conv2D)	(None, 50, 50, 4)	148	add_1[0][0]
conv2d_64 (Conv2D)	(None, 50, 50, 4)	148	conv2d_63[0][0]
conv2d_65 (Conv2D)	(None, 50, 50, 4)	148	conv2d_64[0][0]
conv2d_66 (Conv2D)	(None, 50, 50, 4)	148	conv2d_65[0][0]
add_2 (Add)	(None, 50, 50, 4)	0	conv2d_63[0][0] conv2d_66[0][0]

conv2d_67 (Conv2D)	(None, 50, 50, 4)	148	add_2[0][0]
conv2d_68 (Conv2D)	(None, 50, 50, 4)	148	conv2d_67[0][0]
conv2d_69 (Conv2D)	(None, 50, 50, 4)	148	conv2d_68[0][0]
conv2d_70 (Conv2D)	(None, 50, 50, 4)	148	conv2d_69[0][0]
add_3 (Add)	(None, 50, 50, 4)	0	conv2d_67[0][0] conv2d_70[0][0]
conv2d_71 (Conv2D)	(None, 50, 50, 4)	148	add_3[0][0]
conv2d_72 (Conv2D)	(None, 50, 50, 4)	148	conv2d_71[0][0]
conv2d_73 (Conv2D)	(None, 50, 50, 4)	148	conv2d_72[0][0]
conv2d_74 (Conv2D)	(None, 50, 50, 4)	148	conv2d_73[0][0]
add_4 (Add)	(None, 50, 50, 4)	0	conv2d_71[0][0] conv2d_74[0][0]
conv2d_75 (Conv2D)	(None, 50, 50, 4)	148	add_4[0][0]
conv2d_76 (Conv2D)	(None, 50, 50, 4)	148	conv2d_75[0][0]
conv2d_77 (Conv2D)	(None, 50, 50, 4)	148	conv2d_76[0][0]
conv2d_78 (Conv2D)	(None, 50, 50, 4)	148	conv2d_77[0][0]
add_5 (Add)	(None, 50, 50, 4)	0	conv2d_75[0][0] conv2d_78[0][0]
conv2d_79 (Conv2D)	(None, 50, 50, 4)	148	add_5[0][0]
conv2d_80 (Conv2D)	(None, 50, 50, 4)	148	conv2d_79[0][0]
conv2d_81 (Conv2D)	(None, 50, 50, 4)	148	conv2d_80[0][0]
conv2d_82 (Conv2D)	(None, 50, 50, 4)	148	conv2d_81[0][0]
add_6 (Add)	(None, 50, 50, 4)	0	conv2d_79[0][0] conv2d_82[0][0]
conv2d_83 (Conv2D)	(None, 50, 50, 4)	148	add_6[0][0]
conv2d_84 (Conv2D)	(None, 50, 50, 4)	148	conv2d_83[0][0]

conv2d_85 (Conv2D)	(None, 50, 50, 4)	148	conv2d_84[0][0]
conv2d_86 (Conv2D)	(None, 50, 50, 4)	148	conv2d_85[0][0]
add_7 (Add)	(None, 50, 50, 4)	0	conv2d_83[0][0] conv2d_86[0][0]
conv2d_87 (Conv2D)	(None, 50, 50, 4)	148	add_7[0][0]
conv2d_88 (Conv2D)	(None, 50, 50, 4)	148	conv2d_87[0][0]
conv2d_89 (Conv2D)	(None, 50, 50, 4)	148	conv2d_88[0][0]
conv2d_90 (Conv2D)	(None, 50, 50, 4)	148	conv2d_89[0][0]
add_8 (Add)	(None, 50, 50, 4)	0	conv2d_87[0][0] conv2d_90[0][0]
conv2d_91 (Conv2D)	(None, 50, 50, 4)	148	add_8[0][0]
conv2d_92 (Conv2D)	(None, 50, 50, 4)	148	conv2d_91[0][0]
conv2d_93 (Conv2D)	(None, 50, 50, 4)	148	conv2d_92[0][0]
conv2d_94 (Conv2D)	(None, 50, 50, 4)	148	conv2d_93[0][0]
add_9 (Add)	(None, 50, 50, 4)	0	conv2d_91[0][0] conv2d_94[0][0]
conv2d_95 (Conv2D)	(None, 50, 50, 4)	148	add_9[0][0]
conv2d_96 (Conv2D)	(None, 50, 50, 4)	148	conv2d_95[0][0]
conv2d_97 (Conv2D)	(None, 50, 50, 4)	148	conv2d_96[0][0]
conv2d_98 (Conv2D)	(None, 50, 50, 4)	148	conv2d_97[0][0]
add_10 (Add)	(None, 50, 50, 4)	0	conv2d_95[0][0] conv2d_98[0][0]
conv2d_99 (Conv2D)	(None, 50, 50, 4)	148	add_10[0][0]
conv2d_100 (Conv2D)	(None, 50, 50, 4)	148	conv2d_99[0][0]
conv2d_101 (Conv2D)	(None, 50, 50, 4)	148	conv2d_100[0][0]
conv2d_102 (Conv2D)	(None, 50, 50, 4)	148	conv2d_101[0][0]

add_11 (Add)	(None, 50, 50, 4)	0	conv2d_99[0][0] conv2d_102[0][0]
conv2d_103 (Conv2D)	(None, 50, 50, 4)	148	add_11[0][0]
conv2d_104 (Conv2D)	(None, 50, 50, 4)	148	conv2d_103[0][0]
conv2d_105 (Conv2D)	(None, 50, 50, 4)	148	conv2d_104[0][0]
conv2d_106 (Conv2D)	(None, 50, 50, 4)	148	conv2d_105[0][0]
add_12 (Add)	(None, 50, 50, 4)	0	conv2d_103[0][0] conv2d_106[0][0]
conv2d_107 (Conv2D)	(None, 50, 50, 4)	148	add_12[0][0]
conv2d_108 (Conv2D)	(None, 50, 50, 4)	148	conv2d_107[0][0]
conv2d_109 (Conv2D)	(None, 50, 50, 4)	148	conv2d_108[0][0]
conv2d_110 (Conv2D)	(None, 50, 50, 4)	148	conv2d_109[0][0]
add_13 (Add)	(None, 50, 50, 4)	0	conv2d_107[0][0] conv2d_110[0][0]
flatten_4 (Flatten)	(None, 10000)	0	add_13[0][0]
dense_12 (Dense)	(None, 32)	320032	flatten_4[0][0]
dense_13 (Dense)	(None, 16)	528	dense_12[0][0]
dense_14 (Dense)	(None, 2)	34	dense_13[0][0]

Total params: 328,254
 Trainable params: 328,254
 Non-trainable params: 0

```

In [27]: hist_cnn4 = model.fit(X_train,
                                y_train,
                                batch_size=batch_size,
                                epochs=epochs,
                                verbose=1,
                                validation_data=(X_val,y_val),
                                class_weight = class_weights
                                )

```

Train on 47888 samples, validate on 11973 samples

```

Epoch 1/10
47888/47888 [=====] - 45s 930us/step - loss: 0.5096 - acc: 0.7569 - f
Epoch 2/10
47888/47888 [=====] - 39s 823us/step - loss: 0.4476 - acc: 0.7992 - f
Epoch 3/10
47888/47888 [=====] - 40s 826us/step - loss: 0.4209 - acc: 0.8135 - f
Epoch 4/10
47888/47888 [=====] - 40s 838us/step - loss: 0.4016 - acc: 0.8226 - f
Epoch 5/10
47888/47888 [=====] - 40s 834us/step - loss: 0.3925 - acc: 0.8266 - f
Epoch 6/10
47888/47888 [=====] - 39s 825us/step - loss: 0.3845 - acc: 0.8302 - f
Epoch 7/10
47888/47888 [=====] - 40s 827us/step - loss: 0.3772 - acc: 0.8335 - f
Epoch 8/10
47888/47888 [=====] - 40s 826us/step - loss: 0.3738 - acc: 0.8352 - f
Epoch 9/10
47888/47888 [=====] - 40s 828us/step - loss: 0.3610 - acc: 0.8405 - f
Epoch 10/10
47888/47888 [=====] - 40s 827us/step - loss: 0.3569 - acc: 0.8421 - f

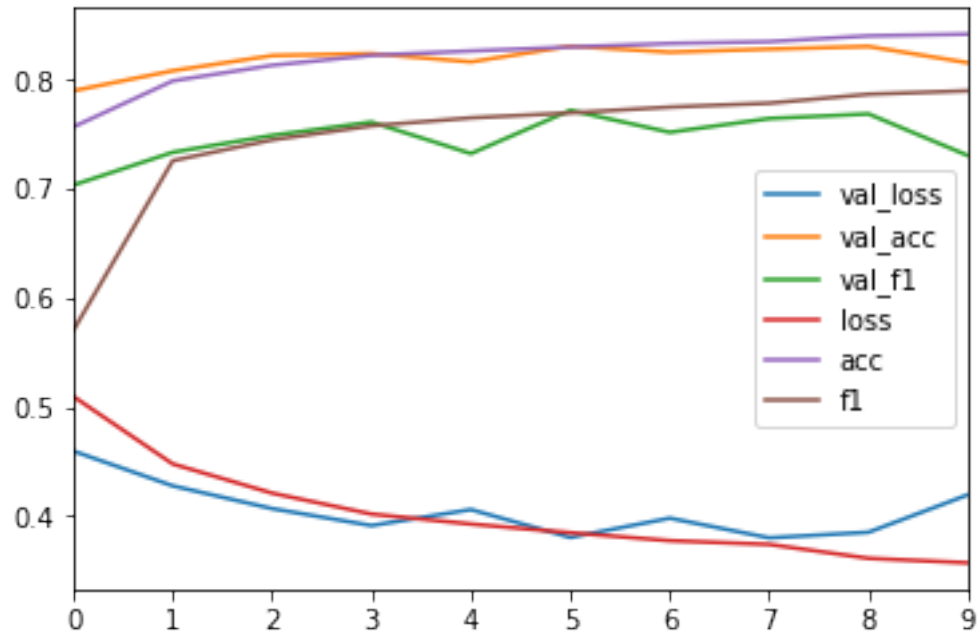
```

```
In [28]: model.evaluate(X_test, y_test)
```

```
14966/14966 [=====] - 3s 224us/step
```

```
Out[28]: [0.4136357147330733, 0.8196578912599256, 0.7326452597153309]
```

```
In [29]: # visualize
_ = pd.DataFrame(hist_cnn4.history).plot()
```

6 Summary

In this final section, we began by building a very deep model with 52 convolutional layers and no residual connections. This ultimately proved to be very ineffective, as the model was too deep to properly learn the data, as evidenced by the training set accuracy and F1 scores of 0.73 and 0.67, respectively. This was almost below our very basic network that we constructed in task 3.1.

For the second part of the task, we added residual connections between every 4 convolutional layers, which turned out to be very effective. The test set performance increased to our best model yet, with accuracy and F1 scores of 0.82 and 0.73, respectively.