

1. Methodology

(1) Classifier:

(a) Model Structure:

- (i) Structure of classifier is basically the same as the sample code , except that we add one more hidden layer.(See red pen marked above)

```
#train
model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3), padding='same', activation='relu', input_shape=(imheight, imwidth, 1)))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(64, kernel_size=(3, 3), padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
#####
model.add(Conv2D(32, kernel_size=(3, 3), padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
#####
model.add(Dropout(0.2))
model.add(Flatten())
model.add(Dense(680, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))
model.summary()
```

(b) Optimizer:

- (i) We also change the default settings of adam optimizer , change the original learning rate from 0.001 to 0.002 , which speeds up the learning process. (beta values are the same as default)
- (ii) Moreover , we increase batch size to 64 which gives us better performance and set the argument shuffle to be true which randomly reorders the samples before each epoch. Also , we abort early stopping because early stopping activates when validation error goes up(similar to preventing overfitting) . But we don't know whether it is because of leaving the local optimal or not. Finally , we set epoch 15(sample code is 22 and we found it is overfitting).

```
reduceLRonPlat = ReduceLRonPlateau(monitor='val_loss', factor=0.5, patience=3,
                                   verbose=1, mode='auto', min_delta=0.005, cooldown=5, min_lr=0.0001)
earlystop = EarlyStopping(monitor='val_top_3_accuracy', mode='max', patience=5)
# callbacks = [reduceLRonPlat, earlystop]
callbacks = [reduceLRonPlat]
#0.001->0.002
adam = keras.optimizers.Adam(lr=0.002, beta_1=0.9, beta_2=0.999, epsilon=None, decay=0.0, amsgrad=False)
model.compile(loss='categorical_crossentropy',
              optimizer=adam,
              metrics=['accuracy', top_3_accuracy])

model.fit(x=X_train, y=y_train,
        #####
        #32->64
        batch_size = 64,
        #####
        epochs = 15,
        #####
        validation_data = (X_val, y_val),
        #####
        shuffle=True,
        #####
        callbacks = callbacks,
        verbose = 1)
```

(2) Generator:

(a) DCGAN :

- (i) We use the model of DCGAN on github (by reference).
- (ii) We alter the model to let image with size of 64*64 to fit in.
- (iii) We decrease the parameter of Dropout to maintain the information of each image.
- (iv) We decrease the learning rate of Generator in order to enhance the accuracy and avoid local minimum.
- (v) We Increase the learning rate of Discriminator to accelerate the training.

2. Evaluation & Test Result

(1) Classifier

(a) Use the test case provided by TA to evaluate the result.

- (i) Accuracy: 97%
- (ii) Test Case: 40/41

```
[7] 1 test = pd.read_csv('./drive/My Drive/input/demo.csv')[['drawing']]
    2 imagebag = bag.from_sequence(test.drawing.values).map(draw_it)
    3 testarray = np.array(imagebag.compute())
    4 testarray = np.reshape(testarray, (testarray.shape[0], imheight, imwidth, 1))
    5 # model = load_model('./drive/My Drive/output/model/classifier.h5')
    6 testpreds = model.predict(testarray, verbose=0)
    7 ttvs = np.argsort(-testpreds)
    8 for idx in ttvs[:,0,1,2]:
    9     print(numstonames[idx[0]])
    10     # print(numstonames[idx[1]])
    11     # print(numstonames[idx[2]])
    12     print('-----')

bee
-----
cactus
-----
banana
-----
fork
-----
wine_bottle
-----

Testing Case

[9] 1 #test
    2 test = pd.read_csv('./drive/My Drive/input/test.csv')[['drawing']]
    3 imagebag = bag.from_sequence(test.drawing.values).map(draw_it)
    4 testarray = np.array(imagebag.compute())
    5 testarray = np.reshape(testarray, (testarray.shape[0], imheight, imwidth, 1))
    6 # model = load_model('./drive/My Drive/output/model/classifier.h5')
    7 testpreds = model.predict(testarray, verbose=0)
    8 ttvs = np.argsort(-testpreds)
    9
    10 # for idx in ttvs[:,0,1,2]:
    11     # print(numstonames[idx[0]])
    12     # print(numstonames[idx[1]])
    13     # print(numstonames[idx[2]])
    14     # print('-----')
    15
    16 predict_label = [numstonames[ttvs[i][0]] for i in range(ttvs.shape[0])]
    17 test['word'] = predict_label
    18 test.to_csv('./drive/My Drive/output/output.csv')
```

```
10] 1 test_ans = pd.read_csv('./drive/My Drive/input/test_ans.csv', index_col=0)
    2 # print(test_ans['word'])
```

(2) Generator

- (a) Save the model : we alter the proper amount of image and epoch and batch size, than save model.
- (b) Test: we randomly generate 100 images and feed our classifier, than compare the result.



3. Demo Result

(1) Classifier

(a) Result:

- (i) Test Case: 36/40
- (ii) Accuracy : 90%

(2) Generator

(a) Result:

- (i) Test Case: 100/100
- (ii) Accuracy : 100%

4. Discussion & Conclusion

(1) Classifier

- (a) Indistinguishable test case: we are confused about the result of our classifier, and eventually we found several ambiguous images
- (b) Overfitting : Cancel Early Stopping

(2) Generator

- (a) During training process of GAN , we save the generator every 1 ~ 3 epochs , and feed the generator into the classifier to perceive how many epochs the GAN has the best performance.
- (b) Our classifier will list three most likely labels , we will use this to determine whether further training does better.
- (c) Conclusion:
 - (i) Easy image label(e.g. hand) → Every doodle drawing game players can draw perfectly(high quality data) -->increase data size to 200000
 - (ii) Difficult label(e.g. raccoon) → Many low quality drawings -->decrease data size to 100000

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